# Geographical Refinement of Nitrogen Fertiliser Management in Irish Grasslands: A Model Based Assessment

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## Glossary

4RNS: 4R Nutrient Stewardship

AMT: Ammonium Transporters

ASEAN: Association of Southeast Asian Nations

AUC: Area Under Curve

B: boron (B)

BD: Bulk Density

BNF: Biological N Fixation

C: Carbon

$Ca(NO_3)_2$: Calcium Nitrate

Ca: Calcium

$CaCO_3$: Calcium Carbonate

CAN: Calcium Ammonium Nitrate

CAP: Common Agricultural Policy

CEC: Cation Exchange Capacity

$CH_4$: Methane

Cl: Chlorine

$CO(NH_2)_2$: Urea

$CO_2$: Carbon Dioxide

Cu: Copper

DayCent: Daily Time-step Version of the CENTURY model

DCD: Dicyandiamide

DM: Dry Matter

DNDC: DeNitrification DeComposition

DNRA: Dissimilatory Nitrate Reduction to Ammonium

DON: Dissolved Organic Nitrogen

ECOSSE: Estimation of Carbon in Organic Soils – Sequestration and Emissions

EPA: Environmental Protection Agency

EPA: Irish Environmental Protection Agency

EPIC: Environmental Policy Integrated Climate

EU: European Union

FC: Field Capacity

Fe: Iron

FYM: Farmyard Manure

GAP: Good Agricultural Practices

GDP: Gross Domestic Product

GHG: Greenhouse Gas

GOGAT: GS/glutamine-2-oxoglutarate Aminotransferase Isoenzyme Cycle

GRA: Global Research Alliance

H: Hydrogen

$H^+$: Hydrogen Ion

$H_2O$: Water

$H_2S$: Hydrogen Sulphide

$HNO_3$: Nitric Acid used

IPCC: Intergovernmental Panel on Climate Change

Irish SIS: Irish Soil Information System

JC: Johnstown Castle

JCL: Loam Soil at Johnstown Castle

JCSL: Sandy Loam Soil at Johnstown Castle

K: Potassium

KaN: Koch Advanced Nitrogen

LU: Livestock Unit

MAE: Mean Absolute Error

MAGIC: Model for Acidification of Groundwater In Catchments

Mg: Magnesium

MIP: Maleic Itaconic Acid Copolymer

Mn: Manganese

Mo: Molybdenum

MoSt GG model: Moorepark St Gilles Grass Growth Model

MP: Moorepark

N: Nitrogen

N: Nitrogen

$N_2O$: Nitrous Oxide

NAG: N-acetyl Glucosaminidase

$NaNO_3$: Sodium Nitrate

NAP: National Action Programme

NBPT: N-(n-butyl) Thiophosphoric Triamide

$NH_3$: Ammonia

$NH_4^+$: Ammonium

$NH_4Cl$: Ammonium Chloride

$NH_4HCO_3$: Ammonium Bicarbonate

$NH_4NO_3$: Ammonium Nitrate

$NH_4OH$: Ammonium Hydroxide

$(NH_4)_2CO_3$: Ammonium Carbonate

$(NH_4)_2SO_4$: Ammonium Sulphate

Ni: Nickel

NMP: Nutrient Management Plan

NO: Nitric Oxide

$NO_2^-$: Nitrite

$NO_3^-$: Nitrate

NUE: Nitrogen Use Efficiency

O: Oxygen

OFAT: One Factor at a Time

$OH^-$: Hydroxyl Ion

P: Phosphorus

PBI: PastureBase Ireland

PD: Particle Density

PTF: Pedotransfer Functions

RD: Relative Deviation

RMSE: Root Mean Square Error

S: Sulphur

SAARC: South Asian Association for Regional Cooperation

SDG: Sustainable Development Goals

SI: Sensitivity Index

SMART2: Simulation Model for Acidification's Regional Trends

SMD: Soil Moisture Deficits

$SO_2$: Sulphur Dioxide

SOC: Soil Organic Carbon

SOM: Soil Organic Matter

TDD: Thermal degree days for maturity

UAS 38%: Urea-Ammonium Sulphate (38% Nitrogen)

UN: United Nations

USA: United States of America

VOC: Volatile Organic Compound

WFPS: Water Filled Pore Spaces

WHC: Water Holding Capacity

WHCNS: Water Heat Carbon Nitrogen Simulator

WP: Wilting Point

Zn: Zinc

# Abstract

Plant available nitrogen (N), commonly applied in agricultural soils through the use of inorganic and organic fertilisers, when surpasses the N requirement to maintain a targeted crop yield, is lost from the soil into the environment where it has negative impacts, including – climate change, ozone layer depletion, air and ground water pollution, eutrophication of water bodies, acidification of soil and water etc. The '4R of Nutrient Stewardship' (4RNS), promotes the application of fertilisers at the *right time, right place, right rate* and from the *right source* - to meet a targeted yield, seeking to prevent surplus N supply. Process-oriented biogeochemical models can help to investigate and identify the potential of incorporating spatially explicit information into N management plans to achieve 4RNS objectives, enabling simulated yield and N loss via different pathways to be estimated, while explicitly accounting for soil and atmospheric variables, management and their impact on nutrient dynamics. In this research we investigate the scope of the DNDC (*DeNitrification DeComposition*) model to inform more geographically refined N management plans, for intensively managed Irish grasslands that are currently managed by aspatial N management strategies at farm and national level. A score of 20 % or less relative deviation of estimated annual yield and N loss was used as a benchmark of deciding reliability of model performance, while tools like mean absolute error, root mean square error and correlation was applied to compare the model performance at a daily scale with respect to existing studies, as required. Our study showed that the DNDC model reliably estimates site-specific grass growth rate and annual yield when the correct parameterisations for the crop phenology and local background atmospheric conditions are accounted for within the model. The model performs well when site-specific soil and management inputs are used, as well as for more generalised inputs - relevant for sites with limited availability of site-specific information. However, to generate reliable annual estimates of both yield and N loss via different pathways, it is necessary to include site-specific soil inputs including water filled pore spaces (WFPS) at field capacity (FC) and wilting point (WP). At a daily scale, the correlation between available measured and estimated N loss was poor. However, the errors at daily scale and relative deviation at annual scale were lower in comparison to existing results published. A scenario analysis showed that key environmental variables explaining spatial variation of nitrate ($NO_3^-$) leaching varies with the annual N application rate. Whereas the key variables relevant for regulating annual yield and annual N loss through ammonia ($NH_3$) volatilisation and nitrous oxide ($N_2O$) emissions, identified through one factor at a time sensitivity analysis (with categorising output on the basis of sensitivity index of greater than 10 % as sensitive, between 0.1 % to 10 % as potentially sensitive and less than 0.1 % as not sensitive), relevant to develop

more simplified and robust models for site-specific N management, were – soil texture and clay content, soil organic carbon (SOC), bulk density (BD), pH, stocking rate and annual N fertiliser application, annual rainfall and average annual temperature. Finally, this work also sought to identify if a robust application of DNDC is possible to reliably simulate spatial variation of grass yield and N loss - when default inputs are used for non-mandatory soil and atmospheric variables, while the model is parameterised for crop phenology of perennial ryegrass. This study showed that such application is only limited for estimation of spatial variation of yield and $NO_3^-$ leaching – while yield itself is an indicator of potential $N_2O$ emissions.

# 1. Introduction

## 1.1. Agriculture for food and its future

Managing for optimum agricultural productivity, that is the ratio of agricultural output generated in an agricultural management unit to the inputs used, is important for achieving optimum food production and generating farm income and economic growth. Abiotic stresses caused by soil and climatic factors pose challenges to attaining the optimum agricultural productivity (Christensen *et al*., 1964; Gollin, 2010; Nyong'a *et al*.,2019; Srivastava *et al*., 2016). This is set within the context of an increasing global demand for food, which is projected to increase by 50-60% by 2050 in comparison to 2019 (Falcon *et al*., 2022). This can largely be attributed to an increase in global population and a rise in per capita income (Fukase and Martin, 2020). The intensification of agriculture, to increase the productivity of crops in an agricultural landscape, is driven by several factors. One, is the farmer's aim to achieve economic prosperity through increased production, although, access to land for agriculture may be a limiting factor (Rudel *et al*., 2009). A second factor is the slower rate of expansion of agricultural land to meet the global increase in demand for food and protein intake (Rudel *et al*., 2009), driven by the rapid increase in population, per capita income and gross domestic product (GDP) (Falcon *et al*., 2022; Fukase and Martin, 2020). Conventional agricultural soil management practices have heretofore led to widespread degradation of soil health and quality (Bedolla-Rivera *et al*., 2023), particularly in the global south. This global decline in soil fertility and increased soil degradation will require increased efforts towards intensification on the available fertile landscapes (Jie *et al*., 2002; Rudel *et al*., 2009) resulting in potential further degradation of already degraded soils (Kopittke *et al*., 2019). Such loss of soil fertility negatively impacts crop yield, ecosystems and ecosystem functioning, biodiversity and human health, through pollution and a reduction in ecosystem services provided by healthy soils (Cheng *et al*., 2021; Giltrap *et al*., 2021; Issaka and Ashraf, 2017; Siciliano *et al*., 2014).

Maintaining soil fertility to optimise agricultural productivity and to reduce the negative impacts of agricultural intensification has become a key focus area for many global and regional policies which aim to achieve more sustainable agriculture and to maintain or improve soil health. Aims for retaining optimum soil physicochemical properties is embedded within many of the sustainable development goals (SDG) of the United Nations (UN) under Agenda 2030. These include food security (SDGs 2 and 6), food safety (SDG 3), urban development (SDG 11), land-based nutrient pollution of the seas (SDG 14), sustainability of terrestrial ecosystem services (SDG 15) and mitigating and adapting to climate change (SDG 13) (Tóth *et al*., 2018). Targets to achieving these goals at international and national levels have resulted in the development and implementation of more sustainable land use and management policies and practices around soil quality and target a reduction in negative environmental impacts of intensive agriculture. Examples of this include the European Green Deal and Farm to Fork Strategy and the 18$^{th}$ goal of the SAARC (South Asian Association for Regional Cooperation) nations etc. (EC, 2020 and 2020a; ISACPA, 2007).

Fertiliser applications to maintain plant available nutrient supply is one of the most important inputs that regulates agricultural productivity (Chaddad, 2016). At the same time, loss of nutrients from soil can have several negative consequences on crop productivity and the wider environment (Gregory *et al*., 2002; Tan *et al*., 2005; Jones *et al*., 2013a). Thus, the sustainable utilisation of soil nutrients and preventing their loss have become key goals of many international sustainable agricultural policies. For example, the Farm to Fork Strategy within the European Green Deal of European Union (EU) aims to reduce nutrient loss from agriculture by 50 % and reduce chemical fertiliser inputs by 20 % while maintaining optimal soil fertility conditions, by 2030. Additionally, the Green Deal also established a targeted reduction of 40 % in GHG emissions compared to the baseline year of 1990 (EC, 2020 and 2020a). The ASEAN (Association of Southeast Asian Nations) nations have developed stringent guidelines for sustainable management of soil and nutrients to improve and maintain soil health and crop productivity, through an integrated approach accounting for the variability of soil, water, nutrients, crop and climate conditions (Nyi *et al*., 2017). The SAARC (South Asian Association for Regional Cooperation) nations have set developmental goals, among which the 18$^{th}$ goal aims to maintain acceptable soil and water quality in the member nations (ISACPA, 2007). The member states within such groups are developing and implementing policies, capacity building and coordinated monitoring strategies nationally and through international cooperation, with the aim of contributing to achieving global food security, maintain good soil health and improve environmental conditions, while at the same time delivering economic prosperity in a more sustainable way (O'Mahony, 2007; Sarker *et al*., 2018).

The increased use of artificial nitrogen (N) fertiliser for agricultural intensification arose mainly to meet the need for high N input beyond the natural supply of N in terrestrial ecosystems in response to increased productivity targets, especially for higher yield crop varieties introduced under the Green Revolution schemes (Matson *et al*, 1997). Chemical N fertiliser input is responsible for the production of around 50 % of the global calorie intake and 12 % of livestock feed (Smerald *et al*., 2023). Globally, the intensification of agricultural has increased the utilisation of N fertiliser, and this trend has been highlighted in several studies. In 2016, N fertilisers accounted for 60 % of the global fertiliser inputs (EC, 2019). Adalibieke *et al*. (2023) showed that between 2011 and 2020, the global average N supply was highest for manure and crop residue (36 kg N/ha), urea (31.3 kg N/ha), compound fertilisers (e.g. ammonium phosphate, NK compounds, NPK compounds) (17.9 kg N/ha), nitrate fertilisers (e.g. ammonium nitrate and calcium ammonium nitrate (CAN)) (5.6 kg N/ha), anhydrous ammonia and N solutions (5.6 kg N/ha) and other synthetic N fertilisers (4.5 kg N/ha). Use of N fertilisers globally is expected to be 225–250 Tg N per year by 2050 up from 116 Tg N in 2016 (Prasad and Shivay, 2019).

### 1.2. Nitrogen: a key nutrient to maintain agricultural productivity

Nitrogen (N) is one of the essential nutrients taken up by plants and is particularly important for amino acid formation within the plant; the basic unit that forms protein through polymerisation. N is a nutrient required for maintaining growth, leaf area-expansion and biomass-yield production, as it is an important structural element for formation of amino acids, chlorophyll, nucleic acids, ATP and phyto-hormones (Anas *et al*., 2020). Plants uptake N from soil in the form of ammonium ($NH_4^+$) and nitrate ($NO_3^-$) for amino acid formation which takes places mostly in leaves and to some extent in the roots (Novoa and Loomis, 1981). N deficiency and toxicity can both impact plant growth and plant physiological conditions (Figure 1.1) (Mihai *et al*., 2023). A lack of amino acid formation due to N deficient conditions can lead to reduced crop growth through the reduction of protein formation (Maia *et al*., 2020), along with reductions in branching and in leaf surface area (Deepika *et al*., 2023). N is also important in plants for the formation of chlorophyll. Thus, deficiency of N in plants leads to yellowing of the leaves (Tucker, 2015), reduced root growth, lateral root initiation and early leaf senescence, while excess N can result in the elongation of lateral roots (Kant *et al*., 2010).

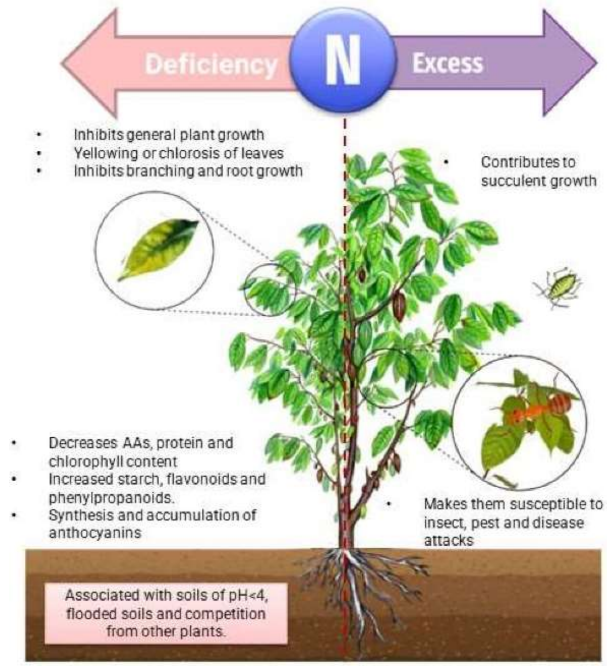


**Figure 1.1** Nitrogen (N) deficiency and toxicity symptoms in plants (Source: Mihai *et al*., 2023)

### *1.2.1. Drivers and impacts of agricultural nitrogen management*

Plant available N, which is fixed in the soil from the atmosphere through biological N fixation (BNF), is also supplied through synthetic N fertilisers to achieve increased crop yield and quality, and can also contribute to maintaining soil fertility in the longer term under proper management practices (Ladha *et al*., 2020). Excess N application leads to the loss of reactive N from agricultural soil to the atmosphere and water courses, depending on the form of loss. The loss of N from agricultural soil negatively impacts the wider environment and ecosystems, such as - increasing air pollution, climate change, depletion of the ozone layer (mainly by the gaseous forms of N loss), while ground water contamination and eutrophication occur when N is lost into water (Ladha *et al*., 2020). Eutrophication also occurs from atmospheric deposition of N (Stark and Richards, 2008). Eickhout *et al*. (2006) indicated that the increased loss of N from agricultural soil due to increased N fertiliser application has become a prominent trend since the 1950s.

Shi *et al*. (2024) found that inorganic and organic N fertiliser application increases the aboveground biomass in grassland by around 42 % and 56 % respectively. They also identified that inorganic N fertiliser reduces species richness, which remains unaffected under organic N fertiliser application. Nutrient use efficiency, defined as the crop yield per unit of applied fertiliser, is typically used to relate farm productivity in terms of agricultural output with respect to key plant nutrient inputs (Sarkar and Baishya, 2017). Baligar *et al*. (2007) indicated that greater nutrient use efficiency leads to greater nutrient uptake and utilisation of the applied nutrient by the crop, which is also an indicator of the potential nutrient loss or fixation into the ecosystems and corresponding potential economic loss. According to a more recent report by Ritchie (2021), only 35 % of the globally applied N fertiliser (115 million tonnes) is actually utilised in crop production with the remaining 65 % as surplus N - that is lost to the environment.

The loss of surplus plant available N from agricultural soil can occur in gaseous forms into the atmosphere through ammonia ($NH_3$) volatilisation or as oxides of N produced through denitrification, including the greenhouse gas (GHG) nitrous oxide ($N_2O$). Whereas, N loss from soil in soluble form occurs through $NO_3^-$ leaching and runoff and accumulates in ground water and surface water bodies (Feng *et al*., 2024; Giordano *et al*., 2021; Jiao et al., 2004; Lehmann and Schroth, 2002). Emitted oxides of N and volatilised $NH_3$ contributes to increased particulate matter concentrations and ozone formation in the troposphere, which are detrimental to human health, while emitted $N_2O$ contributes to the depletion of the stratospheric ozone layer as well as to climate change (de Vries, W., 2021; Pittelkow *et al*., 2013). N lost into the atmosphere can ultimately contribute to soil acidification (Stark and Richards, 2008). $NH_3$ volatilisation indirectly contributes to the formation of $N_2O$ in the atmosphere. High $NH_3$ volatilisation may also contribute to increased $N_2O$ emissions from soil, mainly through wet deposition (Burchill *et al*., 2017; Ferm, 1998). Eutrophication caused of water bodies disrupts the aquatic ecosystems and can result in hypoxic or anoxic conditions leading to the death of fish and other organisms (Stark and Richards, 2008). $NO_3^-$ consumed by humans through drinking water has been linked to health issues like Blue-Baby syndrome and is a carcinogenic substance (Giordano *et al*., 2021).

### *1.2.2. Managing nitrogen loss: EU Policy Direction in a Global Context*

From a global policy perspective, the management of N in agricultural soils is vital due to its potential impacts on the environment and human health. The reduction of N to limit the eutrophication of water bodies, reduction of $NO_3^-$ contamination of drinking water and emissions of $N_2O$ (Liu *et al*., 2008; Stark and Richards, 2008) are important focal points for policy development, with an increasing focus on more targeted implementation strategies. A number of global strategies provide guidelines to explore and identify the key sources of pollution from agriculture. The Intergovernmental Panel on Climate Change (IPCC) provides guidelines to quantify emissions from different land uses, including $N_2O$ emissions from agricultural land use generated from the burning of biomass, emissions from soil and from the application of plant available N (IPCC, 2000). The Tier 1 approach is an accounting based approach at country level to quantify national GHG emissions using globally relevant or default emission factors, whereas the Tier 2 approach seeks to employ more country specific factors (IPCC, 2000). Tier 3, considered the gold standard, is a model based approach which requires the use of verified models and geographically refined information to estimate GHG emissions from land use practices including agriculture (Buendia *et al*., 2019).

Numerous international policies form a basis to develop and implement good agricultural practices (GAP) at farm level for economic, social and environmental sustainability (FAO, 2016). Lal *et al*. (2021) indicated that to achieve the SDG 6 of the United Nations (to improve and maintain good water quality) it is important to control the loss of N through water as $NO_3^-$. Kanter and Brownlie (2019) indicated that within the aims of SDG 12, which focuses on the responsible production and consumption of food, the sustainable management of N is important for reducing emissions of $N_2O$. The sustainable management of N for reducing the susceptibility of water bodies to eutrophication was a key focus of both the OSPAR and HELCOM Conventions, while the reduction of N from agriculture also enables nations to address climate goals established under SDG 13 and the corresponding Paris Climate Agreement. Kanter and Brownlie (2019) further highlighted that the sustainable management of N in agriculture, through practices like crop residue recycling, cultivating cover crops, precision agriculture, improved livestock feeding, and manure management could contribute to achieving SDGs 2, 3, 6, 14 and 15. They indicate that this would ensue through increased agricultural productivity, reducing pollution through nutrient loss and improved conservation of water quality as well as aquatic and terrestrial ecosystems.

N use and loss in the European Union (EU) is consistent with that of the global scale. According to the report 'Fertilisers in the EU' by the European Commission (2019a), between 2005 to 2017, N accounted for two thirds of all the major nutrient inputs in agricultural soils in the EU. As outlined in the report, the EU imported more than 3 million tons of N fertilisers in 2015, whereas imports of N based products including $NH_3$ were around 6 million tons annually. van Grinsven *et al*. (2013) in their analysis, suggested that the economic benefits of N application in agriculture (€20−80 billion/year) was lower than the cost associated with pollution caused by agricultural N (€35−230 billion/year) in the EU. Europe saw a reduction in $N_2O$ emissions of 21 % between 1990 to 2010, which was primarily driven by the Nitrates Directives (Tian *et al*., 2020). Schulte-Uebbing and de Vries (2021) highlighted that in 2010, approximately 66 %, 74 % and 18 % of area across the EU had faced greater than threshold $NH_3$ volatilisation, N runoff through surface water and $NO_3^-$ leaching respectively. Livestock management is the key cause of 81 % of N contamination of water and 87 % of $NH_3$ volatilisation in EU, while the cost of N loss incurred by the EU is around €70 billion per year (EC, n.d.). Moreover, farmers in the EU face the challenge of price increases in fertilisers, particularly since 2005, at the rate of 3 % annually (EC, 2019a), that further compounds the negative economic impact of N loss from agricultural soil.

EU policies have been developed in line with the global ambition to achieve more sustainable agriculture and have also focused on developing and improving more efficient N management practices. The move towards more sustainable agriculture in the EU is embedded within the European Green Deal. The Farm to Fork strategy seeks to reduce the loss of nutrients from soil by 50% by 2030 through reducing fertiliser inputs by at least 20% within this time frame to support the goals set within the European Green Deal and to achieve climate neutrality across the EU by 2050 (DGE, EC, 2022; EC, 2019). This highlights N use as a key area of concern as the most widely used fertiliser in terms of volume (EC, 2019a), and its documented negative impacts on water, air, climate, biodiversity and human health (Abascal *et al*., 2022; Garnier *et al*., 2020; Malone and Newton, 2020; Tian *et al*., 2020).

The Common Agricultural Policy (CAP), developed in accordance with the Farm to Fork Strategy, specifically targets a reduction in N pollution of air, soil and water from agriculture to meet the goals of the European Green Deal (EC, 2020). The post-2020 CAP also targets reduced $N_2O$ emissions from agriculture while maintaining productivity, with the emphasis on sustainable N fertiliser management plans (Wrzaszcz and Prandecki, 2020). The EU CAP 2023-2027 aims to reduce nutrient loss to support the goals of the Farm to Fork Strategy and to reduce $N_2O$ emissions and $NH_3$ volatilisation. Simultaneously, the CAP aims to increase nutrient use efficiency, maintain water quality, and promote the cultivation of N-fixing crops (EC, 2023). The EU Nitrates Directive aims to engage member states to monitor $NO_3^-$ pollution of freshwater and ground water from agriculture and identify vulnerable zones to implement action plans to reduce the $NO_3^-$ pollution in such sites through good agricultural practices (GAP) (EPC, 1991).

### 1.3. 4R Nutrient Stewardship for sustainability

4R Nutrient Stewardship (4RNS) is based on determining the *right source, right rate, right time, and right place* and is a globally applicable strategy to develop more focused nutrient management plans (Fixen, 2020). The goals of 4RNS is to maintain profitability at farm level while reducing nutrient losses (Bryla, 2020). The integration of the proper timing and form of nutrient applications, along with establishing an optimum application of fertiliser for a specific site, are central to developing nutrient management plans that match the goals of 4RNS (Sarmah *et al*., 2014). Thus, nutrient applications that consider the timing and location could help to ensure the desired nutrient uptake by crops, identified through investigations of nutrient uptake dynamics, accounting for site specific characteristics and the nutrient status and non-nutrient physicochemical properties of soil, all of which would contribute to achieving the goals of 4RNS (Varallyay, 1994). The spatial and temporal refinement of nutrient management plans requires better understanding of the site-specific nutrient requirements of a crop based on the variability in soil and micro-climatic conditions that occur within the field (Patil, 2009). Such refinement may not only be dependent on the crop's nutrient requirement, but can be further improved by better understanding the susceptibility of nutrient loss, contributing to increasing nutrient use efficiency (Corre *et al*., 2002). This ultimately could lead to reduced nutrient loss from agricultural soil while maintaining agricultural productivity (Hedley, 2014) and profitability. This aligns with the objectives of GAP (FAO, 2016). In addition to maintaining productivity and economic viability, reducing nutrient loss would directly support efforts to maintain soil health by reducing the overexploitation of soil resources that can occur with uniform management practices performed under conventional intensive agriculture (Sarkar *et al*., 2017). This is also relevant for sustainable N management in agricultural soils. Poor N use efficiency (NUE) occurs when management strategies do not account for the impact of variations in weather and spatial variations of the land and soil scape on crop demand for N (Shanahan *et al*., 2008; Wu and Ma, 2015). Geographically refined N management would optimally support more sustainable and economical land management from farm to global scale, leading to reduced input costs associated with volatile fertiliser prices and the negative externalities associated with the overuse of N fertiliser (Diacono *et al*., 2012; UNEP, 2019).

For improved N management in agriculture soils, the impact of soil physicochemical properties, climate, and management on different processes within the N cycle need to be better understood along with the availability and loss of N in soil (Andrade-Linares *et al*., 2021; Liu *et al*, 2021). While the IPCC guidelines provide approaches for monitoring and modelling GHG emissions to identify key sources of GHG emissions (Buendia *et al*., 2019; IPCC, 2000), Tier 3 equivalent nutrient management plans require a combination of similar tools in four stages for establishing good agricultural practices and efficient management at site-specific level (Patil, 2009). It begins with information on yield, soil physicochemical properties, terrain etc. at field scale to identify the specific management zones that characterise the spatial diversity of the field or farm. The characterised management zones are used to explore the requirements of specific management plans. The second step focuses on using process-oriented models ranging from crop simulation models to soil-landscape-crop models, empirically calibrated local conditions, to simulate the potential impact of different management strategies at the scale of management zones to identify the optimum management plans. The third stage involves the implementation of optimum management strategies, followed by a fourth stage which monitors the effects of such strategies at site-level to identify any further requirement of change in strategy (Patil, 2009).

### 1.4. Nitrogen management in grassland: Global relevance and scenario in European Union

Globally, grasslands represent the largest agricultural land use, representing two thirds of the total global landscape under agriculture (Ritchie and Roser, 2019). Liu *et al*. (2022a) classified global grasslands into five main categories - tropical grasslands, Mediterranean grasslands, temperate grasslands, semidesert grasslands and other, unspecific types. They identified key economic and environmental services provided by grasslands, such as the supply of food, water and raw materials; regulation of climate, water flow and soil fertility; waste treatment; conserving genetic diversity of biome among a plethora of other benefits. Bardgett *et al*. (2021) found that 49 % of global grasslands are degraded to some extent, while 5 % are severely degraded (Gang *et al*., 2014). Xu *et al*. (2019) estimated that the supply of N input for grasslands through fertiliser, manure application and deposition accounted for 45 % of the global N production between 2000-2016. They also estimated that organic and inorganic N inputs into grasslands had increased from 15 to 101 Tg N/year between 1860 to 2016. Applied N is susceptible to loss also from soil into the environment in different forms, among which the key N loss pathways prevalent in grasslands are $NH_3$ volatilisation, emissions of $N_2$ and $N_2O$ and N leaching (van Beek *et al*., 2008). Grazed grasslands contribute an estimated 28 % of global $N_2O$ emissions (Rafique *et al*., 2011). $N_2O$ emissions from grasslands under natural conditions are primarily driven by soil textural properties and climate (Yu *et al*., 2022). This is particularly important to achieve climate neutrality (de Vries, 2021) as Dangal *et al*. (2019) estimated that between 1961 and 2014 in both intensively managed grasslands (pasturelands) and extensively managed grasslands (rangelands), global $N_2O$ emissions were mainly driven by the deposition of animal excreta (54 %), manure application (13 %) and fertiliser application (7 %). Yang *et al*. (2023) estimated that globally annual $NH_3$ volatilisation from livestock system increased from 14.7 to 29.8 Tg N/year from 1961 to 2018. Ma *et al*. (2020) estimated that globally, grassland had higher background $NH_3$ volatilisation fluxes when compared to croplands and forest, whereas the emission factor of $NH_3$ volatilisation from fertiliser application was higher for fertilised grasslands than croplands and lower than forestlands, important for negative impacts on soil, air and water quality (Burchill *et al*., 2017; Ferm, 1998; Stark and Richards, 2008). However, Hina *et al*. (2024) showed that grassland soils are usually the least susceptible to $NO_3^-$ leaching in comparison to arable lands under cereals or vegetables. Sustainable management of N also becomes important for achieving 4RNS for grassland which, as indicated by Li *et al*. (2022), has a more important contribution to grassland productivity than P management, the other macro nutrient commonly supplied through fertilisers (Schoenholtz *et al*., 2000).

The primary use of grasslands in the EU is to produce feed stuff to maintain livestock of herbivores and ruminants (Smit *et al*., 2008). Lesschen *et al*. (2014) reported that in the EU, grasslands are broadly classified as – natural, semi natural dry, sclerophillous grazed forests, semi-natural tall-herb humid meadows and mesophile grasslands which can be further classified based on habitat types. Whereas their report also mentioned that the management of "permanent grasslands"; primarily used for forage and fodder without any crop rotation for a minimum of five years. Francksen *et al*. (2022) highlighted that one third of the agricultural landscape across the EU is under permanent grassland management. The areas defined as *Atlantic zone* are the highest grass producing zone and includes North Western Spain, Western France, Ireland, Wales and England, the Benelux countries, the North of Germany and the South Western parts of Norway (Lesschen *et al*., 2014). Schils *et al*. (2022) indicated that the extent of permanent grasslands in the EU is challenged by land use changes associated with the expansion of arable land, while the intensification of management in existing permanent grasslands results in decreased ecosystem services provided by such grasslands – including maintaining biodiversity, climate regulation and water purification.

### 1.5. Grassland under Irish dairy farms

Ireland is one of the highest grass producing countries in Europe with an average estimated productivity of 10 t/ha and situated in the highest grass productivity zone – the Atlantic zone (Lesschen *et al*., 2014). Grasslands in Ireland are an important and cheap resource for fodder and forage, accounting for approximately 92 % of the total agricultural land use (O'Donovan *et al*., 2021). According to a study on grassland cover from 1851 to 2000 by Eaton *et al*. (2008), the area under grassland cover in Ireland increased from 1851 to 1901, followed by a drop until 1960, peaking again in 1970, followed by a period of steady decline until 2000. They indicated that the initial increase of grassland cover was mostly associated with a decrease in arable land, whereas the first decrease in grassland was driven by government policy to increase forest cover. The second increase in grassland area was due to the reclamation of marginal land, whereas the subsequent decrease in area from 1970 to 2000 was due to the expansion of heterogeneous agricultural areas, forestry and urbanisation. In 2018, grasslands accounted for approximately 56 % of the Irish landcover (CSO, 2021).

Traditionally, Irish grasslands, managed for the agriculture-based economy, are primarily used for grazing by farm animals, that generally takes place from early spring to late autumn or for cutting hay or silage for animal feed (Bourke *et al*., 2007; Läpple *et al*., 2012). Creighton *et al*. (2011) observed that for Irish dairy farms the extension of the grazing period can vary according to milk quota, while sward renewals by reseeding were performed on around 2 % of Irish grasslands annually. The cows in dairy farms are typically categorised into three categories of milk production by herd and corresponding nitrogen content in excreta. These are milk production of <=4,500kg, 4,501-6,500 kg and >6,500kg and corresponding potential N content in excreta is 80, 92 and 106 kg/cow/year respectively (DAFM, 2023a).

Mihailescu *et al*. (2015) indicated nutrient use efficiency in Irish grassland based dairy farms for N and P is around 24 % and 71 % respectively. The nutrient use efficiency for P in Ireland is much higher than the general global average (10%), while N use efficiency (NUE) is significantly lower than the corresponding global average of 35 % (Baligar *et al*., 2007; Ritchie, 2021). O'Donovan *et al*. (2021) observed that many Irish dairy farms produce only 50 to 60 % of their potential grass yield, based on a national survey. They indicated that the diversity of productivity in dairy farms across Ireland is mainly driven by variations in soil fertility conditions, stocking rate and grazing management. O'Donovan *et al*. (2021) further suggested that to increase productivity in underperforming farms the focus should be on the improvement of soil fertility and grazing management. However, Mihailescu *et al*. (2014) observed a mean reduction in surplus N by 40 % per hectare between 2009-2011, compared to the levels of 2006, in grasslands under dairy farming, with an increase in NUE to 27 % over the same timeline. They attributed this to the implementation of the GAP regulations that led to the decreased application of chemical N fertilisers and increased use of organic N resources. The primary source of N supply to Irish grassland are inorganic N fertilisers - urea and CAN (calcium ammonium nitrate) (Gebremichael *et al*., 2021), followed by organic sources including farmyard manure and slurry (Mihailescu *et al*., 2014). Perennial ryegrass dominates most of these grasslands, accounting for 95 % of grass seed annually, with legumes, including white clover, being used (4 % of seeds sold annually) as a source of N through biological nitrogen fixation (BNF) (O'Donovan *et al*., 2021).

### *1.5.1. Environmental regulators of the nutrient cycle in Ireland*

Environmental factors, including climate and soil, that interact with management practices to drive the availability, uptake and loss of nutrients, vary across the Irish landscape. Ireland has a temperate maritime climate that supports near year-round grass growth. Mean annual temperature in Ireland typically varies between 8.5°C to 10.8°C, although mean annual temperatures can be higher in coastal regions (Curley et al., 2023, Walsh, 2012) (Figure 1.2). Mean seasonal temperatures are highest in the summer, followed by autumn and spring and lowest in winter. On average, annual rainfall is 1288 mm across the island, but higher in the West and in regions of higher elevations, decreasing towards the east (Figure 1.2). Seasonal variations are also evident in rainfall, with spring and summer being typically the driest seasons and autumn and winter being the wettest (Curley et al., 2023, Walsh, 2012).

The main soil types found in Ireland which, under the broadest level of classification within the Irish Soil Information System, include ombrotrophic peat soils, mineratrophic peat soils, rendzinas, lithosols, alluvial soils, groundwater gleys, surface-water gleys, podzols, brown podzolics, luvisols and brown earths (Creamer *et al*., 2018) (Figure 1.3). According to a national study on topsoil under permanent grasslands, McDonald *et al*. (2014) indicated that Irish grassland soils mainly belong to the USDA textural classifications of loam, clay loam, loamy sand and silt loam soil (Brady & Weil, 2002). However, Abdalla *et al*. (2010) highlighted

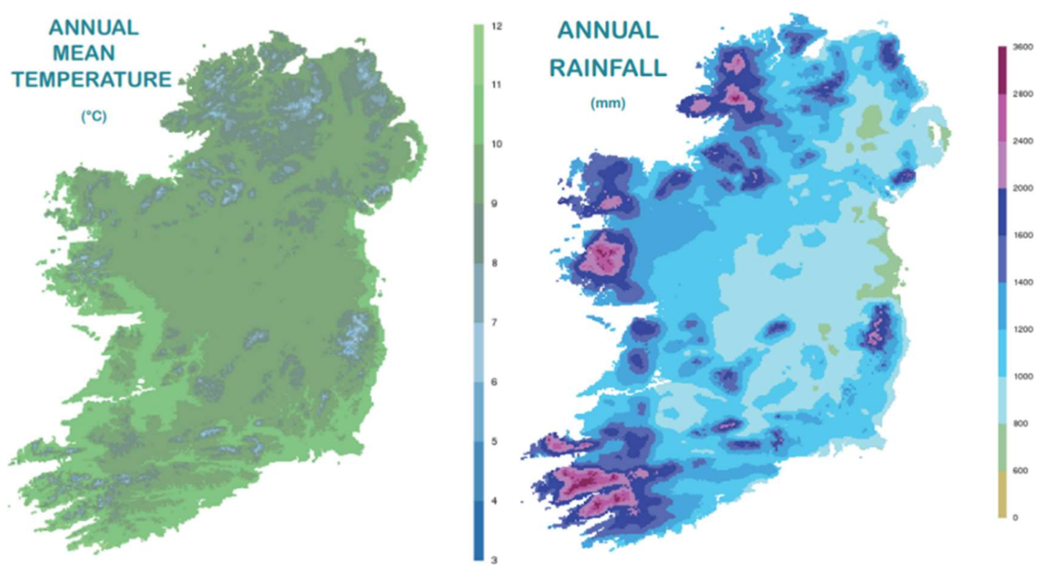


**Figure 1.2** Spatial diversity of climatic conditions across Ireland – (a) mean temperature (left) and (b) rainfall (right) (Source: Walsh, 2012)

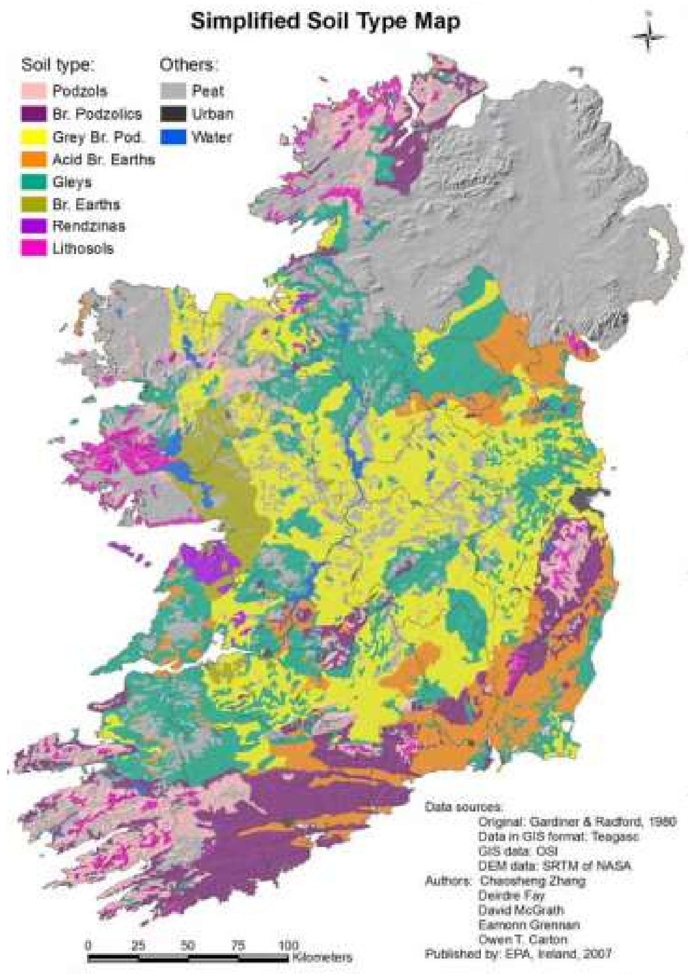


**Figure 1.3** Simplified soil map of Ireland (Source: Fay *et al*., 2007)

the predominance of sandy loam soil, which represent approximately 30 % of Irish soil types. Soils studied by McDonald *et al*. (2014) showed that most grassland soils in Ireland were mineral soils with soil organic matter (SOM) ranging from 6.25 % to <20 %. Only one sample in the analysis undertaken by McDonald *et al*. (2014), from Corduff in County Monaghan (23.45 % SOM), matched the criteria of minimum SOM in organic soil (Renou-Wilson *et al*., 2015). Brogan (1966) found that soil organic carbon (SOC) in Irish pastures varied from 2 % to 17.8 %, without any significant difference in the quality of SOM in terms of humic acid content.

### *1.5.2. Current nitrogen fertiliser advisory approaches*

Irish governmental bodies and research organisations are working in line with global and EU goals to develop strategies aimed at reducing the negative impacts of N loss from agriculture within specific timeframes. For Irish dairy farming, the aim is to reduce the use of chemical N-fertilisers by 20 % from the peak level of 2018 (Teagasc, 2021). Ireland aims to reduce the national $NH_3$ volatilisation, primarily through the management of fertilisers and manure, by 5 % from 2005 levels by 2030. One such ambitious project is 'LowAmmo', implemented in 2013, that primarily focuses on monitoring, modelling and identification of the abatement potential of $NH_3$ volatilisation from Irish farms, mainly caused by animal excreta (Burchill *et al*., 2016). The Climate Action Plan 2023 targets a reduction in $NH_3$ volatilisation, $N_2O$ emissions, eutrophication and water pollution by soluble N, while the Ag Climatise roadmap aims to aid the development of a climate neutral agricultural system in Ireland with particular focus on agricultural $N_2O$ emissions (DAFM, 2021a; DECC, 2023). The Danú Farming Group project in Ireland has successfully shown that maintaining yields while reducing synthetic N fertiliser input and using biological farming principles, in line with the goals of the Climate Action Plan 2023 (DECC, 2023), is achievable. Reducing $N_2O$ emissions from N-fertilisers applied in Ireland is one of the aims of the Global Research Alliance (GRA) Flagship Project, with focuses on identifying the optimum fertiliser type and application strategies at spatial and temporal scales (Teagasc, 2023). The Fifth Nitrates Action Programme 2022-2025 is being implemented with the aim of maintaining/achieving good water quality across Ireland (DHLGH and DAFM, 2022). The current Nitrates Derogation strategy in Ireland has reduced the maximum permissible livestock stocking density from 250kg organic N/ha to 220 kg organic N/ha, applicable from January 1st, 2024 and plans to continue until 2027, with the aim to reduce losses of soluble N from livestock farming (Callaghan, 2023). The strategy limits the stocking rate and N fertiliser application in Irish dairy farms based on banding of the cow herds according to potential N content in their excreta, estimated from milk production (DAFM, 2023a; Teagasc, 2023a) as outlined above (Section 1.5).

O'Donovan *et al*. (2022) highlighted the contribution of research on Irish grassland productivity for the last 60 years. They indicated that these studies have targeted a range of practices associated with grassland management, such as N application to increase dry matter (DM) to support higher livestock unit/ha; the impact of soil type/drainage, N fertiliser application rate, genetic merit of cows, concentrate supplementation and grass species/variety on farm outputs, extension of grazing season on animal performance, replacing chemical fertilisers with forage legumes and reducing loss of applied N fertilisers – have been contributing to improvement of management of Irish grasslands. While there are active national level strategies in Ireland to reduce N loss from agriculture, there are also ambitious plans to increase sustainable agricultural productivity in Ireland, for which improving NUE in Irish dairy farming becomes important. For example, Food Wise 2025 aims to increase primary productivity in Ireland by €10 billion and exports by €19 billion by 2025 from the level of 2015, while maintaining sustainable agricultural practices in line with CAP 2020 (DAFM, 2021). Grasslands management by farmers is supported by systems like PastureBase Ireland (PBI) (that also maintain a corresponding national database), courses like Grass10, farm level Nutrient Management Plan (NMP-Online) based on land parcel data, livestock information and soil analysis results. General knowledge transfer and advice on nutrient management based on stocking rate and nutrient requirements at different phases of grass growth are available to Irish farmers (Hanrahan *et al*., 2017; Maher *et al*., 2021; Wall and Plunkett (eds.), 2020). However, at present, national strategies focused on sustainable N management do not account for the geographical variability of NUE and N loss driven by the interaction of soil, weather and management conditions.

### *1.5.3. Nitrogen pollution in Ireland from agriculture*

The growth of the Irish dairy farming sector presents challenges from which negative environmental impacts arise. For example, the Irish Environmental Protection Agency (EPA) (2022) reported that volatilisation of $NH_3$ increased by 12.4 % from 1990 to 2020. In 2020 alone, agriculture contributed up to 99.4 % of the national $NH_3$ emissions. 90.1 % of the volatilised $NH_3$ in 2020 came from manures applied to soil and from animal excretion during grazing. Consequently, Ireland was unable to comply with the EU Emissions Reduction commitment in 2021 for Ammonia Compliance, with an observed increase of $NH_3$ volatilisation by 1 % in 2021 due to higher livestock numbers and increased use of fertiliser (EPA, 2023). The EPA (n.d.) reported that $N_2O$ emissions in 2022 were 12.3 % lower than the levels of 1990, even though $N_2O$ emissions had increased between 2015 and 2022. The primary reason for the increase in $N_2O$ emissions between 2015 to 2022 was attributed to the expansion of the dairy sector and increase in use of chemical N fertiliser, with 92.9 % of national $N_2O$ emissions associated with agriculture. Despite the framing and implementation of policies to comply with the European Green Deal, Ireland is currently projected to only achieve a 29 % reduction by 2030 according to emissions projections, falling short of the national target of 51 % (EC, n.d.a).

The management of grasslands also pose a threat to human and ecosystem health in Ireland through the contamination of water resources resulting from the accumulation of $NO_3^-$ content in water. $NO_3^-$ concentrations in water was found to be higher than 50 mg/L (more than drinking water standard) in 1 % of the monitoring sites across Ireland (EPA, 2023a). It was higher than 37.5 mg/L and 25 mg/L in 6 % and 20 % of the remaining national monitoring sites respectively, which are considered high for drinking water standards. Moreover, 40% of rivers nationally and

20% of estuarine and coastal water bodies had high $NO_3^-$ concentrations (>above 8 mg/L) (EPA, 2023a; EPA, 2023b), thus increasing the potential of eutrophication (Giordano *et al*., 2021). It has also been identified that in rural Ireland, 85 % of N supplied to catchments are derived from fertilisers applied from agriculture (EPA Catchments Unit, 2021).

The level of accumulation of these N pollutants in the air and water varies across Ireland due to variations in the interactions between the environment and management, which ultimately shapes pollutant distribution. $NO_3^-$ concentration in river water (Figure 1.4a) as well as in ground water (Figure 1.4b) increases along a gradient from west to east. Concentrations of $NO_3^-$ greater than 11.5 mg/l in river water are generally found in rivers in the south-east and southern river catchments, whereas concentrations of $NO_3^-$ in groundwater greater than 25 mg/l are found in the south-east and south-west of Ireland (EPA, 2023b). Doyle *et al*. (2017) outlined that the concentration of $NH_3$ varies spatially from 0.20 μg/m$^3$ to 10.51 μg/m$^3$ in the air, with a general pattern of an increase from the west to the east of Ireland, coinciding with the regions of higher livestock management in the north-east midlands and south-east (Figure 1.5). They also found that the midlands generally have higher $NH_3$ atmospheric concentrations in comparison to western coastal areas, associated with the dominant westerly airflow and absence of $NH_3$ source regions over the ocean.

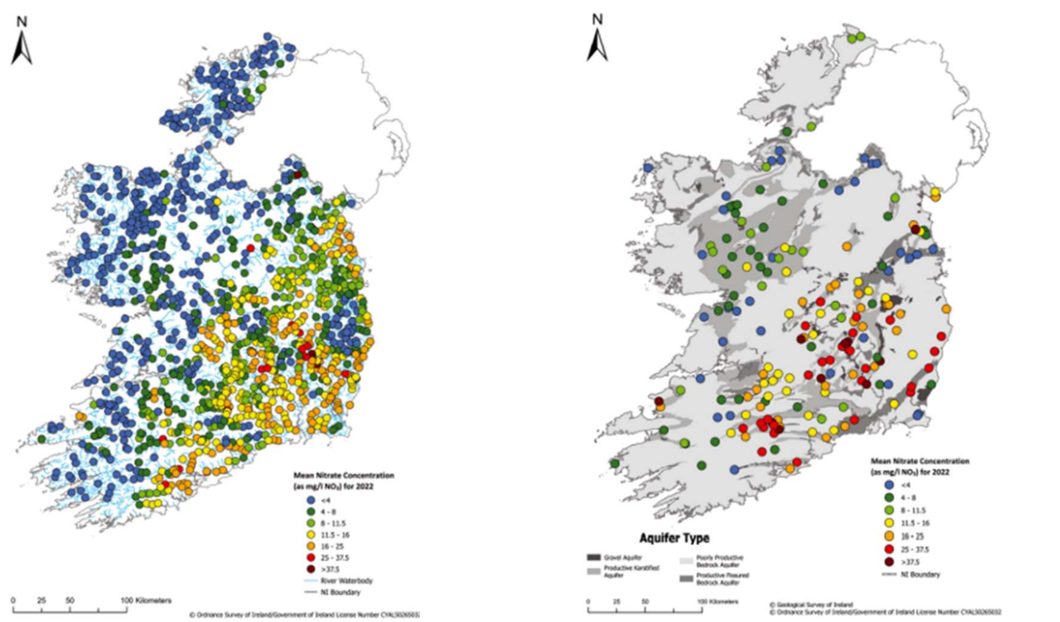


**Figure 1.4** Pattern of $NO_3^-$ concentration in (a) river (left) and (b) ground water (right) across the Republic of Ireland (Source: EPA, 2023b)

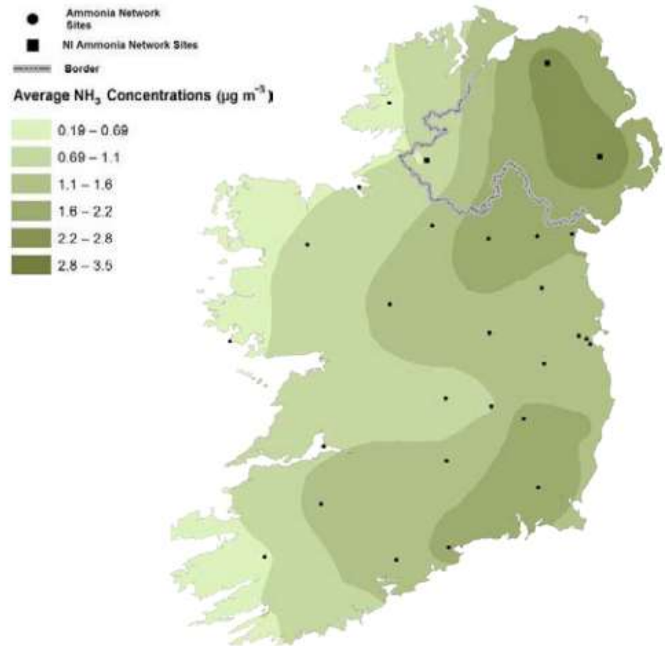


**Figure 1.5** Spatial pattern of ammonia concentration (µg/m$^3$) in air over the island of Ireland (Source: Doyle *et al*., 2017)

### *1.5.4. Relevance of sustainable nitrogen management for Irish policies*

The aim to propagate GAP in Ireland is reflected in the farm specific advice provided through the NMP online tool, national fertiliser application advice provided through the Green Book and Nitrates Derogation strategies (Callaghan, 2023; Hanrahan *et al*., 2017; Maher *et al*., 2021; Wall and Plunkett, (eds.), 2020). However, these strategies do not consider the impact of environmental conditions on N dynamics at field or farm scale. Including such information in advisory services has the potential to help meet the targets of the existing policies of maintaining optimum yield while reducing N loss simultaneously, through further spatial refinement of N management strategy in Ireland (DAFM, 2021; Patil, 2009, Van Grinsven *et al*., 2013).

Geographically refined nutrient management in grasslands is not common in the high grass producing regions of North Western Europe, including Ireland, primarily driven by the complexity of soil physicochemical properties, vegetation dynamics, climatic variables and economic barriers in grasslands (Higgins *et al*., 2017 and 2019; Lesschen *et al*., 2014). In Ireland, this challenge is particularly reflected in N management in grassland, where the N application is driven by the limits prescribed by generalised nutrient application advice and Nitrates Derogation strategies. These limits are based on the requirement of N input for the targeted grass yield in various phases of grass growth to produce feed to maintain a specified stocking rate (Callaghan, 2023; Hanrahan *et al*., 2017; Maher *et al*., 2021; Teagasc, 2017e; Wall and

Plunkett (eds.), 2020). Adhering to the N requirement based on grass growth phases for N fertiliser rate and timing application guidelines (Wall and Plunkett (eds.), 2020) and limiting the fertiliser application rate and stocking rate in the Nitrates Derogation strategies (Callaghan, 2023) matches with the *right rate* and *right time* agenda of 4RNS (Fixen, 2020). However, there is a gap in the integration of the *right place* determined by soil conditions and yield diversity. Furthermore, there is also a gap in the integration of the potential impacts of N management on both the spatial and temporal patterns of N loss from grasslands through major pathways (van Beek *et al*., 2008), which is a requirement for improving the geographical refinement of N management (Corre *et al*., 2002) including choosing the *right product* (Fixen, 2020). Unlike P and K, the soils under grasslands are yet to be indexed based on the availability of N for more precise N management due to the lack of reliable methodologies (Teagasc, 2017e).

The implementation of sustainable N management policies comes with societal challenges. For example, McCormack *et al*. (2022) indicated that farmers' willingness to adopt nutrient management plans in Ireland, as the case of NMP-Online, is directed by its perceived usefulness (i.e., benefits, followed by perceived ease of use), whereas policy goals are more focused on increasing productivity while reducing the negative impacts of agriculture on environment (DAFM, 2021; DHLGH and DAFM, 2022; DECC, 2023). Dillon *et al*. (2014) indicated that for Irish agriculture the challenge lies in maintaining the economic viability of farms while also delivering environmental sustainability, in line with EU goals. A change from existing farming strategies to those that promote sustainable N management can be challenging for Irish dairy farmers, especially the reduction of N fertiliser input and stocking rate (Kelly *et al*., 2020). In the case of reducing stocking rates, dairy farms may need additional grassland for farm expansion, to which land mobility in Ireland is a challenge (Geoghegan and O'Donoghue, 2018). Increasing output while following national and EU environmental targets, increased fertiliser cost and the continuous decline in the CAP budget also pose significant economic challenges for farmers (Baffes and Koh, 2023; Conefrey, 2018; FAO and WTO, 2022) seeking to earn an economically sustainable income from agriculture.

#### *1.5.4.1. Modelling approaches for precision nitrogen management in grasslands - a feasible solution?*

Due to the importance of agriculture here and the associated challenges, Ireland represents an ideal location to identify and test the potential for refined N management practices in grasslands to meet the aims of GAP and potentially provide a template for similar management approaches in grasslands elsewhere. Though N fertiliser recommendations for Irish grasslands are based on soil fertility level, there is an absence of mapping N requirements at field level (Teagasc, 2017e). This gap can potentially be addressed using a modelling approach that can estimate grass growth and N loss, similar in approach to the IPCC Tier 3 methodology (Buendia *et al*., 2019). Modelling approaches to explore N dynamics and crop response to N application at field or farm level, using a process-oriented modelling approach such as DNDC, ECOSSE, DayCent etc. (Zimmermann *et al*., 2018) that can connect soil, landscape, crop and weather (Patil, 2009), can address some of the challenges to develop spatially refined N management practices in grasslands due to the complexity of soil physicochemical properties, climatic variables and economic barriers (Higgins *et al*., 2017 and 2019). A modelling approach could potentially inform the improved implementation of existing policies, from field to national level, using a more nuanced approach based on crop response to N application and susceptibility of surplus N to loss. Patil (2009) indicated that limitations in the robustness of such models is a common challenge for their use due to need to parameterise any model to reflect local or site conditions. Since perennial ryegrass is the dominant grass species in Ireland (O'Donovan *et al*., 2021), a robust model parameterised for perennial ryegrass which can reliably simulate N dynamics and grass yield, with the interaction of management and local soil and climate conditions, could contribute to improving our understanding of N management to deliver more sustainable grassland management practices (Patil, 2009; Schellberg *et al*., 2008). This would also inform future research seeking to understand the role of important model parameters for deploying them for precision N management. A similar approach can be considered for soil and climatic inputs to overcome the challenges of data unavailability and creating minimum input databases depending on robustness of the model (Patil, 2009).

### 1.6. Summary & Research Questions

It is evident from the policies and goals regarding Irish agriculture that they are aimed at meeting global and EU goals for food security, agricultural productivity and reducing the negative impacts of intensive agriculture on the environment and human health. However, the challenge persists in achieving the productivity targets (DAFM, 2021) while reducing the current level of N pollution of the air and water resulting from N loss from agricultural soils (EPA, n.d.; EPA, 2023, EPA, 2023a). Geographically refined N management strategies could offer an effective approach to tackling this challenge. However, there are knowledge gaps between the proposed field specific requirements to inform improved N management and the generalised N management strategies for Irish grasslands which do not account for the variation in grass growth and N dynamics under the influence of spatially and temporally diverse interactions between soil, weather, climate and management (Callaghan, 2023; Hanrahan *et al*., 2017; Maher *et al*., 2021; Teagasc, 2017e; Wall and Plunkett, (eds.), 2020). This is similar to the North-West European scenario in nutrient management for grasslands (Higgins *et al*., 2017) and presents a case study region to evaluate the potential of maintaining grass yield and reducing N loss through precision N management, relevant for the wider EU. At the same time, it would help in future research to explore solutions to similar challenges posed for grasslands globally through a modelling based approach (Schellberg *et al*., 2008).

Process-oriented modelling can be an effective tool to explore the scope of improved N management strategies in Irish grasslands, but the robustness of process-oriented models and their required parameterisation to local or management unit conditions and species heterogeneity remains an ongoing challenge (Higgins *et al*., 2017; Patil, 2009; Schellberg *et al*., 2008). This research, in reference to the dominance of perennial ryegrass paddocks used for feed production in Irish dairy farms (O'Donovan *et al*., 2021), employs a process-oriented modelling approach (Vereecken *et al*., 2016; Wimalasiri *et al*., 2023) to explore the following research questions –

- Can a process-oriented modelling approach be reliably used to explore spatial and temporal crop response and N Loss to management considering local conditions of soil, climate and weather across Irish dairy farms?
- What are the key regulators of grass growth and N loss in intensively managed grasslands under Irish dairy farming?
- Is there potential to improve the robustness of the modelling approach?

The objectives of the research are to-

- ☐ Identify a process-oriented model that can account for detailed soil processes of N dynamics, crop growth and weather, suitable for use in the context of grassland farms.
- ☐ Evaluate the model's ability to simulate the growth of perennial ryegrass under conditions typical of dairy farming management practices and identifying the optimum spatial and temporal scale of reliable model performance.
- ☐ Evaluate the model's ability to simulate key N loss pathways in grasslands under conditions typical of dairy farming management practices and identifying the optimum

spatial and temporal scale of reliable model performance, including the need for more or less detailed input data and parameters.

- ☐ Utilise the parameterised process-oriented model to explore the potential requirement of spatial and temporal refinement of N management strategies for optimum grass yield and reduction of N loss in Irish dairy farms.
- ☐ Explore the simulated results to identify the key regulators of grass growth and N loss at field scale in Ireland.

The outcomes of the work will be beneficial for refining the existing N management strategies for grasslands in Irish dairy farms to achieve optimum productivity targets and to reduce environmental impacts of N loss. The outcomes of the study will also be relevant for policymakers and could be useful to inform more effective N management strategies, as well as for researchers involved in modelling biogeochemical processes involving soil, crop, weather and climate. The study seeks to provide a framework that could be replicated elsewhere. The key focus of the research will be on using a modelling approach to choose the *right place* and *right rate* of N fertiliser application based on estimation of grass growth and N loss, since the current nutrient management strategies that require spatial and temporal refinement of N fertiliser application recommendations are primarily based on the annual limits set for N management (Callaghan, 2023; Wall and Plunkett (eds.), 2020). However, the performance of the model for estimating temporal variations of grass growth and N loss will also be explored to identify opportunities for future research on choosing *right product* and deciding *right time* of N fertiliser applications based on weather conditions (Fixen, 2020).

## 1.7. Thesis Layout

Chapter 1 of the thesis provides an overview of the background of this research aimed at informing N management strategies in Irish grasslands under dairy farming to improve productivity and profitability while reducing N loss, in alignment with 4RNS for sustainable N management – relevant in context of EU and globally. The detailed review of existing literature on N biogeochemistry and its drivers, role of spatial scale and employability of processes based models for refinement N management strategies to meet 4RNS objectives and challenges associated with modelling approach is provided in Chapter 2 – that ultimately forms the basis on which this research progresses, using the DNDC model to explore N dynamics in Irish grasslands. The Chapter 3 provides a detailed overview, scope and limitations of DNDC model. It also describes the overview and aims of the experiments designed, the description of selected sites, the methods applied for model validation and application of the validated model. The first experiment, including - parameterisation and validation of DNDC, used data and methods, the results and inferences, aimed at validating DNDC for estimating growth rate and yield of perennial ryegrass is described in Chapter 4. The Chapter 4 also includes a sensitivity test, employed to identify key drivers of grass yield. In the next experiment, upon generating reliable performance of DNDC in estimating grass growth rate and yield, the model was employed for simulation of daily and annual estimation and validation of $N_2O$ emissions and $NH_3$ volatilisation using parameterisation and relevant suite of input data following Chapter 4. The aim was to estimate reliability of the model to estimate N loss and identification of required details of site-specific inputs, as well as, employing sensitivity tests to identify the key drivers of $N_2O$ emissions and $NH_3$ volatilisation. The experiment with its details on data, method, results and inferences is described in Chapter 5. The parameterised DNDC with ideal suite of site-specific inputs was employed in the next experiment to identify the spatial variation of the environmental factors relevant to N dynamics for three different grassland sites in Ireland through comparing the variation of yield and different forms of N loss with the variation of environmental factors. The aim was to identify the key factors that can be potential indicators of yield and N loss, and the ones that need to be accounted for while exploring effectiveness of N management strategies to meet their sustainability objectives. This experiment, with methods, results and inferences is described in Chapter 6. Further, in the Chapter 7, the details of following experiment that aimed at evaluation of DNDC, when parameterised for phenology of perennial ryegrass, for employability with default soil and atmospheric as a robust tool to estimate variation of yield and N loss at spatially diverse Irish grassland sites, is discussed with methods and outcomes. The Chapter 8 summarises the findings from all four experiments conducted in this study, discusses the relevance of the findings for shaping spatially refined N management and seeks opportunities of future research – ultimately proposing a generalised research framework.

# 2. Literature Review

## 2.1. Soil fertility management and its significance for sustainable agriculture

Soil fertility is the capacity of soil as a medium to support the growth of plant biomass through the provision of nutrients and water (Blum, 2014; Freyer *et al*., 2023). The optimum availability and uptake of nutrients and water is a key requirement for the growth of plant biomass, whereas over- or under-availability can negatively impact plant growth (Li *et al*., 2009a). Thus, understanding soil fertility conditions and its suitability for crop growth is particularly important for developing sustainable agricultural management strategies. Soil fertility regulates the growth of crops in agricultural soil through regulating the uptake of nutrients, which depends on the status of nutrient and water availability in soil, are ultimately regulated by the physicochemical properties of soil, management and climatic conditions (Chakraborty and Mistri, 2015; Rodelo-Torrente *et al*., 2022). Nutrient application, along with spatial and temporal variations in weather, and over longer timescales climate, play an important role in maintaining soil fertility. Inadequate nutrient availability and uptake can lead to nutrient deficiency, while an excess of nutrients in the soil can often lead to nutrient toxicity in crops - both of which negatively affect the agricultural productivity (St.Clair and Lynch, 2010). Thus, understanding soil fertility conditions, its relationship with nutrient availability and uptake, environment and management, can help inform nutrient management for optimising sustainable agricultural productivity. It ultimately contributes to maintaining food security and economic growth (Gollin, 2010; St.Clair and Lynch, 2010).

### *2.1.1. Nutrient availability and uptake – relevance for maintaining fertile soil conditions*

Nutrient availability and uptake ultimately govern the capacity of soil to sustain plant growth, thus is one of the key aspects of examining soil fertility conditions. Streich *et al*. (2014) identified key elements required by plants and indicated how soils and management play important roles as a source of these nutrients. Plants require 17 elements to sustain their growth and physiological processes (Figure 2.1). Of these, with the exception of carbon (C), hydrogen (H) and oxygen (O), the remainder are supplied from soil and classified into two groups: macro nutrients (required in relatively greater amount) and micronutrients (required in smaller amounts). Macronutrients are further divided into two groups. The elements nitrogen (N), phosphorus (P), potassium (K), required in larger amounts, are called primary nutrients, and are commonly supplied through the application of fertilisers. Other macronutrients, including magnesium (Mg), calcium (Ca) and sulphur (S), are secondary nutrients. The availability of macronutrients in soil in different forms is often used as a common indicator of soil fertility

(Schoenholtz *et al.*, 2000). The micronutrients are - iron (Fe), zinc (Zn), copper (Cu), boron (B), manganese (Mn), molybdenum (Mo), chlorine (Cl) and nickel (Ni).

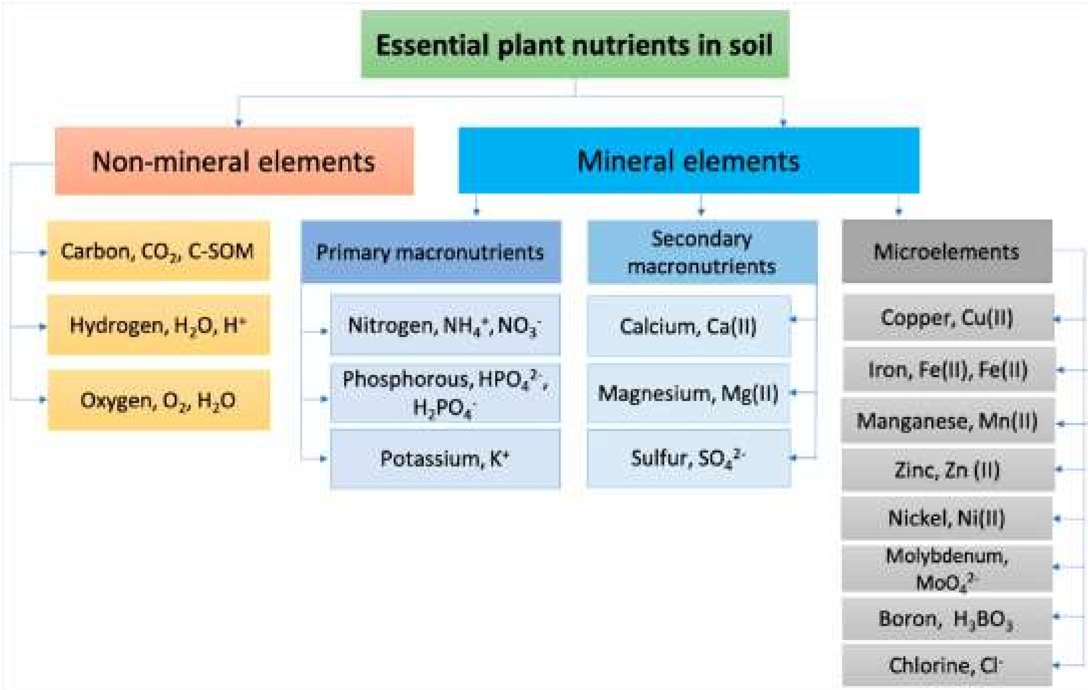


**Figure 2.1** Essential plant nutrients (Nadporozhskaya *et al.*, 2022)

The optimum availability of these macro and micro elements and their uptake, driven by available soil moisture, are basic requirements of a healthy soil to sustain plant growth (Soares *et al.*, 2019). The deficiency and toxicity of nutrients in plants is governed by their availability and the soil moisture content, which determines the solubility and transport of the nutrients (Langridge, 2022; St. Clair and Lynch, 2010). Thus, maintaining an optimum supply of soil nutrients requires understanding the impact of interactions between climate and management with soil physicochemical properties on their retention, uptake and loss, and is essential for maintaining soil fertility (Orwin *et al.*, 2015; Soares *et al.*, 2019).

#### *2.1.1.1. Nutrient availability in soil*

In natural conditions, atmospheric N can be fixed in soil through biological N fixation (BNF) by microbe *Rhizobium* living in symbiosis with legume plants or by free living microbes like *Azolla* and *Anabaena* (Bohlool *et al.*, 1992; Sharma *et al.*, 2023). The availability of the remaining macro- and micro- nutrients in soil depends upon the weathering of primary and secondary minerals present in the parent material (Singh & Schulze, 2015). For agricultural land, these nutrients are usually supplied through chemical fertilisers, such as - compounds of ammonium

($NH_4^+$), nitrate ($NO_3^-$) or supplying urea for N (Bucher and Kossmann, 2007; Gray, 2023), superphosphate for P (Annis, 2016), chlorides and sulphates of K (Bafoev *et al.*, 2022) - to increase productivity. Secondary minerals are also supplied according to the requirements for achieving soil fertility conditions. S is supplied to soil through sulphate and thiosulphate fertilisers of N, sulphate fertiliser of K, gypsum and even as elemental S (White *et al*., 2021). Mg can be supplied through dolomitic lime, oxide and sulphate of Mg, and potassium magnesium sulphate (Lyod, 2021). Common chemical sources of Ca supplied to soil are carbonates, hydroxides and oxides of Ca (Minson, 1990). Besides the primary and secondary nutrients, micronutrients are applied through salts or chelates that supply macronutrients or by mixing with macronutrient fertiliser and through aerosol spray, to avoid deficiency symptoms in plants (Mikula *et al*., 2020). However, in natural conditions as well as in agroecosystems, macro- and micro- nutrients utilised by living organisms for growth are also returned to soil through the decomposition of organic matter, supplied as animal excreta or as crop residue or dead biomass. For this reason, organic amendments are often supplied to agricultural soils as sources of nutrients to replace the use of chemical fertilisers (Dhaliwal *et al*., 2023; Kabasiita *et al*, 2022). The diverse characteristics of soil ultimately governs its continuous interaction with both the environment and management practices which regulate the soil's ability to retain, store or lose nutrients. The characteristics of soil depends on the proportion of the soil forming components of the soil, namely – minerals (sand, silt, clay), organic matter, air and water (Kalev and Toor, 2018). An ideal proportion of the soil components is shown in Figure 2.2, although in general, the composition of soil forming materials vary spatially and temporally depending on parent material, climate, topography, biota and anthropogenic activity and time (Figure 2.3) (Dror *et al*., 2022).

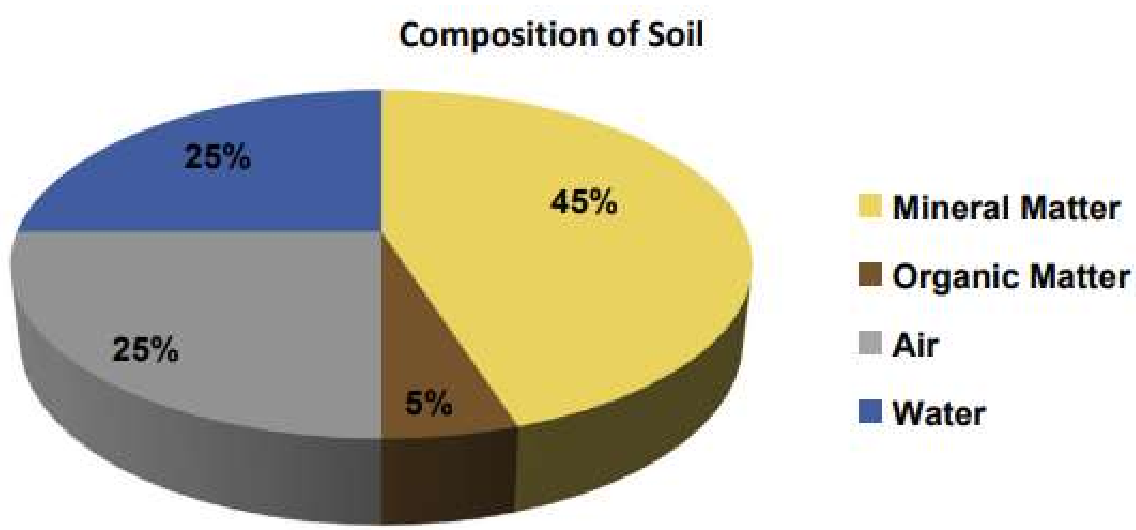


**Figure 2.2** Optimum composition of soil (Source: Kalev and Toor, 2018)

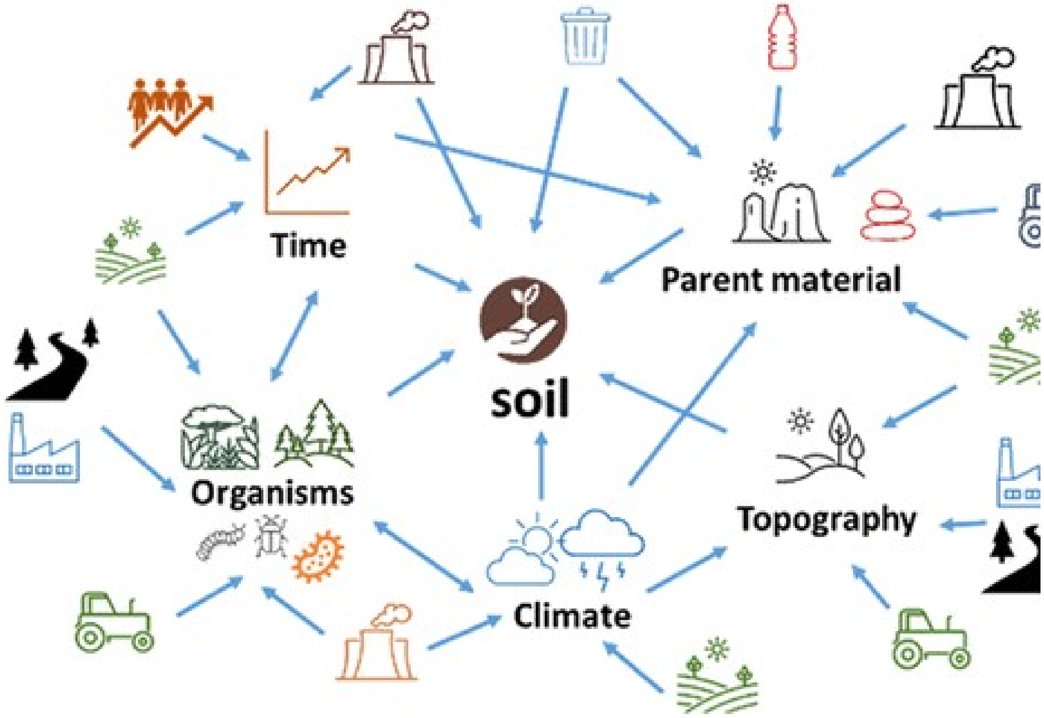


**Figure 2.3** Environmental and anthropogenic regulators of soil characteristics (Dror *et al*., 2022)

*2.1.1.2. Environmental factors governing soil fertility and nutrient dynamics*

Anderson (1988) and De Deyn and Kooistra (2021) described the diversity of parent materials on soil formation, their stability and susceptibility to weathering from physical, chemical and biological processes, as well as the rate of weathering as factors that ultimately governs the natural supply of most of the major macro- and micro-nutrients in soil, except N. These factors also determine the textural composition of soil (Figure 2.4), which determines the ease with which water can move laterally or vertically in the soil, the susceptibility of nutrients to leaching, and the retention of soil moisture. Leaching of nutrients and water are usually higher in soils with more sand content and lower in soils with high clay content (Anderson, 1988; Schuster *et al.*, 2023). Clay content increases the aggregation and macroaggregate stability, providing buffering capacity in soil against changes in soil pH, cation exchange capacity (CEC), while reducing bulk density (BD) (Costa *et al*., 2004; Djajadi and Hinz, 2012; Soinne *et al*., 2023; Sparks *et al*., 2024; Zhang *et al*., 2017). Besides clay, the soil organic matter (SOM) in soil that is supplied from biomass (Kalev and Toor, 2018) also contributes to increasing the buffering capacity of soil against changes in pH, aggregation and macroaggregate stability of soil, water holding capacity, CEC and reduction of BD (Blanco-Canqui and Benjamin, 2015; Djajadi and Hinz, 2012; Libohova *et al*., 2018; Ramos *et al*., 2018; Zhang *et al*., 2017). However, SOM also plays a vital role in supplying nutrients to the soil through decomposition, as a source of N, P and S and for solubility of micronutrients like Fe, Cu, Zn – though has least impact on solubility of K and Mn (Gerke, 2022; Robertson and Paul, 2000). The CEC of soil is particularly important due to its ability to increase retention of nutrient cations and high CEC indicated high clay and SOM that leads to high moisture retention – ultimately regulating nutrient availability (Caravaca *et al*., 1999; Ćirić *et al.*, 2023; Schuster *et al.*, 2023). Increases in soil pH also contribute to increases of CEC of both clay content and SOM and also regulates the dynamics of soil nutrients by regulating rates of sorption, adsorption, availability and uptake of nutrients from the soil (Barrow and Hartemink, 2023; Helling *et al*., 1984). Neutral to alkaline pH in soil generally facilitates the microbial activities related to the decomposition of SOM, leading to the release of nutrients, while pH regulates the activity of enzymes involved in hydrolysis and oxidization of SOM and community structure, diversity and physiological processes of the microbes involved in decomposition process (Yao *et al*., 2009; Wang & Kuzyakov, 2024). Higher BD in soil leads to a reduction of water infiltration and the decomposition of SOM (Li *et al*., 2009; Ola and Lovelock, 2021) that ultimately regulates the availability and uptake of nutrients by plants.

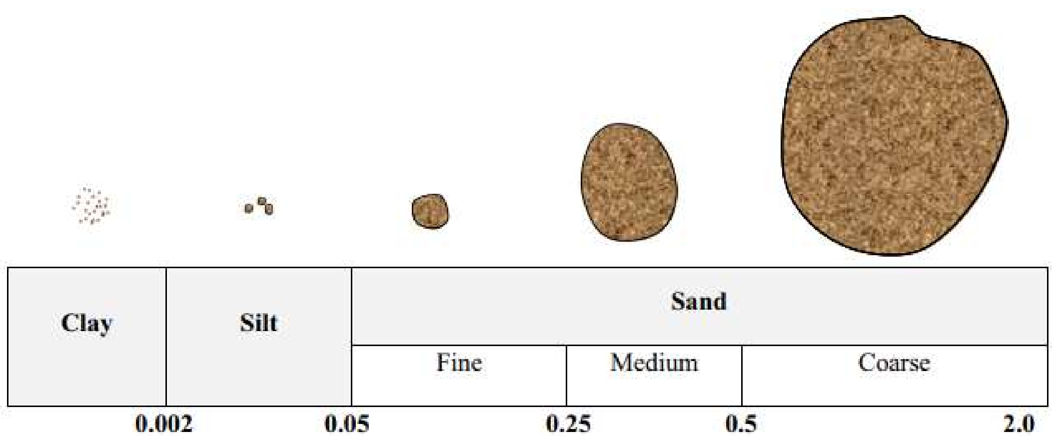


**Figure 2.4** Diameter (mm) of minerals in soil, the proportion of which determines the soil's texture (Source: Kalev and Toor, 2018)

Atmospheric deposition adds nutrients to soil, contributing to the regulation of soil fertility conditions (Cole, 1995; Seok *et al.*, 2021). Wet and dry atmospheric depositions of $NH_4^+$, $NO_3^-$, sulphate, phosphate and Ca to soil not only act as nutrient resources, but also alter soil nutrient dynamics by regulating the soil properties like pH, the C:N ratio and N:P ratio (Matzner and Murach, 1995; Seok *et al.*, 2021). Wind erosion of sediments carry nutrients like N, P, K, Ca, Mg, Cu, Fe, Mn, Al that are bound to the sediment and thus may lead to an export or import of soil nutrients (Lackóová *et al.,* 2021; Sankey *et al*., 2012; Visser *et al*., 2005). Wind regulates the diffusion of ammonia ($NH_3$) into the atmosphere from soil (), therefore, increased wind speeds can amplify the loss of N by increasing volatilisation of $NH_3$ (Harty *et al.*, 2024; Freney *et al*., 1981; Smith *et al*., 2008). Loss of N through nitrous oxide ($N_2O$) increases under wetter soil conditions, driven by rainfall and the soil's water holding capacity (WHC) and under warmer weather conditions (Griffis *et al*., 2017; Liu *et al*., 2022b; Zhang *et al*., 2021). Increased temperature enhances the decomposition of SOM leading to the release of nutrients which increase the susceptibility to both uptake and loss of the nutrients. It also contributes to increased leaching of nutrients like P by increasing the rate of chemical weathering and leaching of N in cooler regions through increased freeze and thaw cycles (Gianniny *et al*., 2024; Joseph *et al*., 2008; Wang *et al*., 2021). In addition to leaching, rainfall also drives the loss of nutrients from soil through runoff in dissolved form (Liu *et al*., 2014; Martínez-García *et al*., 2017) and the nutrients bound through adsorption to eroded soil minerals and organic colloids (Bertol *et al*., 2003).

Topography plays an important role in regulating the climatic impact on soil nutrient dynamics. Slope generally increases the loss of nutrients from the upper reaches of the sloped landscape to the lower reaches through increased runoff and erosion by water, which may be amplified with length and steepness of slope (Kleinman *et al*., 2006; Zhang *et al*., 2021a). A decrease in temperature at higher elevations (e.g. lapse rate) results in reduced decomposition of organic matter and subsequent nutrient supply to soil (Sundqvist *et al*., 2013).

#### *2.1.1.3. Management effect on soil nutrient dynamics*

The overall fertility and nutrient availability of agricultural soils is dependent both on the application of nutrients and other management practices that indirectly impact the availability, uptake and loss of nutrients, aeration and moisture content in soil. Nutrient application becomes unbalanced either when the applied rate of nutrient is below the requirement of crops, which can lead to nutrient deficiency in crop, or when the application is in excess of the crop requirement, resulting in a surplus of nutrient availability in soil (Cherry *et al*., 2008; Tan *et al*., 2005). Conventional tillage is a common agricultural management practice, performed to disperse or break up soil aggregates to increase aeration and facilitate better diffusion of fertilisers with soil water. However, increased aeration in soils by tillage can negatively impact soil quality by increased oxidation of SOM and exposes the soil to a higher risk of erosion and runoff losses (Odinaka and Yadav, 2022).

Holland *et al*. (2018) highlighted that liming acidic soils can increase nutrient supply through increased organic matter mineralisation, improving soil health by adsorption of heavy metal and increasing hydraulic conductivity by microaggregate formation, contributing to nutrient use efficiency of crops, especially with regards to the uptake of Mg and K. However, liming can also limit the availability of Fe, Al, Mn, Zn, Cu and phosphate through increased precipitation, which may pose a problem in nutrient deficient soils but can be beneficial in the case of potential nutrient toxicity (Holland *et al*., 2018). Mulching soil with organic matter improves the retention of moisture and nutrient availability, reduces soil salinity, improves soil's BD, porosity, and aggregate stability (Jordán *et al*., 2010; Ngosong *et al*., 2019). Harvesting of crop residue can impact soil quality by reduction of SOM and SOC, total N and mineralisation of N, S and CEC, while increasing the soil's BD, erosion, and nutrient leaching (Merino *et al*., 1998; Laird and Chang, 2013).

Grazing by livestock can have spatially diverse impacts on soil physicochemical properties. For example, Marriott *et al*. (2010) observed increased SOC and availability of N and P and a decline in K availability under higher grazing intensities in Texas, while Lai and Kumar (2020) identified an increase in BD and a decrease in SOC, total N, C: N ratio, soil moisture and K at a global scale under higher grazing intensity conditions.

#### *2.1.1.4. Relevance of maintaining healthy soil conditions*

Maintaining optimum soil fertility conditions is not only important for agricultural productivity, but is also important for environmental quality, which is critical for sustainable agriculture. Healthy soil conditions contribute to the reduction of pollutants entering surface and ground water, not only from agriculture sources, but also from other pollution sources, through the decomposition of harmful compounds, removal of ions by biological and physicochemical processes and precipitation of metals. Sustainable agricultural practices can reduce the loading of runoff water and leachate with nutrients that degrade the quality of potable water and harm aquatic ecosystems (Cheng *et al*., 2021; Stefanowicz *et al*., 2012). Degradation of soil and nutrient loss impact water quality and aquatic ecosystems through the deposition of pollutants, siltation, increased salinity, and eutrophication (Issaka and Ashraf, 2017). Giltrap *et al*. (2021) highlighted that soil can play both a positive and negative role in reducing air pollution. Their work indicated that unsustainable management of soil can degrade air quality locally through increased emissions of gases such as oxides of N, ammonia ($NH_3$), volatile organic compounds (VOCs), hydrogen sulphide ($H_2S$) and sulphur dioxide ($SO_2$). At a global scale, the impact of soil on air quality is related to the release of particulate matter and emissions of greenhouse gases (GHG), including $N_2O$ (which also contributes to depletion of ozone layer), carbon dioxide ($CO_2$) and methane ($CH_4$). At the same time, soil contributes to the removal of gases and particles from the air that are then converted to forms that are suitable for uptake by plants once they undergo soil biogeochemical processes after wet or dry deposition from the atmosphere. Soil fertility conditions govern the community structure and activity of soil microbes that are important for biogeochemical processes that regulate availability of plant nutrients and for controlling air and water pollution generated from soil (Cheng *et al*., 2021; Giltrap *et al*., 2021; Siciliano *et al*., 2014). Subsequently, soil fertility conditions are a large determining factor in the diversity of plants and soil macrofauna and is critically important for achieving sustainable agro-ecosystems (Ayuke *et al*., 2011; Sander and Wardell-Johnson, 2011).

#### *2.1.1.5. Unsustainable management of agricultural soils-a global phenomenon*

Loss of fertile soil due to intensive agriculture is now a global phenomenon. Pacheco *et al*. (2018) indicated that around 40 % of global agricultural land is degraded due to intensive management. Coppus (2023) observed that 75 % of the global degraded landscape are grazed, whereas agricultural expansion occurred over 64 % of the globally degraded landscapes. Montanarella *et al*. (2016) indicated that in different agroclimatic regions the major threats to soil quality vary spatially - mainly due to nutrient imbalances, erosion, soil sealing, change in organic C, salinization and sodification. Tilahun *et al*. (2018) found that 75 % of land degradation occurs in humid regions and 22 % in dry regions. Panagos *et al*. (2022) indicated that in Europe, 70 % of soils are already in an unhealthy condition. Intensive management is one of the major, but not the only, driver of soil degradation. Tan *et al*. (2005) estimated that 59%, 85%, and 90% of global soils under the cultivation of wheat, rice, maize and barley, respectively, are deficient in N, P and K, while 49%, 31 %, 15 %, 14 %, 10 % and 3 % soils globally are deficient in micronutrients Zn, B, Mo, Cu, Mn and Fe (Graham, 2008; Sillanpää, 1982), respectively. The annual cost of land degradation globally accounts for 0.41 % of global gross domestic product (GDP), primarily driven by land use and its change (Nkonya *et al*., 2015). These losses are mainly associated with the loss of ecosystem services and the consequential economic cost (Nkonya *et al*., 2015). The negative impact of nutrient losses from agriculture on environmental quality is also evident globally. de Raús Maúre *et al*. (2021) estimated that around 1.15 million $km^2$ of coastal waters globally are susceptible to eutrophication, while one quarter of the global anthropogenic GHG emissions originate from agriculture (Bennetzen *et al*., 2016). Zhang *et al*. (2021) found that global eutrophication has been increasing since 1960 and that 63 % of global inland waters had turned eutrophic by 2012.

### 2.2. Soil nitrogen: An essential nutrient for plant growth and biomass production

Nitrogen (N) is of significant importance to living organisms for the formation of proteins, nucleic acids, chlorophyll, and other biological macromolecules (Zhang *et al*., 2020). Two atoms of N form a molecular nitrogen ($N_2$) that is a colourless, odourless, non-combustible and non-toxic gas (NCBI, 2024). $N_2$ forms approximately 78.0818 % of the volume of atmosphere, whereas $N_2O$ constitutes just 0.00003 % of the atmosphere (Pinti, 2021). $N_2O$ is the third most important GHG which also contributes to ozone layer depletion (Ming *et al*., 2016). $NH_3$ is a colourless gas with a distinct odour (NCBI, 2024a) and contributes to the formation of fine particulate matter (Wyer *et al*., 2022) and oxides of nitrogen including $N_2O$ (Pai *et al*., 2021). Nitric oxide (NO) is also a reactive gaseous component of N that regulates the formation and destruction of atmospheric ozone and contributes to acid rain (Pilegaard, 2013). Nitrogen dioxide ($NO_2$) is a highly reactive oxide of N that contributes to the formation of nitrate aerosols (Fino, 2019).

N, although abundant in the atmosphere, cannot be utilised by plants directly. Besides being supplied to soil through BNF by diazotrophs, it is also supplied naturally to soil through atmospheric deposition, decomposition of SOM, or artificially through fertiliser application (Bajpai *et al*., 2019; Delwiche, 1970; Ladd and Jackson, 2015; McNeill and Unkovich, 2007; Teagasc, n.d.). Plants uptake available N in soil in forms of $NH_4^+$ or $NO_3^-$ or soil microbes can utilise it - both cases resulting in biomass formation (Dubeux Jr. and Sollenberger, 2020; Novoa and Loomis, 1981). Surplus N in soil can either be retained in soil or can be lost through leaching, runoff, volatilisation of $NH_3$ and through the emissions of gaseous oxides of N or molecular N produced through nitrification and denitrification (Freney *et al*., 1981; Martens, 2005; Skiba, 2008; Wang *et al*., 2023). The biogeochemical processes involved include the transformation and transfer of N in different forms between the atmosphere, soil and water, is known as the nitrogen (N) cycle (Figure 2.5) (Fisher and Newton, 2003; McNeill and Unkovich, 2007; Robertson and Groffman, 2024).

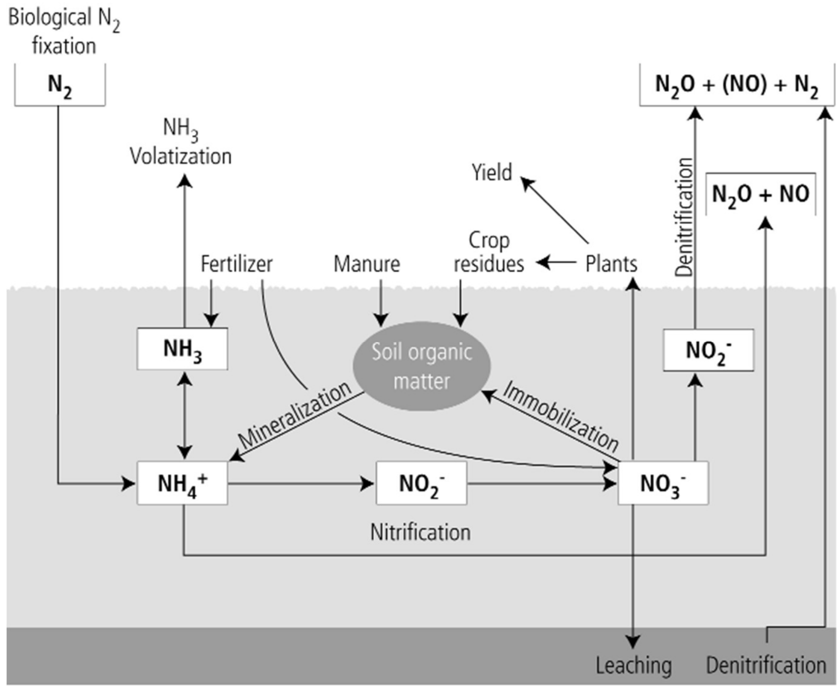


**Figure 2.5** The nitrogen cycle (Source: Hofman and Cleemput, 2004)

## 2.3. Biogeochemical steps involved in terrestrial nitrogen cycle

### *2.3.1. Nitrogen Input*

#### *2.3.1.1. Biological nitrogen fixation (BNF)*

BNF is the process through which atmospheric $N_2$ is converted to $NH_3$ by diazotrophs (Norman and Friesen, 2016). $NH_3$ produced in this process is utilised by these diazotrophs for amino acid glutamate formation by the activity of enzymes α-ketoglutarate and glutamate dehydrogenase (Zhang *et al*., 2020). The organisms that perform BNF are prokaryotes and are highly diverse, such as aerobes, anaerobes, microaerophilic bacteria, photosynthetic bacteria, blue-green algae, and nodule bacteria. These are commonly referred to as diazotrophs, all of which have the ability to produce Nitrogenase enzymes (Chanderban *et al.,* 2023; Havelka *et al*., 1982).

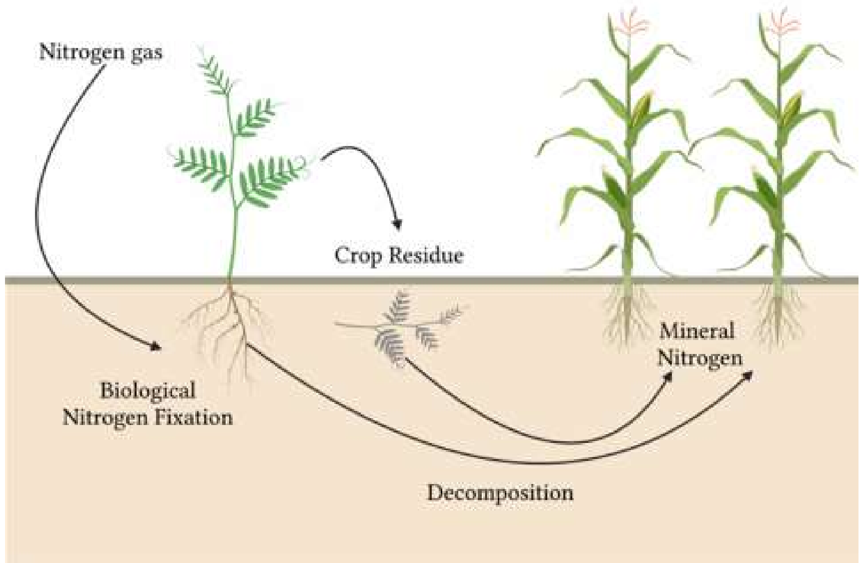


**Figure 2.6** Biological nitrogen fixation (BNF) for soil nitrogen supply (Source: Fudge, 2022)

In terrestrial ecosystems, the process of BNF is performed by free-living microbes from the groups of *Clostridium* and *Paenibacillus*, and by bacteria including *Rhizobium* and *Frankia* that develop symbiotic relationships with legumes and actinorhizal plants by forming root nodules (Delwiche, 1970; Diagne *et al*., 2013; Koirala and Brözel, 2021; Norman and Friesen, 2016). Symbiotic diazotrophs supply N fixed from the atmosphere to the host plants as a resource of N required for their biomass formation (Figure 2.6) (Beringer and Johnston, 1984; Xu and Wang, 2023). N fixed into biomass through the process of BNF ultimately produces the N enriched SOM that serves as a key resource of mineral nitrogen in soil (Blesh, 2019).

### *2.3.1.2. Atmospheric deposition*

Atmospheric dry deposition (Figure 2.7) is the process through which the particles being transported by air are settled on earth surface by gravitational force or gaseous exchange occurring between soil and atmosphere (Farmer *et al.*, 2021; Sutton *et al*., 1994; Wesely and Hicks, 2000). Wet deposition (Figure 2.7) is an atmospheric process in which elements are deposited through precipitation or fog either in dissolved or in particulate forms (Conko *et al*., 200; Guerrieri *et al.*, 2021). N is supplied to soil from air by dry deposition mainly through the gaseous exchange of $NH_3$ and deposition of aerosols containing $NH_4^+$ and $NO_3^-$ (Farmer *et al.*, 2021; Sutton *et al*., 1994). Dry deposition of NO and $NO_2$ can occur between the atmosphere and vegetation (Hertel *et al*., 2012). Wet deposition of N occurs in dissolved forms of N in precipitation, such as $NH_4^+$ sourced from atmospheric $NH_3$ and aerosols of $NH_4^+$, dissolved $NO_3^-$

sourced from atmospheric NO and $NO_2$ and dissolved organic nitrogen (DON) (Jiang *et al.*, 2024; Russell *et al.*, 1998).

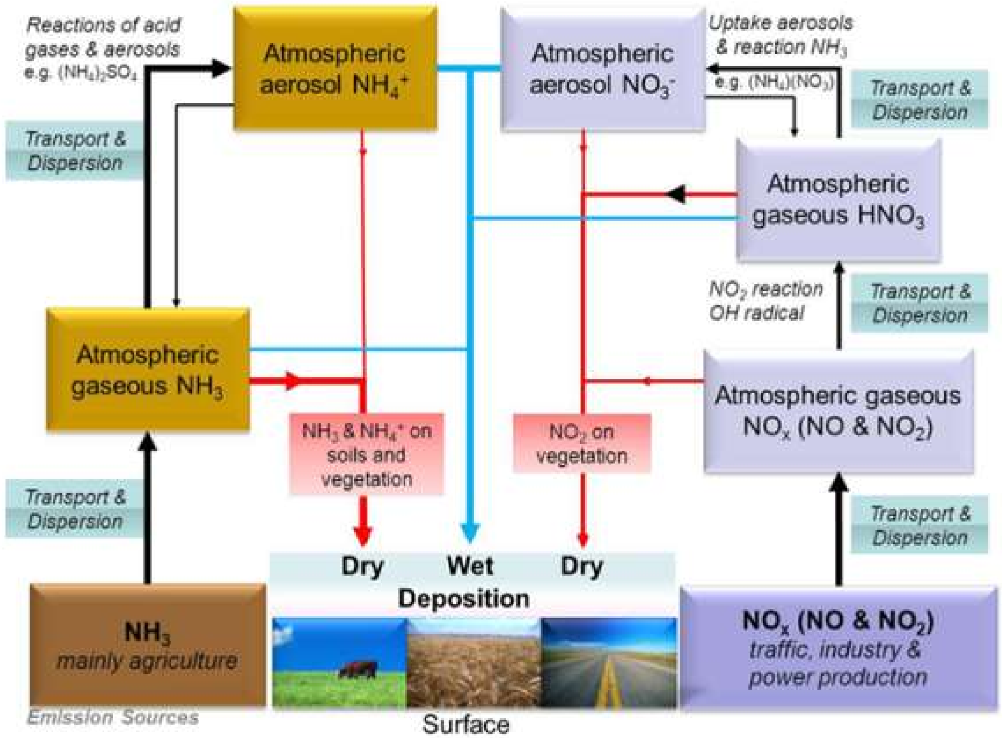


**Figure 2.7** Mechanism of atmospheric nitrogen deposition (Source: Hertel *et al.*, 2012)

### *2.3.1.3. Organic matter*

Organic matter in soil (SOM), supplied naturally or through applied organic amendments like manure and slurry, are a source of N bound into biomass that can be converted into plant available N through decomposition and mineralisation (Blesh, 2019; Litskas, 2023; Teagasc, 2017). Decomposition of SOM produces oligomers and monomers from macromolecules of SOM that becomes the substrate of mineralisation processes like ammonification (Knicker, 2004; Ladd and Jackson, 2015). Microfauna in soil can support the decomposition of SOM primarily by breaking down SOM, whereas heterotrophic soil microorganisms, as diverse as bacteria, fungi, actinomycetes and protozoa, perform the decomposition of SOM using extracellular enzymes to access the energy and nutrients required for cell growth (Khatoon *et al.*, 2017).

### *2.3.1.4. Anthropogenic fixation and application*

Industrially produced synthetic N fertilisers are applied to agricultural soils to maintain targeted yield. These fertilisers supply either or both plant available $NH_4^+$ and $NO_3^-$ (Bajpai *et al.*, 2019;

Teagasc, n.d.). Anhydrous $NH_3$ is the primary component used in the production of most synthetic N fertilisers and is mainly produced using atmospheric N through the Haber Bosch process. $NH_3$ can be used directly to produce fertilisers such as ammonium sulphate ($(NH_4)_2SO_4$), urea ($CO(NH_2)_2$), ammonium chloride ($NH_4Cl$) etc., or can be used to produce nitric acid ($HNO_3$) used in the production of ammonium nitrate ($NH_4NO_3$), calcium nitrate ($Ca(NO_3)_2$), sodium nitrate ($NaNO_3$) etc. Derivatives from these forms of fertilisers are also produced for agricultural application (Boswell *et al*., 1985; Litskas, 2023). The N in fertiliser becomes available to plants for uptake after application through dissolution in moisture contained in the soil (Sigtryggsson *et al*., 2020).

*2.3.2. Nitrogen transformations in soil leading to uptake, immobilisation and loss*

*2.3.2.1. Mineralisation of organic nitrogen*

*Aminisation*

Mineralisation of N from decomposed SOM begins with the conversion of protein content in SOM into amino acids, amides, and amines by microbes like *Rhodospirillum rubrum* that can produce protease enzymes (Kaviya *et al*., 2019; Strock, 2008). Enzymes like *N*-acetyl glucosaminidase (NAG), arylamidase (Muruganandam *et al*., 2009) are involved in this process. These enzymes perform hydrolysis of the protein compounds and produce substrates usable for further mineralisation during ammonification. The process is represented by Equation 2.1, where *R* indicates the carbon chain and *R*-$NH_2$ is the N enriched derivative of aminisation that is utilised by microbes for ammonification (Hodges, 1995).

$$\text{proteins} = \text{R-NH}_2 + CO_2 + \text{energy} + \text{other products} \qquad \text{Equation 2.1}$$

*Ammonification*

N bound to *R*-$NH_2$ compound (amino acids, amides, and amines etc.) is released into soil through the process of ammonification (Ladd and Jackson, 2015; Strock, 2008). In this process, the primary product $NH_3$ reacts with water to produce $NH_4^+$ (Figure 2.8) that is suitable for uptake and utilisation by plants and microbes (Hodges, 1995; Seifan and Berenjian, 2019). The production of $NH_3$ from amino acids occurs through deaminase enzymes that carbonize the amino acids (Jeannotte, 2014). The microbes involved in the process of ammonification can be diverse, ranging from saprophytic bacteria, such as - *Clostridium spp*., to fungi (Rascio and La Rocca, 2013).

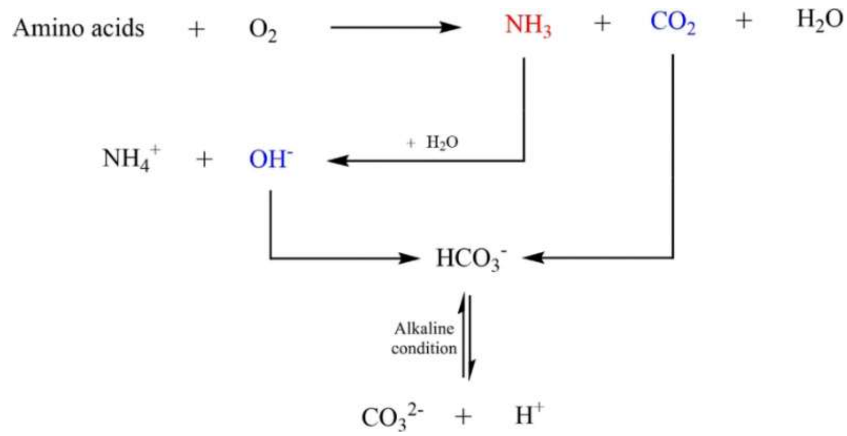


**Figure 2.8** Ammonium production through ammonification (Source: Seifan and Berenjian, 2019)

*Nitrification*

Available $NH_4^+$ in soil can also be oxidised by bacteria like *Nitrosomonas* into nitrite ($NO_2^-$) and $NO_2^-$ can be oxidised into plant-available $NO_3^-$ by bacteria known as *Nitrobacter*, under aerobic condition. This process cumulatively is called nitrification (Ayiti and Babalola, 2022; Sahrawat, 2008). The process of $NO_2^-$ production from $NH_4^+$, which involves the activity of enzymes ammonia monooxygenase and hydroxylamine oxidoreductase, is known as nitritation (Equation 2.2), while the conversion of $NO_2^-$ to $NO_3^-$ that involves the activity of enzyme nitrite oxidoreductase is called nitratation (Equation 2.3) (Ayiti and Babalola, 2022; Beylier *et al*., 2011). $NO_3^-$ produced by nitrification is a form of N that plants can uptake, whereas $NO_3^-$ also is a substrate for the following process of denitrification (Rummel *et al*., 2020).

$$NH_4^+ + 2HCO_3^- + 1.5O_2 \rightarrow NO_2^- + 2CO_2 + 3H_2O \quad \text{Equation 2.2}$$

$$NO_2^- + 0.5O_2 \rightarrow NO_3^- \quad \text{Equation 2.3}$$

*2.3.2.2. Utilisation of soil nitrogen for biomass formation*

*Nitrogen uptake and assimilation by plants*

Plants uptake N from soil through root hair mainly as $NH_4^+$ and $NO_3^-$ that is present in soil solution by translocation of $NH_4^+$ and $NO_3^-$ by corresponding transporters present in plant roots (Masclaux-Daubresse *et al*., 2010; von Wirén *et al*., 1997; Zayed *et al*., 2023) (Figure 2.9). The N transporters are types of specific proteins that are present in root membrane that can sense forms of N and transport N from soil into root (Muratore *et al*., 2021). Zayed *et al*. (2023) described that uptake of $NO_3^-$ is driven by transporters like NRT1, NRT2, chloride channel and slow anion channel-associated 1 homolog 3, while uptake of $NH_4^+$ is driven by ammonium transporters (AMT). They further mentioned that plants can also uptake amino acids under abundance of SOM through corresponding transporters like- amino acid permease, proline transporter, lysine transporter and histidine transporters. Assimilation of N into plant biomass occurs through amino acid formation. $NH_4^+$ transported into the plant from soil can be directly used to form amino acid through GS/glutamine-2-oxoglutarate aminotransferase isoenzyme cycle (GOGAT), whereas $NO_3^-$ after entering the plant from soil is converted to $NO_2^-$ by nitrate reductase and $NO_2^-$ is converted to $NH_4^+$ prior to amino acid formation (Fortunato *et al.*, 2023; Xu *et al*., 2012) (Figure 2.9).

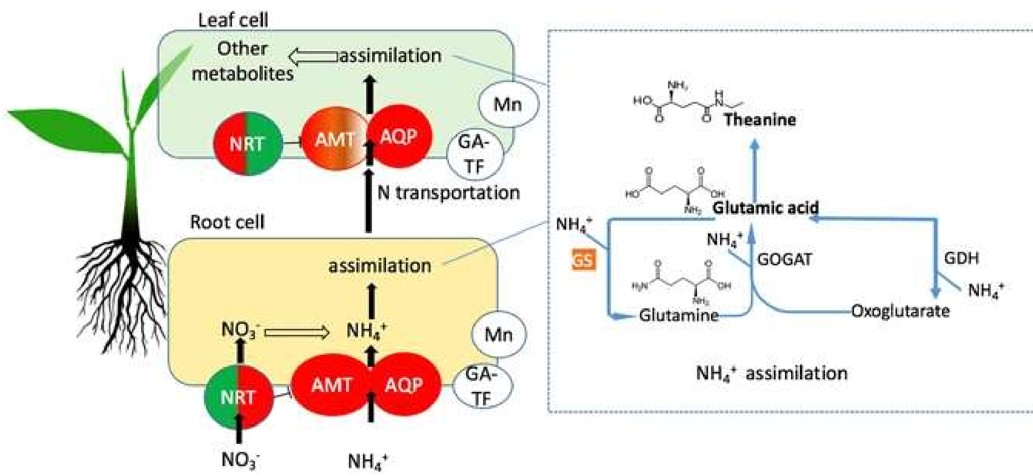


**Figure 2.9** Nitrogen uptake and assimilation in plants (Source: Li *et al*., 2017)

*Nitrogen immobilisation by microbes*

N can be present in soil, within the rooting zone, yet can be unavailable to the plants for uptake. This occurs if soil microbes have already used the N for their own growth, resulting in a process known as immobilisation of N (Dubeux Jr. and Sollenberger, 2020). Immobilisation of N in soil is performed by heterotrophic microbes including both bacteria and fungi (Li *et al*., 2021). Net N immobilisation occurs when rate of N mineralisation is lower than N immobilisation (Hagemann *et al*., 2016).

*Dissimilatory nitrate reduction to ammonium*

Dissimilatory nitrate reduction to ammonium (DNRA) is the microbial process through which $NO_3^-$ is reduced to $NO_2^-$ and then $NH_4^+$ (Figure 2.10). This conversion is mainly performed by facultative and obligatory anaerobic bacteria generally under anaerobic condition, either for fermentative or respiratory purposes. This process reduces the availability of $NO_3^-$ for losses like leaching or denitrification yet keeps the converted N in plant-available form of $NH_4^+$ (Huang *et al*., 2020; Pandey *et al*., 2020). The conversion of $NO_3^-$ to $NO_2^-$ is performed by the enzyme nitrate reductase while conversion of $NO_2^-$ to $NH_4^+$ is performed by the nitrite reductase (Huang *et al*., 2020). Bacteria, such as those from the families *Sulfurospirillum* and *Lachnospiraceae* can perform the anaerobic process of DNRA (Chutivisut *et al*., 2018). However, some bacterial strains like *Pseudomonas putida* Y-9 can also perform DNRA under aerobic conditions (Huang *et al*., 2020).

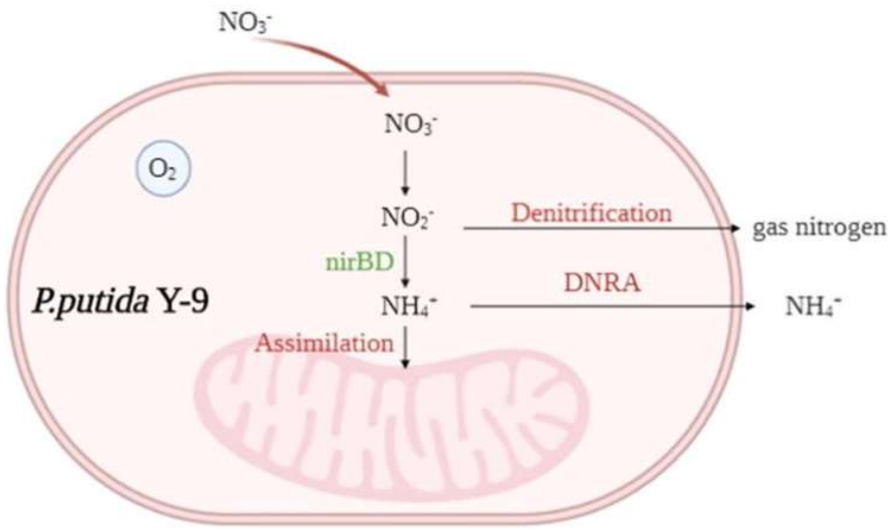


**Figure 2.10** Dissimilatory nitrate reduction to ammonium (Source: Huang *et al*., 2020)

*2.3.2.3. Nitrogen loss from soil*

<u>*Volatilisation of ammonia*</u>

$NH_4^+$ or its salts in soil can convert into $NH_3$ by different mechanisms. $NH_3$ can be released from the soil into the atmosphere depending on the condition of equilibrium between $NH_4^+$ and $NH_3$ in soil. $NH_4^+$ can release $H^+$ (hydrogen ion) into soil solution and combine with hydroxyl ion ($OH^-$), forming ammonium hydroxide ($NH_4OH$). This compound then dissociates to produce a water molecule ($H_2O$) and $NH_3$ as products of the reaction (Equation 2.4 and 2.5) (Hearn *et al.*, 2023; Freney *et al*., 1981a). Sulphate or phosphate salts of $NH_4^+$ can react with calcium carbonate in soil and form ammonium carbonate ($(NH_4)_2CO_3$) that reacts with soil moisture to produce $NH_3$, carbon dioxide ($CO_2$) and $H_2O$ (Equation 2.6) (Freney *et al*., 1981a; Powlson and Dawson, 2022). However, in the presence of carbonic acid and calcium carbonate, the intermediate stage can be ammonium bicarbonate ($NH_4HCO_3$) instead of $(NH_4)_2CO_3$ (Feagley and Hossner, 1978). The process of N loss from soil into air in the form of $NH_3$ is called ammonia ($NH_3$) volatilisation (Hearn *et al.*, 2023; Freney *et al*., 1981a).

$NH_4^+ \rightleftharpoons NH_3 + H^+$ Equation 2.4

$H^+ + OH^- \rightleftharpoons H_2O$ Equation 2.5

$(NH_4)_2CO_3 + H_2O \rightleftharpoons 2NH_3 + 2H_2O + CO_2$ Equation 2.6

*Denitrification and gaseous emissions*

Available $NO_3^-$ in soil can be utilised by certain groups of bacteria (mostly heterotrophs), known as *denitrifiers,* as a terminal acceptor of electron transport phosphorylation, predominantly under anaerobic conditions. This process is referred to as denitrification (Braker and Conrad, 2011; Zumft, 1997; Rohe *et al.*, 2021). During this process, the *denitrifier* bacteria reduce $NO_3^-$ into $NO_2^-$, NO, $N_2O$ and $N_2$ gradually by using the available oxygen in these ions and compounds (Figure 2.11) for oxidation of organic matter (Heinen, 2006; Knowles, 1981; Rohe *et al.*, 2021). The most common *denitrifier* bacteria belong to the group of *Pseudomonas* and *Alcaligenes* (Tiedje, 2014). The enzymes involved in these steps are nitrate reductase, nitrite reductase, nitric oxide reductase, and nitrous oxide reductase respectively (Mpongwana *et al.*, 2019). The denitrifying bacteria in soil are mainly facultative aerobic bacteria. They use the oxygen present in ions like $NO_3^-$ or $NO_2^-$ etc., in anaerobic condition, as a replacement of oxygen from air, and thus denitrification is predominant under anaerobic soil conditions (Ergas and Aponte-Morales, 2014; Megonigal *et al*., 2003). The main loss of N from soil during denitrification occurs in the forms of $N_2O$ and $N_2$ into atmosphere (Rohe *et al.*, 2021; Skiba, 2008).

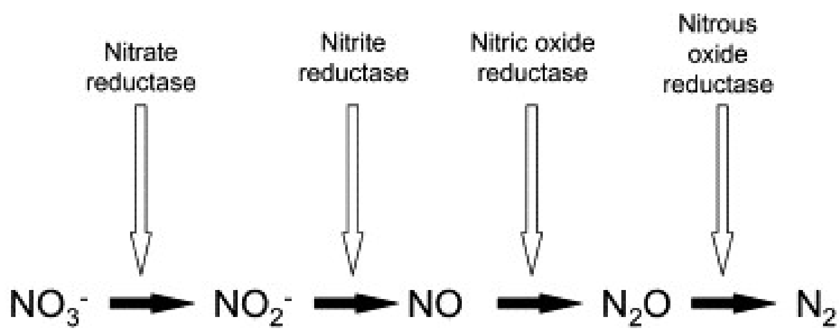


**Figure 2.11** From nitrate to molecular nitrogen, steps of denitrification (Source: Wrage *et al*., 2001)

However, some chemolithotrophic microbes like *Thiosphaera pantotropha* can continue using $NO_3^-$ and perform denitrification under air saturation up to 90 %, and produces sulphur and sulphate or sulphate only (Fichtner *et al.*, 2021; Robertson and Kuenen, 1984). Nitrification can also contribute to the production and emissions of $N_2O$ and NO, a process that is called nitrifier denitrification, performed by ammonia oxidizing bacteria that use $NH_4^+$ instead of $NO_3^-$ and directly produce $NO_2^-$ through oxidation, unlike the reduction of $NO_3^-$ performed under the general denitrification process (Davidson *et al*., 1986; Lu *et al.*, 2020). The reduction of $NO_2^-$ occurs later, producing $N_2O$, NO and $N_2$ gradually (Rohe *et al.*, 2021; Wrage *et al*., 2001).

*Leaching*

Leaching of nutrients is the process through which nutrients dissolved in soil water move downward through the soil profile as the water percolates into deeper layers of soil and into groundwater (Figure 2.12) (Jiao *et al*., 2004; Lehmann and Schroth, 2002). Leaching of $NO_3^-$ is the major form of loss of soluble N, where the $NO_3^-$ dissolved in soil water moves downward through the soil profile and becomes unavailable from the zone where plants can uptake it (Huang *et al*., 2017; Govindasamy *et al.*, 2023). Leaching of dissolved $NH_4^+$ and DON also occurs, albeit less prevalent (Hussain *et al*., 2020; Xiong *et al*., 2010). The infiltration of water into soil that leads to leaching can arise due to both gravitational and capillary forces of soil. However, the gravitational force is the dominant factor under high soil moisture conditions (Siyal *et al*., 2012).

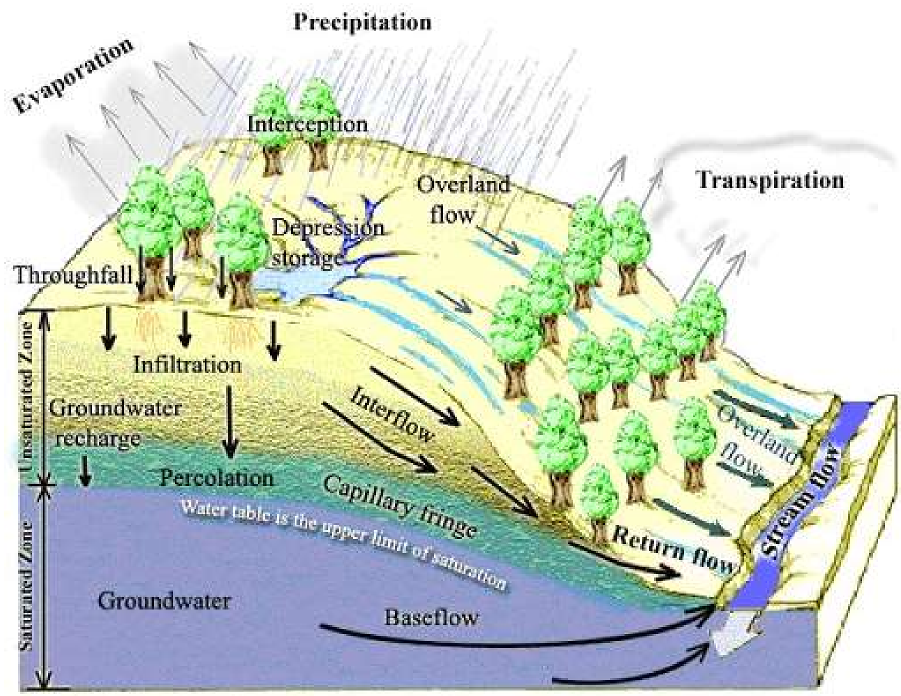


**Figure 2.12** Movement of water in soil leading to leaching, overland flow and subsurface runoff through interflow and groundwater flow (baseflow) (Source: HRG-UWRL, n.d.)

*Runoff*

Runoff of water from soil can happen through overland and subsurface flow (Figure 2.12) (Sharma and Machiwal, 2021). It occurs when the soil surface or the subsurface layer of soil contains water beyond the infiltration capacity of those soil layers (Kidron, 2020). Both dissolved and particulate N is lost from soil through runoff (Wang *et al*., 2023). Surface runoff can remove N in the forms of dissolved organic nitrogen (DON), fertiliser N, organic and inorganic particulate N, $NO_3^-$, $NH_4^+$ and $NO_2^-$ (Li *et al*., 2016; Govindasamy *et al.*, 2023). Loss of DON, $NO_3^-$ and $NH_4^+$ also occurs through subsurface runoff (Hill *et al*., 1999; Xu *et al.*, 2022). Subsurface flow of N occurs through both interflow and groundwater flow, enriched from the N leached from surface, and is common in sloped landscapes (Hayashi and Hatano, 1999; Zheng *et al*., 2017).

## 2.4. Regulators of nitrogen availability, uptake and loss in agricultural soil

### *2.4.1. Influence of soil*

The impact of soil on N dynamics is ultimately influenced by the physicochemical properties of soil. The key building blocks of soil are minerals - sand, silt, clay (their ratio determines the soil texture), SOM, air, water and living organisms (Needelman, 2013). Soil texture and SOM determines water retention, aeration and compaction in soil (Kakaire *et al*., 2015; King *et al*., 2020; Lal, 2020; Mobilian and Craft, 2022; Upadhyay and Raghubanshi, 2020). Among the minerals, higher soil clay content has a positive impact on the retention of water and N, CEC, and buffering capacity of soil against changes in pH - the properties that play a direct role in regulating N availability, uptake and loss (Newman, 1984).

Mineralisation of N generally increases under an increase in total C in soil and reduces under high pH and BD (Elrys *et al*., 2021), although, it can reduce in soils with high clay content due to the reduced dissolution of partially decomposed SOM (Sahrawat, 2008). Zhenghu and Honglang (2000) indicated that higher soil pH and high concentration of calcium carbonate content ($CaCO_3$) and total salt contents in soil increases the $NH_3$ volatilisation, whereas it reduces under higher SOM content, cation exchange capacity (CEC) and clay content. Nitrification in soil is higher under high C:N ratios and lower soil pH (Hu *et al*., 2021). Nitrification rates generally decline in soils with high water filled pore spaces, due to reduced aeration, and high clay content, due to lower dissolution of partially decomposed SOM (Sahrawat, 2008). Denitrification, being an anaerobic process, increases under higher water filled pore space in soil, whereas soils under increased compaction can also increase denitrification by reducing porosity and aeration (Yin *et al*., 2020). Transformation of $N_2O$ to $N_2$ may increase under relatively higher pH, while $N_2O$ emissions are generally higher from fine textured soils than coarse textured due to their higher water retention capacity, leading to increased anaerobic condition (Newman, 1984; Saggar *et al*., 2013; Sahrawat, 2008). Klemedtsson *et al*. (1988) observed that in soils with up to 90 % saturation of water holding capacity (WHC), the $N_2O$

emissions by nitrifier denitrification can surpass the $N_2O$ emissions by denitrification, but in completely water saturated soil $N_2O$ denitrification surpasses the rate of nitrification.

High clay and SOM in soil generally reduces N loss through reduced leaching and runoff (Whetton *et al*., 2022). Wei *et al*. (2021) indicated that the leaching of N from soil tends to be greater in soils with coarser textures due to lower water retention capacity and higher infiltrations rates. Such conditions also increase aeration in soil leading to increased mineralisation of SOM resulting in increased N loss through leaching and runoff. The physicochemical properties of soil is also an important regulator of BNF since soil water content, BD, soil organic carbon, silt content and pH are key regulators shaping the diversity and structure of N-fixing microbial communities in soil (Li *et al*., 2021a; Yang *et al*., 2022).

#### *2.4.2. Role of weather*

Weather plays an important role in regulating N-availability, uptake and loss in soil. Soil temperature is regulated by solar radiation, soil moisture content, air temperature and precipitation (Haskell *et al*., 2010; Yolcubal *et al*., 2004). Higher precipitation supports an increase in soil moisture content, while higher air temperature leads to its reduction (Feng and Liu, 2015) due to an increase in the vapour pressure deficit between the soil and the overlying atmosphere, increasing evapotranspiration. Barneze *et al*. (2022) indicated that the uptake of N from soil by roots can increase under higher temperature. Optimal soil moisture content can promote N uptake by plants, while soil moisture content also regulates the preferred form of N to be taken up (Liang *et al*., 2022).

Higher precipitation and soil temperature increases the rate of N mineralisation of soil (Elrys *et al*., 2021; Xu *et al*., 2018). Higher soil temperature increases initial $NH_3$ volatilisation after fertiliser application, whereas higher soil moisture content results in accumulated high $NH_3$ volatilisation at a prolonged scale even at lower temperature (Milchunas *et al*., 1988). An increase in mean annual air temperature has been observed by Li *et al*. (2020) to increase the rate of nitrification in soil. They also indicated that although mean annual precipitation can be a triggering factor for nitrification in soil by increasing microbial biomass N, an increase in mean annual precipitation can reduce the nitrification rate. Nitrification in soil increases under higher soil temperature due to increased N mineralisation (Xu *et al*., 2018). This likely happens due to increased anaerobic conditions that results in increased denitrification (Sahrawat, 2008) as well as loss of N through $NH_3$ volatilisation leading to lower supply of $NH_4^+$ for nitrification process

(Milchunas *et al*., 1988). Soil moisture content at or near field capacity generally maximises the nitrification rate (Sahrawat, 2008). Denitrification increases under high precipitation conditions that increases the water filled pore spaces (WFPS) in soil leading to more anaerobic conditions (Yin *et al*., 2020). Saggar *et al*. (2013) indicated that generally higher temperatures increase denitrifier activity, which may increase the transformation of $N_2O$ to $N_2$, thus reducing $N_2O$ emissions during denitrification. However, increased substrate availability and denitrifier activity can still promote denitrification. Saggar *et al*. (2013) also suggested that in addition to promoting anaerobic soil conditions, high rainfall increases denitrification through increasing substrate availability and denitrifier activity. Braakhekke *et al*. (2017) described the effect of temperature on N leaching to be ambiguous since higher temperature can potentially increase N leaching through increasing the rate of mineralisation, whereas higher temperature promoting N uptake can reduce the susceptibility of soluble N to leaching. However, Jabloun *et al*. (2015) showed that N leaching can increase under both higher temperature and higher precipitation, but their relative importance can vary depending on management and season. N runoff from soil generally occurs during extreme precipitation events (Ballard *et al*., 2019). Rousk *et al*. (2018) indicated that BNF is regulated by soil moisture content and temperature in an interdependent way and tends to be more efficient under optimum soil moisture and temperature conditions. They further indicated that the rate of BNF would depend on the adaptability of N-fixing organisms to temperature conditions, whereas higher temperature can reduce BNF with increased drying of soil.

### *2.4.3. Management strategies and intensity*

Globally, management practices vary according to different agricultural practices. Mixed cropping of legumes in arable land or grass-legume mixture in grassland management is performed to supply N to soil through BNF (Eichler-Löbermann *et al*., 2021; Kebede *et al*., 2016; Li *et al*., 2015). Tillage is a common agricultural practice in managed croplands across the world. Though conventional tillage is the predominant practice in croplands, there is an increasing tendency to adopt less intensive tillage practices globally (Porwollik *et al*., 2019). Grasslands, which are generally permanent, are sometimes reseeded (i.e. sward renewal), involving conventional to minimum tillage practices (Creighton *et al*., 2016; McKenna *et al*., 2019). Inputs of N through synthetic or organic fertiliser application are common practices performed globally in croplands and managed grassland (Liu *et al*., 2010; Xu *et al*., 2019). While arable lands are used for food, fibre and animal feed, the primary use of grasslands are for grazing and feed production (Tramberend *et al*., 2019). Each of the major practices – tillage, BNF in mixed cropping, fertiliser application, grazing etc. have significant relevance in N management in agriculture (Dobbie and Smith, 2003; Harty *et al*., 2017; Piñeiro *et al*., 2010; Wang *et al*., 2020).

#### *2.4.3.1. Impact of mixed cultivation of legume with other crops in soil nitrogen dynamics*

Besides fixing N in soil, legumes cultivated for BNF generally produce exudates with a lower C:N ratio, thus reducing N immobilisation in soil (Jensen and Hauggaard-Nielsen, 2003). Ladha *et al*. (2022) indicated that the susceptibility of N loss from soils supplied with N from BNF becomes lower than chemical fertilisers as the rate of release of plant-available N from SOM produced by BNF is much slower and more synchronised with N demand for the crops. However, they also indicated that BNF, in the absence of a cover crop, increases susceptibility of N loss through leaching and $NH_3$ volatilisation after the growing season. The rate of BNF in agricultural soil can itself be diverse depending on a number of management factors. Soussana and Tallec (2009) indicated that the basic potential of BNF in agricultural soils depends on the capacity of the host species to nodulate, the capacity of the infecting strain to fix atmospheric N and physiological control of nitrogenase activity and can be lower in soils deficient of P and S. In the case of grassland, higher BNF can occur under optimum grass to legume ratio where their ratio can support the uptake of N fixed by BNF by the non-legume plants without creating interspecific competition (Li *et al*., 2016a).

#### *2.4.3.2. Impact of nitrogen fertiliser application on soil nitrogen dynamics*

For N fertilisers, their application rate and chemical nature regulate the supply of plant available N, as well as the extent of their uptake and loss. Loss through $N_2O$ emissions can be higher for ammonium-nitrate based fertilisers than for urea, whereas using nitrification inhibitors can reduce the $N_2O$ emissions further (Cowan *et al.*, 2020). Harty *et al*. (2017) showed that the application of N through fertilisers like calcium ammonium nitrate (CAN) only, urea only, urea application with urease inhibitor N-(n-butyl) thiophosphoric triamide (NBPT), with maleic itaconic acid copolymer (MIP), with nitrification inhibitor dicyandiamide (DCD) or urea with NBPT and DCD and a blend of CAN and urea produced a nearly similar amount of grass dry matter yield. However, the efficiency of N uptake by plant was identified by them to be varying depending on the fertiliser types, inhibitors used and across the sites that varied in terms of soil and weather conditions. Forrestal *et al*. (2015) observed a lower potential of $NH_3$ volatilisation from soils treated with CAN in comparison to soils treated with urea, whereas a substantial reduction of $NH_3$ volatilisation from urea treated soils can be achieved by the simultaneous application of NBPT and a combination of NBPT and DCD respectively. For organic fertilisers, such as farmyard manure, its equivalence to chemical N fertiliser is a key determinant of the potential residual N in soil. However, they may impact yield regulation longer than synthetic N fertiliser depending on the rate of decomposition of the organic matter that mineralises organic-N into plant available forms of N (Schröder *et al*., 2007). BNF can reduce under increased supply of fertiliser N (Soussana and Tallec, 2009).

#### *2.4.3.3. Impacts of grazing on soil nitrogen dynamics*

Kurz *et al*. (2006) showed that free grazing by cattle can reduce macroporosity and penetrability of soil and increase bulk density, influencing the interactions of soil and weather on soil N dynamics (Elrys *et al*., 2021; Lai and Kumar,2020). Animal excretion during grazing supplies N to soil through dung and urine (O'Connell, *et al*., 2004). Piñeiro *et al*. (2010) described the potential positive and negative impact of grazing on soil N dynamics. They indicated that the excess N supply from animal excreta in grazed grasslands would increase the potential of N loss, however, grazing can also reduce N loss by increasing root biomass. They further showed that grazing generally increases the C:N ratio in SOM and results in net N loss that limits the N availability in soil, while they identified $NH_3$ volatilisation as the most dominant pathways of N loss from grazed grassland.

#### *2.4.3.4. Impact of tillage on soil nitrogen dynamics*

Wang *et al*. (2020) identified that increased N uptake by crops under conservation tillage would reduce the susceptibility of N loss through $N_2O$ emissions and leaching in comparison to conventional tillage or zero-tillage system. Furthermore, they showed that $N_2O$ emissions can be higher under conventional tillage due to the increased susceptibility of pore spaces in soil to fill with rainwater, whereas $NO_3^-$ leaching in conventional tillage can be higher due to increased infiltration of water through the soil profile. However, they observed greater $NH_3$ volatilisation under conservation and zero-tillage systems in comparison to conventional tillage. They attributed this to greater urease and microbial activity in soils under conservation and zero-tillage, while under conventional tillage the soil oxygen availability required for ammonia volatilisation is reduced due to deeper fertiliser placement. Patra *et al*. (2004) also observed higher $NH_3$ volatilisation in irrigated soils under zero-tillage. Zero-tillage agriculture generally reduces N loss through runoff but has the potential to increase N runoff in flooded agricultural systems (DeLaune and Sij, 2012; Liang *et al*., 2016). In the case of grassland, sward renewals can attain higher seasonal and annual grass dry matter yield in comparison to old permanent pastures – indicating better efficiency in N uptake by grass (Creighton *et al*., 2011). However, sward renewal of grassland also increases the susceptibility to increased loss of N through $N_2O$ emissions, though leaching loss may not change significantly for renewed swards in comparison to permanent grasslands, irrespective of renewal method employed (Creighton *et al*., 2016; Kayser *et al*., 2018; Seidel *et al*., 2006).

## 2.5. Spatial resolution: a challenge for refining nitrogen management strategies

One of the challenges associated with exploring the potential of any spatial refinement in N management is to identify the optimum spatial scale for research and implementation of the optimum N application strategy. Zhang *et al*. (2020a) described that the gap between nutrient budgeting that generally exists among plot and farm scale, watershed scale, national scale and global scales due to uncertainty in quantification of the budget terms, can result in significant variation among the spatial scales and nutrients. They indicated that the basic nutrient budgeting systems can vary between five different system scales, namely - soil-plant system, animal system, animal-plant-soil system, agro-food system and landscape system (Figure 2.13). Zhang *et al*. (2020a) indicated that both top-down and bottom-up approaches used in estimates for downscaling (national to regional to farm) or upscaling (farm to landscape) of strategies for N budgeting face a number of uncertainties. These estimations are generally made for N fertiliser; N content in product, atmospheric N deposition, BNF, N content in manure, N loss mechanisms and legacy effect. Such uncertainties may result in reducing the efficacy of policies designed for one spatial scale that is subsequently implemented on another. Shirmohammadi *et al*. (2008) found that reduced efficiency of outcomes in policies aimed at sustainable N management can also arise from downscaling a regional policy due to spatial variability of soil, nutrient dynamics, landscape conditions and biological diversity. They indicated that in order to successfully improve sustainable nutrient management practices, prioritisation should be given to user groups and data transferability between scales for each element of the policy.

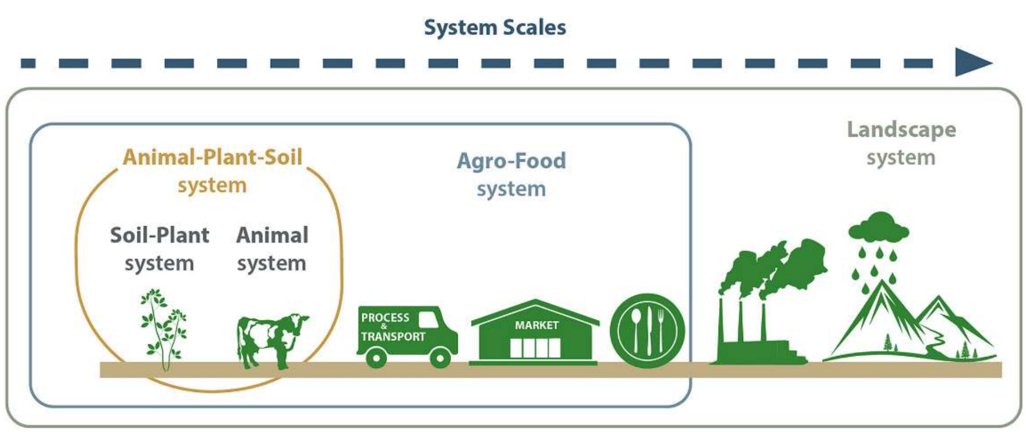


**Figure 2.13** System scale for quantifying nutrient budgets (Source: Zhang *et al*., 2020a)

From a management and productivity perspective, spatial areas or zones can be identified based on yield data and general land use practices (Colaço *et al.*, 2024). Weather variables including temperature and precipitation play a critical role in crop production (Sihi *et al*., 2022). These variables ultimately govern the uptake of applied N and the surplus N that is susceptible to loss. Identifying an optimum spatial scale, based on homogeneity or diversity of weather and background climate conditions, can be performed to estimate potential yield. This could lead to exploration and improvement of strategies for climate smart agriculture to improve efficiency of management as well as help inform additional strategies to overcome potential climatic limitations (Khatri-Chhetri *et al*., 2017). An optimum spatial scale, based on homogeneity of climate across the landscape, can be derived based on weather of at least 15 years for rain fed agriculture and at least 5 years of weather data for irrigated agriculture (van Wart *et al*., 2013). Soil zones can be classified depending on similarities and dissimilarities of the inherent physicochemical properties and topographic conditions. These zones can support the development of strategies according to the primary environmental factors that govern N uptake and loss in a specific zone (Franzen *et al*., 2002). The intersection between soil and climatic zones can potentially explain the observed yield gaps that can be helpful for improving N management (Rattalino Edreira *et al*., 2017). Such exploration, if it can be integrated with the management zones for a region, may further support efforts to address the knowledge gaps required to make informed management decisions that increase the precision of N management (Licker *et al*., 2010).

However, actual soil characteristics are often much more diverse at scales smaller than the resolution of zone based approaches. Soil heterogeneity at field scale is an important factor to consider for more spatially refined N management strategies (Diacono *et al*., 2012). Zoning based on nutrient deficiencies can also be an effective way to identify specific requirements for nutrient management, which can be diverse even at farm scale for N along with other fertility parameters (Vasu *et al*., 2017). Higher resolution zoning at farm scale and sub-field variability may support site-specific management requirements for optimum N use efficiency (Jin *et al*., 2019; O'Donovan *et al*., 2021). Verma *et al*. (2020) indicated that site-specific nutrient management can contribute to increased nutrient use efficiency and reduced nutrient loss by identifying nutrient stress at field level and developing appropriate nutrient management strategies, based on the spatial and temporal requirements of crops at a corresponding scale.

## 2.6. Modelling approach in agriculture and exploration of nitrogen biogeochemistry

### *2.6.1. Modelling approaches for biogeochemistry*

Haraldsson and Sverdrup (2013, pp. 277) state that "*a model is a simplified representation of an observed aspect of the real world*"; the purpose of which is to synthesise understanding of a system and to logically predict an outcome based on current understanding. They provided a detailed categorisation of models based on their predictive capacity, accountability and spatial resolution. Type 1 models are static, qualitative in nature and lead to categorisation of potential events. Type 2 models are static but quantitative in nature. However, their predictive capacity is limited by initial conditions that cannot be influenced by external factors and requires recalibration for new initial and boundary conditions. Type 3 models take a differential approach, where variables are accounted for in the model depending on their order, spatial distribution, concentration, and adaptation capabilities. Type 3 models require parameterisation and validation prior to their use in order to obtain reliable predictions. They further categorised models as good or bad, where a good model is one for which the principle of the modelling is visible and reviewable, and the outcomes of the models can be tested. Haraldsson and Sverdrup (2013) indicated that a global model can have a higher number of input variables but a lower level of detail (e.g. low spatial resolution) in comparison to local models (Figure 2.14). van Oijen *et al*. (2018) described that the empirical models used to connect agriculture, climate and soil, such as - linear and multivariate regression, generalised liner models, additive mixed models, nonlinear species-interaction models and structural equation models - as static models that explain the relation between response and driver variables. They indicated that empirical models are useful for descriptive and analytical purpose rather than being used as predictive tool. They identified process-oriented models that account for processes and mechanisms of the system, such as ecological, biogeochemical and agricultural models, as dynamic models. Dynamic models can be used for predictive purpose but are limited in utility due to oversimplification. For example, the absence of spatial heterogeneity in the regulating variables for crop and nutrient dynamics. Ecological models are simpler in terms of parameters and variables than biogeochemical and agricultural models (van Oijen *et al*., 2018). Haraldsson and Sverdrup (2013) categorised models into three major groups. These are empirical, equilibrium principles-based and process-oriented kinetics-based.

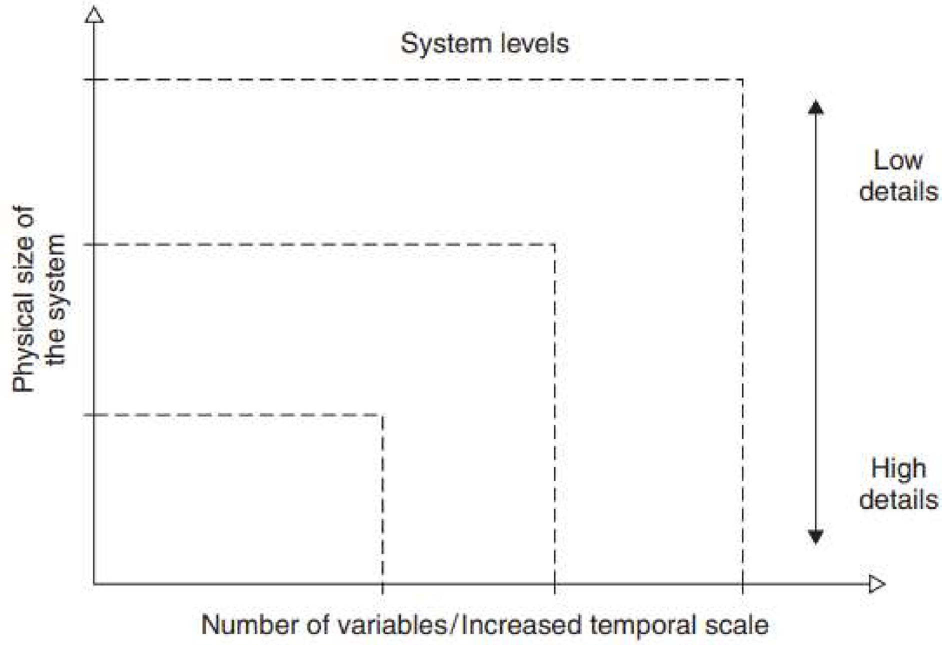


**Figure 2.14** Relation between focus of observation of model, number of variables and detailing (Source: Haraldsson and Sverdrup, 2013)

Biogeochemical modelling used for intensive agricultural management can help in defining, identifying and understanding interactions among the natural processes regulating biogeochemical cycles and their interaction with management practices. Such modelling approaches can help explain C and nutrient dynamics in landscapes under the influence of different environmental and management factors (Roque-Malo *et al*., 2022). Model based approaches, from crop simulation models to soil-crop-landscape models, enable us to explore management opportunities to refine nutrient management plans at field level by incorporating the variability of soil and crop yield at field conditions (Patil, 2009). Outcomes of such model simulations can also be used to develop simplified models (e.g. emulator models) that can generate complex assumptions from lower input data. These simplified models may be used as tools to support to decision making processes (Haraldsson and Sverdrup, 2013; Lim, 2021).

Vereecken *et al*. (2016) indicated that modelling soil processes has been used primarily for studies to understand the 'supporting' soil processes (e.g., soil formation, structure, biological activity, nutrient cycling and primary production), as well as 'degrading' soil processes (e.g., erosion, surface sealing, compaction, salinisation, acidification and loss of nutrients, organic matter and biodiversity) - under the impact of natural and anthropogenic drivers. Wimalasiri *et al*. (2023) indicated that modelling approaches for crops are relatively newer than soil modelling, and such models are used to simulate and explore crop growth and yield under different soil, climate, management and species composition as well as their impact on GHG emissions, economy, C and N dynamics etc. Besides their predictive ability, process-oriented models also offer the opportunity to investigate the relative importance of input variables on regulation of the targeted output variable (Shan *et al*., 2021), assuming the model can adequately replicate the associated or relevant processes.

### *2.6.2. Types of process-oriented modelling used in exploring biogeochemistry of nitrogen in agricultural soils*

Modelling approaches have been used extensively across the world to explore N dynamics in agricultural soils. Cannavo *et al*. (2008) reviewed the utility, scope and limitations of 62 biogeochemical models that are relevant for exploring soil N dynamics. Bell *et al*. (2011) indicated that complex process-oriented models provide the scope to investigate the interactions among soil, weather, climate, management, crop growth and N dynamics at a very detailed scale, although the level of detailed input data requirements and its availability is a key limiting factor to utilising these models successfully. At the same time, the optimum temporal scale for reliable performance among such models can also vary (Giltrap *et al*., 2010; Zimmermann *et al*., 2018). Cannavo *et al*. (2008) indicated that the optimum spatial scale of these models can vary from field to farm, soil profile to field, watershed and field to watershed. Similarly, the outputs from these models varies in terms of time scales, ranging from daily, weekly, monthly, annual, and crop cycle. Their study further showed that only a small number of models that simulate soil N dynamics, like DNDC, EPIC and AMINO, account for all the major processes of the soil N biogeochemical cycle – mineralisation, leaching, volatilisation, nitrification, denitrification, uptake and BNF. Most of the remaining models lack do not explicitly account for at least one or more of the relevant biogeochemical processes. For example, models like DAISY, SUNDIAL, LEACHN and DayCent do not account for BNF, while the SOIL-N model does not account for ammonia volatilisation.

De Vries *et al*. (2010) investigated the potential of employing several existing dynamic models for exploring soil N dynamics. They indicated that the soil model SMART2 (Simulation Model for Acidification's Regional Trends) can estimate C:N ratio and N availability in soil using input information on atmospheric deposition, litterfall, mineralisation, root uptake and immobilisation of N. They also indicated that the MAGIC (Model for Acidification of Groundwater In Catchments) model estimates the same outputs but with the inclusion of soil-water chemistry, using empirical relationships between net N retention and the C:N ratio in the soil. On the other hand, crop models like SUMO generate estimates of biomass growth using input information on available light, N, P, water and temperature. The inclusion of management impacts, in soil models such as SMART2 and MAGIC, can be explored to better understand N dynamics (De Vries *et al*., 2010).

The SOIL-N model is a process-oriented model that simulates N dynamics at field level and at a daily timestep (Henrik and Beier, 1998). This model simulates transport and transformation of N in the soil while accounting for climate and soil water distribution simulated from meteorological information, supply of N to soil from organic and inorganic resources, decomposition and mineralisation, nitrification, denitrification, leaching, while N uptake is the key output of the model (Bergström *et al*., 1991; Wu and McGechan, 1998). Wu and McGechan (1998) also compared models including ANIMO, DAISY and SUNDIAL which simulate N uptake by plants and uses the N input from fertiliser, organic resources and deposition of N. The AMINO model accounts for mineralisation, volatilisation, nitrification, denitrification, immobilisation, adsorption and desorption of N. The DAISY model accounts for mineralisation, immobilisation, nitrification and denitrification and also the N leaching. Unlike the AMINO model, the DAISY model does not account for adsorption and desorption. The SUNDIAL model includes the soil processes of mineralisation, volatilisation, nitrification, denitrification, but does not account for leaching, adsorption, desorption and immobilisation. None of the models (SOILN, ANIMO, DAISY and SUNDIAL) accounted for runoff or rely explicitly on key soil fertility indicators (Wu and McGechan, 1998). The LEACHN model, used to estimate N leaching from cropping systems based on meteorological conditions and hydrological conditions of the soil, accounts for fertiliser input, C:N ratio of humus and biomass, mineralisation, $NH_3$ volatilisation, nitrification, denitrification and uptake of N (Acutis *et al*., 2000).

Complex models that integrate the diversity of soil, climate, weather and management with various degrees of detailed input requirements are being developed and utilised to better understand N dynamics in agricultural soils. Using the WHCNS (Water Heat Carbon Nitrogen Simulator) model, Shi *et al*. (2020) identified that increasing the frequency of irrigation can maintain optimum maize yield and reduce N leaching even under reduced water input and N fertiliser applications, in oasis farmland in the Shiyang River Basin in China. Leghari *et al*. (2019) used the WHCNS model to estimate and compare the potential grain yield, water and N use efficiencies under different cropping systems - winter wheat–summer maize, winter wheat–

summer maize–spring maize and spring maize in North China Plain. Richards *et al*. (2016), using the ECOSSE (Estimation of Carbon in Organic Soils – Sequestration and Emissions) model, identified that replacing rotational crops with *Miscanthus* can reduce $N_2O$ emissions in the United Kingdom by reducing the requirement for N fertiliser application that ultimately leads to reduced availability of $NO_3^-$ in soil, required for denitrification. Zhang *et al*. (2013), in their study using the DayCent model (daily time-step version of the CENTURY model), found that the reduction of N fertiliser inputs with increasing age of turfgrass lawns in the semiarid regions of Colorado is required to reduce potential N leaching, whereas a reduction in irrigation reduced the biomass production. Using the DayCent model, Qin *et al*. (2018) estimated that under a projected increase in spring wheat yield, driven by climate change in the Canadian prairie, an increase of N fertiliser input beyond 100 kg N/ha/year would have a marginal effect on increasing yield and would contribute more to increased $N_2O$ emissions and N leaching. Qingnan *et al*. (2023) estimated, using the DNDC (DeNitrification DeComposition) model, that the combined application of chemical and organic fertilisers in a tropical rice-wheat cropping system in China would reduce loss through $NH_3$ volatilisation in comparison to only chemical fertiliser application or only organic fertiliser application, while improving yield at the same time. They were also able to estimate the optimum N input requirements to achieve optimal rice-wheat production under the mixed application of chemical and organic fertilisers, using DNDC. In a study using the DNDC model to examine the impact of various management practices on diverse soil and climate conditions in the Midwest corn production zone of the United States of America (USA), Ingraham and Salas (2019) estimated that urea fertiliser and nitrification inhibitors may reduce both $N_2O$ emissions and $NO_3^-$ leaching without significantly reducing corn yield. However, on the contrary, they found that reducing N fertiliser input to reduce $N_2O$ emissions and $NO_3^-$ leaching rate negatively impacted the yield. Using the EPIC (Environmental Policy Integrated Climate) model, Choruma *et al*. (2021) estimated that for the Eastern Cape of South Africa, an application of 200 kg N/ha and irrigation of 580 mm per growing season resulted in the highest model estimates for maize production. Their simulations also identified that N fertiliser is the key driver of $NO_3^-$ leaching and increasing N fertiliser application to achieve a yield beyond 11.4 Mg/ha may not result in any significant difference in yield but can significantly contribute to increasing the $NO_3^-$ leaching.

Such models vary in terms of the suite of variables required for inputs, accountability to biogeochemical processes associated with N dynamics and suite of outputs generated and the corresponding temporal scale. The WHCNS model utilises inputs on climate and field management to produce simulated outputs on dynamics of crop growth, soil climate conditions, SOC, and dynamics of N (including variables like soil $NO_3^-$ and $NH_4^+$ conditions, mineralisation and immobilisation of N, nitrification, denitrification, $N_2O$ emissions and N uptake by plant) (Liang *et al*., 2016a). The ECOSSE model is a dynamic and complex soil-climate-management model that integrates detailed inputs on climate at a monthly scale, weather data on a daily scale (variables include rainfall, potential evapotranspiration and temperature), detailed inputs on soil physicochemical properties and hydrological parameters, and year-specific inputs on land use practices (land use type, yield of crops, application of fertiliser, manure and crop residues). This model generates emissions of $N_2O$, $N_2$, $NH_3$ volatilisation, leached N, and accounts for decomposition, mineralisation, immobilisation, nitrification and denitrification (Bell *et al*., 2011). The DayCent model operates at a sub-daily time step to simulate the soil hydrology, ultimately to estimate daily emissions of $N_2O$ and other gases generated during denitrification, soil $NO_3^-$ and $NH_4^+$ content and leaching of $NO_3^-$, and weekly biomass and plant growth at monthly scale. It uses inputs on daily weather, soil texture and management of nutrients and cropping (Del Grosso *et al*., 2008). The DNDC model performs at a site-specific level to simulate soil N dynamics (Gilhespy *et al*., 2014). It is a process-oriented model that utilises detailed environmental inputs on daily weather, climatic inputs on N concentration in precipitation, $NH_3$ concentration in air, $CO_2$ concentration in air and its increase over time, as well as detailed soil physicochemical properties. To run the model, information on events and intensity of the management system are required as inputs. These include cropping, tillage, grazing regime, biomass harvest events, organic and inorganic fertiliser applications, mulching and water supply. The simulated outcomes of the DNDC model include estimates of C and N dynamics. The N dynamics include estimates of N uptake, emissions of $N_2O$, NO, $N_2$, volatilisation of $NH_3$, leaching of $NO_3^-$ and urea, inorganic N in runoff, mineralisation, DON, available N in soil, N trapped in ice - at a daily scale that can then be accumulated to generate annual estimates Daily and annual crop yield is also simulated by the model (ISEOS, UNH, 2012; Gilhespy *et al*., 2014). The outputs include the estimated rates of biogeochemical processes of nitrification, denitrification, soil N fixation and litter incorporation. Wang and Chen (2012) identified that parameter uncertainty is higher for DayCent in comparison to DNDC for $N_2O$ emissions estimation, whereas key input requirements for soil physicochemical properties and management practices are more detailed for DNDC in comparison to DayCent (Giltrap *et al*., 2020). The EPIC model performs at daily time step and simulates denitrification, N uptake, N immobilisation, $NH_3$ volatilisation, BNF, N fixation, hydrological transport of $NO_3^-$, including leaching and organic N transport by sediment with inputs of soil, weather and management. However, the EPIC model requires a much detailed parameterisation for crop phenology in comparison to DNDC (Cavero *et al*., 1998; Gaillard *et al*., 2018).

### *2.6.3. Model Selection*

The primary challenge in selecting a model to explore the scope of sustainable N management practices can arise from identifying commonalities or exploring the scope of upscaling or downscaling that is achievable from the model outputs. Such a selection process needs to be based on the spatial and temporal resolution of the management strategy considered by the study, as well as the optimum spatial and temporal resolution to generate reliable performance of the model being considered (Cannavo *et al*., 2008; Milne *et al*., 2020; Zhang *et al*., 2020a). Patil *et al*. (2009) indicated that the general challenges that emerge while using a modelling approach to identify optimum nutrient requirements arise from limitations associated with data requirements, the requirement of localised calibration, the practical use and application of the model, and potential for integrating management options. Generally, models focused on lower spatial resolution (global scale) have a higher number of input variables whereas higher spatial resolution (local scale) model may require fewer but more detailed inputs (Haraldsson and Sverdrup, 2013). This raises the challenge of matching the management strategy and model with the availability of the data inputs required to run the model (Patil *et al*., 2009). However, Milne *et al*. (2020) indicated that unless there is an interaction between the scales at which information is available, hierarchical upscaling of a model derived strategy is the most feasible approach to reduce the challenge arising from scale mismatches. They found that sustainable management strategies derived from a higher resolution modelling approach remains unchanged at lower resolution if the two spatial scales do not interact. They indicated that strategies for sustainable nutrient management derived from a model optimised at multiple field scales can be combined and used for exploring landscape scale solutions and strategies, although this requires alignment between appropriate scales for efficient application.

Not all biogeochemical models used for simulating soil N dynamics account for all major steps of the N cycle, mostly due to their limited objective to determine particular components of the N cycle. This usually simplifies the model but also requires a number of assumptions with regards to the processes unaccounted for (Cannavo *et al*., 2008) leading to increased uncertainty (Zhang *et al*., 2020a). Thus, the challenge in choosing a suitable model also arises from the level of spatial detail sought for the N management strategy (Haraldsson and Sverdrup, 2013). However, Kouadio and Newlands (2014) indicated that the requirement for input data and model parameterisation increases with the complexity of a model. They further indicated that increased complexity improves the utility of the process-oriented model for research purposes as this implies a more elaborate estimation of the underlying biogeochemical processes that take place in agricultural landscape under specific crop phenology, environmental and management conditions; however, the extent to which this finding is generalisable is not clear as complex models, requiring numerous parameters, are subject to uncertainties and interactions between the parameters. On the contrary, simpler models may account for interactions between crop phenology and environmental conditions in a more general way, but are better suited for operational purpose due to the reduced requirements for more detailed parameters (Kouadio and Newlands, 2014).

*Grassland modelling in Ireland*

Model based approaches have been extensively used in Ireland to investigate grass growth and the dynamics of N in soil (e.g., Abdalla *et al*., 2009; Khalil *et al*., 2016; Rafique *et al*., 2011a; Zimmermann *et al*., 2018). These approaches can be broadly categorised into studies that have focused on estimating grass yield and studies focused on soil N dynamics. Hurtado-Uria *et al*. (2012) tested the performance of two dynamic grass growth models on Irish grasslands. One was a model developed by Johnson & Thornley (1983) (J&T model) in England that simulates grass growth at a daily scale, primarily based on weather inputs. The second model evaluated was developed by Jouven *et al*. (2006) (J model) in France that simulates grass growth at seasonal and annual scales, integrating the impact of management. Hurtado-Uria *et al*. (2012) also explored the performance of an empirical grass growth model for Irish grasslands developed by Brereton *et al*. (1996) (B model) that simulates grass growth based on weather inputs. They found that the dynamic J model and the empirical B model performed best in predicting grass growth. Ruelle *et al*. (2018) modified the J model (Jouven *et al*., 2006) into the Moorepark St Gilles grass growth model (MoSt GG model) to estimate grass growth for intensively managed perennial ryegrass paddocks in Ireland, through the inclusion of sub-models on soil, plant N and soil water. The model uses inputs on physicochemical properties of soil (mineral N, SOM, clay and sand content); area of paddock and starting biomass; maximum, minimum and average air temperature, daily rainfall and solar radiation; management of grazing, biomass cutting and N fertiliser applications (Ruelle *et al*., 2018; O'Donovan *et al*., 2022). McDonnell *et al*. (2019) identified that the MoSt GG model could reliably estimate short term grass growth using weather forecast data, useful for N management decision making at weekly time scales in line with the objectives of *right rate* and *right time* of N application of the 4RNS (4R Nutrient Stewardship) strategy (Fixen, 2020).

Separately, model based approaches have also been employed to explore the soil processes relevant to understanding N dynamics, including process-oriented models such as DNDC, DayCent and ECOSSE. For example, Abdalla *et al*. (2009) used DNDC (v9.2) to estimate $N_2O$ emissions from grasslands at the Teagasc research facility in Oak Park, Co. Carlow, and identified poor model performance in estimating $N_2O$ emissions. They identified the overestimation of water filled pore space (WFPS) and a high model sensitivity to soil organic carbon (SOC) input, a required model parameter, as possible reasons for the poor model performance. Similar results were obtained by Abdalla *et al*. (2010) in a model comparison study between DayCent and DNDC model (v8.9) to estimate $N_2O$ emissions and biomass production at the same location. The authors found that DayCent performed better than DNDC for estimating $N_2O$ emissions and biomass production. In contrast, Li *et al*. (2011) found DNDC (v9.3) performed well in estimating $N_2O$ fluxes, especially under grazing conditions, in a study performed at the Teagasc Solohead research farm. Their study differed from that of Abdalla *et al*. (2009) and Abdalla *et al*. (2010) in terms of input parameterisation for soil; Li *et al*. (2011) employed site specific inputs for clay fraction, hydro-conductivity and concentrations of $NH_4^+$ and $NO_3^-$ in soil. Rafique *et al*. (2011a) also produced estimates of the annual $N_2O$ emissions using DNDC (v9.3) across eight grassland sites located across the southern part of Ireland. These authors employed more site-specific information on the C:N ratio for SOC partitioning and porosity of soil. However, they indicated that DNDC was insensitive to stocking rate and more sensitive to organic N input than inorganic N input. Li *et al*. (2011) observed that DNDC resulted in poor estimates of the background $N_2O$ emissions. The limited ability of DNDC to estimate $N_2O$ under reduced N fertiliser input conditions was identified by Abdalla *et al*. (2009). Abdalla *et al*. (2009) identified the minimum N fertiliser input, > 140 kg N/ha, required to achieve a reliable performance of the DNDC model to estimate $N_2O$ emissions. Khalil *et al*. (2016) found that the ECOSSE (v5+) model was better at estimating emissions of $N_2O$ over grassland at Oak Park in comparison to both DNDC (v9.4) and DailyDayCent. Zimmermann *et al*. (2018) also found that the ECOSSE model performed better for simulating $N_2O$ emissions from a selection of grassland sites, Johnstown Castle, Wexford and Moorepark in Ireland and at Hillsborough in Northern Ireland, in comparison to DayCent and DNDC (v9.4 and v9.5).

*Model Selection Criteria*

The focus of this research is on exploring the key environmental and human regulators of grass yield and N loss in Irish grasslands. Therefore, a model based approach that estimates grass yield and can account for the major soil processes relevant to N dynamics, including at least two of the major three N loss processes ($NH_3$ volatilisation, $N_2O$ emissions, $NO_3^-$ leaching) associated with grassland, so the proportion of the third can be assumed (Hoekstra *et al*., 2020; van Beek *et al*., 2008), was required. The primary criteria for choosing a specific model was to identify models that account for inputs on soil, climate and/or weather, climate and management to simulate the processes of N dynamics. Thus, choosing a more complex process-oriented model, like DNDC, DayCent or ECOSSE, instead of a purely crop or soil process model was considered more appropriate (Bell *et al*., 2011; Del Grosso *et al*., 2008; Gilhespy *et al*., 2014). The second requirement was that the model could account for all the targeted output variables. The ECOSSE model simulates $N_2O$ emissions, $NH_3$ volatilisation and N leaching but does not explicitly estimate the crop yield, rather estimates biomass and is not explicitly designed for grasslands (Abdalla *et al.*, 2016; Abdalla *et al.*, 2023; Bell *et al*., 2011). The DayCent model estimates $N_2O$ emissions, $NH_3$ volatlisation, biomass and $NO_3^-$ leaching, however, do not explicitly account for the impact of soil microbial pools on N dynamics, unlike DNDC (Del Grosso *et al*., 2008; Gabbrielli *et al*., 2024). In contrast, the DNDC model estimates biomass (from which crop yield can be derived), $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ including other N loss pathways like N runoff, emissions of NO, $N_2$ etc., while explicitly accounting for soil microbial pool (Gabbrielli *et al*., 2024; Gilhespy *et al*., 2014). Based on the model selection criteria, DNDC represented the most suitable model for addressing the research aims and objectives. Further, the DNDC model accounts for all the important biogeochemical processes related to N cycling in soil, including - mineralisation, leaching, volatilisation, nitrification, denitrification, uptake and BNF (Cannavo *et al*., 2008). DNDC model enables to include the effect of grazing on grazed grasslands among which the impact of animal excreta as source of nutrients within soil litter and accounting for losses due to milk production, as well as the impact of grazing on soil compaction and stimulating effect of grazing on grass production (Kang *et al.*, 2013). Thus, DNDC can become an important tool to estimate yield and N loss for the predominantly grazed Irish grasslands (Bourke *et al*., 2007; Läpple *et al*., 2012), if performing reliably. DayCent also has a grazing module, but ECOSSE does not have it (Grant *et al*., 2016). Whereas MostGG do not produce output on N loss other than N leaching and do not simulate simulate aspects of microbial mechanisms regulating N dynamics other than mineralisation and immobilisation (Ruelle *et al.*, 2018).

**Table 2.1.** Comparison of Major Process-Based Model Used in Studies Performed in Ireland, Capable of Simulating Impact of Nitrogen Application and Integrating Soil, Atmospheric and Management Data, in Terms of Overview of Inputs and Outputs Relevant for Grassland Studies

| Model | Key Input Modules | | | | Targeted Outputs | | | | References |
|---|---|---|---|---|---|---|---|---|---|
| | Soil Physico-chemical properties | Weather | Grazing Regime | N Fertiliser Application Regime | Yield / Net Primary Productivity | $NH_3$ Volatilisation | $N_2O$ Emissions | $NO_3^-$ Leaching | |
| ECOSSE (Implicit Microbial Pool) | ✓ | ✓ | X | ✓ | ✓ | ✓ | ✓ | ✓ | Abdalla *et al.*, 2016; Abdalla *et al.*, 2023; Zimmermann *et al.*, 2018 |
| DayCent (Implicit Microbial Pool) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Grant *et al.*, 2016 |
| MostGG (Implicit Microbial Pool) | ✓ | ✓ | ✓ | ✓ | ✓ | X | X | ✓ | Ruelle *et al.*, 2018 |
| DNDC (*Explicit Microbial Pool) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Grant *et al.*, 2016 |

## 2.7. Summary

Nitrogen is an important soil nutrient required for the operation of physiological processes and biomass growth in plants and also supplies nutrients to other organisms present in the food chain (Ohkouchi *et al*., 2017; Zhang *et al*., 2020). While BNF is the natural primary mechanism of N supply from the atmosphere to soil that recycles through SOM formation and decomposition (Blesh, 2019) and to some extent by atmospheric deposition (Hertel *et al*., 2012), for agricultural soils N is commonly supplied through synthetic and organic N fertilisers (Matson *et al*., 1997; Teagasc, 2017). The application of N fertilisers is increasing globally associated with the intensification of agriculture (Heffer and Prud'homme, 2016). Therefore, the negative impacts of N lost from agricultural soil on environment and ecosystem, such as the emissions of the $N_2O$, eutrophication, groundwater pollution etc. are thus also increasing globally (Abascal *et al*., 2022; Malone and Newton, 2020; Tian *et al*., 2020). The monetary impact of global N loss is also evident on the economy (UNEP, 2019). This has led to an increased global effort to develop strategies for more sustainable N management practices to reduce N loss from agriculture while maintaining optimum productivity targets (EC, 2020; Kanter and Brownlie, 2019). To achieve improved sustainability through policy implementation, it is a requirement to spatially and temporally refine the strategies and policies based to the optimum spatial scale and suitability for the objective (Milne *et al*., 2020; Shirmohammadi *et al*., 2008; Zhang *et al*., 2020a).

Exploring N dynamics in agricultural soil using process-oriented models for more informed strategy development for sustainable N management can be a viable option for refining and optimising N fertiliser applications (Cannavo *et al*., 2008; Patil, 2009). However, research and development of sustainable N management is difficult due to the offset between the spatial scale of a model's optimum performance and the spatial scale of the implemented policy (Patil, 2009; van Oijen *et al*., 2018; Zhang *et al*., 2020a). The spatial variability of N dynamics and its natural and anthropogenic regulators can often make sustainability strategies derived at a lower spatial resolution to be sub-optimal for implementation at higher resolution site scale (Shirmohammadi *et al*., 2008). Between two spatial scales that are not interacting, a strategy optimisation using models at higher resolution sites can inform and improve regional, landscape or national strategies (Milne *et al*., 2020). However, dynamic process-oriented models need to be parameterised to local conditions and validated prior to using it for decision-making. This comes with the challenge of choosing the most useful model according to the stated goals of the research, the model's performance at/across different spatial scales, and the availability of suitable input data at a scale appropriate for the model and processes that the researcher is interested in (Haraldsson and Sverdrup, 2013; Patil, 2009). The selection of a suitable model also depends on the parity between types of biogeochemical processes accounted for within the model and the ones that are targeted in the research (Cannavo *et al*., 2008; Haraldsson and Sverdrup, 2013). However, according to the objectives of this research, DNDC appears to be the most suitable model due to the detailed level of biogeochemical process of soil N dynamics it accounts for, along with its ability to produce outputs on a wide range of daily to annual N loss fluxes mechanisms and crop dynamics (Cannavo *et al*., 2008; Gilhespy *et al*., 2014).

# 3. Experimental Framework and Methods

## 3.1. Introduction

Process-oriented models have been proposed and utilised to explore the relative importance of key environmental variables and management activities on grass growth and N dynamics at field scale and therefore could inform the geographical refinement of field level N management strategies, including the NMP-Online tool (Higgins *et al*., 2017; Patil, 2009; Schellberg *et al*., 2008). Identifying the key variables that govern grass yield and N loss at field scale would also assist in refining national level and more generalised management strategies seeking to improve efficiency, reduce N loss and maintain sustainable yields (Milne *et al*., 2020; Wang *et al*., 2016). A model-based approach can also facilitate an assessment of the impact of current management strategies on grass growth and N loss across diverse locations (Choruma *et al*., 2021; Qingnan *et al*., 2023; Zhang *et al*., 2013).

While the use of process-oriented models offers the potential to inform improved N management, they have a number of limitations. Process-oriented models require detailed inputs of soil, weather, crop phenology and management and need to be parameterised and subsequently evaluated, for which the availability of measured data remains a challenge (Haraldsson and Sverdrup, 2013). Here, the *DeNitrification and DeComposition* (DNDC) model was employed to investigate the growth dynamics of perennial ryegrass and N loss, due to its ability to estimate the relevant biogeochemical processes involved in regulating N dynamics considering the impact of environmental and management factors, and for its ability to generate detailed output of the dynamics of crop yield and N loss (Cannavo *et al*., 2008; Gilhespy *et al*., 2014). There are other variants of DNDC that simulates scenarios of grassland but were not included in this study, such as - Landscape-DNDC, NZ-DNDC, NEST-DNDC etc (Gilhespy *et al*., 2014), however one challenge for this is that these models are not available in the openly available platform of DNDC (Source: http://www.dndc.sr.unh.edu/) thus can become a challenge for robust application of modelling. Whereas DNDC 9.5 is the common openly available modelling software that includes the dedicated module to simulate scenario of grasslands under grazing and silage harvest in different landscapes at site-specific level (ISEOS, UNH, 2012). This model has already been used in studies performed in Irish landscape (e.g. Abdalla *et al*., 2009; Abdalla *et al*., 2010; Li *et al*., 2011; Rafique *et al*., 2011; Zimmermann *et al*., 2018) – thus many aspects of the model's data requirement, scopes and limitations are known in Irish context. Thus, a successful parameterisation and validation of this model can lead to improving the model's utility for Irish grasslands, using available database for model input. Whereas a method employed to improve the utility of DNDC 9.5 in a targeted way for geographical refinement for Irish grassland will remain relevant as a framework for modelling approach for such refinement employing other versions of DNDC, other models targeting other nutrients, in grasslands and other agroecosystems. However, gaps exist in the parameterisation of DNDC representing the phenology of perennial ryegrass and local climatic conditions and corresponding validation of the estimated grass growth and N dynamics. Thus, we explore the use of the DNDC model, parameterised and validated for perennial ryegrass dominated dairy farms (Haraldsson and Sverdrup, 2013; O'Donovan *et al*., 2021), for informing refined N management strategies for grasslands under dairy production. Furthermore, we also explored the scope of using DNDC to generate reliable estimates where only limited site-specific data is available (Giltrap *et al*., 2010; Patil, 2009) to evaluate the potential of the model for more widespread application.

### 3.2. Overview and Structure of the DNDC model

The development of the DNDC model began in 1989 by Bruce Company of Washington D. C., and was further developed by contributions from Changsheng Li, Steve Frolking and Robert Harriss at University of New Hampshire, who integrated the impacts of weather, soil, crop type and management practices on estimating denitrification and decomposition processes in soil (Li, 1996). Since then, the DNDC model has gone through a process of continuous development. Beginning with three sub-models on soil-climate/thermal-hydraulic flux, decomposition and denitrification, its capacity to account for detailed biogeochemical processes was expanded with the integration of sub-models on crop-growth, nitrification, fermentation (Figure 3.1), which provides the current framework for DNDC version 9.5 (Gilhespy *et al*., 2014). The plant-growth sub-model was primarily introduced in DNDC for winter wheat (Li *et al*., 1994) while the phenological crop-model was first introduced by Zhang *et al*. (2002). Modification of DNDC to simulate $N_2O$ emissions in grazed grasslands under dairy farming was performed by Saggar *et al*. (2004) for farm locations in New Zealand. Saggar *et al*. (2007) further modified DNDC for grass-clover (perennial ryegrass-white clover) pasture by modifying the N fixation rate and accounting for biomass increase using a regional and seasonal crop growth curve for potential optimum yield. Water stress, N availability and temperature conditions determine the potential reduction of grass growth from a maximum or optimum growth rate. The soil hydraulic conductivity sub-model in DNDC uses pedotransfer functions (PTF) based on the van Genuchten (1980) equations, for a matrix of 12 textural classes of soil (Costa *et al*., 2021). Zhang and Yu (2021) indicated that simulation of the nitrification process in DNDC is driven by estimates of nitrifier biomass, soil $NH_4^+$ content, dissolved organic carbon content, soil temperature, WFPS and soil pH, whereas the simulation of denitrification process is driven by estimates of denitrifier biomass, total N as the sum of $NO_3^-$, $NO_2^-$, NO and $N_2O$, dissolved organic carbon content, soil temperature, and soil pH.

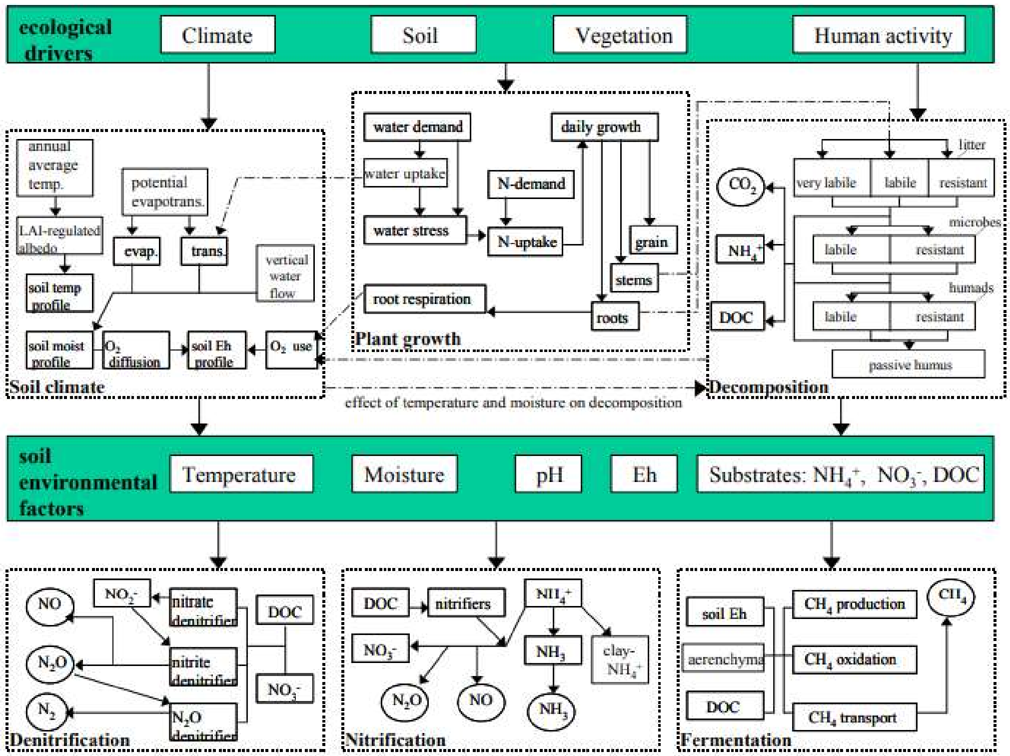


**Figure 3.1**. Schematic overview of the DNDC model including inputs and sub-model components (Source: ISEOS, UNH, 2012)

The most recent version of DNDC (Denitrification-Decomposition) Model (version 9.5) (Source: http://www.dndc.sr.unh.edu/), employed here (hereafter referred to as DNDC), requires inputs of daily weather, soil physicochemical properties, vegetation type and management practices (ISEOS, UNH, 2012). The model has two modes of operation - site and regional mode. The site level option was employed here with the aim of investigating the scope for upscaling from field level to regional scale (Gilhespy *et al*., 2014; Giltrap *et al*., 2010; Milne *et al*., 2020). N uptake and temperature are the key determinants of plant growth in DNDC (ISEOS, UNH, 2012). DNDC includes a sub-routine for cropping practice and management, that is based on N uptake (dependent on relative abundance of plant-available N in soil) as determined from the potential maximum yield, the C:N ratio in the crop biomass and a generalised crop growth curve (for crops other than winter wheat) (Zhang and Niu, 2016). With relevant site-specific inputs on weather, soil and management, DNDC produces estimates of C and N dynamics, including the daily growth rate and annual yield of the specified crop in terms of leaf, stem, root and grain in kg C/ha (Gilhespy *et al*., 2014). DNDC requires the specification of a number of site-specific inputs (Table 3.1), whereas other input variables are provided as model defaults and can be modified according to requirements (e.g. data availability etc) (Table 3.1).

**Table 3.1.** Mandatory and default (can be modified) inputs for DNDC simulation (adapted from Gilhespy *et al.*, 2014)

| Inputs | Site | Weather | Soil | Farming management practices |
|---|---|---|---|---|
| Mandatory | • Site<br>• Latitude | • Daily mean or max./min. air temperature (°C)<br>• Daily precipitation (cm) | • Land use type<br>• Soil texture<br>• pH<br>• SOC at surface (kg C/kg soil)<br>• Use SCS and MUSLE functions (yes/no) | **Crop:**<br>• Type (62 default types)<br>• Crop rotation (no. crops per year)<br>• Planting and harvest date<br>• Cover crop (yes/no)<br>• Perennial crop (yes/no)<br><br>• **Fertiliser**<br>Type, method, rate, no. of applications, dates, depth<br>• **Manure**<br>Type, method, rate, no. of applications, dates, depth<br>• **Tillage**<br>Method, no. of applications, dates<br>• **Grazing or cutting**<br>No. of grazing/cutting applications, dates; grazing livestock type, grazing hours per day & stocking rate<br>• **Irrigation Method**<br>rate, no. of applications, dates<br>• **Flooding Method**<br>dates, N in flood water, water leaking rate<br>• **Plastic**<br>No. of plastic (mulch/greenhouse) applications, dates, % of plastic coverage |
| Default | | • Daily average wind speed (m/s)<br>• Humidity (%)<br>• Daily solar radiation ($MJ/m^2/day$)<br>• N concentration in precipitation (mg N/l or ppm)<br>• Atmospheric background $CO_2$ concentration (ppm)<br>• Atmospheric background $NH^3$ concentration ($\mu g\ N/m^3$)<br>• Annual increase rate of atmospheric $CO_2$ concentration (ppm/year) | • Bulk density ($g/cm^3$) (based on SOC)<br>• SOC partitioning (fraction & C:N ratio of litter, humads, humus and char C)<br>• SOC profile: depth of topsoil with uniform SOC content (m); SOC decrease rate below topsoil (0.5–5)<br>• Clay fraction (0–1)<br>• Soil structure: Bypass flow rate (0–1); depth of water retention layer (m); drainage efficiency (0–1)<br>• $NO_3^-$ concentration at surface soil (mg/kg)<br>• $NH_4^+$ concentration at surface soil (mg/kg)<br><br>• Field capacity (WFPS; 0–1)<br>• Wilting point (WFPS; 0–1)<br>• Porosity (0–1)<br>• Hydro-conductivity (m/hr)<br>• Microbial activity index (0–1)<br>• Slope (0–90°)<br>• Soil salinity index (0–100)<br>• Rainwater collection index (0–1) | **Crop:**<br>• Fraction of leaves & stems left in field after harvest (0–1)<br>• Annual N demand (kg N/ha/year)<br>• C:N ratio of grain, leaf, stem & root<br>• Biomass fraction of grain, leaf, stem & root (0–1)<br>• Maximum biomass production (kg/C/ha/year)<br>• Thermal degree days for maturity (days)<br>• Water demand (g water/g dry matter)<br>• Optimum temperature for crop growth (°C)<br>• N fixation index (crop N/N from soil)<br>• Vascularity index for wetland plants (0–1)<br><br>**Manure**<br>C:N ratio of manure |

*Limitations and research gaps in the context of using DNDC model for Irish grassland research*

Similar to grasslands globally, the key N loss pathways for grasslands in Ireland are $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching (Hoekstra *et al*., 2020; van Beek *et al*., 2008; Woodmansee *et al*., 1981). While most studies exploring soil N dynamics using DNDC in Ireland focus on estimating $N_2O$ emissions, there is a knowledge gap in exploring its performance on other major N loss pathways including $NH_3$ volatilisation or $NO_3^-$ leaching. An extensive body of research has been performed on grasslands in Ireland, primarily located on Teagasc research farms (Teagasc, 2017a) - located at Ballyhaise (County Cavan), Clonakilty College (County Cork), Curtins Farm (County Cork), Johnstown Castle (County Wexford), Dairygold Farm (County Cork), Moorepark (County Cork), Solohead (County Tipperary) and Kilworth (County Cork) (Teagasc, 2017a). Research outputs for a selection of these sites include the measured in-situ data required to run DNDC. While some detailed site-specific data and information is available from these intensively studied sites, it is ultimately the lack of such detailed site information elsewhere that limits the use of a model based approach to inform improved N management nationally. Here, we sought to assess to what extent does employing more generalised information, such as for series leader soil information from the Irish Soil Information System (Irish SIS) for a site's location (O'Sullivan *et al*., 2018), and idealised management scenarios based on stocking rate, similar to the generalised advisories and Nitrates Derogation strategies (Callaghan, 2023; Wall and Plunkett (eds.), 2020), impact on the models ability to reliably estimate yield and N emissions, compared to model estimates using site-specific and more detailed information. Essentially, to evaluate at what extent can generalised 'required' inputs still produce reliable model estimates (e.g. absolute values or relative differences between sites) was explored.

There are a number of challenges in using DNDC. Byrne and Kiely (2008) indicated that the scope of employing the DNDC model can be limited by the input data requirements. Existing works indicated the potential for improving the estimation of $N_2O$ emissions using DNDC for grasslands through calibration or increasing the specificity of the soil inputs (e.g. Abdalla *et al*., 2009; Abdalla *et al*., 2010; Hoekstra *et al*., 2020; Li *et al*., 2011; Rafique *et al*., 2011a). Furthermore, if there is an optimum scale (spatial, temporal) at which DNDC can produce 'reliable' model estimates (Haraldsson and Sverdrup, 2013; Milne *et al*., 2020; Patil, 2009), that could be useful for informing and/or refining national policies, is not known. For example, Giltrap *et al*. (2010) indicated that the reliability of daily estimates from DNDC varies as the model displayed poor statistical performance due to leads or lags in comparison to the actual measurements, yet outcomes at a longer timeframe have been found to be reliable. To what extent can a model that generates poor estimates at a daily scale be considered reliable at aggregated timescales needs to be explored.

The grassland module of DNDC, which was originally developed for grass-clover pasture by Saggar *et al*. (2007) for New Zealand, may not perform as well for other species compositions. Li *et al*. (2019) found that when DNDC was not parameterised for their sward type of interest - perennial ryegrass - DNDC overestimated annual $N_2O$ emissions fluxes by 61 %, whereas, for grass-clover sward treated with additional N input through fertiliser the results were very close to measured conditions. Abdalla *et al*. (2009) also found poor model performance for DNDC in estimating annual $N_2O$ emissions even for a grass-clover sward, when the crop phenology was not parameterised for local conditions (e.g. phenological conditions based on ratio of grass to clover). Abdalla *et al*. (2010) validated the estimated biomass for a grass-clover field by DNDC without parameterising the default grassland phenology and found the model underestimated aboveground biomass by 75 %, with high overestimation of the cumulative $N_2O$ emissions (132%, for fertilised plots and +258% for control plots). Khalil *et al*. (2020) modified the biomass yield, fraction and C:N ratio in the fractions with site-specific inputs for Northern Ireland grassland plots, mixed species sward with white clover. They found the model performed acceptably in terms of simulating density and changes in SOC. In a study by Zimmermann *et al*. (2018), the annual maximum grass yield input in DNDC was modified for maximum grass yield along with the growing season length for Ireland; they found that DNDC performed poorly in comparison to both the DayCent and ECOSSE models in estimating annual $N_2O$ emissions. Explicit validation was not performed to assess the reliability of the model estimated grass growth and yield in Khalil *et al*. (2020) and Zimmermann *et al*. (2018). However, there are number of crop phenology inputs in DNDC that can be specified for perennial ryegrass swards, these include the nature of crop, C:N ratio of grain, leaf, stem and root, biomass fraction of grain, leaf, stem and root, thermal degree days for maturity, water demand, N fixation index (Gilhespy *et al*., 2014). These variables may require detailed parameterisation to achieve a more reliable overall model performance and not produce seemingly correct estimates due to error cancellation or other shortcomings in the model representation of the real world. In general, limitations exist with previous studies employing DNDC in terms of estimating grass growth. Only a limited number of studies modified some of the crop phenology inputs representative of the dominant grass species in Ireland, namely perennial ryegrass (O'Donovan *et al*., 2021) and instead utilised the default model parameters developed for New Zealand (Saggar *et al*., 2007). Importantly, if the model is to produce reliable or robust estimates of N, then the crop phenology first needs to be evaluated. Parameterising crop phenology input to validate the estimated crop growth is a necessary step for assessing the reliability of estimated grass growth and associated N uptake that generates surplus N estimation for subsequent processes of N dynamics by the model (Zhang *et al*., 2015).

## 3.3. Experimental framework and data resources

Four key experiments – comprised of questions or case studies - were designed to explore the potential of using the process based DNDC model for improving our understanding of the dynamics of grass growth and N loss in Irish grasslands used for dairy farming. An overview of the experiments' designs and the metrics used for validation are described below.

### *3.3.1. Experiment 1: Chapter 4 – Evaluation of DNDC and identification of key variables to estimate grass growth in an intensively managed grassland*

This experiment was performed with the aim of exploring the ability of DNDC to reliably estimate grass growth rate and yield for intensively managed grasslands under dairy production. The primary focus here was on the crop phenology to assess if DNDC could reliably simulate the growth of perennial ryegrass. Four Case Studies were designed. The focus of Case Studies 1 and 2 was to simulate grass growth rate and yield with soil inputs specific to the paddock (Case Study 1) and using soil information for the farm (Case Study 2) according to soil types. Case Studies 3 and 4 were performed to investigate if the model could perform reliably using more generalised soil inputs. This included inputs such as the lead soil series (main soil type in the spatial polygon in which the experimental sites fall) obtained from the national soil mapping project (Irish Soil Information System – SIS) (O'Sullivan *et al*., 2018), for paddocks and the farm respectively. Sample sites were selected based on the availability of the corresponding detailed records for management for specific years, annual and average daily grass growth rates along with the availability of field level data or representative data for specific paddocks within selected farms. The atmospheric inputs for the model, on N concentration in rainfall and $NH_3$ concentration in atmosphere, were parameterised with site data/information available from Jordan (1997) and Doyle *et al*. (2017) respectively. Even though these inputs can be different in present period of time as stoking rate and intensity of dairy farming has increased as per the latest reports leading to an increased emission of $NH_3$ and $N_2O$ (EPA, 2023; EPA, n.d.), there were no other corresponding records available that is relevant for out sites of experiment. The required weather data was sourced from the nearest meteorological station. The default model values for water filled pore space (WFPS) at field capacity (FC) and wilting point (WP), specific to a textural class, were employed across the four case studies. Similarly, the impact of fertiliser type was not considered, as the amount of N supplied through fertiliser rather than its forms generally shows more significance for grass growth (Harty *et al*., 2017). Finally, the model was run with the default inputs for non-mandatory input variables to test the model's robustness to identify if the model could be used as a tool to estimate grass growth rate and yield for sites with limited data applicability. A schematic diagram of the experimental design is shown in Figure 3.2. The results of the simulations were then employed to assess the model's performance using a range of performance metrics (Abdalla *et al*., 2020; Giltrap *et al*., 2010). A sensitivity analysis was also performed to identify the relevant and potentially important regulators of grass yield within the model (Sweetapple *et al*. 2013; Wang *et al*., 2016).

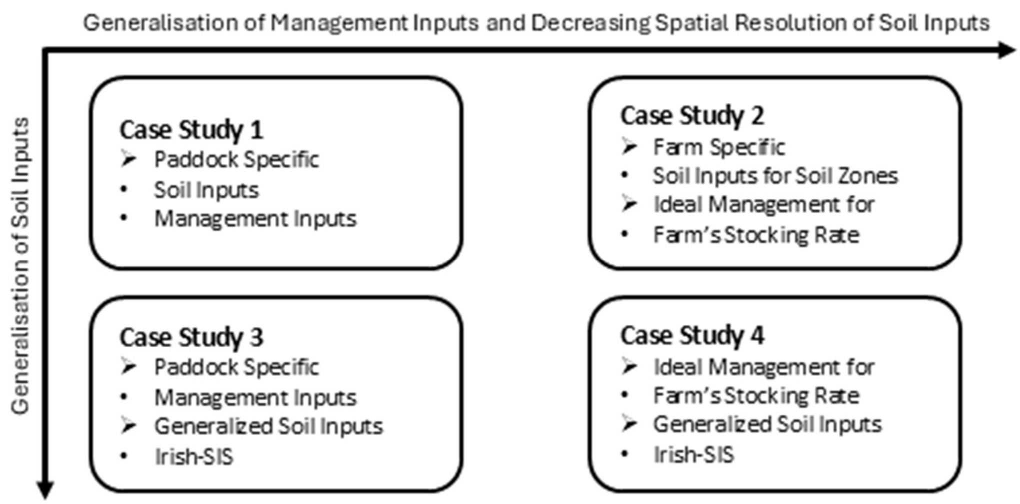


**Figure 3.2**. Design for the four case studies conducted in Experiment 1

### *3.3.2. Experiment 2: Chapter 5 – Evaluation of DNDC and identification of the key variables to estimate nitrous oxide emissions and volatilisation of ammonia from an intensively managed grassland*

The primary objective of Experiment 2 was to evaluate the ability of DNDC to estimate $NH_3$ volatilisation and $N_2O$ emissions, employing the outcomes from Experiment 1, which sought to identify optimised parameters for modelling crop phenology. Abdalla *et al*. (2009) indicated that the estimates of $N_2O$ emissions by DNDC were highly sensitive to the model estimated WFPS. However, in Experiment 1 site-specific inputs for WFPS at FC and WP were not used as they are not recorded in the Irish SIS (O'Sullivan *et al*., 2018), and we wanted to maintain consistency of the suite of variables used throughout the case studies in Experiment 1. Thus, we additionally sought to evaluate the impact of using modified inputs for WFPS at FC and WP specific to soil types in the farm.

Susceptibility of N loss through different pathways in field conditions can vary among fertiliser types depending on the primary form of N from the fertiliser (Forrestal *et al*., 2015; Rahman and Forrestal, 2021). This is consistent with Abdalla *et al*. (2009) who indicated that the performance of DNDC is sensitive to fertiliser type for estimating $N_2O$ emissions. Hence, the aim was to identify the performance of DNDC under applications of two major N fertiliser types used in Irish grasslands – urea and CAN (Gebremichael *et al*., 2022). The experiment design (Figure 3.3) was based on two broad simulation types (Case Study 5 and 6).

For Case Study 5, the DNDC simulations were performed for sites, selected based on availability of data for model input and validation, treated with either urea only or with CAN only (Krol *et al*., 2020; Forrestal *et al*., 2015). Inputs for WFPS at FC and WP were kept as the default model provided inputs for the soil textural class of the corresponding site (paddock). In Case Study 6, the same simulations were performed but with modified inputs of WFPS at FC and WP specific to the soil textural class in the studied sites, calculated from Zimmermann *et al*. (2018). A sensitivity analysis was undertaken to identify the regulators to which the annual $NH_3$ volatilisation and $N_2O$ emissions are sensitive within the model. Sites for the focus of this experiment were largely selected on the basis of data availability on management, measured grass yield and N losses, as well as having the required detailed soil inputs. Atmospheric inputs were obtained for the nearest location from Jordan (1997) and Doyle *et al*. (2017). Weather data inputs were obtained from the nearest meteorological station to experimental sites.

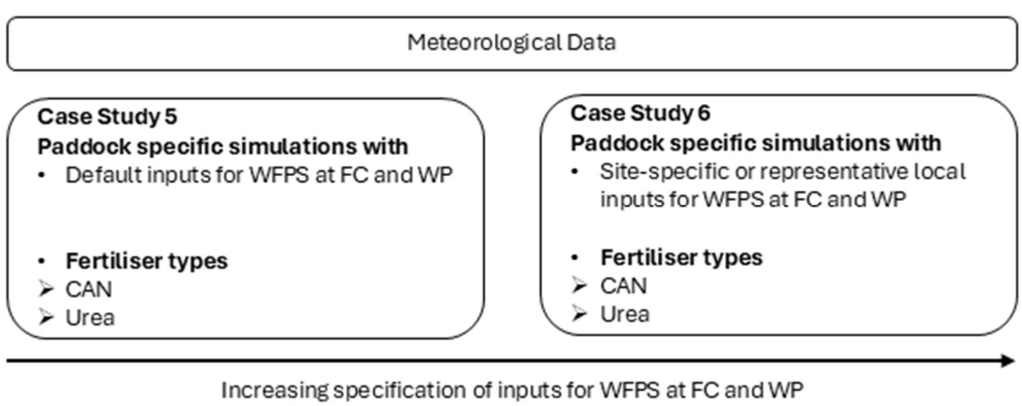


**Figure 3.3**. Schematic diagram of design of simulations for Experiment 2

### *3.3.3. Experiment 3: Chapter 6 - Application of DNDC using a scenario analysis approach.*

Experiment 3 was designed to identify the variables that influence the variation of growth of perennial ryegrass and N loss across spatially diverse soil and management conditions using a scenario analysis approach (Giltrap *et al*., 2010), building on the findings from Experiment 1 and 2. A secondary aim was to explore the potential impact of idealised high and low N fertiliser input scenarios based on stocking rates according to the general Teagasc advisory (Wall and Plunkett (eds.), 2020) and the Fifth Nitrates Action Programme (DAFM, 2023b) and the variables that influence the differences between their potential impact. Sites were selected for which detailed data for soil inputs required for reliable performance of DNDC, as identified in Experiment 1 and 2, were available. Weather data was sourced from synoptic stations in closest proximity to the study sites. Similarly, atmospheric $NH_3$ concentration and N concentration in rainfall from the closest available locations, such as meteorological stations or similar facilities, to the experimental sites, obtained from Jordan (1997) and Doyle *et al*. (2017) were used, due to absence of more recent corresponding measurements at sites of interest. The simulated outcomes, generated with using parameterisation of crop phenology module in DNDC following Experiment 1, on yield and N loss were compared to the variation of soil physicochemical properties and atmospheric conditions across the studied sites to identify the variables that explains the estimated variation of yield and N loss and the variation of their difference under the two different management regimes. The outcomes of this study were intended to inform more appropriate management practices, considering additional factors such as soil and weather conditions, that could deliver more sustainable N management strategies from the existing ones (DAFM, 2023b; Wall and Plunkett (eds.), 2020).

### *3.3.4. Experiment 4: Chapter 7 – Exploring the scope of using the DNDC model to estimate potential changes of grass yield and nitrogen dynamics for sites with limited site-specific data availability.*

Existing research indicated that the performance of DNDC simulations on Irish grasslands is sensitive to soil physicochemical properties (Abdalla *et al*., 2009; Abdalla *et al*., 2010; Li *et al*., 2011; Rafique *et al*., 2011a). However, the relevance of inputs on atmospheric constants currently remains unexplored. The aim of Experiment 4 was to explore the robustness of DNDC, i.e. identifying if parameterisation of default soil and atmospheric inputs is required to reliably simulate perennial ryegrass yield and N loss under ideal management scenarios, when the crop phenology inputs are parameterised (Gilhespy *et al*., 2014; Patil, 2009; Shirato, 2005). This study is relevant to understand if using the default inputs for optional variables on soil and atmospheric conditions for DNDC (Gilhespy *et al*., 2014) is able to simulate similar variations in yield and different forms of N loss across the studied site (relative differences), in comparison to those obtained using the suite of detailed site-specific inputs following Experiment 1 and 2. Spatially diverse sites, used in Experiment 3, were also used in Experiment 4 for estimation of yield of perennial ryegrass and N loss using DNDC. Thus, the mandatory inputs, e.g. daily weather conditions, the fertiliser management regime according to the Green Book (Wall and Plunkett (eds.), 2020), grazing regime and parameterisation of crop phenology were identical to that of Experiment 3. Whereas, simulations were performed in Experiment 4 with DNDC-default inputs for all non-mandatory soil and atmospheric variables (Table 3.1) and estimated yield and N loss in different forms were compared with those from Experiment 3, performed with site-specific inputs for the corresponding variables (Shirato, 2005). The study sought to identify if DNDC, parameterised for phenology of perennial ryegrass, is suitable to estimate variation of yield and N loss across sites in a data limited environment in terms of soil and background atmospheric conditions (Shirato, 2005).

## 3.4. Selected Sites

Based on the research objectives, data availability and existing scientific reports, sites were selected for each individual experiment. For Experiment 1, two paddocks were chosen from the winter milk dairy farm, a Teagasc research farm, located in Johnstown Castle (JC), County Wexford, Ireland (52°17’N 06°30’W) (Teagasc, 2017b) – Paddock 11.1 (a loam soil paddock) and Paddock 15.4 (a sandy loam soil paddock) (Gebremichael *et al*. 2022; Sheil *et al*., 2015), that were under grazing, N fertiliser application and silage cutting. For Experiment 2, the site used was Paddock 43 at JC. Paddock 43 contains both a sandy loam (Krol *et al*., 2020) and loam soil (Forrestal *et al*., 2015) within it, that was ungrazed and thus received N input from no other sources except N fertiliser application. Experiments 3 and 4 were performed for three sites. Two of the existing sites from Johnstown Castle and a third site located in Moorepark (MP) (52.2°N 8.3°W) in County Cork, Ireland - a sandy loam soil site. The soil properties at these sites were reported by Zimmermann *et al*. (2018). The details of the site locations, available data and their use are described in the corresponding chapters in this thesis.

*<u>Sites-specific inputs for WFPS at FC and WP</u>*

Finding site-specific inputs on WFPS at FC and WP is a challenge as these are not commonly measured soil physicochemical properties. Hence, site-specific inputs for WFPS at FC and WP for Experiment 2, 3 and 4 had to be calculated from the soil volumetric water content at FC and WP measured by Zimmermann *et al*. (2018). Underestimation of WFPS driven by lower than actual inputs for FC and WP can lead to poor performance of DNDC in estimating $N_2O$ emissions (Beheydt *et al*., 2007). Kodešová *et al*. (2011) observed soil moisture retention can be higher for grassland than arable soil due to a better developed capillary soil-pore system. Thus, it can be expected that site-specific WFPS at FC and WP should be higher for grassland sites than arable soils. Thus, for this study two different methods were considered for calculating the WFPS at FC and WP from the corresponding measured volumetric water contents, following Fichtner *et al*. (2019) (Equation 3.1) and Franzluebbers (1999) (Equation 3.2), with the intention to employ the higher calculated values from either equation as input for DNDC, justified on the basis of previous research for grasslands. Values for WFPS at FC and WP were higher using Equation 3.2 (Table 3.2). The estimated plant available water (PAW) in pore spaces, that is, the difference between WFPS at FC and WP (Pragg *et al*., 2024), was highest for all sites when derived using Equation 3.2 in comparison to that from DNDC default inputs and from Equation 3.1.

$$WFPS = \frac{SWC}{\left(1-\frac{BD}{PD}\right)} \qquad \text{Equation 3.1}$$

$$WFPS = (SWC\ x\ BD)/(1 - BD/PD) \qquad \text{Equation 3.2}$$

where,

*SWC* is the soil water content (g/g)
*BD* is the bulk density ($Mg/m^3$)
*PD* is the particle density (2.65 $Mg/m^3$) (Source: Franzluebbers,1999)

**Table 3.2.** Default and Calculated WFPS at FC and WP (up to two decimal places) with Determination of Plant Available Moisture Content

| Sites | Default | | | Equation 3.1 | | | Equation 3.2 | | | References |
|---|---|---|---|---|---|---|---|---|---|---|
| | WFPS at FC | WFPS at WP | Pant Available Moisture | WFPS at FC | WFPS at WP | Pant Available Moisture | WFPS at FC | WFPS at WP | Pant Available Moisture | Fichtner *et al.* (2019); Franzluebbers (1999); Pragg *et al.*, (2024) |
| **Sandy Loam - JC** | 0.32 | 0.15 | 0.17 | 0.49 | 0.23 | 0.26 | 0.54 | 0.26 | 0.28 | |
| **Loam - JC** | 0.49 | 0.14 | 0.35 | 0.56 | 0.27 | 0.29 | 0.71 | 0.34 | 0.37 | |
| **Sandy Loam - MP** | 0.32 | 0.15 | 0.17 | 0.51 | 0.26 | 0.25 | 0.61 | 0.31 | 0.30 | |

## 3.5. Evaluation Metrics

### *3.5.1. Validation of model performance*

Several methods of evaluation were used to evaluate the outcomes of the experiments according to the data type and continuity of measurement over time. Mainly two broad types of methods were applied in each case – visualisation and statistical methods. In this research, typically two temporal scales are analysed – daily and annual (Gilhespy *et al*., 2014). For daily validation, the measured data were of two types. Grass growth data, in terms of dry matter (DM), was obtained for selected locations from PastureBase Ireland (PBI) based on measured data (e.g. plate meter measurements) available at discrete intervals throughout the year (Hanrahan *et al*., 2017). In contrast, the available $N_2O$ emissions data or $NH_3$ volatilisation was typically only available for distinct measurement periods, usually after fertiliser application events (Forrestal *et al*., 2015; Krol *et al*., 2020). Thus, to explore the performance of DNDC at a daily scale, there was a need to identify validation metrics appropriate for the measurement period and consistency of the records. The outputs at the annual scale, reflecting the more commonly cited temporal resolution of DNDC simulations to estimate absolute error in the model's performance (Giltrap *et al*., 2010), were used directly for model validation without considering the pattern of measurement events. The methods employed to assess the performance of DNDC are outlined below.

*Pearson's correlation coefficient*

Pearson's correlation coefficient (Equation 3.3) between the average daily measured data and corresponding simulated results was used to evaluate the model's performance at daily scale (Moriasi *et al*., 2007). This included the measurement periods of N loss rates after fertiliser application (Forrestal *et al*., 2015; Krol *et al*., 2020) in Experiment 2 as well as for the overall pattern of grass growth rate throughout the year that had roughly homogeneously distributed measurement events (Hanrahan *et al*., 2017) in Experiment 1. The Pearson's R value between estimated and measured data at daily scale was derived using R-Studio (Yadav and Wang, 2021). The formula of deriving Pearson's correlation coefficient between two vectors a and b is (Mu *et al*., 2018),

$$P(a,b) = cov(a,b)/\sqrt{(var(a)\ x\ var(b))} \qquad \text{Equation 3.3}$$

where,

*cov* is the covariance
*var* is the variance

Model error estimation

Mean Absolute Error (MAE) (Equation 3.4) was used to estimate the size of prediction error at daily scale only while comparing simulated results with measured data that were in regular intervals over the year, i.e. grass growth rate in Experiment 1 (Abdalla *et al*., 2011; Kouadri *et al*., 2021). Root Mean Square Error (RMSE) (Equation 3.5) was used to estimate the absolute prediction error (quadratic) at daily scale irrespective of the regularity or the timeframe of measurement period in both Experiment 1 and 2 (Abdalla *et al*., 2011; Forster *et al*., 2022; Kouadri *et al*., 2021). Calculations of MAE and RMSE were performed in R-Studio.

$$MAE = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n} \qquad \text{Equation 3.4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \qquad \text{Equation 3.5}$$

where,

$P_i$ is the predicted value
$O_i$ is the observed value
$n$ is the number of observations
$i$ is the current observations

<u>*Area under curve*</u>

To assess the model's performance over the year in Experiment 2, data from measurement periods for $N_2O$ emissions and $NH_3$ volatilisation—limited to shorter, seasonal durations following fertiliser application events—were used. The area under the curve (AUC) was derived using the trapezoid formula for repeated measurements (Pruessner *et al*., 2003) in MS Excel for both the measured and corresponding estimated data for each measurement event throughout the year, for each individual scenario of the DNDC simulation. The formula used was (Pruessner *et al*., 2003)-

$$AUC = (X_2 + X_1) \cdot \frac{(D_2 - D_1)}{2} + (X_3 + X_2) \cdot \frac{(D_3 - D_2)}{2} + \cdots .$$

$$.. + (X_n + X_{n-1}) \cdot \frac{(D_n - D_{n-1})}{2} \qquad \text{Equation 3.6}$$

where,

$X_n$ is the n$^{th}$ measurement
$X_{n-1}$ is the measurement just prior to the n$^{th}$ measurement
$D_n$ and $D_{n-1}$ are the corresponding Julian day of measurement respectively.

Single factor ANOVA and two-sample t-tests, assuming unequal variances between AUCs for simulated results and corresponding measured records for a management site in a year, were performed to find out if there was any significant difference between the means of the AUCs for simulated results and measured values, over the course of the year (Pruessner *et al*., 2003). For both ANOVA and the t-test, if the p-value was less than 0.05 then the null hypothesis (i.e. there is significant difference between the means) was rejected (Bodin *et al*., 2012; Chi *et al*., 2020).

Scatterplots between AUCs from simulated results and corresponding measurements, with corresponding linear regression and $R^2$ values were derived to explore correlation of modelled output and actual measurement over the year and accuracy of the model's performance (Dutta *et al*., 2016; Li *et al*., 2005; Liu *et al*., 2022).

*<u>Relative deviation</u>*

Relative deviation in percentage (RD %) of the annual estimated and measured outputs were calculated to explore the model's performance at annual scale (Abdalla *et al*., 2020) for estimation of annual grass yield in Experiment 1 and 2 and for annual estimation of $N_2O$ emissions and $NH_3$ volatilisation in Experiment 2. The formula used to calculate RD % is (Abdalla *et al*., 2020) –

$$RD\% = \frac{(Mi - Si)}{Mi} \cdot 100 \qquad \text{Equation 3.7}$$

where,

$M_i$ is the measured value
$S_i$ is the value simulated by DNDC.

A negative RD% indicates an overestimation of annual yield by DNDC while a positive value indicate underestimation. In Experiment 1 and 2, absolute value of RD % (i.e., |RD%|) was derived. The |RD%| was considered acceptable if it was less than or equal to 20 %, whereas a value > 50 % would indicate strong relative deviation (Babu *et al*., 2006; Cai *et al*., 2003). Deriving RD % and using those values for analysing performance of DNDC was performed using MS-Excel.

*<u>Sensitivity analysis</u>*

One factor at a time (OFAT) sensitivity analysis was performed to identify the key variables regulating grass yield and N loss through $NH_3$ volatilisation and $N_2O$ emissions. Sensitivity analysis was conducted by increasing and decreasing the value of key input parameters from soil, weather and management within the possible ranges, one variable at a time, to evaluate the impact or sensitivity of the model estimates to a change in the input variable or parameter (Wang *et al*., 2016). The OFAT method is not a suitable tool to estimate the sensitivity of interactions between variables, rather it helps to understand the relative importance of the changes in key input variables for the change in the targeted output variables through altering the whole interaction in the system, even when the other input variables remain constant (Kardynska *et al*., 2022). Thus, it serves as a tool to identify the key input variables that are the most significant regulators of the targeted output variables. Increases or decreases in each input variable were used to derive the corresponding sensitivity index (SI) used for comparing their relative importance. The calculation of the SI was as follows (Wang *et al*., 2016),

$$SI = |O_{alternative} - O_{baseline}| / O_{baseline} * 100 \qquad \text{Equation 3.8}$$

where,

$O_{alternative}$ is the output generated by the alternative input scenario

$O_{baseline}$ is the output generated by baseline input scenario.

A value of SI that is lower than 0.1 % indicates that the output is insensitive to the corresponding change of the input variable. If the SI value is between 0.1 and 10 % then the conclusion is that the output is potentially sensitive to the change in the input variable. If the SI is greater than 10 % then the output is considered sensitive to the change of the input variable (Wang *et al*., 2016). Since two alternate scenarios were used for each input variable in this study, the output variable was concluded to be sensitive to that input if at least one of the two SI values from the two alternatives was >10 %. The output was considered potentially sensitive to the input if either both of the SI values were between 0.1 % and 10 % or at least one of the SI is between 0.1 % and 10 % while the other was <0.1 %. The output variable was only to be considered insensitive to the change in input variable if both of the SI values were <0.1 %.

### 3.6. Summary

The refinement and optimisation of N management practices, based on the spatial and temporal variability of soil, climate, weather and management, is key to achieving the goals of the 4RNS for sustainable N management (Corre *et al*., 2002; Diacono *et al*., 2012; UNEP, 2019). The potential impact of existing policies on sustainable N management on grass yield and N loss also need to be tested to identify the requirement of geographically refined national level strategies for supporting optimum yield while reducing the potential for N loss. A model based approach can be a useful tool to explore the relevance of key variables at various spatial and temporal scales required to deliver more sustainable N management strategies and deliver on the 4RNS goals (e.g., Choruma *et al*., 2021; Higgins *et al*., 2017; Milne *et al*., 2020; Patil, 2009; Qingnan *et al*., 2023; Schellberg *et al*., 2008; Zhang *et al*., 2013).

The DNDC model was identified as the most suitable potential model for this study. The primary reason was the scope of DNDC for estimating annual biomass (relevant for grass yield estimation) and N loss through the major pathways relevant to grasslands – namely, $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching (Gilhespy *et al*., 2014; van Beek *et al*., 2008;).

The other reason was its accountability for the key mechanisms of soil N dynamics (mineralisation, leaching, volatilisation, nitrification, denitrification, uptake and BNF) (Cannavo *et al*., 2008). However, the model required parameterisation for local soil and atmospheric conditions and crop phenology of perennial ryegrass and validation to investigate the reliability of its performance under the parameterisations performed (Haraldsson and Sverdrup, 2013).

Four experiments were designed according to the goals of the research and to assess the reliability of DNDC for locally parameterised conditions, under perennial ryegrass management. Experiment 1 was designed to explore the parameterised model's performance to estimate annual grass growth rate and yield through validation, identifying an optimum spatial resolution for the generalisation of input parameters. Further, in Experiment 1, identification of key regulators of annual grass yield at field level through the OFAT sensitivity analysis method (Abdalla *et al*., 2020; Wang *et al*., 2016), if the simulated yield was to be found reliable, was set as a goal. The design of Experiment 2 was primarily aimed at exploring the performance of DNDC to estimate the rate and annual N loss through $NH_3$ volatilisation and $N_2O$ emissions under the parameterisations performed in Experiment 1 and identifying further requirements of parameterisation through model validation. Identifying key drivers of annual $NH_3$ volatilisation and $N_2O$ emissions were included in the objectives. Experiment 3 was aimed at exploring the need and scope of geographical refinement of the national level N management strategies, such as the ones provided in the Green Book (Wall and Plunkett (eds.), 2020) and those following the nitrate regulation strategies according to the Fifth Nitrates Action Programme (DAFM, 2023b), using a scenario analysis based approach. Experiment 4 served to identify if the default values for optional soil and atmospheric inputs in DNDC, already parameterised for phenology or perennial ryegrass, generates spatial variation of yield and N loss across different sites at annual scale consistent with the ones generated using corresponding detailed site-specific inputs (Gilhespy *et al*., 2014; Patil, 2009).

# 4. Evaluation of DNDC and Identification of key variables to estimate grass growth in an intensively managed grassland

**Abstract**

Plant available nitrogen (N), if surplus to the requirement of the plant, can be lost from the soil into the environment. In agricultural landscapes, N is supplied to the soil for crop growth through organic and inorganic fertilisers, typical for managed grazed grasslands. Interactions between management, soil and atmospheric conditions are factors known to impact both N uptake and loss from grass. To mitigate the potential negative impacts due to N losses, it is important to apply N fertiliser at an optimum rate to achieve sustainable grass yield. The DNDC (*DeNitrification-DeComposition*) model is a process-oriented model that connects soil, weather and management with grass yield and can be employed to explore N dynamics in grasslands. However, there has been limited attention given to evaluate the ability of DNDC to reliably simulate crop phenology for perennial ryegrass, which is essential to accurately represent the timing and ability of plants to uptake available resources, including water and nutrients. To address this, in this study the DNDC model was initially employed to estimate growth rate and yield of perennial ryegrass at the Johnstown Castle Research Farm (County Wexford, Ireland), where detailed management and grass growth records are available. The aim was to evaluate if the model could replicate measured grass growth at the paddock scale, a spatial scale representative of the minimum grassland management unit. In recognition of the paucity of detailed site-specific soil information more generally, model estimates of yield were generated using both detailed/measured paddock specific soil and management information as well as more generalised farm level information. The model outputs were compared to corresponding paddock level and aggregated farm level grass yield measurements, respectively. Our findings indicate that DNDC can reliably simulate growth rate and the annual yield of perennial ryegrass, at both paddock and farm level, using both the detailed and generalised model inputs for soil, when the model parameters relating to crop phenology are specified and using regional atmospheric chemistry measurements.

## 4.1. Introduction

In Ireland, grassland management is the major land use practice and represents 59% of the total national land cover (CSO, 2023). Mean monthly soil temperature in Ireland is generally around or above $5^0$C (Cappello *et al*., 2021) which supports near year-round growth of perennial ryegrass, for which vegetative growth can occur as low as $0^0$C soil temperature, while higher growth rates are observed above $5^0$C (Wingler and Henessey, 2016). Chemical N fertiliser, mainly CAN (calcium ammonium nitrate) and urea (McNamara, 2019), is the main source of N for Irish grasslands (Dillon *et al*., 2018). Organic sources of readily available ammonium ($NH_4^+$) and mineralisable N, such as dung, urine, farmyard manure (FYM) and slurry, are also applied (Sullivan, 2008; Vangeli *et al*., 2022). Nitrogen use efficiency (NUE) in Irish dairy farms currently is around 25 % (Teagasc, 2021a), i.e. 75 % of N applied to grasslands under dairy farming is susceptible to loss. The major pathways of N loss from grasslands are ammonia ($NH_3$) volatilisation, nitrous oxide ($N_2O$) emissions and nitrate ($NO_3^-$) leaching (van Beek *et al*., 2008). Volatilised $NH_3$ degrades air quality through the formation of particulate matter and tropospheric ozone and is also an indirect source of atmospheric $N_2O$; while $N_2O$ itself is a greenhouse gas (GHG) that also contributes to depletion of stratospheric ozone (Burchill *et al*., 2017; de Vries, 2021; Ferm, 1998; Pittelkow *et al*., 2013). $NO_3^-$ accumulation in surface water leads to eutrophication with negative consequences for aquatic ecosystems. High $NO_3^-$ concentrations in drinking water leads to health issues acting as a carcinogen and increases susceptibility to diseases such as Blue-Baby syndrome (Giordano *et al*., 2021). Deposition of atmospheric N contributes to soil acidification and eutrophication, resulting from the increased supply of N to the atmosphere from agriculture (Stark and Richards, 2008).

Overall, Irish agriculture accounts for 92.6% of national $N_2O$ emissions and 99% of national $NH_3$ emissions (EPA, 2024; EPA, 2024a). Grassland management practices are estimated to be responsible for around 90 % of national $N_2O$ emissions in Ireland, attributed to fertiliser application, animal excreta during grazing, and slurry storage and spreading; contributing 38%, 23% and 14% of agricultural $N_2O$ emissions respectively (Krol, 2020; Teagasc, 2017f). The loss of agricultural N has a significant negative impact on the environment and human health. In a recent report from the Irish Environmental Protection Agency (EPA), the water quality of an estimated 46% of surface waters in Ireland was found to vary between moderate, poor or bad quality in terms of $NO_3^-$ concentration (EPA, 2021). Ireland has a goal to increase agricultural productivity sustainably under the Food Wise 2025 programme (DAFM, 2021). It also aims to reduce national greenhouse gas emissions by 25% from the 2018 baseline and national $NH_3$ emissions by 5% from the 2005 baseline (Burchill *et al*., 2017; DECC, 2023a), while also reducing $NO_3^-$ leaching (DHLGH and DAFM, 2022). The national goals to reduce N loss from agriculture is reflected in the Irish Government's Climate Action Plan 2023 and the Fifth Nitrates Action Programme 2022-2025 (DECC, 2023; DHLGH and DAFM, 2022), which align with the goals set out in the Farm to Fork strategy in the EU Green Deal for climate neutrality (EC, 2020).

Knowing the *right source, right rate, right time,* and *right place* for more focused and efficient nutrient management in agriculture are the pillars of 4R Nutrient Stewardship (4RNS), which seeks to maintain agricultural productivity while reducing susceptibility of nutrient loss (Bryla, 2020; Fixen, 2020). This could potentially be achieved with improved nutrient management information at the field level through the investigation of the site-specific nutrient requirements of a crop, based on the spatial and temporal variability in soil and climate conditions (Patil, 2009; Varallyay, 1994). In Ireland, the farm level Nutrient Management Planning (NMP-Online) system is an online management tool that provides advice on nutrient planning to farmers, taking into consideration soil fertility test results and livestock information for geo-referenced fields/land management unit areas (Mechan *et al*., n.d.; Wall and Plunkett (eds.), 2020). However, NMP-Online does not currently account for the spatial variability in soil N dynamics regulated by the spatial variability of soil and climate and the variability of weather conditions. Considering the impact of these factors and their interaction with management on N uptake and loss could lead to a significant refinement of existing N application strategies. These strategies are currently aspatial, based on a targeted stocking rate and bound by generalised upper limits set for stocking rates and N inputs established by national level guidelines and policies (Callaghan, 2023; Corre *et al*., 2002; Hedley, 2014; Patil, 2009; Wall and Plunkett (eds.), 2020; Wu and Ma, 2015).

Process-oriented models that connect crop growth with soil, climate, weather and management can be utilised to identify, understand and explore the influence of key drivers of N uptake and loss. These aspects need to be accounted for to achieve improved N management in agricultural soils (Delgarm *et al*., 2018; Patil, 2009). The *DeNitrification DeComposition* (DNDC) model is a process-oriented model that generates estimates of carbon (C) and N dynamics and crop growth (Gilhespy *et al*., 2014), based on soil, weather, plant phenology and management information. To date, DNDC has been widely used as a research tool to estimate agricultural GHG emissions, particularly for $N_2O$ (Zhang and Niu, 2016). A number of previous studies have employed DNDC in the context of grasslands in the Republic and Northern Ireland, focusing on $N_2O$ emissions, soil organic carbon (SOC) and carbon dioxide ($CO_2$) emissions (e.g. Abdalla *et al*., 2009; Abdalla *et al*., 2010; Abdalla *et al*., 2011; Hsieh *et al*., 2005; Khalil *et al*., 2020; Li *et al*., 2011; Rafique *et al*., 2011a; Zimmermann *et al*., 2018). While the model has demonstrated some skill in this context, the impact of parameterisation of the crop phenology for perennial ryegrass, the dominant grass species in Irish dairy farms (O'Donovan *et al*., 2021), remains unknown. At the same time, there is gap in the validation of the estimation of perennial ryegrass growth by DNDC for Irish dairy farms, a requirement for the reliable estimation of surplus N, after plant uptake (Zhang *et al*., 2015). If this gap can be addressed, DNDC could potentially provide a reliable means to identify the key regulators of grass growth through exploring the sensitivity of grass yield to environmental and management factors, and within the framework of improving our understanding of N dynamics to support improved N management at field or farm level (Kardynska *et al*., 2022; Wang *et al*., 2016).

For reliable DNDC simulations, the availability of detailed input data remains a key challenge (Byrne and Kiely, 2008; Giltrap *et al*., 2010). The robustness of the model, i.e., lower requirement of input parameterisation for representative local conditions, increases the potential scope of its practical utilisation by reducing input data requirements (Patil, 2009). Moreover, analysis of the performance of DNDC to estimate grass growth rate and yield is lacking. Hence a corresponding optimum spatial (paddock or farm) and temporal scale (daily or annual) remains unknown. Identifying the potential spatial scales at which DNDC can produce reliable estimates, reflecting more generalised input information, could assist in efforts to scale DNDC beyond specific data rich research sites to those locations where data does not exist (Cannavo *et al*., 2008; Milne *et al*., 2020; Zhang *et al*., 2020a). To understand the robustness of DNDC, it is important to explore its reliability to estimate grass growth using generalised parameterisation for soil inputs (for example using input information from national soil datasets) and idealised management scenarios for stocking rates (e.g. national advised) instead of site-specific management (Higgins *et al*., 2017; O'Sullivan *et al*., 2018; Patil, 2009; Schellberg *et al*., 2008; Shirato, 2005) which can be difficult to obtain. Here, we sought to explore the performance of the DNDC model to estimate grass growth rate and annual yield under varying parameters of crop phenology for perennial ryegrass using paddock, farm-specific and national soil inputs and paddock-specific and idealised farm level management. We also performed a sensitivity analysis to identify the key variables regulating annual grass yield (Kardynska *et al*., 2022; Wang *et al*., 2016). Further, we also investigated the performance of DNDC to estimate grass growth rate and yield with default inputs provided within the model setup to see if the default model parameters can produce reliable outputs when site-specific information for such variables is not available for a site (Giltrap *et al*., 2010; Patil, 2009).

## 4.2. Data and Methods

### *4.2.1. Site Locations*

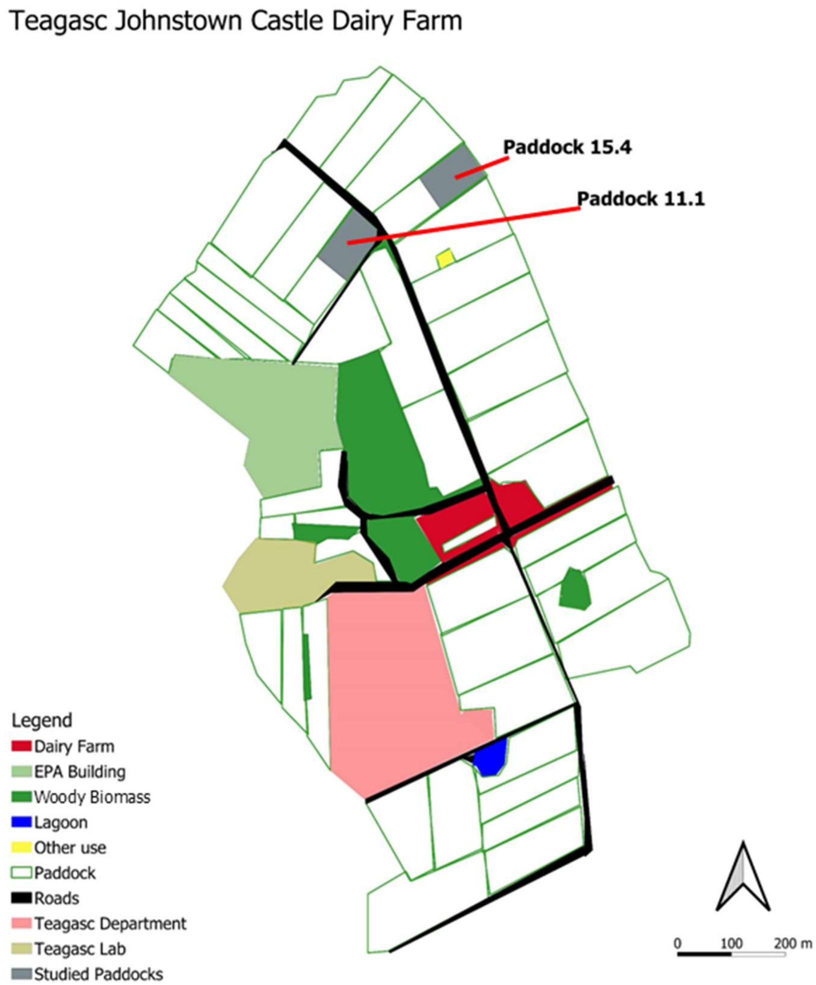


**Figure 4.1:** Paddocks used for the experiment at Teagasc, Johnstown Castle dairy farm (Source: Farm Data)

This study was conducted using data from the Teagasc dairy farm (winter milk system) at Johnstown Castle (JC) in County Wexford, Ireland, (06°30'W, 52°17'N) (Teagasc, 2017b), an agricultural research farm operated by Teagasc, the Irish Agriculture and Food Development Authority. Average annual rainfall (1990-2010), recorded at the synoptic weather station located on the farm, is 1036 mm and mean annual temperature is 10.4$^{0}$C (Cahalan *et al*., 2015). Usually, higher rainfall amounts and lower temperature conditions are observed during the autumn and winter months, compared to spring and summer (Antille *et al*., 2015). Mean soil temperatures up to 20cm depth, obtained from measurements at the nearby synoptic station, located in Rosslare, Co. Wexford, typically vary between 5.8$^{0}$C in winter to 17$^{0}$C in summer (Met Éireann, n.d). These conditions support year-round growth for perennial ryegrass (Wingler and Hennessy, 2016). According to the Irish Soil Information System (Irish SIS), soils in the vicinity of JC dairy farm are under the 1030a (Crosstown) soil association. Creamer *et al*. (2014; 52) described the soil association as comprised of 'surface-water Gleys and Stagnic Brown Earths on drift with siliceous stones, with inclusions of Groundwater Gleys'. Soils within the JC dairy farm are classified as moderate to well drained brown earth, brown podzolic/brown earth and poorly drained gley soil, according to the Irish SIS-Great Soil Group classification (Creamer *et al*., 2018).

The farm contains 58 paddocks used for grazing and/or silage and are dominated by perennial ryegrass, distributed over approximately 70 hectares; with limited availability of red and white clover, rough blue grass, couch grass, chicory and plantain in designated paddocks (Gebremichael *et al*., 2022; Teagasc, 2017b; Teagasc, 2022a). For this study, two paddocks (Figure 4.1) were selected from the JC dairy farm for which detailed soil information was available – one belonging to the brown earth group (Paddock 15.4) and the other a gley soil (Paddock 11.1) (Gebremichael *et al*. 2022; Sheil *et al*., 2015) (Table 4.1). Gebremichael *et al*. (2022) reported that the dominant grass species in both paddocks was perennial ryegrass, but some other species, like rough blue grass, couch grass and white clover may be present to a lesser degree. Cows are typically grazed for around 21.5 hours a day during the main grazing season (and when conditions permit) and around 3.5 hours a day at the beginning of the grazing period in February to March and from November to the closing date. The main fertilisers applied in all paddocks for supply of N is in the form of KaN (Koch Advanced Nitrogen), CAN (Calcium Ammonium Nitrate), UAS 38% (Urea-Ammonium Sulphate) and Alzon urea 46%, along with the focused applications of P, K and S and cattle slurry, farmyard manure and soiled water in designated paddocks. Reseeded paddocks generally show higher grass growth than permanent paddocks under a same fertiliser management regime (Creighton *et al*., 2016). Thus, the year 2019 and 2020 were selected for the simulations as reseeding had not been performed in these paddocks immediately before or during these years.

**Table 4.1:** Soil Physicochemical Properties of the Paddocks and Representative of Soil Zone in the Farm

| Paddock / Representative of Soil Zone | Soil Physicochemical Properties | | References |
|---|---|---|---|
| Paddock 15.4 / Representative of Brown Earth Soil Zone | Soil texture | Sandy loam | Gebremichael *et al*., 2022; Sheil *et al*., 2015 |
| | Bulk density (g/cm³) | 1.30 | |
| | pH | 5.8 | |
| | SOC* at surface (kg C/kg soil) | 0.0361 (i.e. 3.61%) | |
| | Clay Fraction (0-1) | 0.146 (i.e. 14.6%) | |
| Paddock 11.1 / Representative of Gley Soil Zone | Soil texture | Loam | |
| | Bulk density (g/cm³) | 1.28 | |
| | pH | 5.68 | |
| | SOC*at surface (kg C/kg soil) | 0.0286 (i.e. 2.86%) | |
| | Clay Fraction (0-1) | 0.178(i.e. 17.8%) | |

*SOC=Soil Organic Carbon

### *4.2.2. Data*

DNDC requires detailed inputs of soil, weather, atmospheric conditions and management. Meteorological data recorded at the synoptic station on the farm, including daily maximum and minimum temperature, daily rainfall and solar radiation, was available from Met Éireann (n.d.) (the Irish national meteorological service). Information on N concentration in rainfall is measured at the nearby coastal location at Rosslare, County Wexford (Jordan, 1997) and atmospheric background $NH_3$ concentration measured at Clonroche, County Wexford (Doyle *et al*., 2017). Paddock-specific soil information was available from Sheil *et al*. (2015) and Gebremichael *et al*. (2022). Generalised soil information for the Irish SIS association 1030a was available from O'Sullivan *et al*. (2018). Grass growth data, measured using a rising plate meter and recorded approximately every 10 days, was available for all paddocks in the JC farm from PastureBase Ireland (PBI) (Hanrahan *et al*., 2017). PastureBase Ireland (PBI) also provides average daily grass growth (DM/ha/day) derived using a grass growth model, for the paddocks and the farm. The annual grass yield (kg DM/ha) for each paddock was obtained, from which the annual grass yield for the entire farm was calculated. The paddock level information on fertiliser application, grazing and silage cutting regimes and other relevant management practices were also recorded and available in PBI (Hanrahan *et al*., 2017), while more details were available in the farm data records. Ideal farm level nitrogen management advice for an indicative stocking rate, was guided by recommendations provided in the Green Book (Wall and Plunkett (eds.), 2020).

### *4.2.3. DNDC Model Inputs and Parameters*

Version 9.5 of the DNDC Model (Source: http://www.dndc.sr.unh.edu/) was used in this research (Tang *et al*., 2024). DNDC works with six sub-models - soil-climate/thermal-hydraulic flux, decomposition, denitrification, crop-growth, nitrification and fermentation. The model simulates biomass growth and dynamics of N biogeochemical cycle and losses for soils managed under agriculture with detailed input on soil physicochemical properties, weather and management (Gilhespy *et al*., 2014). The DNDC module to simulate grass growth was primarily developed by Saggar *et al*. (2007) for grass-clover swards in New Zealand. For a detailed description of the model, see Gilhespy *et al*. (2014) and the model manual (ISEOS, UNH, 2012).

For all simulations a number of inputs within the management module of DNDC were held constant, as follows - no tillage, no irrigation, no plastic mulching applied, the land use was set as 'moist grassland/pasture' and crop type was set to 'perennial grass'. The planting regime was set to occur on Day 1 of the year and harvest on the last day of the year. This prevented the model from estimating the management scenario as a long-term practice as paddocks in the farm tend to be modified from year to year for experimental research purposes. For farm and paddock specific simulations, the crop phenology inputs were parameterised with a focus on simulating the grass growth (herbage) specific to perennial ryegrass paddocks. Whereas atmospheric variables were modified according to regional measurements. The data used for model parameterisation are outlined in Table 4.2. Thermal degree days for maturity (TDD) in degrees C, also known as growing degree days (Dutta *et al*., 2018), reflects cumulative heat energy received by crop over a given period of time and are derived based on minimum required temperature and daily maximum and minimum temperature (McMaster and Wilhelm, 1997). However, there is an absence of research on the TDD threshold for the growth of leaf and stem of perennial ryegrass. Thus, TDD for each year was calculated for perennial ryegrass following Hart *et al*. (2013) taking into account the weather for the year and considering year-round herbage growth for perennial ryegrass (Wingler and Hennessy, 2016) instead of seed production as an indicator of crop maturity. For the input of atmospheric N concentration in precipitation the value obtained for the nearby Rosslare synoptic station (Jordan, 1997) was used. The atmospheric background $NH_3$ concentration was set according to the measured values obtained at Clonroche (located 23.13 km from the experimental site) (Doyle *et al*., 2017). The model simulation for Paddock 11.1 (Table 4.1) was not performed in 2019 due to the unavailability of grass growth records for validation for this paddock. Only a few of the paddocks in the farm were reseeded each year which were not accounted for during the farm scale simulations. The year 2019 was considered a 'typical' year with no significant weather events occurring (Met Éireann, n.d.b). In 2020, no major weather events occurred, with the exception of Storm Ellen on the 19th August, which occurred in the proximity of JC (Met Éireann, n.d.b).

**Table 4.2:** Default and Modified Inputs for Crop Phenology and Atmospheric Conditions

| | Variables | Default | Modified | References |
|---|---|---|---|---|
| **Crop Phenology** | **C:N ratio for seed/ leaf/stem** | 35/20/20 | 19/19/19 | Whitehead *et al*., 1990 |
| | **C:N ratio for roots** | 30 | 23 | |
| | **N-fixation index (crop N/N from soil)** | 1.5 | 1 | ISEOS, UNH, 2012 |
| | **Water demand (g water/g DM)** | 200 | 550 | Byrne and Kiely, 2008 |
| | **Thermal degree days of Maturity** | 2000 | 3781 (year 2019) 3776 (year 2020) | Hart *et al*., 2013 Wingler and Hennessy, 2016 |
| **Atmospheric Conditions** | **Atmospheric N concentration in precipitation (mg N/l or ppm)** | 0 | 1.02 | Jordan, 1997 |
| | **Atmospheric background $NH_3$ concentration µg N/m$^3$** | 0.06 | 2.83 | Doyle *et al*., 2017 |
| | **Atmospheric background $CO_2$ concentration (ppm)** | 350 | 409.8 | Ullas Krishnan and Jakka, 2022 |
| | **Annual rate of increase Atmospheric background $CO_2$ concentration (ppm)** | 0 | 2.3 | Prasad *et al*., 2021 |

### *4.2.4. Experimental Design*

*Case Study 1: DNDC simulations with paddock specific soil and management inputs*

Case Study 1 (Figure 4.2) was designed to explore the performance of DNDC in estimating grass growth rate and annual yield in Paddock 11.1 and Paddock 15.4. Paddock-specific inputs on soil physicochemical properties (Table 4.1) and management activities from farm data records, including N application, timing of grazing, stocking rate and silage harvest, were employed (Gebremichael *et al*., 2022; Sheil *et al*., 2015). For both paddocks total carbon was considered as soil organic carbon (SOC), since the pH was lower than 6.5 in both of them (Franzluebbers and Stuedemann, 2002). The N content in fertilisers in the form of urea or $NH_4^+$ or $NO_3^-$ was estimated (Table 4.3) for the applied fertiliser types as there was no corresponding direct input options in DNDC. However, direct or indirect inputs for nutrients other than N were not considered, assuming their applications were performed based on soil fertility conditions (Wall and Plunkett (eds.), 2020). Validation of simulated grass growth rate and yield was performed against records of grass growth for the corresponding paddocks and year of simulation, obtained from PBI (Hanrahan *et al*., 2017). Estimated average daily grass growth rate for a paddock in a year between the measurement events were calculated following the corresponding measurement regime recorded in the PBI (Hanrahan *et al*., 2017).

**Table 4.3.** Preparation of Nitrogen Resource Equivalence for DNDC Fertiliser Inputs Based on Total Nitrogen Content and Chemical Characteristics of Applied Form

| Actual Applied Fertiliser | Input of Nitrogen (N) Content as (with conversion factors) | References |
|---|---|---|
| KaN | Urea (total N content input as urea as it is urea-based fertiliser) | Dairygold Agri Business Limited, n.d. |
| CAN | Total N divided into ammonium (50%) and nitrate (50%) | Teagasc, 2017d |
| UAS 38% | Urea and ammonium in 4:1 ratio respectively | Rahman *et al*., 1994 |
| Alzon Urea 46% | Urea (total N content input as urea as it is urea-based fertiliser) | Marsalkova and Ryant, 2014 |
| Cattle Slurry | Ammonium (1kg N/m$^3$=0.0039 kg N/gallon) | Teagasc, 2022 |

*Case Study 2: DNDC simulations with farm specific representative soil inputs and ideal nitrogen fertiliser application based on a stocking rate*

Case Study 2 (Figure 4.2) was designed to test the performance of DNDC in estimating aggregated farm level grass growth under farm specific representative soil inputs, grazing regimes and the maximum N fertiliser application advice for 2019 and 2020. The simulations for the farm area under brown earth soil and gley soil were carried out separately, using soil information from the corresponding representative paddocks (Table 4.1). Inputs for grazing days were collected from farm records for each year. The stocking rate was calculated from data available in the farm profile (Teagasc, 2017c). Grazing hours per day was set as 20 hours/day for the entire grazing period and applied for each simulation (Byrne and Kiely, 2008), where the grazing period in the farm in each corresponding year was determined from farm records. Silage cutting was not selected in the model set-up, as it was not common to all the paddocks. However, silage cutting and grazing events do not directly affect the grass growth rate in DNDC, whereas the estimated excreta from animals during grazing is re-used as an N input in DNDC (Saggar *et al*., 2007). The farm is intensively managed and therefore, for fertiliser inputs, only the maximum N fertiliser advised by the Green Book (Wall and Plunkett (eds.), 2020) for the farm's stocking rate was used as an ideal scenario. Splits of application were on the last date of January, March, April, May, July and September, designed according to the monthly regime suggested in the Green Book. The variation of fertiliser type was not considered, and N fertiliser was input as urea, as Harty *et al*. (2017) had indicated that for Irish grasslands, the applied amount of N fertiliser regulates grass yield more significantly than the type of the fertiliser. Total accumulated daily predicted growth rate for each year for the area under both soil types was calculated from the simulated growth per day for each soil type, following the recorded dates in PBI. The weighted average of estimated grass growth rate and annual yield for the two soil types in the farm, based on the proportion of farm area under each soil type (farm area under brown earth soil and gley soil is 58% and 42% respectively), was derived and aggregated over the farm for the corresponding year for validation.

*Case Study 3: Paddock-level DNDC simulations using Irish Soil Information System Data*

Case Study 3 (Figure 4.2) was designed to assess the performance of DNDC for simulating grass growth using representative 'generalised' soil information for the Irish SIS of soil association 1030a (O'Sullivan *et al*., 2018) (Table 4.4) in place of paddock-specific soil data for Paddock 15.4 in 2019 and 2020 and Paddock 11.1 in 2020. The remainder of the inputs and parameters were kept unchanged from Case Study 1. Validation was performed to assess the ability of DNDC to estimate grass growth rate and annual yield against the corresponding measured data from PBI (Hanrahan *et al*., 2017).

**Table 4.4.** Soil Physicochemical Properties of the Lead Soil of Association 1030a (Crosstown:1030CO) in Irish Soil Information System

| **Soil Physicochemical Properties** | | **Source** |
|---|---|---|
| **Soil texture** | Loam | Irish Soil Information System Database |
| **Bulk density (g/cm³)** | 1.23 | |
| **pH** | 6.4 | |
| **SOC at surface (kg C/kg soil)** | 0.021(i.e. 2.1%) | |
| **Clay Fraction (0-1)** | 0.19 (i.e. 19%) | |

*Case Study 4: Farm-level DNDC simulations using Irish Soil Information System Data and ideal nitrogen fertiliser application based on a stocking rate*

Case Study 4 (Figure 4.2) was designed to assess the performance of DNDC to estimate farm level grass growth for 2019 and 2020, when using generalised and readily accessible soil inputs based on Irish SIS (O'Sullivan *et al*., 2018) soil association 1030a (Table 4.4) for the whole farm instead of representative soil inputs from farm. All remaining model inputs were kept unchanged from Case Study 2. Validation of the outcomes were performed for reliability of the estimated average daily grass growth rate and annual yield against the validation dataset from PBI for the farm for the corresponding years (Hanrahan *et al*., 2017), similar to Case Study 2.

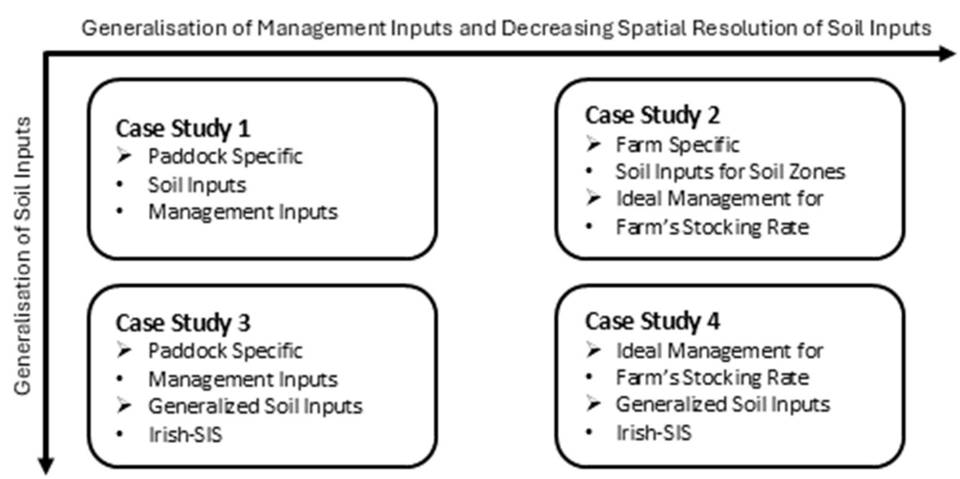


**Figure 4.2**. Experimental design

*Robustness test: Simulation with DNDC-default inputs for non-mandatory variables*

To test the robustness of DNDC, the model was run with DNDC-default atmospheric, soil and crop phenology inputs for non-mandatory variables (Gilhespy *et al*., 2014; ISEOS, UNH, 2012). The optimum spatial scale between paddock-specific and farm level ideal management, identified from Case Studies 1 and 2 was used for the model simulation. The atmospheric inputs that were kept as DNDC-default were - N concentration in rainfall, atmospheric background $NH_3$ concentration, atmospheric background $CO_2$ concentration and annual increase rate of atmospheric $CO_2$ concentration. For each soil type, DNDC-default values were used for clay content, whereas DNDC generated input for bulk density (BD) specific to textural class and SOC was also not further modified. The crop phenological inputs were kept as the DNDC-default inputs for perennial grass. Depending on the selected scale of model simulation, the outcome was compared against the respective 'parent' case study between Case Study 1 or Case Study 2, along with performing validation.

### *4.2.5. Outcomes and evaluation metrics*

DNDC simulates daily growth rate and annual yield in kg C/ha in terms of grain, leaf, stem and root. The aboveground grass growth rate was calculated as the sum of daily grain, leaf and stem growth converted from kg C/ha into dry matter (DM) in kg/ha by dividing with 0.4 (ISEOS, UNH, 2012) for validation. The Pearson's correlation coefficient was used to evaluate the agreement between the average daily measured and simulated grass growth rates (Legates and McCabe, 1999; Moriasi *et al*., 2007). The Mean Absolute Error (MAE) was used to estimate the size of prediction error and Root Mean Square Error (RMSE) to estimate the absolute prediction error (quadratic) (Abdalla *et al*., 2011; Forster *et al*., 2022). The relative deviation in percentage (RD %) of the annual yield in kg/ha from measured annual yield was calculated for each site within the case studies and the robustness test (Abdalla *et al*., 2020). A negative RD % indicates overestimation of annual yield by DNDC while positive value indicated underestimation. Absolute value of RD% (i.e. |RD %|) if ≤ 20 % then the simulated annual yield was considered reliable and if ≥ 50 % then the estimation is considered to be strongly deviated from the actual annual yield (Babu *et al*., 2006; Cai *et al*., 2003).

### *4.2.6. Sensitivity analysis*

One-factor-at-a-time (OFAT) sensitivity analysis was performed to identify the most significant soil, weather and management parameters in terms of regulatory impact on the annual grass yield (Kardynska *et al*., 2022). Sandy loam, loam and silt loam are three of the main soil textures found in Co. Wexford (Gebremichael *et al*., 2022; McDonald *et al*., 2014). Each of these can have clay content (Brady & Weil, 2002) that matches the gley soil site in our study, which was a key consideration for the variation of soil texture during OFAT. Using the same logic for the variation of clay it was important that the increased and decreased clay content should not exceed the upper and lower limit of clay content for the baseline textural class. Thus, the gley soil (loam texture) based simulation for 2019 was used as the baseline since one of our aims was to find out the impact of textural class on yield, driven by higher sand or silt content, when the clay content and all other variables are constant. The year 2019 was selected for the baseline simulation as this year did not show any significant extreme weather event (Met Éireann, n.d.b). As the textural class input in DNDC is categorical (Gilhespy *et al*.,2014), the variations of textural class were selected to represent higher sand (sandy loam) and higher silt soils (silt loam) from the baseline, following the soil types available in Wexford (Gebremichael *et al*., 2022; McDonald *et al*., 2014). For the rest of the properties of soil (other than textural class) and the weather and management variables, OFAT was performed by changing each of the inputs individually to feasible upper and lower numerical values as a percentage difference from the baseline. As fertiliser input is increased or decreased annually, the total amount of fertiliser applied was split according to the same application dates as the baseline simulation and using the ratio of the fertiliser applied in each split to the total applied fertiliser. A Sensitivity Index (SI) was calculated and input variables were grouped using the SI, following Wang *et al*. (2016) to identify if the annual grass yield is sensitive (SI > 10 %), potentially sensitive (10 % > SI > 0.1 %) or not sensitive (SI < 0.1 %) to the change of the corresponding input variable. The chosen baseline and the variation used is shown in Table 4.9 in the Result section 4.3.6.

## 4.3. Results

### *4.3.1. Case Study 1*

The correlation between paddock-specific simulated (paddock specific soil, environment and management) and measured daily grass growth rate varied between negative and positive values for Paddock 15.4 and 11.1 in the same year, and for Paddock 15.4 between the two years (Table 4.5). Both the MAE and RMSE for Paddock 15.4 was lower in 2019, and lowest for Paddock 11.1 in 2020 (Table 4.5). RD % always had a positive value and |RD %| was lower than 20 % for all paddock-specific simulations (Table 4.5). The temporal alignment between average daily measured and estimated grass growth rate is shown in Figure 4.3 (top-left) and (top-right) for Paddock 15.4 in 2019 and Paddock 2 in 2020, respectively. The curves of the cumulative average daily grass growth rates are shown in Figure 4.3 (bottom-left) and (bottom-right) for Paddock 1 in 2019 and Paddock 2 in 2020, respectively.

**Table 4.5.** Performance of DNDC in Terms of Evaluation Metrics (Section 4.2.5) for Case Study 1

| Experiment | Daily Grass Growth Rate | | | | Annual Yield |
|---|---|---|---|---|---|
| | Site, Year | Correlation | MAE | RMSE | RD% |
| Case Study 1 | **Paddock 15.4, 2019** | 0.267 | 26.81 | 32.64 | 9.39 |
| | **Paddock 15.4, 2020** | -0.042 | 30.41 | 41.04 | 12.15 |
| | **Paddock 11.1, 2020** | 0.395 | 20.93 | 27.06 | 12.76 |

*Negative RD % indicates overestimation and positive RD % indicates underestimation by DNDC

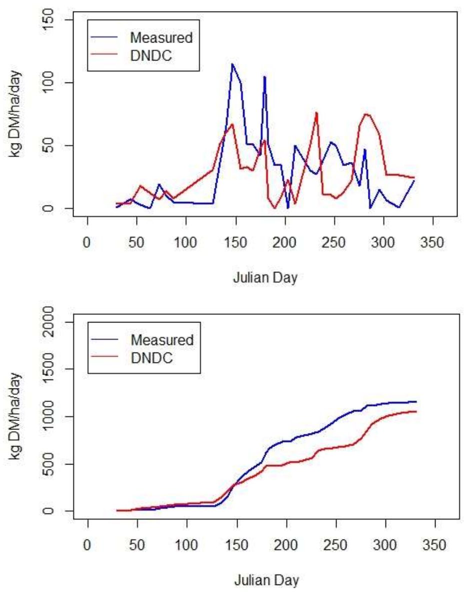


**Figure 4.3**. Average daily grass growth rate measured and predicted by DNDC in Case Study 1 for Paddock 15.4 in 2019 (top-left) and Paddock 11.1 in 2020 (top-right) and cumulative average daily grass growth rate for Paddock 15.4 in 2019 (bottom-left) and for Paddock 11.1 in 2020 (bottom-right), with respect to the corresponding measured values, for paddock specific soil inputs, paddock and year specific inputs on nitrogen fertiliser application, grazing and silage cutting

### *4.3.2. Case Study 2*

The correlation between spatially aggregated (farm level) simulated (farm soil zone specific, under year specific grazing regime and ideal N fertiliser input) daily grass growth with measured average grass growth rate over the farm was higher and the MAE and RMSE were lower for both years (Table 4.6), when compared to the paddock-specific simulations of Case Study 1 (Table 4.5). RD % had a positive value for the annual yield at farm level for both years (Table 4.6). However, the |RD %| in 2019 was smaller than all paddock-specific simulations of Case Study 1, while in 2020 it was greater than 20 %. The simulated and measured average daily grass growth rate is shown in Figure 4.4 (top-left) and (top-right) for the farm in 2019 and in 2020, respectively. The curves of cumulative average daily grass growth rate for the farm are shown in Figure 4.4 (bottom-left) and (bottom-right) for Farm in 2019 and 2020, respectively.

**Table 4.6.** Performance of DNDC in Terms of Evaluation Metrics (Section 4.2.5) for Case Study 2

| Experiments | Daily Grass Growth Rate | | | | Annual Yield |
|---|---|---|---|---|---|
| | **Site, Year** | **Correlation** | **MAE** | **RMSE** | **RD%** |
| **Case Study 2** | **Farm, 2019** | 0.534 | 19.06 | 22.63 | 6.13 |
| | **Farm, 2020** | 0.455 | 19.39 | 23.84 | 23.7 |

*Negative RD % indicates overestimation and positive RD % indicates underestimation by DNDC

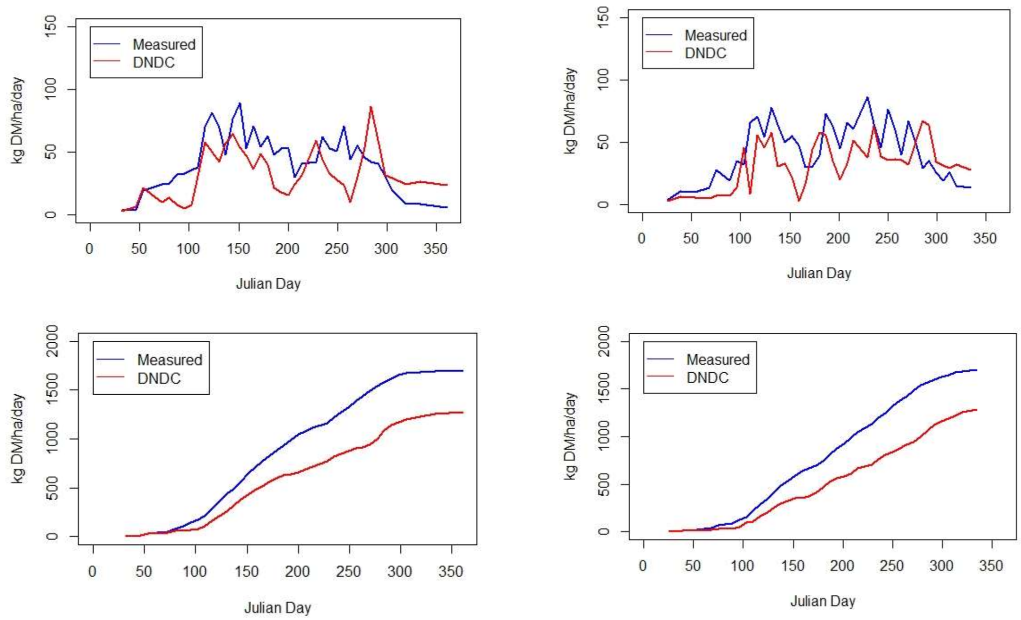


**Figure 4.4:** Average daily grass growth rate measured and predicted by DNDC in Case Study 2 for the farm in year 2019 (top-left) and in 2020 (top-right), with the cumulative average daily grass growth rate for the farm in 2019 (bottom-left) and in 2020 (bottom-right), with respect to corresponding measured values, for farm level specific representative soil inputs, stocking rate and ideal advised nitrogen fertiliser inputs and farm's year specific grazing inputs

### *4.3.3. Case Study 3*

The correlations between measured and simulated grass growth were positive for each simulation, when simulations of the paddock-specific soil inputs were replaced with soil inputs for Irish SIS in Case Study 3 (Table 4.7). The correlations increased for Paddock 15.4 in both years, but decreased slightly for Paddock 11.1 (Table 4.7) when compared to corresponding simulations in Case Study 1 (Table 4.5). The MAE and RMSE between measured and simulated grass growth rate in each simulation were lower for each corresponding scenario than in Case Study 1 (Table 4.5). The RD % of estimated annual yield from corresponding measured value were positive for all paddock level simulations in Case Study 3 (Table 4.7), but |RD %| was smaller compared to the corresponding values in Case Study 1. However, in comparison to spatially aggregated farm level simulation (specific soil and idealised management) of Case Study 2 (Table 4.6) the correlation was always lower and MAE and RMSE were always higher for Case Study 3 (Table 4.7). The visual alignment between average daily grass growth rate in Case Study 3, both simulated and measured is shown in Figure 4.5 for Paddocks 15.4 in 2019 (top-left) and Paddock 11.1 in 2020 (top-right). The corresponding alignment between curves of cumulative average daily estimated and measured grass growth rate are shown in in Figure 4.5 (bottom-left) and (bottom-right) for Paddock 15.4in 2019 and Paddock 11.1 in 2020, respectively.

**Table 4.7:** Performance of DNDC in Terms of Evaluation Metrics (Section 4.2.5) for Case Study 3

| Experiments | Daily Grass Growth Rate | | | | Annual Yield |
|---|---|---|---|---|---|
| | **Site, Year** | **Correlation** | **MAE** | **RMSE** | **RD%** |
| **Case Study 3** | **Paddock 15.4, 2019** | 0.413 | 22.33 | 28.37 | 4.03 |
| | **Paddock 15.4, 2020** | 0.208 | 28.98 | 36.19 | 2.07 |
| | **Paddock 11.1, 2020** | 0.365 | 20.89 | 27.44 | 10.79 |

*Negative RD % indicates overestimation and positive RD % indicates underestimation by DNDC

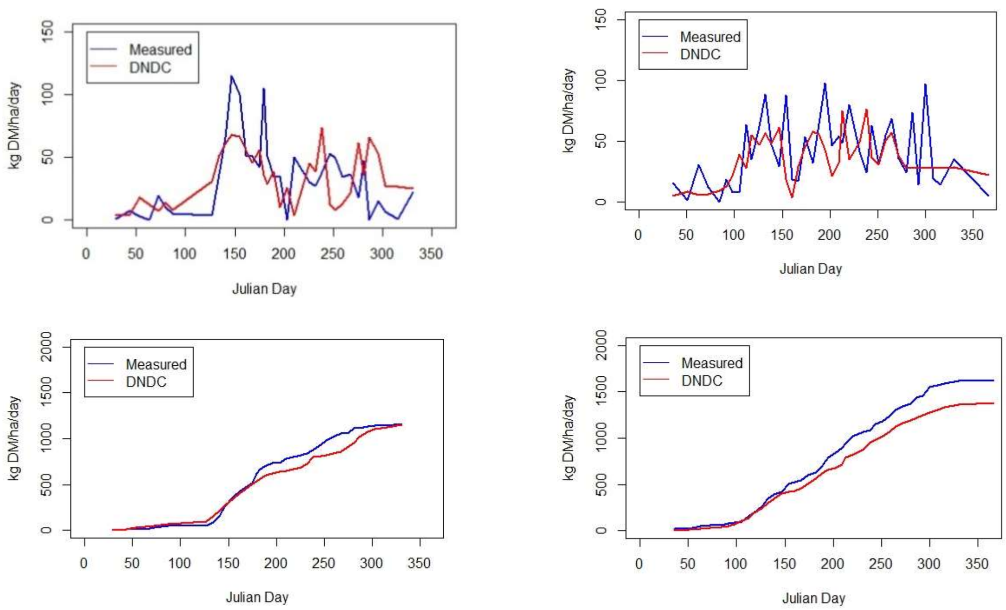


**Figure 4.5**: Average daily grass growth rate predicted by DNDC in Case Study 3 with respect to measured grass growth rate, for Paddock 15.4 in year 2019 (top-left) and Paddock 11.1 in 2020 (top-right), with the cumulative average daily grass growth rate for Paddock 15.4 in 2019 (bottom-left) and for Paddock 11.1 in 2020 (bottom-right) with respect to corresponding measured values, with Irish SIS inputs, paddock and year specific inputs on nitrogen fertiliser application, grazing and silage cutting.

### *4.3.4. Case Study 4*

Using the soil inputs from Irish SIS and ideal N fertiliser input based on stocking rate for the whole farm in Case Study 4 resulted in a higher correlation between simulated and measured daily grass growth rates, and lower MAE and RMSE (Table 4.8) from the corresponding observations of Case Study 2 (Table 4.6). The RD % was negative for annual yield at farm level for 2019 and was positive for 2020 (Table 4.8). However, the |RD %| of annual yield for the farm was lower in both years in comparison to Case Study 2 (Table 4.6). In comparison to all paddock level simulations with Irish SIS based soil inputs in Case Study 3 (Table 4.7) and paddock-specific simulations in Case Study 1 (Table 4.5) the correlation was higher, and the MAE and RMSE were lower, for each farm level simulation in Case Study 4 (Table 4.8). The |RD %|of annual yield estimation was smaller for 2019 and larger for 2020 for the farm level simulation in Case Study 4, in comparison to the any |RD %| observed at paddock level in Case Study 1 and 3. However |RD %| in 2020 in Case Study 4 was greater than 20 %. The visual alignment of curves between average daily grass growth rate simulated and measured at farm level in Case Study 4 for both years is shown in Figure 4.6 for the farm in 2019 (top-left) and 2020 (top-right). The visual alignment between the curves of cumulative of average daily grass growth rate are shown in Figure 4.6 (bottom-left) and (bottom-right) for Farm 2019 and 2020, respectively.

**Table 4.8:** Performance of DNDC in Terms of Evaluation Metrics (Section 4.2.5) for Case Study 4

| **Experiments** | **Daily Grass Growth Rate** | | | | **Annual Yield** |
|---|---|---|---|---|---|
| | **Site, Year** | **Correlation** | **MAE** | **RMSE** | **RD %** |
| **Case Study 4** | **Farm, 2019** | 0.609 | 16.65 | 19.77 | -0.46 |
| | **Farm, 2020** | 0.482 | 18.91 | 22.93 | 20.50 |

*Negative RD % indicates overestimation and positive RD % indicates underestimation by DNDC

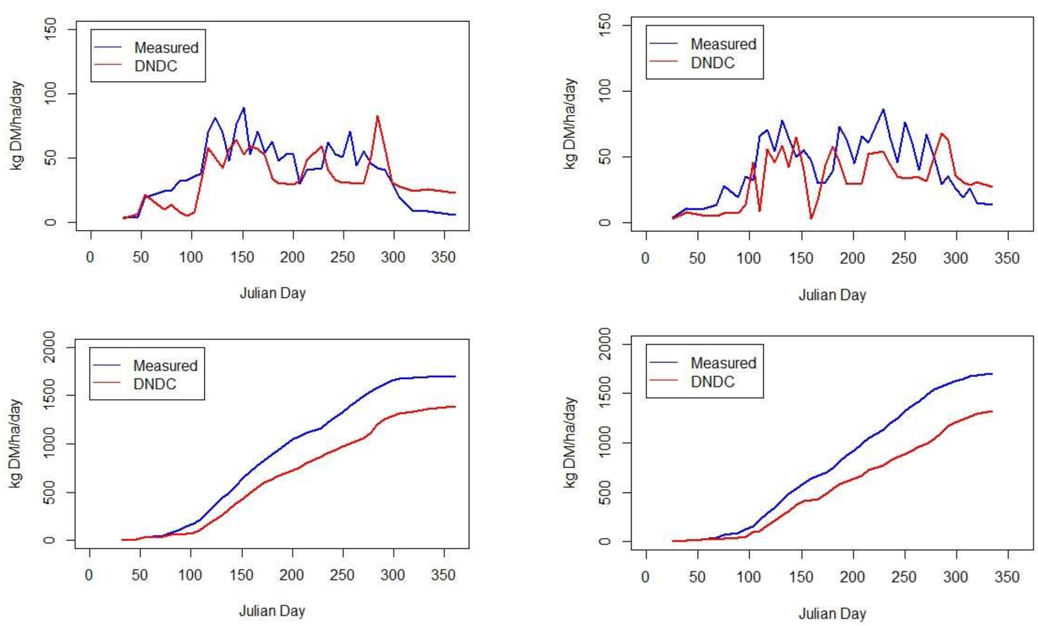


**Figure 4.6**: Average daily grass growth rate measured and predicted by DNDC in Case Study 4 for the farm in year 2019 (top-left) and in 2020 (top-right), with the cumulative average daily grass growth rate for the farm in 2019 (bottom-left) and in 2020 (bottom-right), with respect to the corresponding measured values, for Irish SIS soil inputs and farm level specific stocking rate and advised ideal nitrogen fertiliser inputs and farm's year specific grazing inputs

### *4.3.5. Robustness Test*

The Robustness Test was performed using Case Study 2 as the parent case study. DNDC simulated annual grass yield for the farm level ideal management scenario with DNDC default inputs for non-mandatory atmospheric, soil and crop phenology inputs, resulted in |RD %| was much higher than 20 % and higher than any other paddock or farm level simulation including the parent case study (Table 4.9). For both years, the RD % was positive. The MAE and RMSE were higher than the corresponding values for both Case Study 2 and 4 in corresponding years. Except in comparison to the 2019 simulation in Case Study 2, the correlation of grass growth rate simulated by robustness test with measured grass growth rate was lower than the corresponding from Case Study 2 and 4. However, the correlations were higher than the paddock level simulations. The estimated and measured daily grass growth rate for the farm for year 2019 and 2020 is shown in Figure 4.7 (top-left) and (top-right) respectively, while the corresponding cumulative is shown in Figure 4.7 (bottom-left) and (bottom-right) respectively.

**Table 4.9**: Performance of DNDC in Terms of Evaluation Metrics (Section 4.2.5) for Robustness Test

| Parent Case Study | Daily Grass Growth Rate | | | | Annual Yield |
|---|---|---|---|---|---|
| | **Site, Year** | **Correlation** | **MAE** | **RMSE** | **RD%** |
| **Case Study 4** | **Farm, 2019** | 0.541 | 22.60 | 27.67 | 34.20 |
| | **Farm, 2020** | 0.444 | 23.02 | 28.55 | 46.67 |

*Negative RD % indicates overestimation and positive RD % indicates underestimation by DNDC

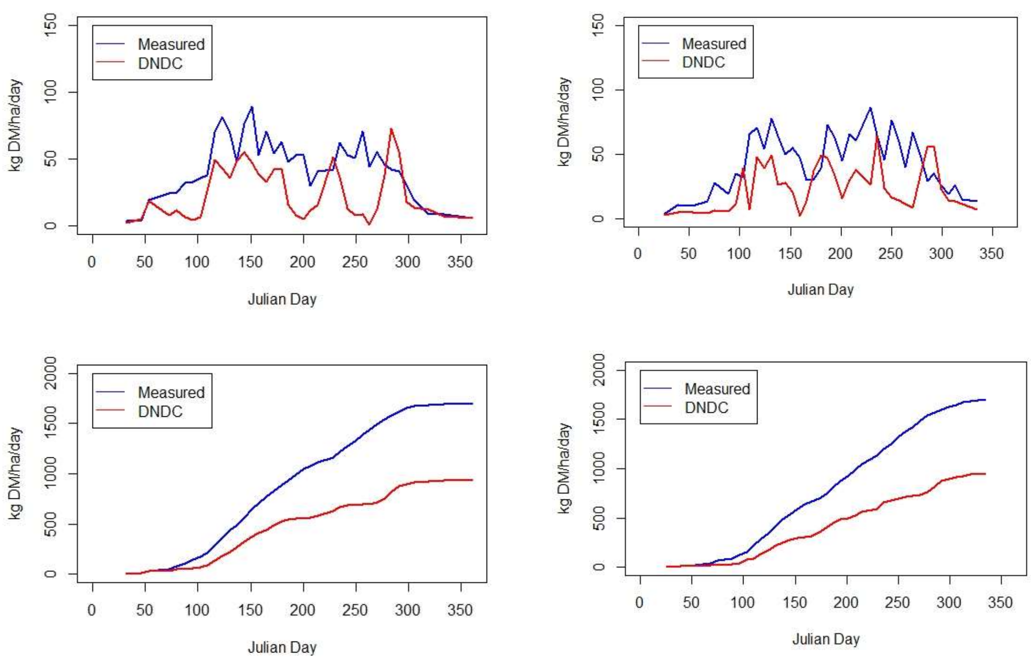


**Figure 4.7**: Average daily grass growth rate measured and predicted by DNDC in robustness test for the farm in year 2019 (top-left) and in 2020 (top-right), with the cumulative average daily grass growth rate for the farm in 2019 (bottom-left) and in 2020 (bottom-right), with respect to the corresponding measured values, for farm level specific stocking rate and advised ideal nitrogen fertiliser inputs and farm's year specific grazing inputs

### 4.3.6. *Sensitivity Test*

Using the variations shown in Table 4.10, the OFAT sensitivity test was conducted using the farm-specific management regime for the gley soil zone in 2019 as the baseline condition. The results are shown in Table 4.11. The results show that SI (%) for texture sandy loam and reduction of average daily rainfall by 20 % resulted in > 10 % difference of estimated annual yield from baseline. While only for increasing clay content by 20 % the difference of annual yield was <0.1 % from baseline. For the rest of the cases the differences of annual yield from baseline fell between 0.1 and 10 %.

**Table 4.10.** Baseline and Variations Used for Sensitivity Test

| Variables | Variation 1 | Baseline | Variation 2 | Reference |
|---|---|---|---|---|
| **pH** | 6.82 (+20%) | 5.68 | 4.5 (-20%) | Gebremichael *et al.*, 2022 |
| **SOC (kg C/kg soil)** | 0.0343 (+20%) | 0.0286 | 0.0229 (-20%) | |
| **BD (g/cm$^3$)** | 1.54 (+20%) | 1.28 | 1.02 (-20%) | |
| **Clay** | 0.214 (+20%) | 0.178 | 0.142 (-20%) | |
| **Texture** | Sandy Loam | Loam | Silt Loam | |
| **Average Daily Rainfall** | 20% High | Daily Johnstown Castle Climate of 2019 | 20% Low | Met Éireann (n.d.) |
| **Maximum average daily temperature** | $1^{0}$C High | | $1^{0}$C Low | |
| **Minimum average daily temperature** | | | | |
| **Grazing hours** | 22hours/day (+10%) | 20hours/day | 18hours/day (-10%) | Byrne and Kiely, 2008 |
| **Stocking Rate** | 2.25 cows/ha (+20%) | 2.04 cows/ha | 1.84 cows/ha (-20%) | Teagasc, 2017c |
| **Fertiliser** | 271 kg N/ha (+20%) | 226 kg N/ha | 181 kg N/ha (-20%) | Wall and Plunkett (eds.), 2020 |

**Table 4.11.** Sensitivity Index (SI) as Percentage (%) of Variation of Estimated Annual Grass Yield from Baseline with the Variation of Each Individual Input Variables

| Variables | Variation from Baseline | Sensitivity Index (%) |
|---|---|---|
| pH | Variation 1 | 0.11 |
| | Variation 2 | 0.12 |
| SOC | Variation 1 | 1.90 |
| | Variation 2 | 0.35 |
| Bulk Density | Variation 1 | 1.48 |
| | Variation 2 | 0.44 |
| Clay | Variation 1 | 0.01 |
| | Variation 2 | 1.56 |
| Texture | Variation 1 | 10.25 |
| | Variation 2 | 4.44 |
| Rainfall | Variation 1 | 3.75 |
| | Variation 2 | 15.51 |
| Average Daily Temperature | Variation 1 | 1.81 |
| | Variation 2 | 9.41 |
| Average Daily Grazing Hours | Variation 1 | 0.13 |
| | Variation 2 | 0.13 |
| Stocking Rate | Variation 1 | 0.20 |
| | Variation 2 | 0.32 |
| Annual Nitrogen Fertiliser Application | Variation 1 | 6.04 |
| | Variation 2 | 2.89 |

## 4.4. Discussion

### *4.4.1. Analysis of correlation between measured and DNDC-simulated daily grass growth rate*

The curves derived to compare the measured and estimated grass growth – including the daily grass growth rate and cumulative growth over the year - largely show good agreement, for simulations on both paddocks and the farm. However, a tendency of the model to underestimate growth is evident. As per the Pearson's correlation coefficient, the results show that under both (specific and Irish SIS based) soil input scenarios, the grass growth rate simulated by DNDC was better correlated with the corresponding measured data for all simulations at farm level (under ideal N management inputs for the farm-specific stocking rate) (Table 4.5 and 4.7), including the robustness test (DNDC-default inputs for atmospheric, soil and crop phenology inputs), than at any paddock level simulations (with paddock-specific management inputs) (Table 4.4 and 4.6). In fact, correlations were higher at farm level when the more general Irish SIS based inputs were used at farm level (Case Study 4) compared to the outputs simulated using farm soil-zone specific representative soil inputs (Case Study 2). The variation in the number of grazing days over the year and daily weather inputs could potentially explain the variation in correlations between 2019 and 2020 at farm level for simulations in both Case Study 2 and 4. Overall, the results of the correlation analysis indicate that the predicted grass growth rate at farm level, for both site-specific and generalised soil and management inputs, as well as, for most of the paddock level simulations under specific and generalised soil inputs (with specific management inputs), except Paddock 1 in 2020 in Case Study 1, were positively associated with measured grass growth rate with stronger correlations at farm level.

### *4.4.2. Analysis of performance of DNDC based on MAE and RMSE*

A decrease in the value of MAE and RMSE indicates better performance in a model (Al-Musaylh *et al*., 2018). Considering this, the results imply that the performance of DNDC was better at farm level (with ideal N fertiliser inputs based on stocking rate) for both years than the simulations at paddock level (with specific management inputs), under both (specific and Irish SIS based) soil input scenarios. The performance of the model increased after changing the soil inputs from site specific to Irish SIS based soil inputs for both paddock and farm level simulation for both years of simulation. At farm level, the performance of DNDC was better for 2019 than 2020, under both soil inputs, likely driven by the variation in grazing regime and/or daily weather. For the robustness test at farm level, with DNDC default inputs for non-mandatory atmospheric, soil and crop phenology inputs, the model performed poorer in terms of MAE and RMSE in comparison to Case Study 2 and 4. However, no conclusion could be drawn when both the MAE and RMSE of the farm level robustness test was compared with results at paddock level. RMSE can be a better indicator of model performance than MAE, particularly when the difference between predicted and observed values is greater than 1.0 for a significant number of datapoints in the dataset (Babu *et al*., 2006; Willmott, 1982), as was the case in this study. The RMSE for the farm level simulations in Case Study 2 and 4 fell within the range of values of RMSE as estimated by Hurtado-Uria *et al*. (2012) for grass growth rate at Moorepark, Ireland from 2005-2009 using the site-specific grass growth model of Brereton *et al*. (1996) (14.6-23.8). However, the range of Case Study 1 and 3 fell beyond its upper-limit. The RMSE values for Case Study 2 and 4 fell within the range of the mechanistic dynamic model by Jouven *et al*. (2006) (14.4-32.2), while the range of Case Study 1 and 3 overlapped with the range by Hurtado-Uria *et al*. (2012). However, the RMSE of estimated average daily grass growth rate using Most GG model by Ruelle *et al*. (2020) is lower than the DNDC simulations, though the inputs regarding soil, weather and crop phenology are more diverse in DNDC including the temporal pattern (Ruelle *et al*., 2018).

### *4.4.3. Analysis of relative deviation (RD%) of DNDC-simulated annual grass yield from measured annual grass yield*

Except for the farm level simulation (ideal N fertiliser input for a targeted stocking rate) in 2019 with soil inputs for Irish SIS, in the rest of the cases - both at paddock (specific management inputs) and at farm level, and under both (specific and generalised Irish SIS) soil input scenarios, as well as for the robustness test at farm level (with DNDC-default inputs for atmospheric, soil and crop phenology inputs) - DNDC underestimated the annual grass yield. Apart from the robustness test, the |RD %| between estimated and measured annual grass yield for all paddock level simulations and for the year 2019 at farm level under both soil input scenarios were lower than 20 %, indicating an improvement from the simulations with default inputs (DeSilva *et al*., 2003). The farm level simulation in 2020 produced values greater than 20 % under both soil input scenarios in Case Study 2 and 4, but was much lower than the threshold of indicating a strong relative deviation (> 50%) (Cai *et al*., 2003). Using Irish SIS based soil inputs instead of site-specific soil inputs both at paddock and farm level, improvement in annual grass yield estimation in DNDC in terms of |RD %| were evident while the results were poor for the robustness test. In a study by Abdalla *et al*. (2011), though for grass-clover paddock, DNDC underestimated the annual yield of aboveground biomass by a |RD %| of 23 % at paddock scale. In comparison, this study shows that the performance of DNDC in annual grass yield estimation at paddock level can be closer to reality when crop phenology was modified for perennial ryegrass and the atmospheric inputs were more representative of site/regional conditions.

### 4.4.4. *Explanation of anomalies*

Soil physicochemical properties can be important causes of spatial and temporal differences between DNDC estimated and measured grass growth, through the regulation of N availability and uptake. The key input variables of soil in this study were texture, pH, bulk density and SOC. Soil texture, especially the clay content, contributes to retention of $NH_4^+$, while soil organic matter (SOM) (represented here by SOC) contributes by supplying mineralisable N as well as reducing N leaching (Malcolm *et al*., 2019; Provin and Hossner, 2021). The influence of texture and SOM on N availability or loss can be modified by soil moisture content, further regulated by weather and overall bulk density (Jordán *et al*., 2010; Newman, 1984; Ngosong *et al*., 2019; Sahrawat, 2008; Saggar *et al*., 2013; Whetton *et al*., 2022). Soil pH can influence N dynamics by regulating decomposition of SOM, but this can also be influenced by weather (Kemmit *et al*., 2006., Li *et al*., 2022a). While the soil physicochemical properties used in this study were representative of paddock and farm conditions, yet physicochemical properties of soil can vary spatially within microsites within a paddock or a farm, while this may also regulate the impact of weather driven temporal variation of N dynamics including the activity of microbes unaccounted for in the DNDC simulations – thus ultimately regulating the uncertainty between the estimated and measured aspect of N dynamics, including N availability that regulates grass growth. Similarly, the study site used here represents the typical weather of southern Ireland, but do not account for weather extremes like drought (e.g. Ishola *et al*, 2022) or diverse climatic conditions of rainfall, temperature or solar radiation across Ireland (Curley et al., 2023; Walsh, 2012). These, along with the model's sensitivity to factors like rainfall, temperature and SOC, can be contributing factors to anomalies observed in the estimated grass growth rate and annual yield depending on the accuracy of the paddock or farm condition represented by inputs used (e.g. Abdalla *et al*., 2020; Cain *et al*., 1999; He *et al*., 2020; Jones *et al*., 2011; Larios *et al*., 2016; Shen *et al*., 2018; Shah *et al*., 2020; Wang *et al*., 2012; Wu *et al*., 2021). Thus, future studies need to be performed by using classification of landscape and/or climatic zones to choose representative sites for developing database for model simulation, validation and application, for the extent of spatial area represented by the inputs.

Crop phenological parameters used in this study were focused on perennial ryegrass, which is the dominant species at Johnstown Castle Dairy Farm and in the studied paddocks (Gebremichael *et al*., 2021). The response of crop phenology of other plant species, present in specific paddocks in the farm, to the weather, management and soil can be significantly different from that of perennial ryegrass. Growth rates of different plant species in grassland can vary due to different growth responses to soil temperature. When compared to legumes like clover, where growth may not occur below $8^0C$ (Lynch, 2021), perennial ryegrass can display higher growth at temperatures above $5^0C$ and its vegetative growth can even occur at $0^0C$ (Wingler and Henessey, 2016). N availability in soil and uptake can also vary greatly depending on grass species composition and climate (Hofer *et al*., 2016). Hence, the impact of year-to-year variations in weather on different grass species present in the field and the corresponding effect on N dynamics may have contributed to the differences between measured and actual grass growth rate in same paddock. This might have also occurred in different years at farm level, where species composition was more diverse among many designated experimental swards across the farm. Thus, for a robust application of DNDC, including multispecies swards and grass-clover swards – that is being increasingly practiced in Ireland (Egan *et al.,* 2022; Gilliland, 2022), to reduce the potential uncertainty due to the phenology parameterisation of the model – it would be a requirement to parameterise and validate the model prior to application, depending on the extent of area under a targeted species composition represented by the phenological parameterisation performed.

Between Paddock 15.4 and Paddock 11.1, which have nearly similar species composition, the N fertiliser application rate was different in the same year. Also, Paddock 11.1 did not receive any applications of P, K or S, while Paddock 15.4 received different rates of N, P, K and S applications in each of the two different years. For slurry application in Paddock 15.4 in 2019 only the N content in slurry was used as DNDC input, while supply of P, K and organic carbon from slurry (Teagasc, 2022) were not considered as the research was primarily focused on N inputs. At the farm scale, each of the 58 paddocks in the JC farm received different nutrient sources and management, in terms of nutrient application rates, liming, grazing intensity and other management practices, both within the same year and between the two years. Even the N fertiliser application rates across the paddocks were different from the advised maximum N fertiliser application used for farm level simulations (Wall and Plunkett (eds.), 2020). Difference in N fertiliser application rates may influence the biomass production by different species at both paddock and farm level (Moloney *et al*., 2020). Application of P can increase grass production (Sheil *et al*., 2015) and Murphy *et al*. (2002) showed S fertilisation can increase grass yield from around 20% to 50% depending on seasons. K application can prompt both grass yield and NUE (FAI and Teagasc, 2020). However, in general there is no input option for K in DNDC. Application of lime or its calcium content at farm level was not included in the study (not an input option in DNDC) but can impact grass growth and N mineralisation (Edmeades *et al*., 1981). The effect of animal excreta during grazing, which can stimulate grass growth and add mineralisable sources of plant-nutrients beyond N to soil (Almeida *et al*., 2019; Garcia *et al*., 2021) is also not considered in DNDC (Saggar *et al*., 2007). Abdalla et al., (2009) had indicated that DNDC is sensitive to fertiliser type. Simplification of fertiliser type and omitting use of other nutrients in simulations intentionally and due to model limitation thus may likely have contributed to the observed difference between simulated and measured grass growth. Such uncertainties may also arise at paddock and farm level in Ireland due to specific management advice provided by NMP Online that uses indexing system for P and K (Teagasc, 2017e). Whereas scope of potential refinement of N management strategies for sustainability, if includes application of N from the *right source* at a *right time* in a *right place* to meet 4RNS objectives (Fixen, 2020) – through a Tier 3 modelling approach (Buendia *et al*., 2019) using DNDC by estimating the impact of the management regime under consideration, becomes limited – unless challenges with sensitivity to fertiliser type and spatial and temporal extent of use of a specific fertiliser is addressed.

At paddock level the fertiliser type input for KaN, UAS 38% and Alzon urea 46% were considered as urea inputs and CAN inputs were used for $NH_4^+$ and $NO_3^-$. At farm level, inputs for all N fertilisers were used under the urea option in DNDC. However, in 2019 the actual N fertiliser types used in the farm in this year was highly diverse across paddocks, while in 2020 most of the farm only received KaN with a few cases of CAN application. KaN contains N-(n-butyl) thiophosphoric triamide (an urease inhibitor), while Alzon urea 46% contains an urease inhibitor N-(2-nitrophenyl) phosphoric triamide and a nitrification inhibitor N-[3(5)-methyl-1H-pyrazol-1-yl) methyl] acetamide (Cantarella *et al*., 2018, Forrestal *et al*., 2015; Kirschke *et al*., 2019). Urease inhibitors reduce the urea dissolution rate, while nitrification inhibitors further reduce consecutive losses that occur after nitrification (Kirschke *et al*., 2019; Marsalkova and Ryant, 2014), and thus regulates the N dynamics, none of which were accounted for in the simulations. Besides being a source of N, UAS 38% is also a source of S that promotes grass growth (Chatterjee, 2018; Murphy *et al*., 2002), which was also not accounted for during the simulations. Hence, the simplification of the fertiliser inputs might be one of the drivers of the differences observed in the DNDC outputs. However, CAN and urea do not show significant difference in grass dry matter yield across Ireland (Keane *et al*., 1974).

### *4.4.5. Key variables regulating annual grass yield*

The results of the OFAT sensitivity analysis, categorised according to Wang *et al*. (2016), showed that in general rainfall and soil texture are the most significant regulators of annual grass yield. The other soil variables – pH, SOC, BD, clay content, weather variables - average daily maximum and minimum temperature, management variables – average daily grazing hours, stocking rate and total N fertiliser applied, appeared to be potentially relevant regulators of annual yield of perennial ryegrass for the studied intensively managed Irish grassland. The SI from OFAT sensitivity test showed that the grass yield is sensitive to an increase in sand content and a reduction in rainfall, whereas it is insensitive to up to 20 % the reduction of the clay content from 17.8 % clay when the soil texture is loam soil. The rainfall in this study was identified as a key driver of grass yield in general, which contrasts with the observations by Hurtado-Uria *et al*. (2013). However, the sensitivity categorisation of rainfall was mainly driven by the decrease in rainfall indicating similar findings to the observation by Hurtado-Uria *et al*. (2013) and Grange *et al*. (2021) that the general rainfall conditions in Ireland may not limit the grass yield by causing waterlogging or water scarcity, but under seasonal or periodic drought events yield of perennial ryegrass can be significantly affected (e.g. Ishola *et al*, 2022). In this study, a significant difference in grass yield was estimated over sandy loam soil in comparison to loam soil, consistent with McDonald *et al*. (2014). In their study, they observed even lower average grass yield on silt loam soil than loam soil, but DNDC estimated a smaller effect of soil texture representing higher silt content than the one representing higher sand content on annual grass yield. The overall sensitivity of annual grass yield was very low (<1 %) to both an increase or decrease of soil pH, average daily grazing hours, stocking rate.

N fertiliser application rate was identified as a potentially important key driver of grass yield and is similar to the observations by Harty *et al*. (2017). Temperature, as identified by Hurtado-Uria *et al*. (2013) was found to be a potentially important regulator of grass growth in Ireland in this study. Douglas and Crawford (1991) observed a significant decrease in yield of perennial ryegrass under higher soil compaction for sites in Scotland under temperate weather conditions, which justifies the identification of grass yield to be potentially sensitive to BD by DNDC. SOM is generally the important decomposable nutrient resource for plants while clay retains soil nutrients, while both regulate soil’s pH, structure, water holding capacity, CEC and BD (Anderson, 1988; Blanco-Canqui and Benjamin, 2015; Costa *et al*., 2004; Djajadi and Hinz, 2012; Libohova *et al*., 2018; Ramos *et al*., 2018; Robertson and Paul, 2000; Soinne *et al*., 2023; Sparks *et al*., 2024; Zhang *et al*., 2017). SOC is an indicator of SOM (Pribyl, 2010). Thus, SOC as well as clay, as identified in this study, can be a potentially important driver of grass yield. Tuñon *et al*. (2013) did not find any significant impact of variation of grazing intensity on yield and tiller density of perennial ryegrass. However, grazing generally reduces soil porosity and increases BD, while it can add SOC and nutrients to soil, yet it may also negatively impact both (Kurz *et al*., 2006; Lai and Kumar, 2020; Marriott *et al*., 2010; Piñeiro *et al*., 2010). Thus, stocking rate and grazing hours both being identified as potentially important regulator of grass yield, though with a low SI, cannot be ignored for sustainable N management in grassland.

However, it may be noted that while the baseline scenario is representative of an ideal soil and management scenario, the objective of the study was only to identify the impact of variation of each targeted individual soil, weather and management property, thus, varied to their extremes as much aligned as possible with the observations from Irish grasslands (e.g. Curley et al., 2023; McDonald *et al*., 2014). Thus, such variations may not represent ideal intensively managed grassland scenario – but would help to develop database for simplified modelling (Haraldsson and Sverdrup, 2013; Patil, 2009), even though the potential of uncertainties remain for the scenarios not included in the variations or even within the range represented by the extremes. Thus, future studies can be performed to improve confidence in identification of key indicators of grass yield through scenario analysis (Giltrap *et al*., 2010) for representative sites for diverse soil, management and climate scenario in line with the landscape classification performed by Carlier *et al*. (2021).

### 4.5. Conclusion

This research sought to investigate the performance of DNDC as a tool to estimate grass growth, due to its importance in determining N uptake, with the broader aim of utilising it for research in sustainable N management in Irish grasslands to refine N management strategies. Overall, the performance of DNDC to estimate annual grass yield as well as the temporal pattern of grass growth rate at both paddock and farm scale under specific or generalised soil input scenarios was found to be reliable, under the parameterisation of crop phenology and atmospheric inputs performed in this study. However, the model performed better at farm level than at paddock level. It was also identified that the model performs poorly in terms of estimating annual yield when such parameterisation is not performed and the DNDC default inputs for non-mandatory soil, atmospheric and crop phenology are used instead; this has implications for N modelling within DNDC. The outcomes indicate that the parameterised DNDC model can be used to estimate growth of perennial ryegrass dominated paddocks at Johnstown Castle dairy farm as well as for other intensively managed perennial ryegrass dominated grassland sites, with a similar level of parameterisation. However, to estimate N loss from Irish perennial ryegrass pastures, the spatial and temporal performance of the parameterised DNDC needs to be further investigated, along with the use of specific crop phenology and atmospheric inputs (other than weather). The reliability of the parameterised DNDC simulation with generalised soil inputs indicates that there may be scope to use the model with less site-specific inputs for soil for sites with limited data availability, though further research is required to understand the extent to which more generalised inputs can impact the model performance.

Due to the large temporal variation in performance observed at paddock and farm level in annual grass growth estimation, DNDC should not be used to estimate N loss without appropriate validation of the crop module. Rather it may be more suitable to explore the potential consequences of a management regime at a site through a scenario analysis approach. The outcome of the study is limited to intensively managed grassland sites only and was not tested for low N input conditions. However, future research could be performed to explore the performance of DNDC for low N input grassland conditions with the parameterisation used in this study, as low N input practices are increasingly being focused upon under sustainable agricultural strategies. Potential remains to further increase the precision of grass growth estimation by DNDC by including options for additional organic and inorganic nutrient inputs, modifying phenological inputs for different species composition and including more specific management for individual grasslands. The study also showed that the yield of perennial ryegrass at farm level is most sensitive to soil texture and rainfall, whereas variables like soil pH, SOC, BD, clay content, air temperature, grazing hours, stocking rate and application rate of N fertiliser are potentially relevant regulators of grass yield. Whether this finding is specific to the study site or applicable more generally applicable requires further exploration.

# 5. Evaluation of DNDC and identification of the key variables to estimate nitrous oxide emissions and volatilisation of ammonia from an intensively managed grassland.

**Abstract**

Nitrogen (N) supplied through fertilisers to agricultural landscapes including grasslands is susceptible to loss when applied N is surplus to the requirement of the plant. With the global trend of increasing N fertiliser use, negative impacts are becoming more and more prominent. In Europe, the Green Deal aims to gradually reduce the supply of surplus N through fertilisers and ultimately achieve climate neutrality in the European Union by 2050. In line with this ambition, the current nutrient management plan (NMP-Online) and general nutrient management guidelines for Irish grasslands under dairy farming aims to increase yield and reduce N loss. However, these policies currently do not account for the impact of spatial and temporal variations in soil, weather and management on yield and N loss. This needs to be addressed to develop more spatially refined N management strategies required to achieve the goals of 4R's of nutrient stewardship (4RNS) for sustainability. Here, we sought to evaluate the *DeNitrification-Decomposition* (DNDC) model to support the incorporation of more spatially refined information, including detailed inputs on soil, weather and management, to simulate grass growth and N dynamics at selected sites. The outcomes of the study indicate that DNDC, correctly parameterised for the phenology of perennial ryegrass and local/regional atmospheric conditions, can reliably estimate annual ammonia ($NH_3$) volatilisation and nitrous oxide ($N_2O$) emissions from intensively managed permanent grasslands. However, representative inputs on water filled pore spaces (WFPS) at field capacity (FC) and wilting point (WP), specific to the studied soil type at the site, are required.

## 5.1. Introduction

Nitrogen (N) is one of the macronutrients commonly supplied to intensively managed Irish grasslands through chemical fertilisers (Murphy *et al*., 2013). Plants uptake N from soil mainly as ammonium ($NH_4^+$) and nitrate ($NO_3^-$). A significant proportion of N supplied, surplus to requirements, is lost mainly through ammonia ($NH_3$) volatilisation, nitrous oxide ($N_2O$) emissions during denitrification under anaerobic soil conditions and $NO_3^-$ leaching. However, the relative proportions of the latter two are known to be small in grasslands, except during high rainfall events (Woodmansee *et al*.,1981). Spatial and temporal variations in soil physicochemical properties, weather, climate and management variables, impact on different N loss pathways by regulating the biogeochemical processes associated with terrestrial N dynamics (e.g. Di and Cameron, 2002; Gu and Riley, 2010; Jones *et al*., 2013; Longepierre *et al*., 2022; Pan *et al*., 2022; Rahman and Forrestal, 2021; Sigunga *et al*., 2002; van Es *et al*., 2006; Zhenghu and Honglang, 2000). N lost from soil negatively impacts environmental quality by contributing to issues such as eutrophication of water resources, climate change, acid rain and water pollution - and is increasingly evident with the increase in intensive N management globally (e.g. Giordano *et al*., 2021; Heffer and Prud'homme, 2016; Ladha *et al*., 2020; Martínez-Dalmau *et al*., 2021; Pilegaard, 2013; UNEP, 2019; Zhang *et al*., 2021b). The European Green Deal aims to reduce GHG emissions by 55 % by 2030, relative to 1990 levels, and to achieve climate neutrality by 2050 in the European Union (EU) (EPRS, 2021). In parallel, the EU Common Agricultural Policy (CAP) aims to reduce pollution from chemical fertilisers while maintaining and/or increasing soil fertility (European Commission, 2022). In line with these goals, Irish governmental bodies are working on agricultural strategies to reduce $NH_3$ volatilisation (DAFM, n.d.), $NO_3^-$ leaching (DHLGH and DAFM, 2022a) and $N_2O$ emissions (DAFM, 2023). In Ireland, the nutrient management plan (NMP-Online) and the generalised advice on N fertiliser application in Ireland (DAFM, 2023a; Wall and Plunkett (eds.), 2020) focus on soil fertility test results, stocking rate and corresponding N content in excreta, and grass growth phases. However, neither of these account for the potential spatial and temporal variations in N loss and uptake that can occur due to complex interactions among soil physicochemical properties, weather and management (Patil, 2009; Sharma and Bali, 2017). A clearer understanding of the relative importance of these factors on different N loss pathways in Irish grasslands may help to prioritise more site-specific N management strategies that could help to achieve more sustainable grass production, aligned with the ambitions of 4RNS (4R Nutrient Stewardship) (Fixen, 2020; Patil, 2009; Sharma and Bali, 2017; Wu and Ma, 2015).

*DeNitrification-DeComposition* (DNDC) is a process-oriented model that uses detailed inputs on soil, climate, crop phenology and management practices to produce detailed outputs on crop growth and dynamics of N and carbon (C) at both daily and annual time scales (Gilhespy *et al*., 2014; Saggar *et al*., 2007). It has been found to reliably estimate grass growth and yield for intensively managed grasslands under dairy farming, with parameterisation for local climate and crop phenology of perennial ryegrass in Experiment 1 (Chapter 4). The existing works prior to that, performed in the context of exploring N dynamics in Irish grasslands using DNDC, primarily focused on $N_2O$ emissions estimation (e.g. Abdalla *et al*., 2009; Abdalla *et al*., 2010; Li *et al*., 2011; Rafique *et al*., 2011; Zimmermann *et al*., 2018). The need for explicit parameterisation and validation of the model for crop growth and yield estimation, necessary for reliably simulating N dynamics (Zhang *et al*., 2015) was not considered. Using the results from Experiment 1 (Chapter 4), we sought to explore N dynamics and major N loss pathways in grasslands including $NH_3$ volatilisation and $N_2O$ emission (Woodmansee *et al*., 1981). However, it is necessary to evaluate its performance for estimating N loss and the spatial resolution for input data required for reliable model performance (Cannavo *et al*., 2008; Haraldsson and Sverdrup; 2013; Milne *et al*., 2020; Zhang *et al*., 2015; Zhang *et al*., 2020a).

Here, we focus on the validation of DNDC, using site specific parameterisations for crop phenology and atmospheric inputs, to simulate $N_2O$ emissions and $NH_3$ volatilisation. Water filled pore space (WFPS) has been identified as an important model input for generating estimates of N dynamics (Abdalla *et al*., 2010; Beheydt *et al*., 2007). Most previous studies performed in Ireland using DNDC used site-specific WFPS at field capacity (FC) and wilting point (WP). However, this data may not always be readily available and therefore limits the potential application of a model based approach more generally. Thus, in this study, the performance of DNDC in simulating N dynamics and grass yield was assessed with the DNDC default and site-specific (based on location and soil texture) inputs for WFPS at FC and WP. Abdalla *et al*. (2022) indicated that model accuracy in simulating soil temperature is important to reliably simulate crop yield and $N_2O$ emissions estimation; soil temperature is also an important regulator of overall N-dynamics in soil (e.g. Dutta *et al*., 2016; Jones *et al*., 2013; Shah *et al*., 2020; Uzoma *et al*., 2015). Thus, a validation of daily estimated WFPS and daily topsoil temperature was also performed. Giltrap *et al*. (2010) indicated that at a daily scale DNDC results may perform poorly in simulating N dynamics due to leads and lags – between measured and modelled outputs, yet the outcomes can be reliable at longer timeframes – assuming that the errors are just related to timing and not magnitudes. In Experiment 1 the performance of DNDC for grass growth estimation was found to be reliable at the daily scale and annually, the performance of DNDC is explored here at daily and annual scale - to determine if an optimum temporal scale exists for evaluating the performance of DNDC to estimate $N_2O$ emissions and $NH_3$ volatilisation.

## 5.2. Data and Methods

### *5.2.1. Site Location*

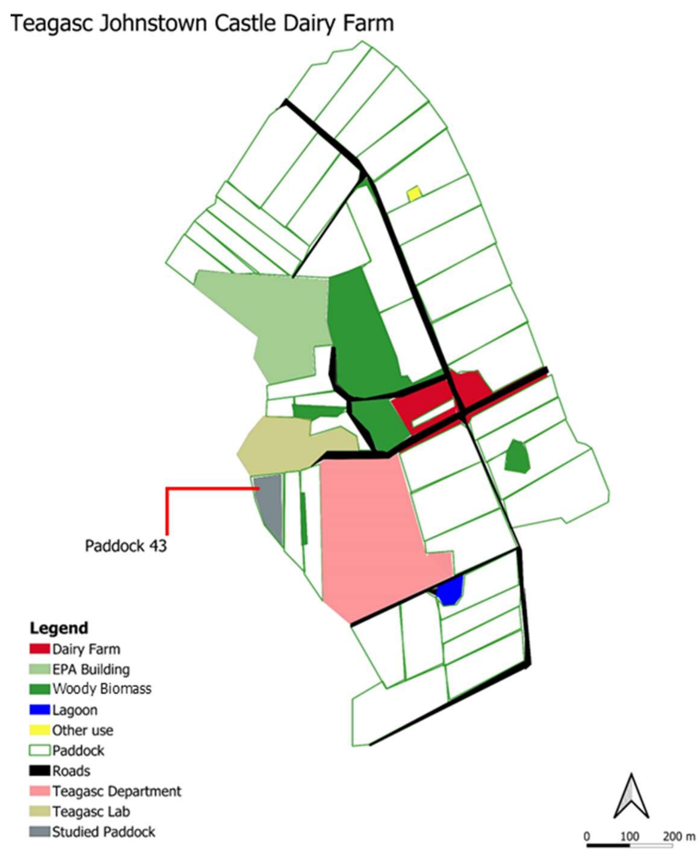


**Figure 5.1:** The studied paddock from Teagasc Dairy Farm at Johnstown Castle (Source: Farm Data)

The grassland sites employed here represent intensively managed paddocks, typical of Irish dairy farms, and are located at the Johnstown Castle (JC) Dairy Unit (County Wexford, Ireland). The Dairy Unit, was established in 2003 by Teagasc as part of the winter milk research system programme (Teagasc, 2017c). It receives an average annual rainfall (1990-2010) of 1036 mm, with a mean annual temperature of approximately 10.4$^0$C, based on measurements from the Johnstown Castle synoptic weather station (Cahalan *et al*., 2015). Higher autumn and winter rainfall and higher air temperatures in spring and summer are typical at this site, similar to the general climate conditions found across Ireland (Antille *et al*., 2015; Walsh, 2012). Temperatures support year-round vegetative growth for perennial ryegrass, as the average monthly soil temperature (1978-2007) within 20cm depth varies between 5.8$^0$C in winter to 17$^0$C in summer (Met Éireann, n.d.a; Wingler and Hennessy, 2016). Data from two previous studies performed in Paddocks 43 from the farm (Figure 5.1) were available and met the requirements for running and evaluating DNDC. These included: (i) measurements of $N_2O$ emissions and/or $NH_3$ volatilisation at daily and annual time scales; and, (ii) corresponding paddock specific soil physicochemical properties, management details and grass growth rate or yield data. One of these studies was on an ungrazed sandy loam soil area of Paddock 43 on which Krol *et al*. (2020) performed their experiment in 2017 (hereafter referred to as Paddock 43.A). Chamber data related to this experiment were available for validation of the estimated $N_2O$ emissions for two separate blocks, treated by either urea only or by calcium ammonium nitrate (CAN) only. The second study was performed on the loam soil area of the same paddock (Paddock 43) by Forrestal *et al*. (2015) from 2014 (hereafter, Paddock 43.B). Corresponding data was obtained, which included $NH_3$ volatilisation on blocks treated either with urea only or CAN only and both were ungrazed, thus receiving no N from excreta. Data related to the aforementioned experiments were used for model simulation and validation of the estimated $NH_3$ volatilisation. Figure 5.1 shows the location of Paddock 43 within the Johnstown Castle dairy farm complex.

### *5.2.2. Data*

For Paddock 43.A and 43.B detailed information on topsoil soil variables (texture, clay percentage, pH and SOC) (Table 5.1), fertiliser management regime, annual estimation of $N_2O$ emissions for Paddock 43.A and annual estimation of $NH_3$ volatilisation for Paddock 43.B derived from daily measurements - were available in Krol *et al*. (2020) and Forrestal *et al*. (2015), respectively. The annual grass dry matter (DM) yield for Paddock 43.A was obtained from Krol *et al*. (2020), whereas for Paddock 43.B the farm data records were used. For Paddock 43.A, soil pH was below 6.5 (Krol *et al*., 2020) and consequently the soil C content was considered as soil organic carbon (SOC) (Franzluebbers and Stuedemann, 2002) (Table 5.1). For the Paddock 43.B, information of SOC was not available from the study by Forrestal *et al*. (2015), although information on SOM was provided. As per the input requirements of DNDC, SOC for Paddock 43.B was estimated by dividing the SOM data by 1.724 (Pribyl, 2010) (Table 5.1). Information on the measurement of WFPS at FC and WP and bulk density (BD) for the paddocks was not available in the associated literature. However, the volumetric water content (%) at FC and WP for a sandy loam soil and a loam soil in the same Paddock 43 was recorded by Zimmermann *et al*. (2018). From this, WFPS at FC and WP were calculated for the corresponding soil type in each paddock using the formula from Franzluebbers (1999) (Table 5.1). The bulk density (BD) of each paddock was calculated using a pedotransfer function for the Ap soil horizon recalibrated for Irish soils by Reidy *et al*. (2016) (Table 5.1).

**Table 5.1:** Soil Inputs Used for Simulations under Each Case Studies (Site specific WFPS parameters in Italics)

| | Variables | Case Study 5 | | Case Study 6 | | References |
|---|---|---|---|---|---|---|
| | **Paddocks** | **43.A** | **43.B** | **43.A** | **43.B** | Forrestal *et al.* (2015); Franzluebbers (1999); Krol *et al.* (2020); Reidy *et al.* (2016); Zimmermann *et al.* (2018) |
| **Site-specific and same for a paddock in both case studies** | **Texture** | Sandy Loam | Loam | Sandy Loam | Loam | |
| | **Clay (%)** | 0.144 (14.4 %) | 0.14 (14 %) | 0.144 (14.4 %) | 0.14 (14 %) | |
| | **pH** | 5.7 | 5.8 | 5.7 | 5.8 | |
| | **SOC (%)** | 0.028 (2.8 %) | 0.041 (4.1 %) | 0.028 (2.8 %) | 0.041 (4.1 %) | |
| | **BD ($g/cm^{3-}$)** | 1.053 | 0.954 | 1.053 | 0.954 | |
| **Default in Case Study 5 and Site-Specific in Case Study 6** | **WFPS at FC** | 0.32 | 0.49 | 0.54 | 0.71 | |
| | **WFPS at WP** | 0.15 | 0.14 | 0.26 | 0.34 | |

Daily measurements of $N_2O$ emissions, measured using a static chamber, were available for selected periods after fertiliser application and daily measured WFPS for corresponding periods were obtained from the researcher responsible, while the annual $N_2O$ emissions data were obtained from Krol *et al*. (2020). The days of measurement events were not continuous within the measurement period. Negative daily $N_2O$ emissions values from the emissions measurements were excluded as DNDC primarily estimates $N_2O$ emissions rather than its sequestration in soil (Abdalla *et al*., 2009). This further reduced the continuity of the chamber measurements in the dataset used for this study. Daily $NH_3$ volatilisation measured by a wind tunnel for short measurement periods after fertiliser application in Paddock 43.B, were obtained from Forrestal *et al*. (2015) and digitised using the online PlotDigitizer (https://plotdigitizer.com/app). Discontinuity in measurement days was also present within each measurement periods in this dataset. The $NH_3$ volatilisation values were converted to kg N/ha/day from time-integrated hourly fluxes (g N/ha/hr), digitised from the published material and multiplied by 24 hours. Published estimates of annual $NH_3$ volatilisation, based on the daily measurements, were also obtained from Forrestal *et al*. (2015).

Meteorological and soil temperature (10 cm) data for the JC farm area was obtained from the synoptic station located on the JC farm, available from Met Éireann (Met Éireann, n.d.), for the years in which the chamber and wind tunnel measurements were available, 2017 and 2014, respectively. Daily precipitation (mm) and solar radiation ($J/cm^2$) data were converted to cm and $MJ/m^2$ as per the input requirements of DNDC. The atmospheric inputs and the crop phenological inputs for the site were kept the same as those used in Chapter 4 (Experiment 1). There is an absence of information on the threshold of thermal degree days (TDD) for vegetative growth of perennial ryegrass in the existing literature. Previously, DNDC was found to provide reasonable estimates of grass growth rate and annual yield when TDD inputs for the site was calculated following Hart *et al*. (2013) for the year, considering the year-round herbage growth of perennial ryegrass (Wingler and Hennessy, 2016). TDD is mainly based on three components; the base temperature for the targeted phenological process and the daily maximum and minimum temperature over the period of the phenological process (McMaster and Wilhelm, 1997). In this study, we calculated the TDD at JC for the year 2017 (3819) for Paddock 43.A and of year 2014 (3865) for Paddock 43.B, following the method prescribed by Hart *et al*. (2013) and considering the year-round growth of perennial ryegrass (Wingler and Hennessy, 2016).

### *5.2.3. DNDC: Model Inputs and Parameters and the Experimental Design*

DNDC is a biogeochemical model that simulates C and N dynamics for agricultural landscapes using sub-models for soil, climate, hydraulic fluxes, decomposition and denitrification, growth, nitrification, fermentation (Gilhespy *et al*., 2014; Li, 1996). It accounts for the key processes associated with the N cycle - mineralisation, leaching, volatilisation, nitrification, denitrification, uptake and biological N fixation (BNF) (Cannavo *et al*., 2008). A detailed description of the DNDC model and its development can be found in the work by Gilhespy *et al*. (2014) and the model manual (ISEOS, UNH, 2012). In this research, simulations were performed to assess the performance of DNDC (version 9.5), available at: [http://www.dndc.sr.unh.edu/](http://www.dndc.sr.unh.edu/) at daily to annual time scales, in estimating $N_2O$ emissions for the experimental blocks in Paddock 43.A and $NH_3$ volatilisation for the experimental blocks in Paddock 43.B, along with the estimation of annual yield in the corresponding blocks. The parameterisation of crop phenology for perennial ryegrass and atmospheric inputs were performed following the strategy used in Chapter 4 (Experiment 1). Phenological inputs were obtained from Chapter 4 (Experiment 1). TDD inputs were set as 3819 and 3865 for the simulation of Paddock 43.A and 43.B respectively. The management inputs for the corresponding measurement years and blocks were based on the description provided by Krol *et al*. (2020) for Paddock 43.A and Forrestal *et al*. (2015) for Paddock 43.B. For blocks treated with urea, the N fertiliser inputs were performed directly as urea, but for blocks treated with CAN the N input was provided as inputs of $NH_4^+$ and $NO_3^-$ content divided into equal proportions (Teagasc, 2017d). Two case studies were performed for each block of Paddock 43.A and 43.B, based on employing either default or site-specific inputs for WFPS at FC and WP (Figure 5.2), as described below.

*<u>Case Study 5</u>*

The DNDC model was set up using default inputs for WFPS at FC and WP based on the soil textural class of the respective paddock. Soil inputs (e.g. texture, clay, pH, SOC, BD - Table 5.1), taken from site specific records following Experiment 1 (Chapter 4), were initially used to simulate $N_2O$ emissions and $NH_3$ volatilisation. All required model inputs, except BD, were either collected or directly derived using relevant methods for Paddock 43.A and 43.B from Krol *et al*. (2020) and Forrestal *et al*. (2015) respectively.

<u>*Case Study 6*</u>

For Case Study 6, the DNDC simulation was performed using derived inputs of WFPS at FC and WP (Table 5.1) for the specific soil textural classes in Paddock 43.A and 43.B, derived from Zimmermann *et al*. (2018) following Franzluebbers (1999). The remainder of the inputs were held the same as Case Study 5.

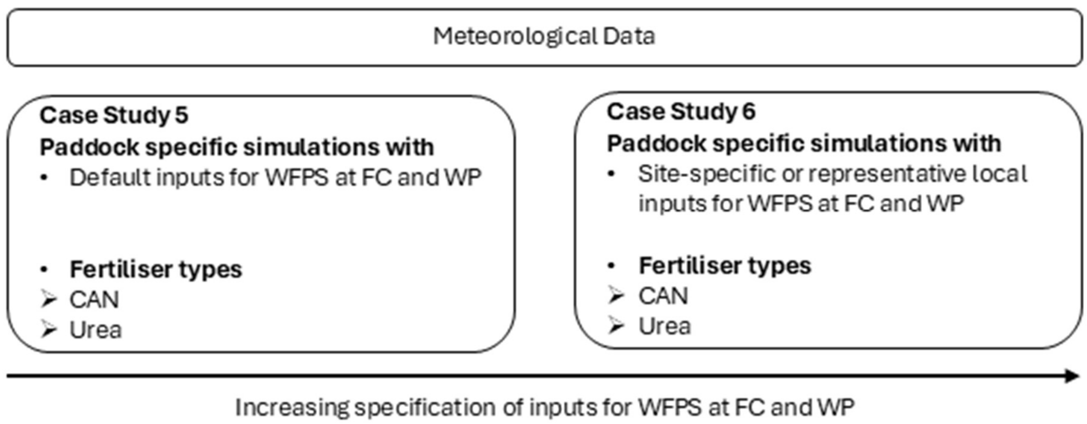


**Figure 5.2:** Experimental design of case studies

### *5.2.4. Outcomes and Evaluation Metrics*

#### *5.2.4.1. Model Validation*

DNDC simulates daily growth rate and annual yield in kg C/ha in terms of grain, leaf, stem and root. The estimated annual grass yields, calculated as the sum of annual grain, leaf and stem yield estimations, was converted from kg C/ha into dry matter (DM) in kg/ha by dividing by 0.4 (ISEOS, UNH, 2012) prior to validation. Relative deviation percentage (RD %) between estimated and recorded annual grass yield for both paddocks, annual $N_2O$ emissions for Paddock 43.A, and annual $NH_3$ volatilisation for Paddock 43.B was calculated for each block for Case Study 1 and 2 (Abdalla *et al*., 2020). If the RD % was negative then DNDC overestimated the corresponding output variable, where a positive RD % would indicate underestimation of an output. Absolute values of RD% (i.e. |RD %|) were derived to determine if the model outputs laid close to the measured values (≤ 20 %) or the estimates deviated strongly from the corresponding records (≥ 50 %) (Babu *et al*., 2006; Cai *et al*., 2003).

For each measurement period after fertiliser application, the area under the curve (AUC) was calculated for both the measured and corresponding simulated $N_2O$ emissions for blocks under Paddock 43.A and $NH_3$ volatilisation for blocks in Paddock 43.B (Pruessner *et al*., 2003). Fuchs *et al*. (2020) indicated that peak $N_2O$ emissions from a management event occur within 14 days or less (peak emissions period), and later peaks may not be directly linked to the management event. Therefore, the AUC for $N_2O$ emissions peaks (identified using daily graphs) that occurred within 14 days or less was also calculated from both measured and estimated $N_2O$ emissions. For $NH_3$ volatilisation, each of the measurement periods for which daily $NH_3$ flux data could be extracted were less than 14 days after each fertiliser application event. Hence, unlike daily $N_2O$ emissions, separate tests could not be performed for daily $NH_3$ volatilisation to evaluate the temporal correspondence in the DNDC simulation for the period of measurement that is equal to or greater than 14 days, after fertiliser application event. Details of the days selected as periods to derive the AUCs for $N_2O$ emissions and $NH_3$ volatilisation are shown in Table 5.2. Single factor ANOVA and two-sample t-tests, assuming unequal variances between AUCs over the year from measured data and estimated result, were derived to find out if significant difference ($p<0.05$) exists between the means of simulated and corresponding measured records for $N_2O$ emissions (for both measurement periods and peak emissions periods) and $NH_3$ volatilisation (Bodin *et al*., 2012; Chi *et al*., 2020; Pruessner *et al*., 2003). Scatterplots, with corresponding linear regressions were employed to quantify the model performance. Slope, intercept and $R^2$ values between AUCs from simulated results and corresponding measurements over the year, for peak emissions periods of $N_2O$ and for measurement periods of both $N_2O$ emissions and $NH_3$ volatilisation were also calculated (Dutta *et al*., 2016; Li *et al*., 2005; Liu *et al*., 2022).

The Pearson's correlation coefficient and RMSE were calculated to evaluate the level of agreement between the measured and estimated daily $N_2O$ emissions and daily WFPS for Paddock 43.A, daily $NH_3$ volatilisation for Paddock 43.B (for each measurement period), and daily topsoil temperature for both paddocks over the year (e.g. Abdalla *et al*., 2020; Macharia *et al*., 2021; Yadav and Wang, 2021). For $N_2O$ emissions, as the number of measurements after each fertiliser application event were low, the entire measurement period after each fertiliser split application event was considered, not only the peak emissions 14-day period. However, this approach reflects the performance of all estimated daily $N_2O$ emissions, including the proportion that may not be directly linked to fertiliser application. Daily measured and estimated WFPS for Paddock 43.A was compared for both Case Study 5 and 6, to compare the effect of using DNDC-default inputs and location and soil specific inputs for WFPS at FC and WP, for both fertiliser-treatment blocks. This was to identify the impact of crop growth on soil water availability, driven by different fertiliser types (Beheydt *et al*., 2007; Kröbel *et al*., 2011; Li *et al*., 2014). The performance of DNDC to estimate daily topsoil temperature was compared for both paddocks, simulated using the site-specific WFPS simulation (justified on the basis of the soil hydro-thermal properties).

**Table 5.2:** Measurement and Peak $N_2O$ Emissions Periods after Fertiliser Application Events

| **$N_2O$ Emissions (Paddock 43.A)** | **Experimental Blocks** | **Application of Fertiliser Split** | **N Application Rate in Corresponding Split (kg N/ha)** | **Measurement Periods (dd/mm Year 2017)** | **Peak $N_2O$ Emissions Period (≤14 days) (dd/mm Year 2017)** | |
|---|---|---|---|---|---|---|
| | | | | | **DNDC Simulation** | **Measured Data** |
| | **Block under Urea Application** | **Application 1** | 20 | 24/01-01/03 (n=11) | 24/01-03/02 (n=9) | 23/01-30/1 (n=10) |
| | | **Application 2** | 40 | 07/03-06/04 (n=9) | 07/03-16/03 (n=9) | 06/03-16/03 (n=10) |
| | | **Application 3** | 40 | 18/04-17/05 (n=12) | 18/04-28/04 (n=9) | 18/04-26/04 (n=6) |
| | | **Application 4** | 40 | 29/05-04/07 (n=13) | 30/05-09/06 (n=12) | 29/05-09/06 (n=9) |
| | | **Application 5** | 30 | 10/07-30/08 (n=15) | 10/07-21/07 (n=13) | 10/07-21/07 (n=9) |
| | | **Application 6** | 30 | 11/09-15/11 (n=10) | 11/09-20/09 (n=7) | 11/09-20/09 (n=5) |
| | **Block under CAN Application** | **Application 1** | 20 | 24/01-01/03 (n=12) | 24/01-03/02 (n=8) | 23/01-30/1 (n=5) |
| | | **Application 2** | 40 | 07/03-06/04 (n=10) | 07/03-13/03 (n=5) | 06/03-13-03 (n=6) |
| | | **Application 3** | 40 | 18/04-17/05 (n=12) | 18/04-28/04 (n=12) | 18/04-26/04 (n=6) |
| | | **Application 4** | 40 | 29/05-05/07 (n=12) | 31/05-09/06 (n=7) | 29/05-09/06 (n=9) |
| | | **Application 5** | 30 | 10/07-30/08 (n=10) | 10/07-20/07 (n=7) | 10/07-20/07 (n=8) |
| | | **Application 6** | 30 | 11/09-20/09 (n=6) | 11/09-20/09 (n=5) | 11/09-20/09 (n=5) |
| **$NH_3$ Volatilisation (Paddock 43.B)** | | | | **Measurement Periods (≤14 days) (dd/mm of Year 2014)** | | |
| | **Block under Urea Application** | **Application 1** | 40 | 10/03-23/03 (n=9) | | |
| | | **Application 2** | 40 | 28/04-06/05 (n=6) | | |
| | | **Application 3** | 40 | 03/06-09/06 (n=6) | | |
| | | **Application 4** | 40 | 07/07-19/07 (n=9) | | |
| | | **Application 5** | 40 | 18/08-26/08 (n=7) | | |
| | **Block under CAN Application** | **Application 1** | 40 | 10/03-21/03 (n=8) | | |
| | | **Application 2** | 40 | 28/04-12/05 (n=7) | | |
| | | **Application 3** | 40 | 03/06-11/06 (n=7) | | |
| | | **Application 4** | 40 | 07/07-19/07 (n=10) | | |
| | | **Application 5** | 40 | 18/08-25/08 (n=7) | | |

*n=Number of observations (i.e. number of measurement events) within each measurement period

### 5.2.4.2. *Sensitivity Test to Identify Key Regulators of N loss*

One factor at a time (OFAT) sensitivity analysis (Kardynska *et al*., 2022) was performed to identify the key variables that regulate annual $N_2O$ emissions and $NH_3$ volatilisation on each soil type, using the most reliable simulation in terms of inputs on WFPS at FC and WP and fertiliser type, as the baseline case. Variation of textural class was not used for OFAT. Instead, separate sensitivity tests were performed for both textures. Crop phenology was also not considered for OFAT, as the study focused on perennial ryegrass. These blocks were ungrazed, and therefore, OFAT for grazing regime was not performed. The baseline scenario and the variations employed for Paddock 43.A and Paddock 43.B is shown in Table 5.3 and 5.4 respectively. Sensitivity analysis of $N_2O$ emissions and $NH_3$ volatilisation to the change in each individual soil, weather and management factors was performed for both paddocks, considering an optimum suite of parameters that can reliably simulate yield and $N_2O$ emissions in Paddock 43.A and $NH_3$ volatilisation in Paddock 43.B, if performance of DNDC was seen to be reliable for each of them individually. The sensitivity index (SI) was calculated and used for identifying if DNDC simulated $N_2O$ emissions and $NH_3$ volatilisation is sensitive (SI >10 %), potentially sensitive (10 % > SI > 0.1 %) or not sensitive (SI < 0.1 %) (Wang *et al*., 2016).

**Table 5.3:** Variations and Baseline for Paddock 43.A (Sandy Loam Soil)

| Variables | | Variation 1 | Baseline | Variation 2 | References |
|---|---|---|---|---|---|
| pH (variation from baseline) | | 6.84 (+20%) | 5.7 | 4.56 (-20%) | Franzluebbers (1999); Krol *et al*. (2020); Reidy *et al*. (2016); Zimmermann *et al*. (2018) |
| BD in g/cm$^3$ (variation from baseline) | | 1.2636 (+20%) | 1.053 | 0.8424 (-20%) | |
| SOC in % (variation from baseline) | | 3.36 (+20%) | 2.8 | 2.24 (-20%) | |
| Clay in % (variation from baseline) | | 17.28 (+20%) | 14.4 | 11.52 (-20%) | |
| Annual N Fertiliser Input in kg N/ha (variation from baseline) | | 240 (+20%) | 200 | 160 (-20%) | |
| Weather | Average Daily Temperature | $1^{0}$C higher | Weather of 2017 | $1^{0}$C lower | |
| | Average Daily Rainfall | 20 % higher | | 20 % (lower) | |

**Table 5.4:** Variations and Baseline for Paddock 43.B (Loam Soil)

| Variables | | Variation 1 | | Baseline | Variation 2 | References |
|---|---|---|---|---|---|---|
| pH (variation from baseline) | | | 6.96 (+20%) | 5.8 | 4.64 (-20%) | Forrestal *et al*. (2015); Franzluebbers (1999); Reidy *et al*. (2016); Zimmermann *et al*. (2018) |
| BD in g/cm$^3$ (variation from baseline) | | | 1.1448 (+20%) | 0.954 | 0.7632 (-20%) | |
| SOC in % (variation from baseline) | | | 4.92 (+20%) | 4.1 | 3.28 (-20%) | |
| Clay in % (variation from baseline) | | | 16.8 (+20%) | 14 | 11.2 (-20%) | |
| Annual N Fertiliser Input in kg N/ha (variation from baseline) | | | 240 (+20%) | 200 | 160 (-20%) | |
| Weather | Average Daily Temperature | $1^{0}$C higher | | Weather of 2014 | $1^{0}$C lower | |
| | Average Daily Rainfall | 20 % higher | | | 20 % (lower) | |

## 5.3. Results

### 5.3.1. *Results: $N_2O$ Emissions from Paddock 43.A*

The performance of DNDC to estimate $N_2O$ emissions were analysed primarily at the annual time scale, consistent with the existing literature on DNDC, then for the measurement and peak emissions periods, followed by daily scale. The |RD %| between annual estimated and measured $N_2O$ emissions was greater than 50 % under Case Study 5 for both CAN and urea treated blocks (Table 5.5). For Case Study 6 the |RD %| was below 20 % for urea treated block but greater than 20 % and less than 50% for CAN treated block. RD % was positive in all cases. The |RD %| of estimated annual grass yield from recorded annual yield estimation was below 20 % for both case studies under both urea and CAN treated blocks (Table 5.5), as well as was always negative. However, |RD %| was lower for yield under Case Study 6 than Case Study 5.

**Table 5.5:** Relative Deviation (RD %) of DNDC-Estimated Annual $N_2O$ Emissions and Annual Yield from Corresponding Records for Paddock 43.A

| Output Variable | Fertiliser Type | Case Study 5 | Case Study 6 |
|---|---|---|---|
| Annual $N_2O$ emissions | Urea Application | 51.06 % | 12.77 % |
| | CAN Application | 67.33 % | 44.67 % |
| Annual grass yield | Urea Application | -6.5 % | -4.05 % |
| | CAN Application | -9.76 % | -3.25 % |

*Negative RD % indicates overestimation and positive RD % indicates underestimation by DNDC

The p-value for both ANOVA and the t-test (Table 5.6) between AUCs of recorded and estimated $N_2O$ emissions in Case Study 6 for Paddock 43.A, for all measurement periods and for all peak emissions periods over the year, for both urea and CAN treated blocks, was greater than 0.05. For Case Study 6, the peak emissions period showed an increase in the corresponding correlation ($R^2$) between AUCs of measured and estimated $N_2O$ emissions over the year (Table 5.6). The intercepts were positive for both fertiliser treatments for the measurement periods as well as peak emissions periods. Whereas slopes were positive for both CAN and urea treated blocks for the measurement periods, and only for urea treated block for the peak emissions period. However, the slopes were closer to 1 and intercepts were closer to 0 for urea treated block than CAN treated block for both measurement period and peak emissions periods.

**Table 5.6:** Relation between Means of Area Under Curve for Measurement and Estimated $N_2O$ Emissions for Paddock 43.A, for Measurement and Peak Emissions Periods – Case Study 6

| Duration of each AUC (days?) | Fertiliser Type | Comparing Mean of AUCs Over the Year | | From $N_2O$ emissions scatterplots between AUCs of DNDC estimation and measurement for measurement periods over the year | |
|---|---|---|---|---|---|
| | | p-Value for Single Factor ANOVA | Two-tail p-Value for Two-Sample t-Test (Assuming Unequal Variances) | Liner Regression | $R^2$ |
| Measurement period (All, n=6) | Urea Application | 0.13 | 0.15 | y = 0.7743x + 0.0515 | 0.083 |
| | CAN Application | 0.19 | 0.22 | y = 0.1357x + 0.2815 | 0.001 |
| Peak emissions period (All, n=6) | Urea Application | 0.47 | 0.47 | y = 0.7584x + 0.0005 | 0.426 |
| | CAN Application | 0.43 | 0.45 | y = -0.4091x + 0.2321 | 0.004 |

*n=Number of observations (i.e. number of measurement events) within each measurement period

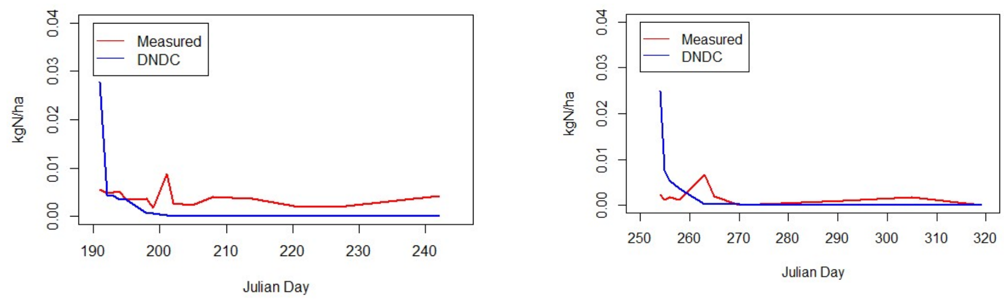


**Figure 5.3**: Measured and estimated $N_2O$ emissions at daily scale for blocks in Paddock 43.A treated with urea during fertiliser application event 5 (left) and 6 (right)

In the case of both fertiliser application events in Case Study 6, DNDC estimated an initial higher daily $N_2O$ emissions value following fertiliser application for both urea and CAN treated blocks in comparison to the actual measured emissions; it underestimated the actual peak emissions and generally is lower than the measured daily emissions. Figure 5.3 shows the measured and estimated $N_2O$ emissions for Application 5 and 6 of urea. While recognising the small sample size, the correlations between estimated and measured daily $N_2O$ emissions for each measurement period for Case Study 6 in Paddock 43.A were mostly negative for simulations of the CAN treated block, except for the first and second fertiliser application event (Application 1 and 2). Correlations are largely positive for the urea treated block, except for the third fertiliser application event (Application 3) (Table 5.7). The RMSE for the daily $N_2O$ emissions ranged from 0.001 to 0.009 for the urea treated block and from 0.019 to 0.095 for the CAN treated block.

**Table 5.7:** Comparison between Estimated and Measured Daily $N_2O$ Emissions for Paddock 43.A

| Fertiliser Type | Fertiliser Application Event | Correlation (Pearson's) | RMSE |
|---|---|---|---|
| **Measurement Periods after each application of Urea** | **Application 1 (n=11)** | 0.431 | 0.001 |
| | **Application 2 (n=9)** | 0.173 | 0.005 |
| | **Application 3 (n=12)** | -0.262 | 0.009 |
| | **Application 4 (n=12)** | 0.310 | 0.005 |
| | **Application 5 (n=15)** | 0.316 | 0.007 |
| | **Application 6 (n=10)** | 0.069 | 0.008 |
| **Measurement Periods after each application of CAN** | **Application 1 (n=12)** | 0.065 | 0.022 |
| | **Application 2 (n=10)** | 0.321 | 0.095 |
| | **Application 3 (n=12)** | -0.317 | 0.021 |
| | **Application 4 (n=12)** | -0.113 | 0.030 |
| | **Application 5 (n=9)** | -0.078 | 0.019 |
| | **Application 6 (n=5)** | -0.321 | 0.031 |

*n=Number of observations (i.e. number of measurement events) within each measurement period

### *5.3.2. Results: $NH_3$ volatilisation from Paddock 43.B*

The performance of DNDC in estimating $NH_3$ volatilisation from Paddock 43.B was analysed initially at the annual scale, followed by exploring the performance over the available measurement period and at daily scale. For Paddock 43.B, the |RD %| between estimated and recorded annual $NH_3$ volatilisation for urea treated block was less than 20 % under both Case Study 5 and 6, but for CAN treated block it was less than 20 % only in Case Study 6 (Table 5.8). However, only for the CAN treated block in Case Study 6, the RD % was positive for estimated annual $NH_3$ volatilisation from corresponding measurement. The |RD %| was lower for both $NH_3$ volatilisation and estimation of annual yield for both CAN and urea treated blocks in Case Study 6 than Case Study 5. The |RD %| between estimated and recorded annual grass yield, in both case studies under both fertilisers' applications, was greater than 20 %, and the RD % was positive for all simulations of annual grass yield (Table 5.8).

**Table 5.8:** Relative Deviation (RD %) of DNDC-Estimated Annual $NH_3$ Volatilisation and Annual Yield from Corresponding Records for Paddock 43.B

| Output Variable | Fertiliser Type | Case Study 5 | Case Study 6 |
|---|---|---|---|
| Estimation of annual $NH_3$ Volatilisation | Urea Application | -9.673 % | -0.033 % |
| | CAN Application | -26.585 % | 4.634 % |
| Estimation of annual grass yield | Urea Application | 28.451 % | 22.240 % |
| | CAN Application | 25.075 % | 21.365 % |

*Negative RD % indicates overestimation and positive RD % indicates underestimation by DNDC

The p-values for both ANOVA and t-test in Case Study 6 for Paddock 43.B were greater than 0.05 between all AUCs of over the year for measured and estimated $NH_3$ volatilisation under both urea and CAN treated blocks (Table 5.9). For $NH_3$ volatilisation, the $R^2$ value derived from the linear regression of scatterplots of AUCs of $NH_3$ volatilisation with respect to recorded values for the measurement periods in Case Study 6, was positive for both fertilisers and higher for the block under urea application than the one receiving CAN application. The slopes of the regression lines were positive and >1, however, for the CAN treated block it was closer to 1. The intercepts were negative and for the CAN treated block the intercept was closer to 0.

**Table 5.9:** Relation between Means of Area Under Curve for Measurement and Estimated $NH_3$ Volatilisation under Case Study 6 for Paddock 43.B, for Measurement Periods and Peak Emissions Periods

| Duration of each AUC | Fertiliser Type | Comparing Mean of AUCs Over the Year | | From $NH_3$ volatilisation scatterplots between AUCs of DNDC estimation and measurement for measurement periods over the year | |
|---|---|---|---|---|---|
| | | p-Value for Single Factor ANOVA | Two-tail p-Value for Two-Sample t-Test (Assuming Unequal Variances) | Liner Regression | $R^2$ |
| Measurement period (All, n=5) | Urea Application | 0.06 | 0.09 | $y = 8.9354x – 47.293$ | 0.9272 |
| | CAN Application | 0.13 | 0.15 | $y = 2.4813x - 0.3363$ | 0.3971 |

*n=Number of observations (i.e. number of measurement events) within each measurement period

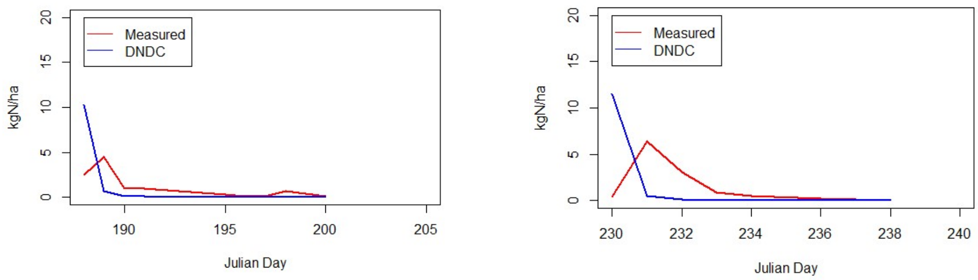


**Figure 5.4**: Measured and estimated $NH_3$ volatilisation at daily scale for blocks treated with urea during fertiliser application event 4 (left) and 5 (right)

In Case Study 6, for daily $NH_3$ volatilisation from blocks in Paddock 43.B, it was observed that for CAN treated block, except for the first and second fertiliser application event (Application 1 and 2), both measured and DNDC-estimated daily $NH_3$ volatilisation peaked from the day of fertiliser application. Whereas for the block treated with urea, DNDC estimated an early high $NH_3$ volatilisation for all applications (Figure 5.4). For the urea treated block, the correlations between simulated and measured daily $NH_3$ volatilisation were mostly negative, except for the 4$^{th}$ fertiliser application event (Application 4), for the measurement periods (Table 5.10). For the block treated with CAN, the correlations after fertiliser application events varied from negative to high positive. In the case of the urea treated block, the RMSE of daily $NH_3$ volatilisation varied from 2.913 to 4.917, whereas for the CAN treated block it varied from 0.046 to 0.360 (Table 5.10).

**Table 5.10:** Comparison between Estimated and Measured Daily $NH_3$ Volatilisation for Paddock 43.B

| Fertiliser Type | Application Event | Correlation | RMSE |
|---|---|---|---|
| **Measurement Periods after each application of Urea** | **Application 1 (n=9)** | -0.046 | 3.841 |
| | **Application 2 (n=6)** | -0.146 | 4.751 |
| | **Application 3 (n=6)** | -0.094 | 4.346 |
| | **Application 4 (n=9)** | 0.414 | 2.913 |
| | **Application 5 (n=7)** | -0.201 | 4.917 |
| **Measurement Periods after each application of CAN** | **Application 1 (n=8)** | -0.063 | 0.360 |
| | **Application 2 (n=7)** | -0.272 | 0.270 |
| | **Application 3 (n=7)** | 0.834 | 0.090 |
| | **Application 4 (n=10)** | 0.008 | 0.338 |
| | **Application 5 (n=7)** | 0.871 | 0.046 |

*n=Number of observations (i.e. number of measurement events) within each measurement period

### *5.3.3. Analysis of WFPS and soil temperature*

For WFPS, the correlation was positive for all simulations in Paddock 43.A and higher for Case Study 6 than Case Study 5 for the corresponding fertiliser type, while the RMSE was higher for Case Study 5 than Case Study 6 for the corresponding fertiliser type (Table 5.11). The correlation between estimated and measured soil temperature in Case Study 6 varied between 0.963 to 0.966, higher than the correlations observed for WFPS, and RMSE varied between 1.952 to

2.470 (Table 5.11). The estimated and measured daily WPFS in for urea and CAN treated blocks Paddock 43.A are shown in Figure 5.5 and 5.6 respectively, and the estimated and measured soil temperature for both years is shown in Figure 5.7 and 5.8.

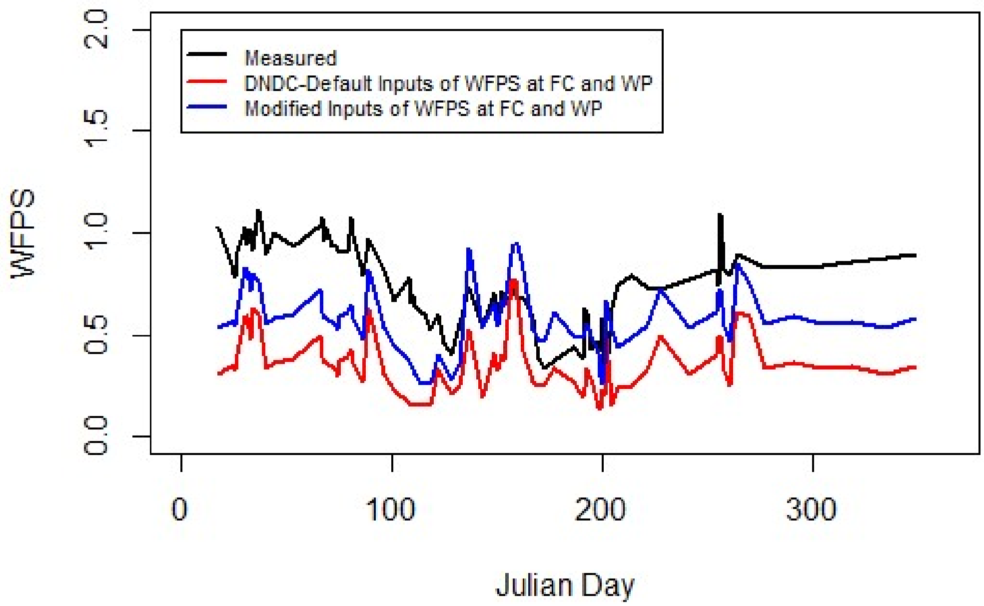


**Figure 5.5**: Measured daily WFPS with respect to simulated daily WFPS under each simulation for urea treated block in Paddock 43.A

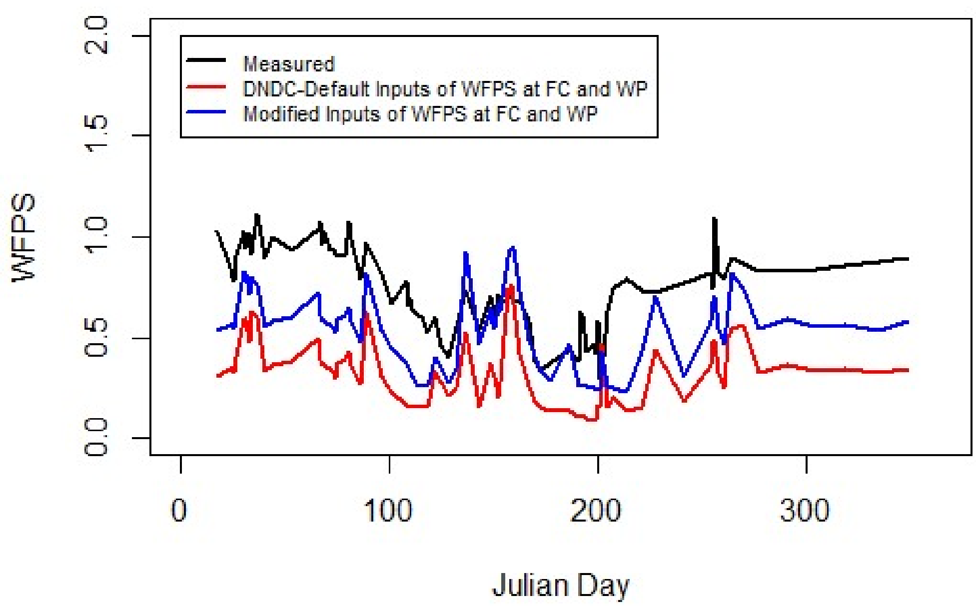


**Figure 5.6**: Measured daily WFPS with respect to simulated daily WFPS under each simulation for CAN treated block in Paddock 43.A

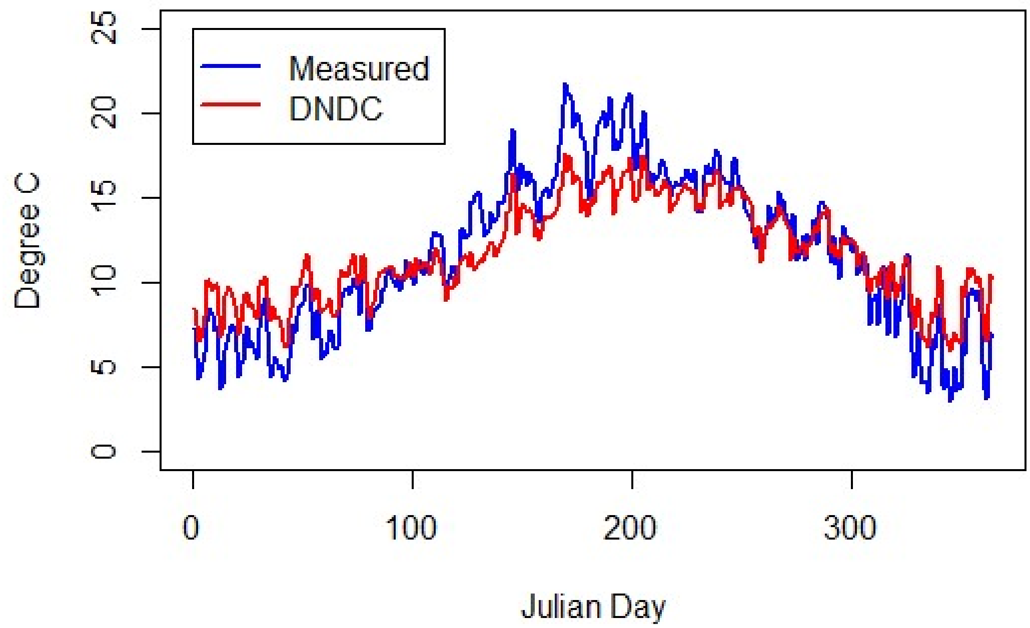


**Figure 5.7**: Comparison of daily soil temperature (10 cm) measured at JC and estimated for Paddock 43.A in 2017

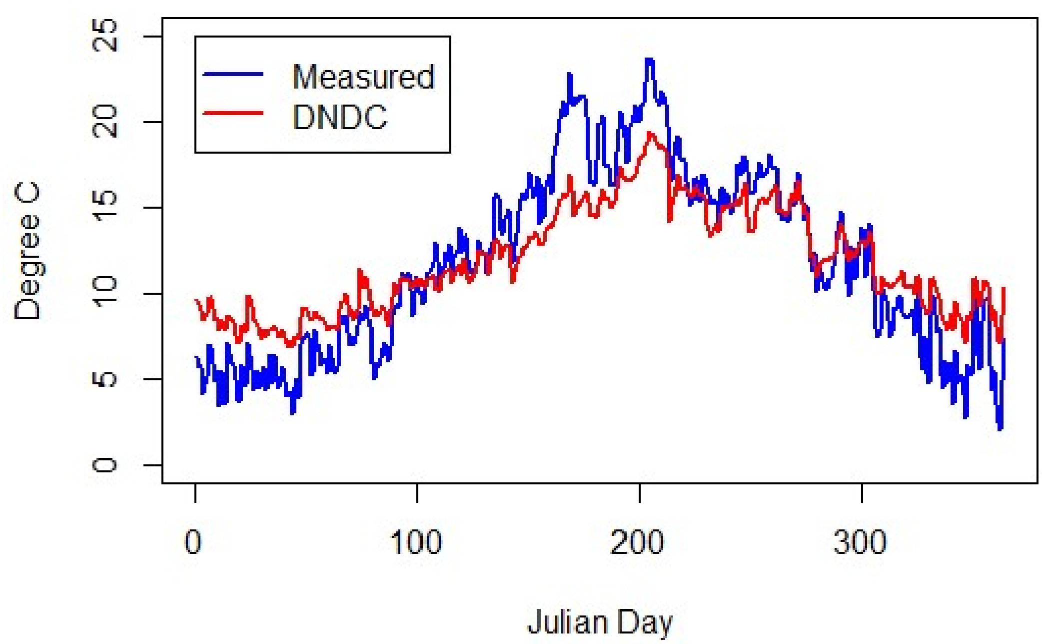


**Figure 5.8**: Comparison of daily soil temperature (10 cm) measured at JC and estimated at daily scale for Paddock 43.B in 2014

**Table 5.11**: Evaluation Metrics between Measured and Estimated Daily WFPS and Daily Topsoil Temperature

| Variables | | Case Study 5 | | Case Study 6 | |
|---|---|---|---|---|---|
| | | RMSE | Correlation | RMSE | Correlation |
| WFPS Measured vs Estimated (Paddock 43.A, Year 2017) | Urea | 0.432 | 0.461 | 0.264 | 0.464 |
| | CAN | 0.455 | 0.563 | 0.284 | 0.611 |
| Topsoil Temperature Measured vs Estimated | Paddock 43.A, Year 2017, Urea Application | | | 1.952 | 0.966 |
| | Paddock 43.B, Year 2014, Urea Application | | | 2.470 | 0.963 |

### 5.3.4. *Results of the sensitivity test*

The results of the sensitivity analysis, performed using the baseline scenarios of urea treated blocks in both paddocks from Case Study 6, showed that the SI was more than 10 % for annual $N_2O$ emissions for both an increase and decrease of pH and fertiliser (urea) input in both soils, decrease of SOC and rainfall in sandy loam and increase of SOC, BD and rainfall in loam soil and increase in air temperature for loam soil (Table 5.12). The SI of annual $N_2O$ emissions was greater than 0.1 % for all of the input variables. For annual $NH_3$ volatilisation from both soils SI % was more than 10 % for both an increase and decrease of N fertiliser input (urea) (Table 5.13). For the remainder of the input variables, the SI was greater than 0.1 % and less than 10 %.

**Table 5.12:** Key Drivers of Annual $N_2O$ Emissions from Soil, Weather and N Fertiliser Input Conditions Based on Sensitivity Test

| $N_2O$ Emissions | Variables | Variations from Baseline | SI (%) | Category |
|---|---|---|---|---|
| Paddock 43.A Sandy Loam | pH | Variation 1 | 31.71 | Sensitive |
| | | Variation 2 | 19.51 | Sensitive |
| | BD | Variation 1 | 7.32 | Potentially Sensitive |
| | | Variation 2 | 9.76 | Potentially Sensitive |
| | SOC | Variation 1 | 9.76 | Potentially Sensitive |
| | | Variation 2 | 12.20 | Sensitive |
| | Clay | Variation 1 | 4.88 | Potentially Sensitive |
| | | Variation 2 | 2.44 | Potentially Sensitive |
| | Fertiliser | Variation 1 | 24.39 | Sensitive |
| | | Variation 2 | 26.83 | Sensitive |
| | Air Temperature | Variation 1 | 2.44 | Potentially Sensitive |
| | | Variation 2 | 2.44 | Potentially Sensitive |
| | Rainfall | Variation 1 | 7.32 | Potentially Sensitive |
| | | Variation 2 | 51.22 | Sensitive |
| Paddock 43.B Loam | pH | Variation 1 | 30.56 | Sensitive |
| | | Variation 2 | 20.83 | Sensitive |
| | BD | Variation 1 | 11.11 | Sensitive |
| | | Variation 2 | 6.94 | Potentially Sensitive |
| | SOC | Variation 1 | 13.89 | Sensitive |
| | | Variation 2 | 8.33 | Potentially Sensitive |
| | Clay | Variation 1 | 5.56 | Potentially Sensitive |
| | | Variation 2 | 6.94 | Potentially Sensitive |
| | Fertiliser | Variation 1 | 30.56 | Sensitive |
| | | Variation 2 | 22.22 | Sensitive |
| | Air Temperature | Variation 1 | 11.11 | Sensitive |
| | | Variation 2 | 9.72 | Potentially Sensitive |
| | Rainfall | Variation 1 | 27.78 | Sensitive |
| | | Variation 2 | 2.78 | Potentially Sensitive |

**Table 5.13:** Key Drivers of Annual $NH_3$ Volatilisation from Soil, Weather and N Fertiliser Input Conditions Based on Sensitivity Test

| $NH_3$ Volatilisation for sites | Variables | Variations from Baseline | SI (%) | Category |
|---|---|---|---|---|
| Paddock 43.A Sandy Loam | pH | Variation 1 | 6.32 | Potentially Sensitive |
| | | Variation 2 | 1.97 | Potentially Sensitive |
| | BD | Variation 1 | 1.15 | Potentially Sensitive |
| | | Variation 2 | 0.84 | Potentially Sensitive |
| | SOC | Variation 1 | 0.48 | Potentially Sensitive |
| | | Variation 2 | 0.22 | Potentially Sensitive |
| | Clay | Variation 1 | 4.64 | Potentially Sensitive |
| | | Variation 2 | 5.41 | Potentially Sensitive |
| | Fertiliser | Variation 1 | 25.26 | Sensitive |
| | | Variation 2 | 24.25 | Sensitive |
| | Air Temperature | Variation 1 | 8.56 | Potentially Sensitive |
| | | Variation 2 | 4.71 | Potentially Sensitive |
| | Rainfall | Variation 1 | 0.65 | Potentially Sensitive |
| | | Variation 2 | 0.99 | Potentially Sensitive |
| Paddock 43.B Loam | pH | Variation 1 | 6.61 | Potentially Sensitive |
| | | Variation 2 | 3.40 | Potentially Sensitive |
| | BD | Variation 1 | 0.13 | Potentially Sensitive |
| | | Variation 2 | 1.47 | Potentially Sensitive |
| | SOC | Variation 1 | 0.28 | Potentially Sensitive |
| | | Variation 2 | 0.29 | Potentially Sensitive |
| | Clay | Variation 1 | 1.98 | Potentially Sensitive |
| | | Variation 2 | 3.62 | Potentially Sensitive |
| | Fertiliser | Variation 1 | 26.33 | Sensitive |
| | | Variation 2 | 24.31 | Sensitive |
| | Air Temperature | Variation 1 | 1.72 | Potentially Sensitive |
| | | Variation 2 | 3.68 | Potentially Sensitive |
| | Rainfall | Variation 1 | 2.01 | Potentially Sensitive |
| | | Variation 2 | 2.23 | Potentially Sensitive |

## 5.4. Discussion

### *5.4.1. Performance of DNDC to estimate annual yield, nitrous oxide ($N_2O$) emissions and ammonia ($NH_3$) volatilisation*

The |RD %| was <20 % for the annual grass yield estimated by DNDC for ungrazed Paddock 43.A for both urea and CAN treated blocks for all simulations for both case studies. This indicates that, under the parameterisation of crop phenology and atmospheric constants according to Experiment 1 (Chapter 4), the capacity of DNDC to simulate annual perennial ryegrass yield remained reliable irrespective of the major fertiliser types used in Ireland and specificity of inputs for WFPS at FC and WP for a soil type (Babu *et al*., 2006; Cai *et al*., 2003). This suggests that the surplus N estimated by DNDC might be reliable (Abdalla *et al*., 2022; Zhang *et al*., 2018). DNDC overestimated yield, observed for both Case Study 5 and 6, i.e. with and without site specific inputs of WFPS at FC and WP respectively, in both urea and CAN treated blocks of Paddock 43.A. This is not consistent with the findings in Experiment 1 (Chapter 4), where the model consistently underestimated the yield for site-specific simulation at paddock and farm level. In Experiment 1 and Case Study 5 of this experiment, site-specific WFPS at FC and WP were not used – it can be inferred that site-specific inputs for WFPS at FC and WP may not be key drivers of the over- and under-estimations observed for yield. However, in terms of |RD %|

(Babu *et al*., 2006; Cai *et al*., 2003), inclusion of WFPS as FC and WP in Case Study 6 improved the accuracy of estimation of annual yield in comparison to Case Study 5.

The underestimation of annual yield was over 20 % (though less than 50 %) for the ungrazed Paddock 43.B for both CAN and urea treated blocks for both Case Study 5 and 6. This was contradictory to the findings for Paddock 43.A as well as to the findings in Experiment 1. However, in the same Paddock of 43.B in an experiment performed by Harty *et al*. (2017) in the same year and under the same management regimes used by Forrestal *et al*. (2015), the observed yield was 14.44 % and 18.91 % higher in CAN and urea treated blocks in 2014 (the year studied here) than from similar blocks (same texture and small difference in other physicochemical properties) with the same treatment performed in 2013. Harty *et al*. (2017) attributed this to lower soil moisture deficits (SMD) in 2014 than 2013, which should have been replicated in the simulations as the findings indicate that model water stress is an important regulator of estimated grass yield in DNDC. However, we identified that the higher yield across Paddock 43.B in 2014 in comparison to 2013 is likely to be associated with the fact that the plots used for the experiment in 2014 was reseeded in the year prior to the measurement, whereas the plots used in 2013 were reseeded three years earlier (Harty *et al*., 2016). This is similar to findings by Necpálová *et al*. (2013) and Creighton *et al*. (2016), who observed a significant increase in grass dry matter yield after ploughing and reseeding compared to permanent grasslands at Solohead and Moorepark sites respectively under uniform management regimes. Thus, the model underestimation of annual yield of more than 20 % for Paddock 43.B does not lead to outright rejection of the efficiency of the parameterised DNDC to reliably simulate yield of perennial ryegrass. Future research could focus on the development of alternative parameterisations for DNDC for simulating yield for reseeded paddocks. However, DNDC, with the parameterisation used in Experiment 1 (Chapter 4), is better suited for yield estimation for permanent grassland rather than the reseeded grasslands.

According to the |RD %|, the urea treated block in Paddock 43.A in Case Study 6 provided reliable estimates of annual $N_2O$ emissions from fertiliser application, as the paddocks were ungrazed, even without modification of the SOC inputs as was indicated by Abdalla *et al*. (2009), who found an improvement in the model estimated $N_2O$ emissions when SOC data from a nearby arable plot for a grassland site was employed in the model. Underestimation of the annual $N_2O$ emissions was observed across both fertiliser types and case studies, likely driven by underestimation of daily WFPS (Beheydt *et al*., 2007) (Figure 5.5). The results from Case

Study 5 shows that the default inputs for WFPS at FC and WP may not be suitable for reliable estimation of annual $N_2O$ emissions; ideally, specific inputs for WFPS at FC and WP for a relevant soil textural class is required for the reliable simulation of $N_2O$ emissions and limited to urea treatments. More specific WFPS parameters would likely lead to improved representation of water stress in the model and consequently the N uptake by grass and loss by $NH_3$ volatilisation, leading to a better quantification of surplus N and for driving the nitrification and denitrification submodels (Beheydt *et al*., 2007; Giltrap *et al*., 2008; Kröbel *et al*., 2011; Li *et al*., 2014; Uzoma *et al*., 2015; Zhang *et al*., 2002). For the annual $N_2O$ emissions estimation under CAN application, the |RD %| was found to be >20 % under both Case Study 5 and 6. Thus, DNDC appears to be sensitive to the fertiliser type, as was found by Abdalla *et al*. (2009) and may require modification to include the specific impact of CAN on N dynamics for more accurate simulations. Smith *et al*. (2002) also indicated that further improvements of $N_2O$ emissions estimation by DNDC may be possible, by including specificity of topography induced water redistribution in the landscape. The $N_2O$ emissions from soil are highly dependent on surplus N in the soil determined by N uptake (Smith *et al*., 2012). Thus, the reliability of annual $N_2O$ emissions found for the permanent paddock (Paddock 43.A) may not be applicable for reseeded paddocks.

The mean of the AUCs of the curves derived from measured and estimated daily $N_2O$ emissions in Case Study 6, for measurement periods as well as peak emissions period, were not significantly different for both CAN and Urea treated blocks in Paddock 43.A, that being ungrazed, received no additional N input from animal excreta. This is in line with the outcomes of annual $N_2O$ emissions from urea treated block but does not explain the poor estimation for CAN applications. For the urea treated block in Paddock 43.A, the slope was closer to 1, while the intercept was closer to 0 and correlation ($R^2$) was higher between AUCs of measured and estimated $N_2O$ emission over the year, suggest that DNDC is better suited to simulations for urea treated paddocks, over those that are treated with CAN (Dutta *et al*., 2016; Li *et al*., 2005). The higher correlation of AUCs for the peak emissions periods, relative to the measurement period after fertiliser, for both blocks in Paddock 43.A with the AUCs of corresponding measurement, indicates that DNDC performs better in estimating the effect of applied N-fertiliser on $N_2O$ emissions than the background emissions (Fuchs *et al*., 2020). Such findings are consistent with the observations by Li *et al*. (2011) and partly explain the poor performance of DNDC in low N-input situations, observed by Abdalla *et al*. (2009).

The |RD %| of annual estimation of $NH_3$ volatilisation was < 20 % for both Case Study 5 and 6 for the application of urea treated block in Paddock 43.B, that also was ungrazed, and was lower for Case Study 6 than Case Study 5. For the CAN treated block, the |RD %| of annual $NH_3$ volatilisation was < 20 % only under Case Study 6. These outcomes indicate that the parameterised DNDC can reliably estimate annual $NH_3$ volatilisation irrespective of fertiliser type, as the studied paddock was ungrazed thus received no N input from animal excreta, when at least the inputs for WFPS at FC and WP are site-specific. This indicates that for $NH_3$ volatilisation estimation, the estimated water stress and corresponding effect on N uptake by grass is potentially regulating the simulated surplus N, proportioned into $NH_3$ volatilisation estimation (Zhang *et al*., 2002). At the same time, improved estimation of WFPS leads to better estimation of $NH_3$ volatilisation (Uzoma *et al*., 2015), likely associated with the model's ability to better represent air filled pore spaces. Anomalies between the measured and estimated magnitude of $NH_3$ volatilisation may result from the partitioning ratio in DNDC used to allocate fertiliser for dissolution and decomposition, or the complex soil biogeochemical processes that are not included in the model (Li *et al*., 2019). The performance of DNDC in estimating $NH_3$ volatilisation can also vary due to issues around accounting for heterogeneity of soil, climate and soil moisture content (Chu *et al*., 2023), especially driven by soil temperature, pH and soil $NH_4^+$ content (Dutta *et al*., 2016; Uzoma *et al*., 2015). Since $NH_3$ volatilisation is less dependent on N uptake and more dependent on application rate and environmental factors that can mask the impact of N uptake on $NH_3$ volatilisation (Bussink, 1994), the reliability of $NH_3$ volatilisation estimated by DNDC from the reseeded paddock (Paddock 43.B) would be valid for permanent paddocks also.

The results of single factor ANOVA and two-sample t-tests performed on the AUCs of estimated and measured $NH_3$ volatilisation showed that the mean of the AUCs for estimated $NH_3$ volatilisation was not significantly different from the corresponding value derived from the measured data, for both urea and CAN treated blocks (Pruessner *et al*., 2003). This indicates the reliability of the simulated annual $NH_3$ volatilisation from fertiliser application found for both urea and CAN treated block, as both paddocks were ungrazed – receiving no additional N input from animal excreta, by DNDC for Case Study 6. For the regression lines between the AUCs of estimated and measured $NH_3$ volatilisation for the urea treated block, the results indicated a poorer fit, in comparison to the CAN treated block. This is contradictory to the improved estimates found for annual $NH_3$ volatilisation under urea application, compared to the CAN application. However, the correlation coefficient ($R^2$) was higher for urea than for CAN. The study shows that performance of DNDC to estimate annual $NH_3$ volatilisation can be sensitive to inputs for WFPS at FC and WP, but the level of sensitivity depends on fertiliser type.

### *5.4.2. Performance of DNDC to estimate daily $N_2O$ emissions, $NH_3$ volatilisation, water filled pore spaces and soil temperature*

The correlations for daily $N_2O$ emissions, in Paddock 43.A, considering all application periods for Case Study 6 for both CAN and urea treated blocks, both of which were ungrazed, were poor. Zimmermann *et al*. (2018) also observed low correlations between DNDC estimated and measured daily $N_2O$ emissions at selected grassland sites, even with site-specific inputs for WFPS at FC and WP, although their work only parameterised the yield component of the crop phenology inputs. He *et al*. (2020) observed poor to fair estimation of daily $N_2O$ emissions by DNDC in spite of good simulations for soil temperature. Similar to the daily $N_2O$ emissions estimation, the correlation between measured and estimated $NH_3$ volatilisation at daily scale, for both urea and CAN treated blocks of the ungrazed Paddock 43.B that received no N input from animal excreta, were also poor, similar to the observation by Li *et al*. (2019). Balasubramanian *et al*. (2017) observed between 0% to 70% of uncertainty in the estimation of daily $NH_3$ volatilisation by DNDC. While the improved parameterisation of the model, according to Experiment 1 (Chapter 4) had led to reliable estimates of the magnitude of daily $N_2O$ emissions and $NH_3$ volatilisation, the timings of the modelled emissions were not consistent with the measured values, despite the improved grass growth estimation in the model.

Potential reasons for the observed low correlations between measured and estimated daily $N_2O$ estimation may be attributable to a timing mismatch between measured peaks in field conditions (Yadav and Wang, 2021) and DNDC simulated daily peaks resulting in lead and lags (Giltrap *et al*., 2010). Abdalla *et al*. (2020) indicated that non-coherence between the pattern of daily $N_2O$ emissions estimated by DNDC and the corresponding measurements at a daily scale, can be driven by an underestimation of daily WFPS, similar to what was observed in this study. These offsets may be due to the seasonal variation in the relative importance between soil temperature and moisture as key drivers of $N_2O$ emissions under field conditions (Cantarel *et al*., 2010) that are not well represented in the model. Causes of anomalies in the pattern of daily $N_2O$ estimation may include the inability of DNDC to account for environment driven dormancy and activity of microbes involved in N cycle across soil microsites, the inability to represent diurnal variability in $N_2O$ emissions driven by soil temperature and irregularities in measurements and limitations associated with measurement techniques (e.g. He *et al*., 2020; Jones *et al*., 2011; Larios *et al*., 2016; Shen *et al*., 2018; Shah *et al*., 2020; Wang *et al*., 2012; Wu *et al*., 2021). However, Abdalla *et al*. (2020) indicated that the high sensitivity of the DNDC model to rainfall events, SOC and temperature as possible causes of offsets in the simulated $N_2O$ emissions peaks.

Li *et al*. (2019) also observed that DNDC estimates high values for $NH_3$ volatilisation on the day of fertiliser inputs, which can be 2-3 days earlier than the actual measured peak. They indicated that anomalies in daily $NH_3$ volatilisation estimation by DNDC may arise due to the model's inability to capture the timing, resulting in differences between the model estimates (which estimates $NH_3$ volatilisation for a whole day, for each day of the year) and the measured $NH_3$ volatilisation (that can vary from a sub-daily to hourly scale). Similar to estimation of $N_2O$ emissions, such mismatch of peaks can be driven by varying sensitivity of the model to soil and meteorological factors under different management practices (Deng et al., 2016) and the model's sensitivity to fertiliser type (Abdalla et al., 2009), that can be subject of future research. However, anomalies of daily $NH_3$ volatilisation can also occur from limitations of measurement techniques and methodologies and inability to determine to sub-daily variations within the validation data (e.g. Chu *et al*., 2023; Dutta *et al*., 2016; Forrestal *et al*., 2015; Li *et al*. 2019; Sommer and Misselbrook, 2015). However, there is no prior report of validation of DNDC for estimating $NH_3$ volatilisation in context of Irish grasslands dominated by perennial ryegrass over diverse soil types or intensity of N management. Thus, creating an Irish database for $NH_3$ volatilisation from diverse grassland soils under treatment of major ammonium and/or nitrate supplying fertilisers, similar to that for United Kingdom by Chambers and Dampney (2009), with corresponding details of management regime would help in future studies on parameterisation and validation of DNDC for estimating $NH_3$ volatilisation.

For the estimation of daily $N_2O$ emissions in Case Study 6 in Paddock 43.A, the RMSE for each measurement period was lower than that observed by Abdalla *et al*. (2010), Khalil *et al*. (2016) and Zimmermann *et al*. (2018). The RMSE for $NH_3$ volatilisation under both of the fertilisers' application in Case study 6 for each measurement period was lower than the findings for daily cumulative $NH_3$ volatilisation by Dutta *et al*. (2016), a study performed using DNDC in a temperate region, although their study found good correlations. This confirms that the parameterisation of DNDC according to Experiment 1 (Chapter 4) reduced the model error of N loss estimation at daily scale. The RMSE was generally higher for $N_2O$ emissions in CAN treated paddocks and for $NH_3$ volatilisation in urea treated paddocks, confirming sensitivity of DNDC to fertiliser type (Abdalla *et al*., 2009).

In this study, the estimated daily WFPS had similar covariation to the measured WFPS at daily scale. However, over the course of the year, the magnitude of the measured WFPS in Paddock 43.A for most of the measurement period was greater than the corresponding simulated WFPS for both urea and CAN treated blocks in Case Study 5 and 6 (Figure 5.5 and 5.6). Abdalla *et al*. (2022) also observed good correlations but underestimation of the magnitude for DNDC estimated WFPS. However, in our study the magnitude was lower for Case Study 5 than in Case Study 6, indicating that WFPS at FC and WP specific to the soil texture of the farm improved the estimation of daily WFPS. Beheydt *et al*. (2007) found similar results, stating that the recalculation of WFPS at FC and WP using pedotransfer functions improved their results. Differences are also observed between the WFPS estimated by DNDC for blocks treated with urea and CAN for both Case Study 5 (days 167 to 270) and 6 (day 167 to 265), indicating that fertiliser type may potentially govern the estimated water utilisation by the grass in the model, resulting in these differences (Nowakowski; 1961; Sinclair, 2018). The estimated and measured daily topsoil temperature also showed good agreement for both paddocks, despite periods of small over- and under- estimation of daily soil temperature. DNDC underestimated the soil temperature for Julian days 107 to 251 in Paddock 43.A in 2017 (Figure 5.7), and Julian days 104 to 263 in Paddock 43.B in 2014 (Figure 5.8).

Causes of anomalies observed at daily scale can ultimately result in anomalies observed at annual scale. While the limitation of the site-specific measurement can result in uncertainties at both daily and annual scale. The measurements of soil physicochemical properties used (Forrestal *et al*., 2015; Krol *et al.*, 2020; Zimmermann *et al*., 2018), represents the portions of the paddock used in those studies. However, how well these factors indicate the physicochemical properties at the soil microsites used for the chambers used for measurement for $N_2O$ emissions and $NH_3$ volatilisation is not known – thus can drive uncertainties of the model estimations. Same logic can be applied to prohibit an upscaled application of DNDC, unless the extent of area represented by soil inputs is known. Else, a simulation may lead to misrepresentation of estimated dynamics of $N_2O$ emissions and $NH_3$ volatilisation both spatially and temporally – that is driven by interaction of soil and weather conditions (e.g. Hu *et al*., 2021; Newman, 1984; Sahrawat, 2008; Yin *et al*., 2020; Zhenghu and Honglang, 2000). Furthermore, the estimation of reliable model performance of urea is not applicable for landscapes other than such treatment only. For, other types of fertilisers used in Ireland that contains other nutrients and may behave differently in terms of rate of supply of N through dissolution, e.g., UAS 38%, KaN, Alzon urea 46 %, manure and slurry, (Cantarella *et al*., 2018, Chatterjee, 2018; Forrestal *et al*., 2015; Kirschke *et al*., 2019; Marsalkova and Ryant, 2014; Murphy *et al*., 2002), can have diverse set of impacts on the N-dynamics that can ultimately regulate N loss, even though grass yield was found by Harty *et al*. (2017) to be less dependent of N fertiliser type. Thus, validation of the model prior to applying to estimate potential impact of such N management practices is a requirement. Similarly, due to potential for diverse set of impact of paddocks under multispecies paddocks or grass-clover on N dynamics (Hofer *et al*., 2016), the parameterisation of crop phenology used in this study limits its study for perennial ryegrass paddocks only – unless further parameterised and validated for other targeted species compositions – to avoid uncertainty in model performance. The finding of this study indicates that DNDC, under the parameterisation used in this study, is ideal for application for an extent of area represented by required soil inputs for reliable model simulation – when dominated by perennial ryegrass monoculture and the chemical N fertiliser applied is urea.

#### *5.4.3. Key drivers of annual $N_2O$ emissions and $NH_3$ volatilisation*

The sensitivity of annual $N_2O$ emissions to input conditions of soil and weather variables varied to some extent between sandy loam and loam soil. For both soils, $N_2O$ emissions was sensitive to soil pH, SOC, N fertiliser application rate and rainfall. However, the sensitivity to SOC in sandy loam soil was driven by low SOC content and by high SOC in loam soil, while low rainfall and high rainfall were drivers of the sensitivity of $N_2O$ emissions in sandy loam and loam soil respectively. Beauchamp *et al*., (1980) observed that in coarser soils lower SOC can reduce denitrification due to low substrate C availability for denitrifiers. In contrast, finer soil textures that have higher susceptibility to anoxic condition and higher SOM content (indicated by higher SOC (Pribyl, 2010)) would further increase the rate of denitrification by an increased supply of labile C (Surey *et al*., 2020). Finer soil textures under increased rainfall can have increased anoxic conditions, leading to higher denitrification due to a greater supply of water and its retention (Hargreaves *et al*., 2021; Surey *et al*., 2020). These factors may explain the observed pattern of significance of SOC and rainfall on denitrification in different soil textures. However, Khalifah and Foltz (2024) observed a reduction in the ratio of $N_2O$ to sum of $N_2O$ and $N_2$ (where $N_2$ is dinitrogen gas) in denitrification products with an increase in soil pH, irrespective of soil texture. In a study by Rahman *et al*. (2021) for a urea treated grassland soil, it was shown that an increased rate of fertiliser application increased the rate of $N_2O$ emissions irrespective of soil textural class. The findings by Khalifah and Foltz (2024) and Rahman *et al*. (2021) indicate a similar scenario to the findings here; that soil pH and N fertiliser application rate regulates annual $N_2O$ emissions significantly, irrespective of the textural class.

The OFAT sensitivity test results indicated that in loam soil the annual $N_2O$ emissions was sensitive to air temperature, but in sandy loam soil it appeared to be only potentially sensitive. In both soils, $N_2O$ emissions were potentially sensitive to clay content of soil. Whereas, $N_2O$ emissions appeared to be sensitive to increase of BD in the loam soil, while remained potentially sensitive to its decrease in both loam and sandy loam soil and to its increase in sandy loam soil. In any of the soils, $N_2O$ emissions appeared to be not sensitive to variations of any of the input variables. The outcomes of this study indicate that the level of significance of temperature for variations of $N_2O$ emissions was dependent on soil texture. Similar to our finding, Cui *et al*. (2023) indicated that $N_2O$ emissions from fine textured soils can be more sensitive to temperature increase than the coarse textured soil, due to greater potential of fine textured soils to maintain anaerobic condition. However, they also found that $N_2O$ emissions across different soil texture can vary due to abundance of type of denitrifiers promoted by an increase in temperature. Skiba and Ball (2006) showed that irrespective of textural class of the soil, BD and clay content can significantly drive the emissions of $N_2O$ from soils, which is also reflected in the results of OFAT sensitivity analysis of our study. While higher BD, seen in coarser soil, is associated with higher drainage and higher clay content increases WFPS (Anderson, 1988), the $N_2O$ emissions are regulated by their combined impact and the WFPS ultimately drives the variation in $N_2O$ emissions (Skiba and Ball, 2006). $N_2O$ emissions being sensitive to increase of BD in the loam soil and remaining potentially sensitive to BD to rest of the scenarios, is similar to the observations by Hernandez-Ramirez *et al*. (2021), from their meta-analysis that showed that heavy textured soils are more susceptible to increases in $N_2O$ emissions driven by increased soil compaction.

From the results of the OFAT sensitivity test, it was observed that $NH_3$ volatilisation was most sensitive to the N fertiliser application rate in both sandy loam and loam soil, where both increased and decreased N fertiliser application rates were found to significantly influence the sensitivity of the model. However, for both soils the $NH_3$ volatilisation appeared to be potentially sensitive to soil pH, BD, SOC, clay content, air temperature and rainfall. $NH_3$ volatilisation was not sensitive to variations of any input variables. Zhenghu and Honglang (2000) observed that increase in soil pH can drive significant increases in $NH_3$ volatilisation in soils treated with urea. They also observed that an increase in SOM can reduce soil pH considerably, which in turn can contribute to a reduction of $NH_3$ volatilisation, thus highlighting the significance of SOC as an indicator of regulation of $NH_3$ volatilisation (Pribyl, 2010). Slower infiltration rate in soils with a higher BD can significantly increase the loss of applied N through $NH_3$ volatilisation, especially for no-till soils which is generally the case for grassland management (Rochette et a., 2008). Higher clay content, which increases CEC in soil, can reduce $NH_3$ volatilisation in urea treated soil by increased adsorption of $NH_4^+$ (Al-Kanani *et al*., 1991; Zhenghu and Honglang, 2000). $NH_3$ volatilisation in soil is strongly influenced by initial soil moisture content, drying process and evaporation of soil water (Al-Kanani *et al*., 1991), which likely explains the identification of rainfall along with clay content as potentially important regulators of $NH_3$ volatilisation. Harper *et al*. (1983) identified that an increase in soil temperature increases $NH_3$ volatilisation by increasing production of $NH_3$ from $NH_4^+$ and increasing its diffusion rate to the surface of soil. Since soil temperature is regulated by soil moisture content, air temperature and precipitation (Haskell *et al*., 2010; Yolcubal *et al*., 2004), the observed potential sensitivity of $NH_3$ volatilisation to both rainfall and air temperature can be important factors to consider for sustainable N management.

As discussed in Experiment 1, in this experiment also the baselines represent ideal cases of intensively managed Irish grasslands, while the extremes used as variations for targeted inputs is focused on understanding significance of their role in regulating N loss – relevant for developing database for simplified modelling (Haraldsson and Sverdrup, 2013; Patil, 2009). Though these variations are developed while considering the values remain close to the extremes possible in Irish grassland in terms of management and spatial variation of soil and climate (e.g. Curley *et al*., 2023; McDonald *et al*., 2014), yet, are not representative of ideal environmental or management seen predominantly across the nation. Thus, remains the scope of potential uncertainty when more ideal yet diverse farms in terms of soil, atmospheric conditions and management is used – where relevance of the identified regulators may vary, indicating the significance of using scenario analysis approach (Giltrap *et al*., 2010) while choosing representative sites for classification of Irish landscape, soil and climatic conditions (e.g. Carlier *et al*., 2021; O'Sullivan *et al*., 2018; Walsh, 2012).

### 5.5. Conclusion

In this study, the performance of DNDC (v9.5) for estimating $N_2O$ emissions and $NH_3$ volatilisations was analysed, to identify if an optimum temporal scale exists to compare the modelled outputs to measured values, when the crop phenology is parameterised for perennial ryegrass. In addition, whether more detailed input data on WFPS at FC and WP is required for reliable model simulation of N dynamics, was also evaluated. The study found that the DNDC model, when parameterised for the crop phenology of perennial ryegrass and local atmospheric conditions, demonstrated improvement in performance in estimating annual grass yield at the selected sites, in comparison to the findings of existing research. This was achievable using either the model defaults or farm specific soil textural inputs for WFPS at FC and WP - irrespective of type of fertiliser applied. However, this was limited to permanent paddocks. Employing site specific inputs for WFPS at FC and WP derived from measured volumetric water content instead of the corresponding DNDC-defaults (based on texture) appears to be a key requirement for improving the model simulations of annual emissions of both $N_2O$ and volatilisation of $NH_3$. However, more accurate annual $N_2O$ emissions simulation was limited to urea applications, as opposed to CAN, whereas improvement in the simulated annual $NH_3$ volatilisation was seen irrespective of fertiliser types. The requirement for measured/site-specific inputs for WFPS at FC and WP for reliable N-dynamics simulation limits the scope of using DNDC for estimating N loss through different pathways where such data is unavailable. For daily $N_2O$ emissions and $NH_3$ volatilisation, DNDC simulations were not consistent with the corresponding measured values; yet the cumulative annual emissions appear to match. This limits the scope of using DNDC for decision making on fertiliser applications over short timescales. The sensitivity test showed that N fertiliser application rate was the common most important factor for both coarse and fine textured soils in Irish grassland for regulating N loss through $NH_3$ volatilisation and $N_2O$ emissions. Thus, optimum N fertiliser requirement for a targeted yield at field level should be determined for reducing N loss. The results also indicated that the interaction of N fertiliser with soil pH, BD, SOC, clay content, air temperature and rainfall in field conditions must be considered to account for potential N loss in geographically refined N management strategies.

# 6. Application of DNDC using a scenario analysis approach

**Abstract**

Grassland management for feed production is the most widespread land use in Ireland. Nitrogen (N) is commonly applied in grasslands to achieve optimum grass yield, required to maintain high stocking rates. Similar to many countries, national N management policies have been developed and implemented to deliver more sustainable grassland production, in line with both national and international goals seeking to reduce N loss and meet international and national obligations on water standards, clean air and climate change. However, a critical shortcoming of these policies is that they are aspatial and lack the geographically-explicit information that could inform improved management, leading to increased nitrogen use efficiency (NUE) and reduced N loss. Thus, the implementation of policies based on national standards may not support optimum productivity and profitability for dairy farms situated in diverse environmental conditions across Ireland. To address this challenge, the 4R Nutrient Stewardship (4RNS) offers an effective framework to support site-specific sustainable N management by focusing on the *right place*, *right time*, *right source* and *right rate* of N fertiliser application. Here, the DNDC (*DeNitrification DeComposition*) model is employed to investigate the potential impact of spatially uniform N management strategies in intensively managed grasslands in Ireland. Two intensive scenarios are considered; the recommended advisory scenario for nutrient management planning as outlined in (i) the Green Book, and (ii) the Fifth Nitrates Action Programme, representing the regulatory scenario. The key environmental drivers that explain the variability of grass yield and N loss across the studied sites are also investigated. The relevance of the identified key variables for shaping management zones for focused N management and for exploring the potential impact of applied strategies are discussed. The study focuses on selected sites in Ireland as a case study, although findings are relevant for intensively managed grasslands elsewhere. The outcomes of the study shows that, depending on the targeted aspect of N dynamics, from yield, ammonia ($NH_3$) volatilisation and nitrous oxide ($N_2O$) emissions, variables - soil sand content, bulk density (BD), soil organic carbon (SOC), annual rainfall, average annual temperature - can be used as indicators for developing management zones for delivering more spatially refined N management strategies. Whereas, for nitrate ($NO_3^-$) leaching, the key indicators may vary depending on the rate of N fertiliser application. Further refinement of N application strategies within management zones or at field level is also possible, if factors identified to be regulating the efficiency of N management strategies are accounted for.

## 6.1. Introduction

Managing grasslands for feed production for livestock is the most important agricultural land use practice in Ireland. It accounts for over 92 % of the national agricultural land use and is dominated by perennial ryegrass (O'Donovan *et al*., 2021). Nitrogen (N) application to Irish grasslands is commonly supplied through the application of inorganic N fertilisers, such as urea and CAN, along with organic fertilisers including farmyard manure and slurry (Gebremichael *et al*., 2021; Mihailescu *et al*., 2014). Of the N applied in Irish grasslands, only an estimated 25 % is recovered (Teagasc, 2021a), meaning the remaining 75 % is susceptible to loss, through ammonia ($NH_3$) volatilisation, nitrous oxide ($N_2O$) emissions and nitrate ($NO_3^-$) leaching (e.g. Hoekstra *et al*., 2020; van Beek *et al*., 2008; Woodmansee *et al*., 1981). The loss of N not only represents an economic and productivity loss to the farmer and negatively impacts the economy but also degrades environmental quality through air pollution from $NH_3$, climate change and ozone layer depletion by $N_2O$, as well as degradation of ground and surface water quality from high $NO_3^-$ concentrations resulting in the eutrophication of water bodies and soil acidification etc. (e.g. Burchill *et al*., 2017; de Vries, 2021; Ferm, 1998; Giordano *et al*., 2021; Pittelkow *et al*., 2013; Stark and Richards, 2008; van Grinsven *et al*., 2013).

The European Union (EU) has set ambitious targets to achieve climate neutrality in the EU through the European Green Deal, under which the Farm to Fork Strategy seeks to reduce agriculture driven environmental degradation (DGE, EC, 2022; EC, 2019). The goals of the Farm to Fork Strategy have led to the development and application of the Common Agricultural Policy (CAP) across EU member states, which seeks to reduce N loss from agriculture through more sustainable land management practices (EC, 2020; Wrzaszcz and Prandecki, 2020; EC, 2023). Additionally, the EU Nitrates Directive focuses on monitoring and preventing the pollution of surface and ground water by $NO_3^-$ from agriculture (EPC, 1991). Ireland, as a member state of EU, has developed national policies that aim to limit N fertiliser application to reduce the surplus N in soil that is susceptible to loss and to improving the overall N productivity. The current agricultural goals set within the Food Wise 2025 programme aims to utilise more sustainable agricultural practices in order to increase primary productivity in Ireland by €10 billion from the levels of 2015 (DAFM, 2021). Ireland's Climate Action Plan 2023 aims to reduce N loss through $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching (DECC, 2023) required to meet our international obligations on greenhouse gas emissions.

In line with these goals, national agricultural policies, particularly those with a focus on delivering improved grassland management practices, have been developed and modified over time. The Green Book, published in 2020, provides nutrient advice, including annual maximum N fertiliser application guidelines for different stocking rate bands and recommends splits of N application based on the phases of grass growth throughout the year. These guidelines, in line with the EU Nitrates Directive - National Action Programme (NAP) regulations, limit the maximum N fertiliser application rate to 279 kg N/ha for stocking rates above 2.47 LU/ha (LU= livestock unit) (that can supply more than 210 kg N/ha in organic form) (Wall and Plunkett (eds.), 2020). More recently, the Department of Agriculture, Food and the Marine (DAFM) implemented a modified Nitrates Regulation policy that categorised dairy livestock into bands according to the potential N content in excreta, estimated based on the herd's milk production (DAFM, 2023b). This guideline provides information on the maximum N fertiliser application for different stocking rates and sets a lower maximum limit of annual N fertiliser application to 225 kg N/ha, once a herd reaches the capacity of supplying 250 kg/ha of organic N. It also classified the country into four zones based on the storage periods of livestock manure and prohibition periods for nutrient application (DAFM, 2023b). The most recent policy update to the Nitrates Derogation strategy reduced the maximum permissible stocking rate to 220 kg of organic N/ha (Callaghan, 2023).

Currently, many dairy farms in Ireland achieve 50 to 60 % of their potential grass yield (O'Donovan *et al*., 2021). Despite this, between 1990 and 2022, $NH_3$ volatilisation increased by 12.4 % and a $N_2O$ emissions decreased by 8.8 %, with an increase evident in $N_2O$ emissions between 2015 to 2022 - driven by an expansion of the dairy sector and increased N fertiliser use (EPA, 2022; EPA, n.d.). High $NO_3^-$ concentrations have also been observed across 40% of river sites and in 20% of estuarine and coastal water bodies (EPA, 2023a). Consequently, there is an urgency to improve N use efficiency (NUE) through more sustainable land management practices (Teagasc, 2021a) and to meet both the productivity targets and environmental goals set within national policy, e.g. Food Wise 2025; Climate Action Plan 2023; Fifth Nitrates Action Programme 2022-2025 (DAFM, 2021; DECC, 2023; DHLGH and DAFM, 2022). Improved NUE and a reduction of N loss can potentially be achieved by determining the *right source*, *right rate*, *right time*, and *right place* of N application, the basic objectives of 4R Nutrient Stewardship (4RNS) (Bryla, 2020; Fixen, 2020). Exploring the impact of both spatial and temporal variations in N dynamics under different weather and soil conditions in managed grasslands could inform the development of more geographically refined N management plans required to meet these objectives (Sarkar *et al*., 2017; Shanahan *et al*., 2008; Varallyay, 1994; Wu and Ma, 2015). The spatial refinement of advice and policies, based on knowledge of the key drivers, is important if the efficiency of N management is to be improved.

Modelling approaches, that incorporate soil, weather and management data to simulate key soil N-dynamics processes – such as, mineralisation, leaching, volatilisation, nitrification, denitrification, uptake and biological N fixation (BNF) – are useful tools to explore variations in N dynamics under diverse environmental and management conditions (e.g. Cannavo *et al*., 2008; Giltrap *et al*., 2010; Haraldsson and Sverdrup, 2013; Patil, 2009). The *DeNitrification-DeComposition* model (DNDC) is a biogeochemical model that captures the key soil processes related to N dynamics (Cannavo *et al*., 2008). Version 9.5 of DNDC was previously parameterised for crop phenology of perennial ryegrass and local atmospheric conditions in Experiment 1 (Chapter 4) and found to reliably simulate perennial ryegrass yield for a typically managed Irish dairy farm, at both farm and paddock level, when site-specific inputs were provided for soil texture, clay content, pH, bulk density (BD) and soil organic carbon (SOC). In Chapter 5 (Experiment 2) it was shown that under such parameterisation, the model was able to generate reliable estimates of annual grass yield and N loss through ammonia ($NH_3$) volatilisation and nitrous oxide ($N_2O$) emissions for perennial ryegrass dominated permanent paddocks, when additional information on site-specific water filled pore spaces (WFPS) at field capacity (FC) and wilting point (WP) is employed in the model. Even though the studied paddock used in Experiment 2 for estimating of N loss through $NH_3$ volatilisation and $N_2O$ emissions were ungrazed paddocks, yet the results can be assumed to be applicable for grazed paddocks, especially based on the findings for urea. The reason is the N supply from both urea as well as from animal excreta in grazed grassland is ammonium ($NH_4^+$) (Kaviya *et al*., 2019; Ladd and Jackson, 2015; Strock, 2008). The model estimates the loss of $NH_4^+$ reliably (Experiment 2) as well as has performed well in Experiment 1 to estimate grass growth – indicating a reliable estimate of uptake and surplus N (Zhang *et al*., 2015). Thus, it can be assumed that the model would reliably estimate N from excreta supplied by animals during grazing, the uptake and loss of $NH_4^+$ through volatilisation and further the rates of nitrification and denitrification as the model estimated $N_2O$ emissions reliably from urea treated paddock in Experiment 2, with a reliable estimation of yield. In Experiment 2 or in existing studies performed in Irish landscape using DNDC (e.g. Abdalla *et al*., 2009; Abdalla *et al*., 2011; Khalil *et al*., 2016; Li *et al*., 2011; Rafique *et al*., 2011a; Zimmermann *et al*., 2018) there is no validation results available for performance of DNDC in estimating N loss, which presumably is due to unavailability of data on field experiments measuring daily and annual $NO_3^-$ leaching with details of recorded management regimes and soil information as per the requirements for reliable DNDC simulations (Experiment 2; ISEOS, UNH, 2012). However, in terms of absolute value of estimated annual $NO_3^-$ leaching the model cannot be judged without proper validation as $NO_3^-$ leaching can be highly diverse across Ireland. For example, from the reports on field studies enlisted by Murphy *et al*. (2024) it can be seen that in Ireland and UK $NO_3^-$ leaching can be as high as 219 kg N/ha for a stocking rate of 2.74 cows/ha with annual N fertiliser application of 250 kg N/ha for a well-drained soil in Moorepark to 2 kg N/ha for a stocking rate of 2.47 cows/ha with annual N fertiliser application of 307 kg N/ha in poorly drained soil. For moderately drained soil it varied from 78 kg N/ha (fertiliser application 326 kg N/ha, no grazing) to 15 kg N/ha (fertiliser application rate 176 kg N/ha and stocking rate 2.66). Therefore, we assumed that if the model can generate reliable estimates of annual $NH_3$ volatilisation and $N_2O$ emissions for grassland, then the estimated $NO_3^-$ leaching for grasslands should also be reliable – since these three are the major pathways of N loss from grassland (Hoekstra *et al*., 2020; van Beek *et al*., 2008; Woodmansee *et al*., 1981).

In this research, DNDC (v 9.5) was employed to explore the annual yield and N loss through annual $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching for a selection of diverse grassland sites, where suitable data was available for the required suite of input variables identified from Experiment 1 and 2. Two different intensive management scenarios are explored: 1) N inputs were based on the advice provided in the latest edition of Green Book; and, 2) the regulations established in the Fifth Nitrates Action Programme on targeted stocking rates (DAFM, 2023b; Giltrap *et al*., 2010; Wall and Plunkett (eds.), 2020). The key aim of the study was to understand the impact of the variability in soil and management on yield and N loss across selected studies sites under uniform N fertiliser application and grazing regimes – ultimately, if the model could be used to explore different advice and policy scenarios. The objective was to explore if national level advice and policies for sustainable N management can support optimum productivity and a reduction of N loss effectively across spatially diverse dairy farms, and if not, then what are the key drivers necessary to refine such policies; recognising environmental and meteorological constraints. The ultimate goal was to develop a replicable strategy to use the DNDC model for exploring the potential impact of N management policies and strategies and seek to inform more spatially refined advice and policy to deliver more sustainable N management.

## 6.2. Methods

### *6.2.1. Site Locations*

Three grassland sites were chosen from two farms (Figure 6.1) for this study largely based on the availability of data but also considering the variability of soil and climatic conditions. The sites included a moderately coarse sandy loam soil site at Moorepark (MP) (52.2°N 8.3°W), located in County Cork, with the remaining two sites located at Johnstown Caste (JC), County Wexford (52.3°N 6.5°W), one of which has moderately coarse sandy loam soil (JCSL) while the other has a medium textured loam soil (JCL) (AA-FC, 2009; Zimmermann *et al*., 2018). For the selected experimental year (2019) for which in-situ data was available, the average daily temperature at MP and JC was $10.28^0$C and $8.55^0$C respectively. The annual rainfall at MP and JC over the analysis period was 1084mm and 1062mm respectively, as calculated from the corresponding weather data (Met Éireann, n.d.).

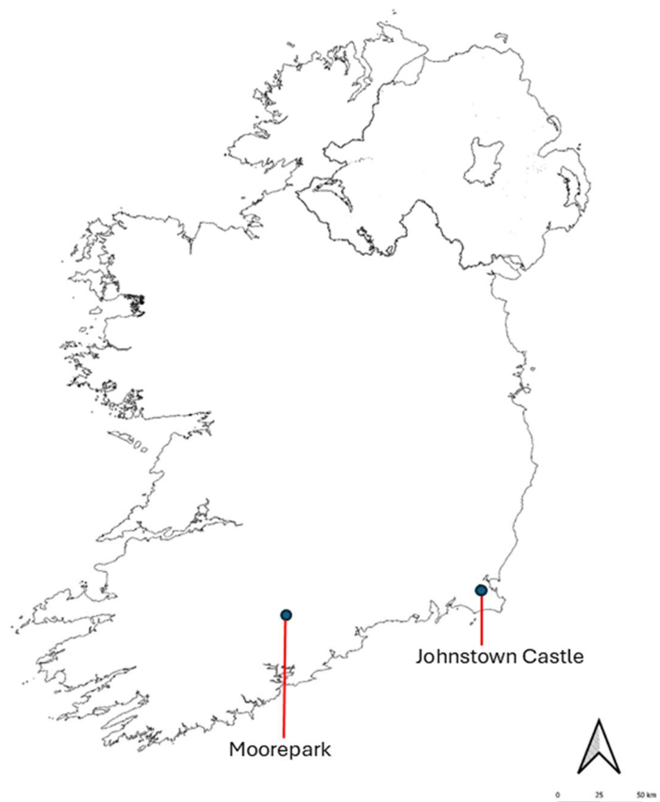


**Figure 6.1**: Location of Teagasc Farms at Johnstown Castle and Moorepark

### *6.2.2. Data*

Daily maximum and minimum temperature, rainfall and solar radiation were obtained for each site from Met Éireann (n.d.) (the Irish national meteorological agency). Daily precipitation (mm) and solar radiation (J/cm$^2$) data were converted to cm and MJ/m$^2$ (ISEOS, UNH, 2012), respectively. For atmospheric $NH_3$ concentration and the N concentration in rainfall, data obtained from environmental monitoring stations in close proximity to the study sites were obtained from Doyle *et al*. (2017) and Jordan (1997), respectively (Table 6.1). Zimmermann *et al*. (2018) contained data on the soil physicochemical properties at MP and JC, including the corresponding soil volumetric water content at FC and WP, from which the corresponding WFPS at FC and WP for the sites were derived using the methods from Franzluebbers (1999) (Table 6.1). As the pH of the soils at these sites was below 6.5 (Zimmermann *et al*., 2018), the total carbon in the soil was considered as SOC for both MP and JC (Franzluebbers and Stuedemann, 2002). The threshold for thermal degree days at maturity (TDD) for vegetative growth of perennial ryegrass was unavailable, the TDD for each site, was calculated using the corresponding Met Éireann (n.d.) weather data. For MP, this was performed following the method of Hart *et al*. (2013) for the year 2019. The whole year was considered as year-round vegetative growth of perennial ryegrass occurs in Ireland (Cappello *et al*., 2021; Wingler and Henessey, 2016), consistent with Experiment 1 (Chapter 4) (Table 6.1). For the JC site, the input for TDD was the same as that used in Experiment 1 (Chapter 4) for 2019, calculated following the same method (Table 6.1).

Two scenarios based on idealised intensive fertiliser application regimes were designed for a stocking rate of 2.36 cows/ha, considering a herd of Band 3 (DAFM, 2023b) cows that would supply 250 kg N/ha in organic form (Table 6.2). A relatively higher maximum N fertiliser input scenario according to the Green Book (Wall and Plunkett (eds.), 2020), suggested for the stocking rate range 2.35 to < 2.47 cows/ha, that does not account for the more recent limitations on annual N fertiliser application set by the banding of cows based on milk production (DAFM, 2023b), referred henceforth as the Green Book (GB) regime. The other regime was a relatively reduced albeit still intensive N fertiliser input scenario according to the Fifth Nitrates Action Programme 2022-2025 that sets a relatively lower limit for the maximum N fertiliser application considering the limits set for Band 3 cows (DAFM, 2023b), referred henceforth as the Nitrates Action Programme (NAP) regime. The annual N fertiliser application was 26.5 % lower for the NAP regime than that recommended in GB (DAFM, 2023b; Wall and Plunkett (eds.), 2020). However, both application regimes are aspatial in nature. To maintain a stocking rate of 2.36 cows/ha, dry matter of 11.8 t/ha is required (O'Donovan, 2016). The first and last grazing dates were set according to the JC farm management records for 2019 and used for all sites (Table 6.2), as the aim was to maintain a uniform grazing regime to focus solely on the impact of soil and weather on grass yield and N dynamics. Considering each soil dataset used in this study to be representing a farm, it was assumed that the fertiliser application timing of day was performed after grazing animals have moved away a paddock within a farm, thus no gaps were present within the entire annual period of grazing. The entire duration of this time period (days) was considered to be grazed, with no silage cutting events. An idealised average grazing hours was set at 20 hrs/day throughout the grazing period (Byrne and Kiely, 2008). Splits of N fertiliser applications were derived according to the Green Book for both fertiliser input scenarios (Wall and Plunkett (eds.), 2020). The application dates remained the same for each split of N fertiliser application under both scenarios.

**Table 6.1:** Site Specific Information

| **Category** | **Sites** | **MP** | **JCSL** | **JCL** | **References** |
|---|---|---|---|---|---|
| Soil | Texture | Sandy loam | Sandy loam | Loam | Franzluebbers, 1999; Zimmermann *et al.*, 2018 |
| | BD (g/cm$^{3)}$ | 1.205 | 1.11 | 1.27 | |
| | Clay (%) | 13.8 | 13.9 | 14.4 | |
| | pH | 5.47 | 5.53 | 5.69 | |
| | SOC (%) | 2.99 | 3.14 | 2.78 | |
| | WFPS at FC (%) | 61.21 | 53.67 | 70.7 | |
| | WFPS at WP (%) | 30.94 | 25.79 | 38.9 | |
| Background Atmospheric Conditions | Atmospheric $NH_3$ Concentration (μg/m$^3$) | 2.04 | 2.83 | 2.83 | Doyle *et al.*, 2017; Jordan, 1997 |
| | N concentration in Rainfall (mg N/l) | 0.56 | 1.02 | 1.02 | |
| Crop Phenology | TDD | 3577 | 3871 | 3871 | Hart *et al.*, 2013; Met Éireann, n.d. |

**Table 6.2.** Idealised Management Scenarios

| | **Input Dates (Day/Month) for 2019** | | | 15/02 | 15/03 | 15/04 | 15/05 | 15/06 | 15/07 | 15/08 |
|---|---|---|---|---|---|---|---|---|---|---|
| **N Fertiliser Application Regimes** | **Case Study** | **Total N fertiliser according to** | **Maximum Permissible Fertiliser** | **Splits of Application (kg N/ha)** | | | | | | |
| | **High N Fertiliser Input (Case Study 7)** | **Green Book (GB)** | **306 kg N/ha** | 31 | 54 | 54 | 56 | 37 | 37 | 37 |
| | **Modified N Fertiliser Input (Case Study 8)** | **Fifth Nitrates Action Programme (NAP)** | **225 kg N/ha** | 23 | 40 | 40 | 41 | 27 | 27 | 27 |
| **Grazing Regime** | **Stocking Rate 2.36 Cows/ha)** | **For both GB and NAP Regimes of N Fertiliser Application** | Start: Month 1 Day 13<br>End: Month 12 Day 23 | | | | | | | |

### *6.2.3. DNDC model: inputs and parameters*

The DNDC model (v9.5) (Source: http://www.dndc.sr.unh.edu/) was used to simulate annual grass yield and annual $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching (Gilhespy *et al*., 2014; Tang *et al*., 2024). A detailed description of the model and its inputs can be found in the work of Gilhespy *et al*. (2014) and in the model manual (ISEOS, UNH, 2012). Site-specific detailed inputs for each location on weather, soil physicochemical properties, background atmospheric $NH_3$ concentration, N concentration in rainfall, and TDD was used in each case (Section 6.2.2). The management inputs for the high (GB) and modified (NAP) N fertiliser input scenarios for a fixed grazing regime were used for simulations as described in Section 6.2.2. Other inputs for atmospheric conditions and crop phenology were used according to Chapter 4 and were kept fixed for all simulations and shown in Table 6.3.

**Table 6.3.** Inputs on Crop Phenology for Perennial Ryegrass and Atmospheric Conditions

| Category | Variables | Modified | References |
|---|---|---|---|
| Crop Phenology | C:N ratio for seed/ leaf/stem | 19/19/19 | Whitehead *et al*., 1990 |
| | C:N ratio for roots | 23 | |
| | N-fixation index (crop N/N from soil) | 1 | ISEOS, UNH, 2012 |
| | Water demand (g water/g DM) | 550 | Byrne and Kiely, 2008 |
| Atmospheric Conditions | Atmospheric background $CO_2$ concentration (ppm) | 409.8 | Ullas Krishnan and Jakka, 2022 |
| | Annual rate of increase Atmospheric background $CO_2$ concentration (ppm) | 2.3 | Prasad *et al*. (2021) |

### *6.2.4. Experimental Design*

Two case studies were designed to evaluate the idealised high GB (Case Study 7) and modified NAP (Case Study 8) N inputs scenarios across the selected sites on grass yield and N loss. Under each case study, the inputs on soil conditions (except textural class for MP and JCSL) were different for each site, to reflect the site-specific conditions. With the exception of the two sites located at Johnstown Castle (JCL and JCSL), the background atmospheric $NH_3$ concentration, N concentration in rainfall, TDD and daily weather varied between the sites and were representative of local conditions to the site of interest. These inputs remained unchanged between the two case studies examined; the differences between the case studies relate to the amount of N fertiliser applied (urea) (Table 6.2).

### *6.2.5. Outcomes and evaluation metrics*

For each simulation, the annual estimated grass yield was derived from the sum of the estimated yield of grain, leaf and stem in kg C/ha and converted to kg DM/ha by dividing with 0.4 (ISEOS, UNH, 2012), while the annual estimation of $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching was generated by DNDC in kg N/ha. The estimated yield was compared with the desired yield of

11.8t, required to maintain a stocking rate of 2.36 cows/ha (O'Donovan, 2016) to determine whether the GB and modified NAP fertiliser input guidelines could sustain the required productivity target. The difference for each site for the estimated yield under each management regime and desired yield was calculated. The difference attained by changing the N management regime from the GB to the NAP scenario in terms of estimated annual yield, $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching at each site, were derived in as a percentage difference. These were compared to see if equivalent changes across the sites are achieved based upon a uniform reduction in N fertiliser inputs (i.e. from GB to NAP). Also, the rank order of physicochemical properties of soil and annual rainfall and temperature was compared with the order of variation of estimated annual grass yield and annual $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching across the studied sites - to explore if they could explain any variations evident between the study sites.

### 6.3. Results

The estimated annual yield, for the studied grasslands for the targeted grazing regime and corresponding N fertiliser application from GB and NAP, N fertiliser management scenario, varied from 10562.78 kg DM/ha at JCSL to 11238.38 kg DM/ha JCL under Case Study 7 (GB regime) and from 8913.23 kg DM/ha at JCSL to 10678.78 kg DM/ha at JCL under Case Study 8 (NAP regime) (Table 6.4; Figure 6.2). An amount equivalent to or greater than the required 11.8 t/ha of DM was not achieved at any of the sites under any of the management regimes. The estimated annual $NH_3$ volatilisation varied from 147.31 kg N/ha at MP to 157.31 kg N/ha at JCSL under Case Study 7 and from 102.6 kg N/ha at MP to 111.06 kg N/ha at JCSL under Case Study 8 (Table 6.4; Figure 6.2). Annual estimated $N_2O$ emissions varied from 0.82 kg N/ha at JCSL to 1.65 kg N/ha at JCL under Case Study 7 and 0.57 kg N/ha at JCSL to 1.07 kg N/ha at JCL under Case Study 8 (Table 6.4; Figure 6.2). The estimated annual $NO_3^-$ leaching varied from 9.08 kg N/ha at JCL to 11.13 kg N/ha at JCSL under Case Study 7 and 3.97 kg N/ha at MP to 4.34 kg N/ha at JCSL under Case Study 8 (Table 6.4; Figure 6.2).

With a reduction of annual N fertiliser input under the NAP regime, the reduction in the estimated annual yield varied from -4.98 % at JCL to -15.62 % at JCSL (Table 6.4; Figure 6.3). The reduction in the estimated annual $NH_3$ volatilisation ranged from -29.40 % at JCSL to -30.35 % at MP (Table 6.4; Figure 6.3). The reduction in the estimated annual $N_2O$ emissions was from -30.49 % at JCSL to -35.15 % at JCL (Table 6.4; Figure 6.3). Whereas for the estimation annual $NO_3^-$ leaching, the reduction varied from -55.51 % at JCL to -61.38 % at MP (Table 6.4; Figure 6.3).

**Table 6.4:** Variation of Estimated Annual Yield and Nitrogen Loss under High and Low N Fertiliser Input Scenarios and their Reduction under Reduction of Nitrogen Fertiliser Inputs from High to Low

| Scenario | Sites | Scenario (Case Studies) | | Percent change (%) between Fertiliser Input from High (GB) to Modified (NAP) |
|---|---|---|---|---|
| | | Case Study 7 | Case Study 8 | |
| N Fertiliser Inputs | | High (GB) | Modified (NAP) | |
| **Annual Yield (kg DM/ha)** | **MP** | 11054.4 | 10334.45 | -6.51 |
| | **JCSL** | 10562.78 | 8913.23 | -15.62 |
| | **JCL** | 11238.38 | 10678.78 | -4.98 |
| **Annual Ammonia Volatilisation (kg N/ha)** | **MP** | 147.31 | 102.6 | -30.35 |
| | **JCSL** | 157.31 | 111.06 | -29.40 |
| | **JCL** | 148.83 | 104.6 | -29.72 |
| **Annual Nitrous Oxide Emissions (kg N/ha)** | **MP** | 1.24 | 0.86 | -30.65 |
| | **JCSL** | 0.82 | 0.57 | -30.49 |
| | **JCL** | 1.65 | 1.07 | -35.15 |
| **Annual Nitrate Leaching (kg N/ha)** | **MP** | 10.28 | 3.97 | -61.38 |
| | **JCSL** | 11.13 | 4.34 | -61.01 |
| | **JCL** | 9.08 | 4.04 | -55.51 |

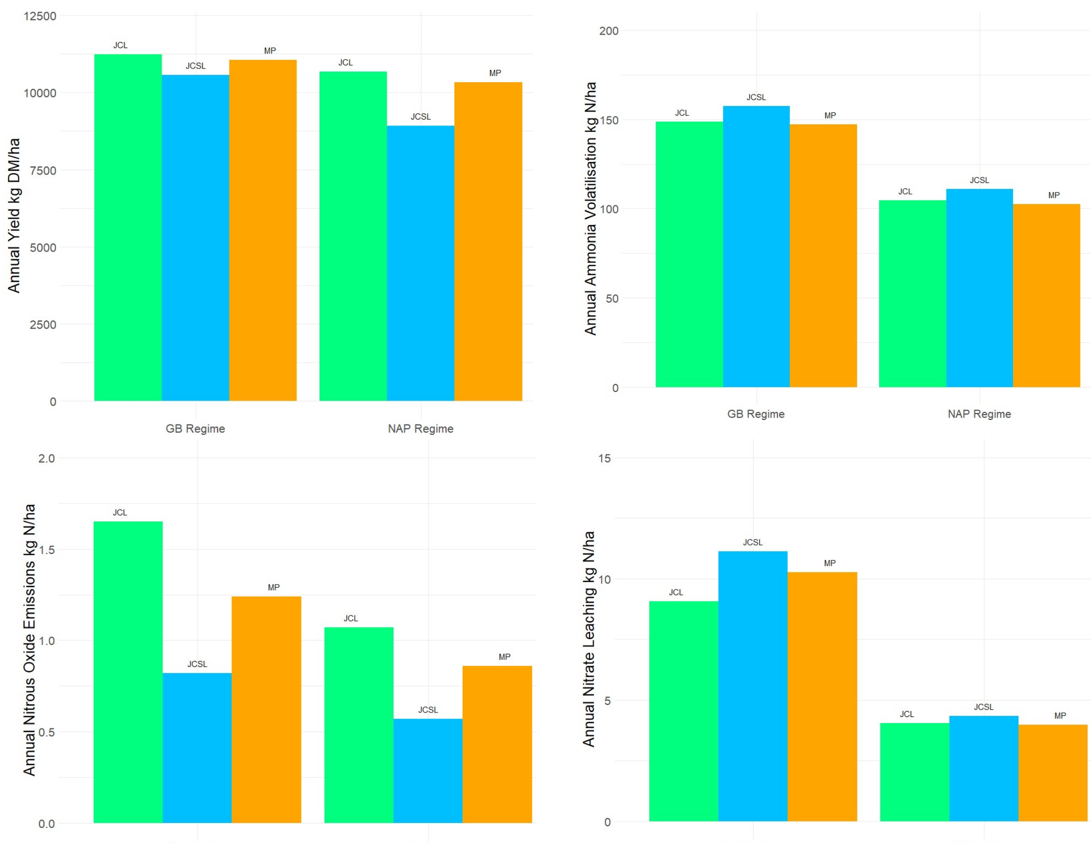


**Figure 6.2**: Variation of annual yield of perennial ryegrass (top-left), ammonia ($NH_3$) volatilisation (top-right), nitrous oxide ($N_2O$) emissions (bottom-left) and nitrate ($NO_3^-$) leaching (bottom-right) under GB Regime (higher N fertiliser input) and NAP Regime (lower N fertiliser input) across the studied sites


**Figure 6.3:** The reduction (%) in annual yield of perennial ryegrass, annual ammonia $NH_3$) volatilisation, annual nitrous oxide ($N_2O$) emissions and nitrate ($NO_3^-$) leaching when N fertiliser input (urea) was reduced from GB Regime to NAP Regime

## 6.4. Discussion

From the results of this study, it was found that for both the GB and the NAP management regimes for grazing and N fertiliser input as urea, the highest yield and annual $N_2O$ emissions were estimated at JCL followed by MP and JCSL, whereas the highest annual $NH_3$ volatilisation was estimated for JCSL, followed by JCL and MP. Both of the regimes failed to produce the estimated yield required to maintain the targeted stocking rate (as per O'Donovan, 2016) at any of the sites. The highest annual $NO_3^-$ leaching under the GB regime was modelled for JCSL, followed by MP and JCL, whereas the highest annual $NO_3^-$ leaching under the NAP regime was modelled for JCSL followed by JCL and MP. With the reduction in annual N fertiliser application from the GB to the NAP regime, the reduction of annual yield was highest for JCSL followed by MP and JCL. The NAP regime resulted in the highest estimated reductions of annual $NH_3$ volatilisation at MP, followed by JCL and JCSL, whereas the highest reduction in annual $N_2O$ emissions was at JCL followed by MP and JCSL. The reduction in annual $NO_3^-$ leaching under the NAP regime was highest at MP followed by JCSL and JCL.

### *6.4.1. Variation of yield across the studied sites*

The higher estimated yield was associated with higher BD and WFPS at FC and WP, and was also associated with lower SOC across the sites, for the targeted grazing regime and corresponding N input regimes from GB and NAP. It was also partially associated with the lower sand content in soil, represented by loam texture at JCL. Lower sand content and higher WFPS at FC and WP (the difference of which also represent higher plant available water) resulting in higher water availability, likely contributed to the increased yields (Anderson, 1988; Pragg *et al.*, 2024). The association of lower SOC with higher yield could not be explained clearly as lower SOM (soil organic matter), represented by lower SOC (Pribyl, 2010), generally has a negative impact on soils water-retention, nutrient supply, soil aggregate stability, buffering capacity against pH, BD and CEC (Blanco-Canqui and Benjamin, 2015; Djajadi and Hinz, 2012; Libohova *et al*., 2018; Ramos *et al*., 2018; Robertson and Paul, 2000; Zhang *et al*., 2017). However, one potential explanation for the association between the relatively lower SOC and higher yield could be due to the decreased potential for seasonal water logging due to lower SOM, common in wetter months Ireland that can particularly affect yield by increasing leaching and denitrification or by inhibiting respiration in roots leading to reduced water uptake (Hurtado-Uria *et al*., 2013; Jiao *et al*., 2004; Lehmann and Schroth, 2002; Smith et al., 2022; Yin *et al*., 2020), where SOC is not a limiting factor. A prolonged period of high soil moisture during winter months was also identified by Schulte *et al.* (2012) as a challenge for grass growth in Atlantic maritime conditions, including Ireland. This may also provide an explanation for the association between higher BD and higher estimated yields, as Fornara and Higgins (2022) showed that an increase in BD is associated with lower carbon content in soil.

The reductions in yield estimates under the NAP regime, were smaller at JCL, a site with a lower sand content. This might also be associated with the relatively lower reduction of $NO_3^-$ leaching under NAP regime observed in this site, indicating greater scope of its uptake (Novoa and Loomis, 1981). The reductions in yield were higher for sites with higher SOC and lower BD, WFPS at FC and WP and plant available water (derived from WFPS at FC and WP), including between the two sandy loam soils at JC and MP. These same factors that were associated with higher yield were also associated with a lower reduction in yield under the NAP regime – suggesting that these factors are driving more efficient uptake of N by grass (e.g. Baligar *et al*., 2007; Orwin *et al*., 2015; Soares *et al*., 2019).

### *6.4.2. Variation of ammonia ($NH_3$) volatilisation across the studied sites*

The study showed that higher annual $NH_3$ volatilisation, under targeted grazing regime with corresponding N input regimes following GB and NAP, was partially associated with lower annual rainfall and average annual temperature. Thompson *et al*. (1990) indicated that the impact of rainfall on $NH_3$ volatilisation is dependent on the timing of fertiliser applications and rainfall events. Thus, no direct conclusion could be inferred from the outcomes in this study between annual rainfall and $NH_3$ volatilisation. Higher air temperature is generally associated with increases in $NH_3$ volatilisation (Huijsmans *et al*., 2001; Sommer *et al*., 2001), which is in contrast to the findings here. However, one possible explanation is the dispersing effect of higher rainfall at MP on urea that prevents the accumulation of $NH_3$ and $NH_4^+$, overriding the effect of temperature (Harper et al., 1983). Higher rainfall may also contribute to increased downward movement of urea in the soil, thereby limiting $NH_3$ volatilisation (Bouwmeester *et al*., 1985). This study could not find a direct association between $NH_3$ volatilisation and yield or $N_2O$ emissions. Under the NAP regime, the variation of annual $NH_3$ volatilisation across the sites was the same as the variation of $NO_3^-$ leaching. However, under the GB regime, the variation of annual $NH_3$ volatilisation differed from the variation of $NO_3^-$ leaching. Thus, the effect of other individual forms of N loss could neither be ruled out nor could be identified as informing factors of potential $NH_3$ volatilisation.

The reduction in $NH_3$ volatilisation due to the reduction of N fertiliser input under the NAP regime (DAFM, 2023b) was greater for the MP site where there was higher annual rainfall and annual average daily temperature. Higher soil moisture, due to high rainfall (Feng and Liu, 2015), has previously been found to increase $NH_3$ volatilisation (Milchunas *et al*., 1988). Higher temperature also increases $NH_3$ volatilisation (Huijsmans *et al*., 2001; Sommer *et al*., 2001). Thus, a reduction in N fertiliser application, especially ammonium supplying fertilisers like urea (Harty *et al*., 2017) in sites with higher rainfall and higher temperature may show higher efficiency in reducing annual $NH_3$ volatilisation, which are also the sites that are relatively less vulnerable to loss of N through $NH_3$ volatilisation due to overriding effect of annual rainfall on average annual temperature, as was also seen in this study. However, unlike annual $NH_3$ volatilisation, higher rainfall overriding the effect of average annual temperature, cannot be identified as the only determinant for the reduction in $NH_3$ volatilisation under the NAP regime.

### 6.4.3. *Variation of nitrous oxide ($N_2O$) emissions across the studied sites*

Under the targeted regime of grazing with N input following GB and NAP regimes, annual $N_2O$ emissions across sites, irrespective of the rate of N fertiliser application, were higher for soils with higher BD, WFPS at FC and WP. Difference between WFPS at FC and WP, indicating higher plant available water (Pragg *et al*., 2024), was also higher for sites with higher annual $N_2O$ emissions. Higher annual $N_2O$ emissions was also associated with sites with lower SOC and was partially aligned with lower sand content represented by soil texture at JCL. WFPS is a key driver of $N_2O$ emissions, potentially due to increased anaerobic conditions under increased WFPS, and ultimately governed by the interaction of soil water holding capacity and rainfall (e.g. Griffis *et al*., 2017; Liu *et al*., 2022b; Newman, 1984; Yin *et al*., 2020; Zhang *et al*., 2021). However, variation in rainfall did not explain the variation in annual $N_2O$ emissions. Coarser soils generally tend to have less susceptibility to denitrification due to reduced water retention and reduced N availability due to higher leaching therefore the association of higher annual $N_2O$ emissions with finer soil texture is justified (Newman, 1984; Saggar *et al*., 2013; Sahrawat, 2008; Wei *et al*., 2021). Lower SOC for sites with higher estimated annual $N_2O$ emissions is counterintuitive with denitrification from SOC, typically associated with the availability of substrate carbon (Beauchamp *et al*., 1980). However, lower SOM, may reduce water retention leading to reduced denitrification (Rawls et al., 2003; Yin *et al*., 2020). The association of lower $N_2O$ emissions estimated for sites with lower BD, that also might be associated with lower SOC in these sites (Fornara and Higgins, 2022), is likely driven by increased anaerobic conditions (Czyż, 2004). Sites with higher $N_2O$ emissions were also those with higher potential yield, indicating similar factors that drive high yield may also drive high annual $N_2O$ emissions - as was seen from this study. It also indicates that the surplus N after uptake by plant (Smith *et al*., 2012) is not the only determinant of $N_2O$ emissions, under the site conditions and management intensity used in this study.

Unlike annual yield and annual $NH_3$ volatilisation, the same factors that were responsible for higher annual $N_2O$ emissions were also associated with the larger reduction in annual $N_2O$ emissions under the NAP regime. The sites with a higher estimated annual $N_2O$ emissions were also associated with a higher reduction in annual $N_2O$ emissions. It indicates that the sites that are more vulnerable to $N_2O$ emissions may respond more efficiently to a reduction in N supply in terms of N loss through $N_2O$ emissions. Whereas larger reductions in annual $N_2O$ emissions, highest at JCL and lowest at JCSL, were aligned with lower SOC and higher BD at these sites. This is possibly due to the effect of higher annual yield coupled with a smaller reduction in annual yield leading to improved NUE in these sites with higher WFPS at FC and WP and plant available water. This suggests lower availability of substrate N for denitrification, further reduced by relatively lower availability of substrate carbon, overriding the intrinsic vulnerability of the site to potential higher denitrification (i.e. higher anaerobic conditions driven by higher BD and finer texture) (Anderson, 1988; Beauchamp *et al*., 1980; Czyż, 2004; Pragg *et al*., 2024; Rawls et al., 2003; Ritchie, 2021; Soares *et al*., 2019; Wei *et al*., 2021; Yin *et al*., 2020).

### *6.4.4. Variation of nitrate ($NO_3^-$) leaching across the studied sites*

The variation of annual $NO_3^-$ leaching across the sites was not same for GB regime and NAP regime of N input for the targeted stocking rate. Thus, it was not possible to identify factors in common with annual $NO_3^-$ leaching. However, this also indicates that depending on the rate of N fertiliser application the susceptibility of a site to annual $NO_3^-$ leaching and its key drivers can vary. Hence policy-specific spatial refinement for reducing annual $NO_3^-$ leaching may be required (Patil, 2009; Sharma and Bali, 2017; Wu and Ma, 2015). Under the GB regime, higher annual $NO_3^-$ leaching was associated with higher SOC and lower - BD, WFPS at FC and WP and plant available water. Lower annual $NO_3^-$ leaching was partially associated with lower sand content in the soil, represented by loam soil texture at JCL, consistent with more general observations (e.g. Anderson, 1988; Wei *et al*., 2021). The association between the higher WFPS at FC and lower annual $NO_3^-$ leaching is justified as higher field capacity would require a higher amount of water for saturation and the consecutive initiation of leaching (Wang et al., 2019). Whereas the association between higher plant available water (difference between WFPS at FC and WP (Pragg *et al*., 2024)) with lower annual $NO_3^-$ leaching indicates reduced availability of $NO_3^-$ leaching due to greater uptake associated with higher yield (Novoa and Loomis, 1981). Higher SOM as indicated by higher SOC (Pribyl, 2010), may reduce the annual $NO_3^-$ leaching due to improved water retention (Whetton *et al*., 2022), and can explain the variation of annual $NO_3^-$ leaching in our study. Sites with higher BD, indicating lower porosity that reduces rate of infiltration, likely explains the lower estimated annual $NO_3^-$ leaching (Panagos et al., 2024). Under the NAP regime, the sites with lower annual $NO_3^-$ leaching at MP site was partially associated with higher annual rainfall and higher average annual temperature. Increased $NO_3^-$ leaching under higher temperature was found by Jabloun *et al*. (2015) and is in contrast to the findings here. Whereas higher rainfall associated with lower annual $NO_3^-$ leaching is likely driven by variations in cumulative rainfall over different seasons (Jabloun *et al*., 2015) or the intensity of rainfall (Sugita and Nakane, 2007). Thus, future research could consider whether the distribution of seasonal rainfall and/or intensity of rainfall produces an overriding of the effect of annual rainfall and average temperatures in Irish grasslands.

Under the NAP scenario, the model estimated reduction in $NO_3^-$ leaching was higher for sites with relatively lower pH and clay. Increased soil acidity can lead to reduced nitrification and a subsequent increased accumulation of $NH_4^+$ (Kemmitt *et al*., 2005), while higher clay content generally contributes to a reduction in N leaching due to higher water retention (Wei *et al*., 2021; Whetton *et al*., 2022). This, when coupled with reduced nitrogen supply, may accelerate the reduction of $NO_3^-$ leaching. A Larger reduction in $NO_3^-$ leaching was partially associated with higher sand content, annual rainfall and temperature. This indicates that sites with higher sand content and/or annual rainfall and temperature that are more susceptible to N leaching (e.g.

Anderson 1988; Wei *et al*., 2021; Jabloun *et al*., 2015; Sugita and Nakane, 2007) may have greater efficiency in reducing $NO_3^-$ leaching under a reduced rate of fertiliser application.

### *6.4.5. Significance for geographically refined national policies for sustainable nitrogen (N) management*

The study shows that a uniform reduction of N fertilisers nationally, for a fixed stocking rate, may not meet the targeted yield for farms under the diverse range of environmental and meteorological conditions experienced here. Such a uniform reduction may be unable to effectively reduce surplus N across spatially diverse sites, which ultimately governs the variation of N loss in different forms (Wu and Ma, 2015). Thus, determining the adequate N fertiliser requirement at farm or field level may help inform the *right rate* of N fertiliser application, as per the 4RNS objectives (Fixen, 2020) to achieve a targeted yield and reduction in N loss. The geographical refinement of national level strategies can be achieved by developing national management zones leading to more focused N management practices based on potential yield and N loss (Patil, 2009; Wu and Ma, 2015). The outcomes of this study indicate such geographical refinement of the existing national sustainable N management strategies in Ireland could be achieved by developing management zones. However, the effectiveness of the policy implementation under diverse soil and meteorological conditions can vary, which will be relevant for upscaling or downscaling of management strategies (Milne *et al*., 2020; Patil, 2009).

To support the implementation of improved, geographically refined, N management strategies, we hereafter classified the key regulators of variability of yield, N loss and their changes across the study sites under a uniform reduction of N fertiliser application, identified from this study, into two groups. Group 1 consists of the variables that explained the variation of N loss across the studied sites and can be used as proxy or indicator variables for estimating potential yield, $NH_3$ volatilisation and $N_2O$ emissions, which could help in the development of N management zones nationally (Nabati *et al*., 2020; Patil, 2009). The variables that explained the absolute reduction in yield and N loss through $NH_3$ volatilisation and $N_2O$ emissions, as well as through $NO_3^-$ leaching, under the NAP regime, were grouped in a second group (Group 2) as effective regulators to achieve targeted sustainability objectives to improve or maintain productivity and the reduction of N loss to support further refinement of strategies policy implementation at a higher spatial and temporal resolution within the management zones (Schipanski *et al*., 2009; Shirmohammadi *et al*., 2008).

*Group 1 Variables*

It was observed that high yielding sites can be potential indicators of high annual $N_2O$ emissions – thus can lead to formation of national to field level management zones for spatial refinement of N management plans that are aimed to achieve a targeted yield while reducing $N_2O$ emissions from grassland soils (Nabati *et al*., 2020; Patil, 2009). Sand content in soil emerged as an independent but common regulator for yield and $N_2O$ emissions, that may be suitable for developing time independent mapping of management zones using data at a national scale (e.g. O'Sullivan *et al*., 2018) for refining national level N management strategies (e.g. Milne *et al*., 2020; Patil, 2009), in Ireland. Although BD and SOC were identified to be indicators of annual yield and $N_2O$ emissions, their interaction with environment and each other, followed by the complex impact on N dynamics (e.g. Czyż, 2004; Fornara and Higgins, 2022; Hurtado-Uria et al., 2013; Jiao et al., 2004; Lehmann and Schroth, 2002; Smith et al., 2022; Yin et al., 2020), may make them unsuitable for developing management zones as individual variables. However, national level spatial data on soil BD (e.g. O'Sullivan *et al*., 2018) and SOC can be useful in combination to develop management zones (Patil, 2009), which in combination with textural zones may increase the spatial resolution of refinement of N management strategies. Although BD and SOC can vary depending on management practices, consistent land use practice over a long period (decades) can stabilise these factors (e.g. Bauer and Black, 1981; Evans et al., 2012). This makes considering the history of land use an important factor to consider if using BD and SOC for developing management zones. However, WFPS at FC and WP, and thus the plant available water (Pragg *et al*., 2024), can be subject to change due management activities like organic matter additions (Minasny and McBratney, 2017). Hence while they may initially indicate the potential of yield and $N_2O$ emissions they may not be suitable for use in developing management zones.

Climate data over a longer time period (e.g. 30 years) (e.g. Walsh, 2012) on annual rainfall and average annual temperature is relevant for identifying management zones (Patil, 2009) to reduce potential $NH_3$ volatilisation, as higher $NH_3$ volatilisation was seen to be associated with lower annual rainfall and lower average annual temperature. Such zones can be compared with national level monitored data on $NH_3$ volatilisation for further refinement (e.g. Doyle *et al*., 2017). However, as long-term climate averages may fail to represent annual variations in weather (Krishnamurthy, 2019), to reduce $NH_3$ volatilisation there would still be a need to monitor and model the potential impact of a management plan and adapting decision support based management to incorporate weather forecast information (Burchill *et al*., 2016; McDonnell *et al*., 2019).

It was seen from this study that, unlike for yield and N loss through $NH_3$ volatilisation and $N_2O$ emissions, the suite of environmental regulators that explain the variation of annual $NO_3^-$ leaching across sites can vary depending on rate of N fertiliser application. For example, we found that the factors that explain the high to low variation in annual $NO_3^-$ leaching across the studied sites under the GB regime were consistent with the factors relevant for explaining low to high variations in annual yield and annual $N_2O$ emissions. Whereas under the NAP regime, the factors that explained the high to low variation in annual $NO_3^-$ leaching were the same factors that explained the high to low variation in $NH_3$ volatilisation. While variation of annual $NO_3^-$ leaching under the GB regime were not associated with the variation of annual $NH_3$ volatilisation and under the NAP regime were not associated with the variation of annual yield and annual $N_2O$ emissions. Thus, for annual $NO_3^-$ leaching, developing time-independent management zones would not be a suitable option, unless the N application rate is consistent. Rather, the effect of a management regime on annual $NO_3^-$ leaching across sites can be determined through modelling or monitoring (EPC, 1991) along with identifying the relative importance of the regulatory factors under that regime, that might help in determining management zones (Patil, 2009) under a specific regime. This could inform the refinement of long-term policies such as the Nitrates Derogation strategy (Callaghan, 2023), applicable from 2024 to 2027.

*Group 2 Variables*

This study also showed that the impact of changes in N management plans in a spatially uniform manner vary, depending upon soil and weather conditions. Thus, it is important to consider the potential effectiveness of any current or potential future policies and their regulators (Schipanski *et al*., 2009; Shirmohammadi *et al*., 2008). In spite of the varying relevance of regulatory environmental factors on annual $NO_3^-$ leaching under the GB and the NAP regime, soil clay content and pH explained the reduction in annual $NO_3^-$ leaching under the NAP regime. Whereas soil sand content, as a common factor, partially explained the reduction in annual $N_2O$ emissions, annual $NO_3^-$ leaching and the reduction of yield under the NAP regime. BD and SOC, initial WFPS at FC and WP and plant available water are also found to be associated with the efficacy of the implemented management regimes to reduce $N_2O$ emissions and achieve sustainability in maintaining yield. Thus, soil textural properties, BD, SOC, pH, WFPS at FC and

WP and plant available water is important to account for when developing sustainable N management plans. However, since soil texture, BD and SOM (represented by SOC) ultimately govern the water holding capacity of soil (Carter, 2002; Pribyl, 2010), accounting for these variables may reduce the need to account for WFPS at FC and WP and plant available water. The identified variables have potential to inform N management strategies at a higher resolution (i.e. more localised scales such as farm or field level) and could be useful to develop sub-divisions of management zones (Milne *et al*., 2020; Patil *et al*., 2009; Shirmohammadi *et al*., 2008). Importantly, the identified variables can be used to expose vulnerability to N loss to analyse the potential outcomes of future national level strategies at more localised scales. Further, monitoring of annual yield, $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching at a higher spatial and temporal resolution, depending on estimated vulnerabilities to inefficient N uptake or reduction of loss, could advance the spatial optimisation of N management plans over time as data gaps are reduced (Doyle *et al*., 2017; EPA, 2023b; EPC, 1991; IPCC, 2000; O'Donovan *et al*., 2021; Patil *et al*., 2009). This can be important to inform and evaluate the success or failure of potential or implemented strategies within designated sub-divisions of management zones and to identify requirement or scope of empirical studies to further refinement of N management strategies – such as choosing right product and right timing (Fixen, 2020) for N fertiliser application. Annual rainfall and average annual temperature were identified to explain the efficiency of NAP in reducing both $NH_3$ volatilisation and $NO_3^-$ leaching, making weather forecast relevant for decision making on N application with respect to timing, location and type (Fixen, 2020; McDonnell *et al*., 2019).

### *6.4.6. Scope for refinement of site-specific N management – future application potential*

Our study indicates that spatially refining N management plans is relevant for sustainable grass yield and achieving a targeted reduction of N loss over uniform national level N management plans, to address the productivity challenge. This research highlights the scope for geographical refinement of national policy and farm level advice that can be tailored to zones in line with the *right place* objective of the 4RNS strategy (Fixen, 2020) and can be further refined by understanding the potential impact of implemented policies on yield and N loss at a higher spatial resolution (e.g. Milne *et al*., 2020; Patil, 2009; Shirmohammadi et al., 2008). We suggest that zoning for Irish landscape can be employed for refinement of N management focusing on zones based on susceptibility to - $NH_3$ volatilisation (V Zone), high denitrification (DN Zone) and high nitrate leaching (L Zone), categorised with prefix '*h*' for 'high' and '*l*' for 'low' vulnerability in each case. For zones susceptible to high $NH_3$ volatilisation (*hV* Zone), application of urease inhibitors for urea application and the use of more nitrate-based fertilisers instead of ammonium- based fertilisers should be encouraged to reduce $NH_3$ volatilisation loss, according to the *right source* objective of 4RNS strategy (Fixen, 2020; Forrestal *et al*., 2015a; Harty *et al*., 2017). For zones susceptible to high denitrification (*hDN* Zone) and high nitrate leaching (*hL* Zone), the application of nitrification inhibitors and the replacement of nitrate-based fertilisers with more ammonium-based fertilisers can be suggested to meet the same objectives (Rahman and Forrestal, 2021; Woodward *et al*., 2021). At the same time, choosing the *right time* for N fertiliser application, based on weather forecast, at the *right place* can also be supported through such zoning to achieve 4RNS goals (Fixen, 2020; McDonnell *et al*., 2019). Application of urea or ammonium-based N fertiliser application should be postponed from a tentative application date days if rainfall has occurred or forecasted on the day before the tentative date and with a forecast of low rainfall on that date and subsequent days, especially in *hV* Zones (Hargrove, 1988). For *hDN* Zones, the application of N fertiliser should be avoided on days immediately after rainfall events or when rainfall is forecasted to occur after the N fertiliser application (Craswell, 1978; Schwenke and Haigh, 2016). Sub-division of existing management zones for yield and other forms of N loss into *hL* Zones, using the variables that were identified regulating the variation of reduction of $NO_3^-$ leaching under NAP regime (Group 2), can help in implementation of GAP (EPC, 1991) to reduce pollution from $NO_3^-$ leaching. Whereas *hL* Zones can also be identified based on regulators of annual $NO_3^-$ leaching under each specific management regime, with the same objectives, depending on duration of the management regime. To reduce potential $NO_3^-$ leaching, nitrate-based fertiliser application should be avoided on days forecasted with high intensity rainfall (Di and Cameron, 2002; Hess *et al*., 2020), especially relevant for *hL* Zones. However, it can be noted that estimated leaching of $NO_3^-$ leaching by DNDC is the amount of N loss through leaching at the study site, thus the *hL* zones would be representing the vulnerability of the site to loose applied N through leaching, with scope of estimating potential N loss through runoff (ISEOS, UNH, 2012) – but would not indicate the fate of soluble N and its ultimate contribution in degrading groundwater and surface water quality. To explore vulnerability of water resources to leached N and through runoff, by knowing the potential concentration of N in drained water due to leaching, runoff and lateral flow, it is important to consider the scope of using alternative modelling approaches (e.g. NGAUGE) (Brown *et al.*, 2005).

### 6.5. Conclusion

This study primarily sought to identify the possible scope of geographical refinement of national level sustainable N management strategies for dairy farming to improve agricultural productivity and to reduce N loss to the environment from grasslands under Irish dairy farming. The DNDC model, that had been parameterised to reliably estimate the annual yield of perennial ryegrass, was used to estimate the impact of two national level intensive N management strategies, that are currently spatially uniform, on grass yield and N loss, with site-specific soil inputs required for reliable estimation of $NH_3$ volatilisation and $N_2O$ emissions. The outcomes showed that there is potential to improve strategies that reduce N loss through $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching, if N management strategies can be geographically refined, considering the key regulators that spatially modify these outcomes. To maintain a targeted yield sustainably, such geographical refinement was found to be a requirement. The study showed that the variability of perennial ryegrass yield and different forms of N loss, seen across the studied sites, are dependent on each other (except for $NH_3$ volatilisation under GB regime), as well as on the diversity of the soil texture, pH, BD, SOC, plant available soil water and on average annual temperature and annual rainfall. It was also evident that combinations of such variables become important for regulating the effectiveness of an implemented N management strategy to maintain yield and reduce N loss. The Group 1 variables that indicate potential yield and N loss may be used to develop national level to farm level management zones for geographical refinement of existing aspatial N management strategies, depending on their temporal stability. Furthermore, accountability to the identified factors in this research that influence the effectiveness of N management strategies (Group 2 variables) offer scope to analyse the impact of policies with respect to meeting both production and environmental targets in line with national ambitions.

# 7. Exploring the scope of using the DNDC model to estimate potential changes of grass yield and nitrogen dynamics for sites with limited site-specific data availability

**Abstract**

The *DeNitrification-DeComposition* (DNDC) model is a process-oriented model that enables the exploration of nitrogen (N) dynamics in agricultural soils while accounting for site-specific soil, meteorology and management conditions. However, a common challenge with applying biogeochemical models to explore potential crop yield and N loss is the requirement for detailed site-specific calibration and validation, which is often limited by data availability. Here, we sought to explore if DNDC is able to simulate the variation (relative) of yield and N loss through ammonia ($NH_3$) volatilisation, nitrous oxide ($N_2O$) emissions and nitrate ($NO_3^-$) leaching using default inputs for the soil and meteorology, when the crop phenology is parameterised for perennial ryegrass. The outcomes of the study indicate that DNDC, with parameterisation for phenology of perennial ryegrass, is capable of producing across site variations in annual yield and $NO_3^-$ leaching across the selected study sites consistent with the site-specific simulations when default inputs for optional soil and meteorological variables are used. However, using default inputs for optional soil and meteorological variables in DNDC simulations (parameterised for phenology of perennial ryegrass) fails to perform in the same way for N loss through the remaining two major pathways - $N_2O$ emissions and $NH_3$ volatilisation.

## 7.1. Introduction

Nitrogen (N) loss from agricultural landscapes, especially under intensive management, is a global challenge to achieving more sustainable crop production (Ritchie, 2021). Intensive N application in agriculture is intended to meet the global increase in food demand due to population growth, increase in per capita income and gross domestic product (GDP) (Falcon *et al*., 2022; Fukase and Martin, 2020; Rudel *et al*., 2009; Tilman *et al*., 2011). Grassland management is spread over two thirds of the total global agricultural landscape (Ritchie and Roser, 2019). Permanent grasslands cover one third of the agricultural landscape in European Union (Francksen *et al*., 2022). In Ireland, it is the most widespread land use practice (approximately 92 % of national agricultural landscape), largely managed for the production of feed required to maintain livestock (O'Donovan *et al*., 2021). The most significant pathways of N loss from grasslands are ammonia ($NH_3$) volatilisation, emissions of nitrous oxide ($N_2O$) and nitrate ($NO_3^-$) leaching (Hoekstra *et al*., 2020; van Beek *et al*., 2008; Woodmansee *et al*., 1981).

N lost from agricultural soil negatively impacts the economy, environment and human health through contributing to air pollution by volatilised $NH_3$, to global warming and depletion of stratospheric ozone by emitted $N_2O$, to groundwater pollution and eutrophication of water bodies by leaching and runoff of $NO_3^-$, and by increasing soil acidification and eutrophication by atmospheric deposition (de Vries, W., 2021; Giordano *et al*., 2021; Pittelkow *et al*., 2013; Stark and Richards, 2008; UNEP, 2019; Wang *et al*., 2023).

Currently, N management of Irish dairy grasslands is guided by agricultural strategies focused on sustainable production. These are Food Wise 2025, the Climate Action Plan 2023 and the Fifth Nitrates Action Programme 2022-2025, the overall ambitions of which seek to improve agricultural productivity and reduce N loss (DAFM, 2021; DECC, 2023; DHLGH and DAFM, 2022). At farm level, N management is supported by an online platform, the 'Nutrient Management Plan' (NMP-Online), and by general guidelines and limits provided through the Green Book and Nitrates Derogation strategies (e.g. Callaghan, 2023; Hanrahan *et al*., 2017; Maher *et al*., 2021; Wall and Plunkett (eds.), 2020). However, a significant shortcoming of both the current national and farm level N management strategies is that they do not account for the variability of grass yield and N loss due to the diversity of soil, meteorological conditions and management across the country. This represents a limitation to realising the stated aims of national policy.

The spatial or geographical refinement of N management strategies at relevant spatial scales which can account for the variability of crop yield and N loss across diverse environmental conditions - soil, meteorological conditions and management- could support evidence based and informed decision making, consistent with the goals of the 4R Nutrient Stewardship (4RNS) objectives. These objectives suggest applying N fertiliser from the *right source*, at the *right rate* and *right time*, and at the *right place* can deliver enhanced sustainability (Bryla, 2020; Fixen, 2020; Sarmah *et al*., 2014; Varallyay, 1994). Employing process-oriented biogeochemical models can help to support such targeted management based on potential yield, targeted forms of N loss and their regulators to develop site-specific N management plans. A process-oriented model can also be employed to identify key regulators of yield and N loss within a management zone, at field level or at national level - depending on the optimum resolution of model performance. These factors need to be accounted for to estimate the effectiveness of N management plans required to meet national and indeed international sustainability objectives (Abdalla *et al*., 2020; Dragosits *et al*., 2002; Haraldsson and Sverdrup, 2013; Kardynska *et al*., 2022; Patil, 2009; Spijker *et al*., 2021; Wang *et al*., 2016).

The *DeNitrification DeComposition* (DNDC) model is a widely used process-oriented model that simulates crop growth and biogeochemical dynamics of carbon (C) and nitrogen (N) in agricultural soils (Gilhespy *et al*., 2014; ISEOS, UNH, 2012). According to the classification by Haraldsson and Sverdrup (2013) it can be classified as a Type 3 category model, that takes a differential approach to replicate the C and N biogeochemistry and accounts for the interactions between soil, meteorology and management (Gilhespy *et al*., 2014). In Chapters 4 and 5 (Experiment 1 and 2 respectively), the model's requirement for parameterisation and detailed input data to generate reliable simulations of yield and N dynamics at paddock to farm level was highlighted through various experiments. However, suitable calibration and validation of a model, particularly one with detailed data requirements, is a challenge for the robust application of DNDC in data sparse locations (e.g. Byrne and Kiely, 2008; Giltrap *et al*., 2010; Haraldsson and Sverdrup, 2013). In Chapter 4 (Experiment 1) the model was shown to reliably estimate the growth of perennial ryegrass in paddocks and at farm level under typical management practices used for Irish dairy farming – but only when correctly parameterised for perennial ryegrass phenology and atmospheric conditions in proximity to the experimental sites. The study also demonstrated the potential to employ more generalised soil inputs in the absence of site-specific or measured data. Based on the findings from Chapter 5 – Experiment 2, DNDC requires site-specific inputs of water filled pore space (WFPS) at field capacity (FC) and wilting point (WP) to reliably estimate grass yield and N loss through $NH_3$ volatilisation and $N_2O$ emissions. Since the $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching are the major pathways of N loss from grasslands (Hoekstra *et al*., 2020; van Beek *et al*., 2008; Woodmansee *et al*., 1981) the DNDC-estimated $NO_3^-$ leaching can be considered reliable. However, the use of default soil and meteorological inputs in DNDC remains to be evaluated along with its potential to inform the geographical refinement of N management strategies across more data limited/poor regions (Patil, 2009). Recognising the need for detailed site-specific inputs for the model to generate reliable absolute values, this research aims to identify if DNDC is able to generate reliable variations (relative/between site) of grass yield and N loss across the sites when default inputs are used instead of site-specific information on soil and meteorology.

## 7.2. Methods

### *7.2.1. Site Locations*

The study was performed for three sites, previously used for the experiment in Chapter 6 – a sandy loam soil site, located in Moorepark (MP, 52.2°N 8.3°W), County Cork and a sandy loam soil (JCSL) site and a loam soil (JCL) site located at Johnstown Caste (JC, 52.3°N 6.5°W), County Wexford (Zimmermann *et al*., 2018). Detailed descriptions on soil and meteorological conditions of these sites are provided in Chapter 6 (Experiment 3). These sites were selected on the basis of the available data required to perform the simulations.

### *7.2.2. DNDC Model*

The DNDC (*DeNitrification-DeComposition*) (v9.5) model (Source: http://www.dndc.sr.unh.edu/) was used (Tang *et al*., 2024) in this study. The DNDC model simulates carbon and N dynamics in agricultural soils based on detailed inputs of soil physicochemical properties, meteorology, vegetation type and management practices, for different crop management practices including grassland. It employs six sub-models on soil-climate/thermal-hydraulic flux, decomposition, denitrification, crop-growth, nitrification and fermentation to simulate the processes of mineralisation, leaching, volatilisation, nitrification, denitrification, N uptake and biological N fixation (Cannavo *et al*., 2008; Gilhespy *et al*., 2014; ISEOS, UNH, 2012; Saggar *et al*., 2007). A detailed description of the model can be found in the work by Gilhespy *et al*. (2014) and the model manual (ISEOS, UNH, 2012).

### *7.2.3. Experimental Design*

Across the three selected sites, site-specific DNDC simulations were initially performed with the same parameterisation as Experiment 1 and 2 (Table 7.1) using the ideal high N fertiliser (urea) application regime, derived from the Green Book (Wall and Plunkett (eds.), 2020), for a fixed grazing regime with a stocking rate of 2.36 cows/ha. These regimes were identical to the management input for the high N fertiliser scenario used for the experiment in Chapter 6 (Grazing regime and N fertiliser application according to Green Book (GB) regime: Table 6.2). Details of site-specific inputs for soil, meteorology and crop phenology for each site, are consistent with those used in Chapter 6 (Experiment 3) (Table 7.2). The weather inputs for 2019 were obtained from Met Éireann (n.d.) for each site, as was used in Chapter 6. These simulations are hereafter referred as 'Site-Specific'.

The model was run at each site with the default inputs of the optional soil and meteorological variables (Gilhespy *et al*., 2014), with the exception of crop phenology inputs that were calculated specific to the site (e.g. 'Site-Specific' simulations outlined in Chapter 6); including thermal degree days of maturity based on the temperature (Hart *et al*., 2013; Wingler and Hennessy, 2016) for the year of interest. The default inputs in DNDC include the clay content in soil, WFPS at FC for the soil texture in the field/paddock, N concentration in rainfall, background concentration of $NH_3$ and $CO_2$ in atmosphere and the annual rate of increase in atmospheric $CO_2$ concentration. The inputs for bulk density, generated by the model based on the site-specific soil organic carbon (SOC), were not modified according to the measured site-specific values of BD and were considered as 'Default'. These model simulations are referred to as the 'Default' simulations in the results. The aim of this study was to assess the impact of altering a suite of 'Default' parameters, not commonly available at sites of interest, on variability of estimated grass yield and N loss through $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching across the studied sites when compared to that of 'Site-Specific' simulations.

**Table 7.1:** Default and Modified Inputs for Crop Phenology and Background Atmospheric Conditions

| | **Variables** | **Default** | **Modified** | | **References** |
|---|---|---|---|---|---|
| **Crop Phenology** | **C:N ratio for seed/ leaf/stem** | 35/20/20 | 19/19/19 | | Whitehead *et al.*, 1990 |
| | **C:N ratio for roots** | 30 | 23 | | |
| | **N-fixation index (crop N/N from soil)** | 1.5 | 1 | | ISEOS, UNH, 2012 |
| | **Water demand (g water/g DM)** | 200 | 550 | | Byrne and Kiely, 2008 |
| | **Thermal degree days of Maturity** | 2000 | 3577 (Site MP, year 2019) 3781 (Site JCSL and JCL, year 2019) | | Hart *et al.*, 2013 Wingler and Hennessy, 2016 |
| **Atmospheric Conditions** | | **Default** | **MP** | **JCSL and JCL** | |
| | **Atmospheric N concentration in precipitation (mg N/l or ppm)** | 0 | 0.56 | 1.02 | Jordan, 1997 |
| | **Atmospheric background $NH_3$ concentration µg N/m$^3$** | 0.06 | 2.04 | 2.83 | Doyle *et al.*, 2017 |
| | **Atmospheric background $CO_2$ concentration (ppm)** | 350 | 409.8 | 409.8 | Ullas Krishnan and Jakka, 2022 |
| | **Annual rate of increase Atmospheric background $CO_2$ concentration (ppm)** | 0 | 2.3 | 2.3 | Prasad *et al.*, 2021 |

**Table 7.2:** Default (Shown in brackets besides site-specific inputs) and Site-Specific Inputs for soil

| **Category** | **Sites** | **MP** | **JCSL** | **JCL** | **References** |
|---|---|---|---|---|---|
| Mandatory Site-Specific Soil Inputs | Texture | Sandy loam | Sandy loam | Loam | Franzluebbers, 1999; Gilhespy *et al.*, 2014; Zimmermann *et al.*, 2018 |
| | pH | 5.47 | 5.53 | 5.69 | |
| | SOC (%) | 2.99 | 3.14 | 2.78 | |
| Optional Soil Inputs - Site specific (Default) | BD (g/cm$^{3}$) | 1.205 (1.0405) | 1.11 (1.0226) | 1.27 (1.0668) | |
| | Clay (%) | 13.8 (9) | 13.9 (9) | 14.4 (19) | |
| | WFPS at FC (%) | 61.21 (32) | 53.67 (32) | 70.7 (49) | |
| | WFPS at WP (%) | 30.94 (15) | 25.79 (15) | 38.9 (22) | |

### 7.2.4. *Outcomes and Evaluation Metrics*

Estimated annual grass yield was derived by dividing the sum of DNDC simulated grain, stem and leaf by 0.4 (ISEOS, UNH, 2012). Variation in estimated grass yield, N loss through $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching across the sites, derived under the 'Default' and 'Site-Specific' simulations, were compared using bar charts (Shirato, 2005).

## 7.3. Results

The outcomes of the study show that, for the 'Site-Specific' simulations estimated yield was highest at JCL and lowest at JCSL. This is consistent with the 'Default' simulations where estimated yield was also highest at JCL and lowest at JCSL (Figure 7.1). The estimated annual $NH_3$ volatilisation was highest at JCSL and lowest at MP for 'Site-Specific' simulations, whereas highest at JCSL and lowest at JCL under 'Default' simulations (Figure 7.2). DNDC estimated highest annual $N_2O$ emissions at JCL and lowest at JCSL under 'Site-Specific' simulations, while highest annual $N_2O$ emissions for 'Default' simulations was estimated at JCL and lowest at MP (Figure 7.3). Highest annual $NO_3^-$ leaching for 'Site-Specific' simulations was estimated for JCSL and lowest at JCL, whereas for the 'Default' simulations highest annual $NO_3^-$ leaching was estimated for JCSL and lowest at JCL (Figure 7.4).

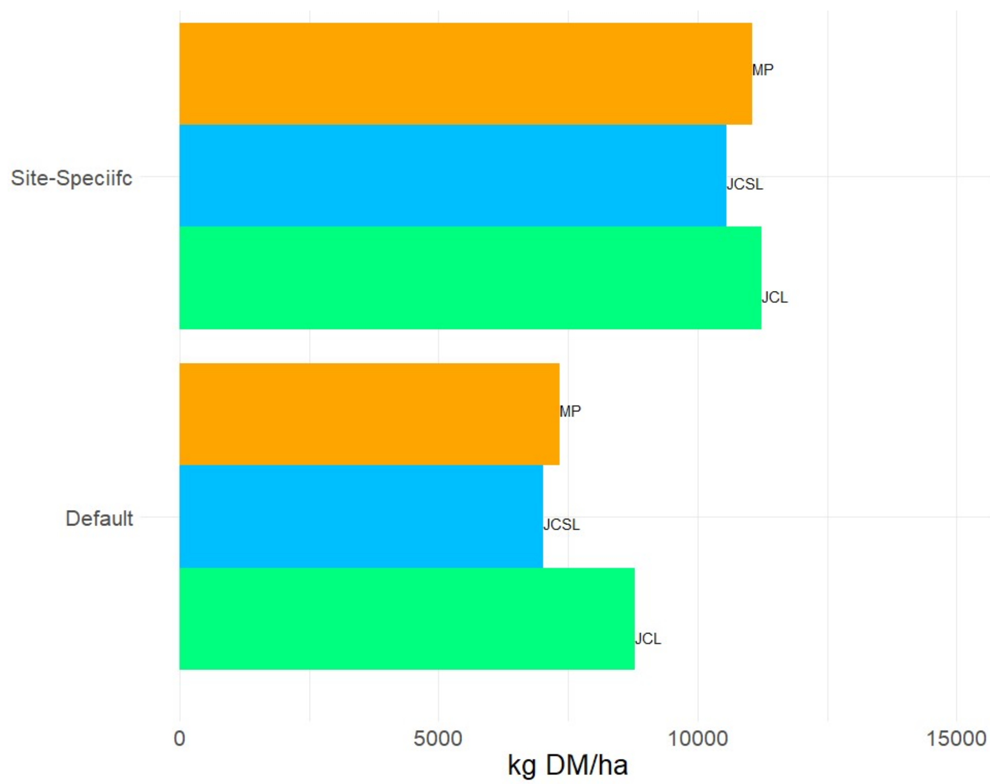


**Figure 7.1**: Variation of estimated annual yield of perennial ryegrass across the studied sites for 'Site-Specific' and 'Default' simulations

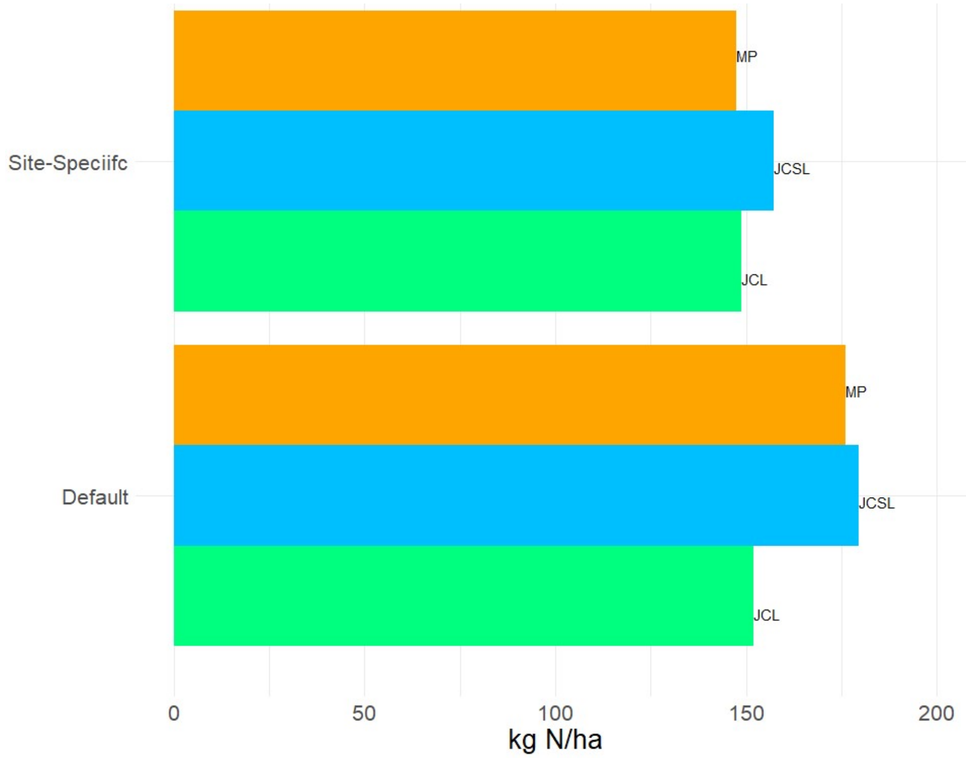


**Figure 7.2**: Variation of estimated annual $NH_3$ volatilisation across sites for 'Site-Specific' and 'Default' simulations

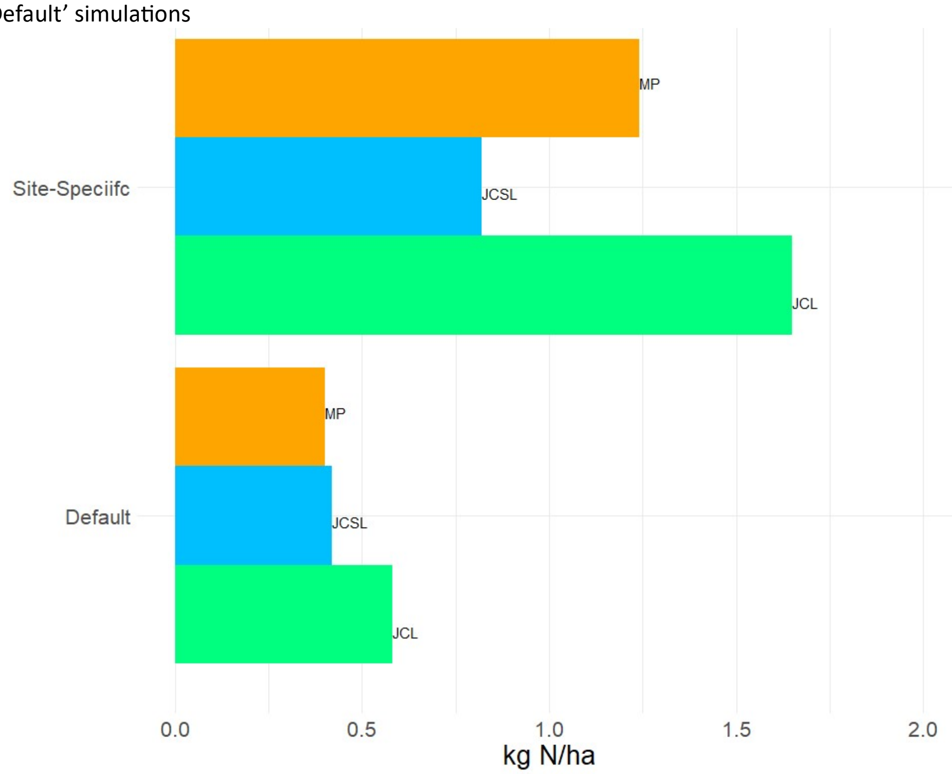


**Figure 7.3**: Variation of estimated annual $N_2O$ emissions across sites for 'Site-Specific' and 'Default' simulations

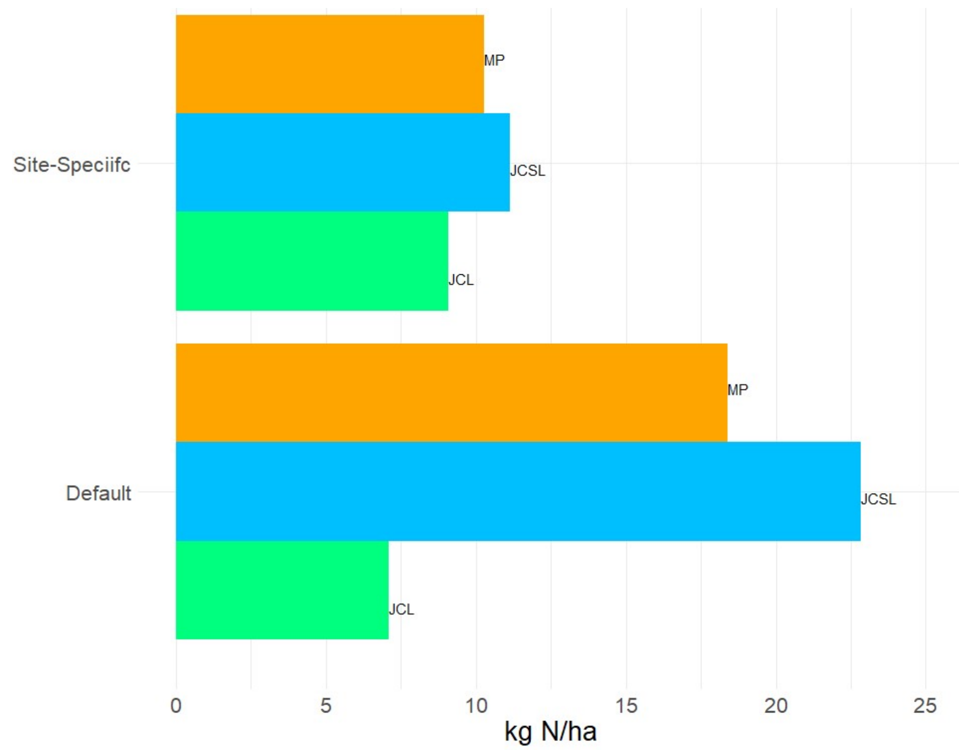


**Figure 7.4**: Variation of estimated annual $NO_3^-$ leaching across sites for 'Site-Specific' and 'Default' simulations

### 7.4. Discussion

In this study, under the parameterisation performed for crop phenology following Chapter 4, DNDC could not produce the same variation obtained for 'Site-Specific' simulations for annual N loss through – $NH_3$ volatilisation and $N_2O$ emissions, under the 'Default' simulations, for the targeted stocking rate and corresponding N input regime based on GB from Experiment 3 – both spatially uniform. However, the variations of 'Site-Specific' and 'Default' simulations were the same for annual yield and $NO_3^-$ leaching. Thus, except for annual yield and $NO_3^-$ leaching, unless relevant data is available for a site, as identified from Chapter 4 and 5, DNDC should not be recommended to inform the decision making process for choosing *right source* of N fertiliser application at a *right time* and at a *right rate* (Bryla, 2020; Fixen, 2020; Sarmah *et al*., 2014; Varallyay, 1994) using default inputs for the optional soil and meteorological variables under the 'Default' simulations (Gilhespy *et al*., 2014). The 'Default' DNDC simulations may be suitable for estimating sites with higher potential yield to improve N use efficiency, thus reducing surplus N that is susceptible to loss, by applying N fertiliser at a *right rate* at a *right place* (Fixen, 2020; Mihailescu *et al*., 2015; Ritchie, 2021). Higher potential yield can also be used as an indicator for higher potential annual $N_2O$ emissions (Chapter 6). Whereas such 'Default' simulations may help to determine susceptibility of a site to $NO_3^-$ leaching in order to identify N requirements and establish good agricultural practices (GAP) to reduce $NO_3^-$ of freshwater and ground water (EPC, 1991).

Employing DNDC to develop management zones nationally or even at a farm scale (Patil, 2009), by identifying potential variation of yield and susceptibility to N loss through different pathways, for more targeted management – would thus also depend on the availability or scope for creating a corresponding dataset required to generate reliable model estimates, considering the diversity of soil and meteorological conditions. Using the 'Default' simulations for zoning based on potential yield can be performed, that can also be an indirect indicator zones of potential $N_2O$ emissions (Chapter 6), even though the variation in estimated $N_2O$ emissions from 'Default' simulations should not be used directly. However, such an indirect approach of using 'Default' simulations for zoning based on $NH_3$ volatilisation will not be applicable as identified from Chapter 6. Zoning by knowing vulnerability of locations to $NO_3^-$ leaching can be particularly helpful to refine N management strategies in line with the goals of the Fifth Nitrates Action Programme 2022-2025 of Ireland and the Nitrates Derogation strategy (Callaghan, 2023; DAFM, 2023b), for which the 'Default' can be useful.

From this study, simulations using the 'Default' suite of optional inputs on soil and meteorological conditions in DNDC, even when parameterised for crop phenology, is not considered suitable for application where the required model input data is not available (Gilhespy *et al*., 2014; Patil, 2009) - if simultaneous estimation of variation of yield and loss of N through $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching is targeted and results are to be used directly. However, it may be suitable in limited circumstances, when annual yield and $NO_3^-$ leaching are the targeted outputs, with the scope of using variation of yield as a proxy for variation of $N_2O$ emissions. However, studies can be performed following Rafique *et al*. (2011a), to optimise the inputs for optional soil and meteorological variables while DNDC is parameterised for phenology of perennial ryegrass, by identifying inputs best fitting yield and fluxes of N loss. Alternatively, emulator modelling (Haraldsson and Sverdrup, 2013; Lim, 2021) is a potential approach that could be employed to develop simplified models using key regulators of yield and N loss, identified from Chapter 4 and 5, that might reduce the need for input data requirement, with scope for more widespread application.

### 7.5. Conclusion

The outcome of the study indicates that DNDC, even when parameterised for crop phenology of perennial ryegrass, does not have the potential to be applied as a robust model, without using site-specific soil and meteorological inputs for - clay content in soil, WFPS at FC for the soil texture in the field/paddock, N concentration in rainfall, atmospheric background concentration of $NH_3$ and $CO_2$ and the annual rate of increase in atmospheric $CO_2$ concentration, to determine the spatial diversity of potential yield, $NH_3$ volatilisation and $N_2O$ emissions from Irish grassland at an annual scale. However, the 'Default' simulations were found to be useful to determine spatial variation of yield and $NO_3^-$ leaching that can support refinement of N management strategies to improve NUE and implementation of GAP to reduce $NO_3^-$ pollution of water, respectively, with potential application of using variation of estimated yield as an indicator of variation of $N_2O$ emissions. Currently the applicability of DNDC is limited to sites where detailed data is available for soil and meteorological conditions, as used and identified from Chapter 4 and 5, to estimate yield and overall N dynamics in Irish grasslands. However, alternative options for robust application of DNDC can be through the creation of relevant database for reliable model simulations.

# 8. Research Discussion and Conclusion

## 8.1. Introduction

Nutrient application through fertilisers for maintaining crop productivity is a common practice in agricultural landscapes across the world. Globally, fertiliser use is increasing, driven by an increased demand for food, associated with a growing population and rise in per capita income (Chaddad, 2016; FAO, 2017; Fukase and Martin, 2020; Rudel *et al*., 2009). The loss of nutrients from agricultural soils can have significant negative impacts on the economy, human health and the environment. Reducing nutrient loss from agriculture while maintaining optimum yield for food security remains a key challenge to delivering more sustainable agriculture (Gregory *et al*., 2002; Tan *et al*., 2005; Tóth *et al*., 2018).

Globally, nitrogen (N) is a commonly supplied plant-nutrient provided through fertiliser into agricultural systems, including managed grasslands (Xu *et al*., 2019). If applied N is surplus to plant requirements, it can be lost through ammonia ($NH_3$) volatilisation, nitrate ($NO_3^-$) leaching and emissions of gases produced through denitrification, such as - nitrous oxide ($N_2O$) (Woodmansee *et al*., 1981) – which results in environmental degradation and economic loss (Cameron *et al*., 2013; UNEP, 2019). The uptake and loss of N from soil is regulated by the supply of N from chemical fertiliser and organic resources, soil aeration and moisture availability and rate of relevant biogeochemical processes, which are dependent on management practices, soil physicochemical properties and weather (Mahmud *et al*., 2021; Masclaux-Daubresse *et al*., 2010).

The prevention of nutrient loss through sustainable management practices, particularly for N, falls under the scope of the United Nations SDGs – 2,3,6,12, 13, 14, 15 (Kanter and Brownlie, 2019). The European Union (EU) has developed the Farm to Fork Strategy as part of the European Green Deal, which aims to reduce nutrient losses by 50 percent by 2030. Objectives of the EU's Common Agricultural Policy (CAP), developed within the framework of the Farm to Fork Strategy, focus on reducing N loss from agriculture especially through $N_2O$ emissions and $NH_3$ volatilisation (EC, 2020; EC, 2023; Wrzaszcz and Prandecki, 2020). Reducing N loss through $NO_3^-$ leaching falls under the EU Nitrates Directives (EPC, 1991). Nationally, the Irish government and relevant agencies have also focused on reducing N loss from agriculture, primarily through decreasing $NH_3$ volatilisation, $NO_3^-$ leaching and $N_2O$ emissions, as part of the Climate Action Plan 2023 and the Fifth Nitrates Action Programme 2022-2025, which are aligned towards achieving the EU goals (DAFM, 2021; DAFM, 2021a; DHLGH and DAFM, 2022; DECC, 2023).

In Ireland, fertiliser application advice is provided to farmers through the Nutrient Management Plan (NMP-Online) which makes use of land parcel data, soil test results and targeted crops – at farm level (Wall and Plunkett (eds.), 2020). At national level, generalised advice is available for targeted crops and potential management strategies are provided through the Green Book (Wall and Plunkett (eds.), 2020). Stocking rate and the maximum N fertiliser application are regulated through the Nitrates Derogation strategy (Callaghan, 2023; Wall and Plunkett, (eds.), 2020). The current challenge with the Irish-NMP Online or national level policies is that they do not account for variations in soil physicochemical properties, meteorology, management and their interactions on grass yield or nitrogen use efficiency (NUE) and N loss (Sharma and Bali, 2017; Wu and Ma, 2015). Thus, there is potential scope to reduce N loss through more geographically focussed N management strategies (e.g. Wu and Ma, 2015). Such geographical refinement of N management plans is closely aligned with the goals of the 4R Nutrient Stewardship (4RNS) to apply nutrients at the *right place* at the *right time* at the *right rate* from the *right source* (Fixen, 2020).

Process-oriented models, that can connect the crop growth to soil, weather and management conditions to simulate N dynamics can facilitate such geographical refinement of N management strategies. This is based on their ability to investigate the potential impact of spatial variability of environment and management on NUE and N loss (Bell *et al*., 2011; Corre *et al*., 2002; Patil, 2009; Schellberg *et al*., 2008; Varallyay, 1994). Such models can assist in identifying the key drivers of crop yield and N loss, which need to be accounted for to inform improved understanding and development of associated policies (Delgarm *et al*., 2018; Kardynska *et al*., 2022; Patil, 2009; Wang *et al*., 2016). The *DeNitrification DeComposition* (DNDC) is one such process-oriented model, which can simulate site-specific crop growth and the dynamics of carbon (C) and N, using site specific inputs on weather, soil and management for different agricultural land use practices (Gilhespy *et al*., 2014). Previous studies performed using DNDC in Ireland have indicated some success in simulating C and N dynamics for Irish grasslands. However, previous studies also identified several limitations with using DNDC, particularly for simulating N-dynamics, including poorer model performance under low N-input scenarios (<140kg N/ha), high sensitivity to soil organic carbon (SOC), etc. (e.g. Abdalla *et al*., 2009; Abdalla *et al*., 2011; Khalil *et al*., 2016; Li *et al*., 2011; Rafique *et al*., 2011a; Zimmermann *et al*., 2018). A gap in the existing research was also identified with regards to DNDC, specifically the explicit parameterisation and validation of the model's performance to estimate yield of the dominant grass species in Ireland - perennial ryegrass (O'Donovan *et al*., 2021), essential to reliably simulating the associated N dynamics. Yield is a key indicator of N uptake and its reliable estimation is important for the estimation of surplus N, that ultimately regulates the estimation of N loss in different forms (Gilhespy *et al*., 2014; Hanrahan *et al*., 2017; Nakagawa *et al*., 2008; O'Donovan *et al*., 2021; Uzoma *et al*., 2015; Zhang *et al*., 2015). A second challenge is that the model is site specific, but the spatial resolution of the environmental inputs required to reliably simulate grass growth and N loss by DNDC are typically obtained from more generalised data – not necessarily on data obtained at the site. This is an important criterion to adjust the input details based on model focus, to maximise use of available data resources or to develop relevant database – to improve the scope of applicability of DNDC in a more robust way (Byrne and Kiely, 2008; Gilhespy *et al*., 2014; Haraldsson and Sverdrup, 2013; Patil *et al*., 2009).

For optimal performance to estimate crop yield and N loss, primarily through – $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching, DNDC requires site-specific inputs of soil physicochemical properties including texture, clay, bulk density (BD), soil organic carbon (SOC) and pH, and may also require more detailed site-specific inputs including water filled pore spaces (WFPS) at field capacity (FC) and wilting point (WP) (Gilhespy *et al*., 2014; Kröbel *et al*., 2011; Li *et al*., 2014; Nakagawa *et al*., 2008; Uzoma *et al*., 2015). DNDC also requires inputs on daily weather records and management details including the type, rate and date of fertiliser application and grazing regime. Besides there is option to include more site-specific details as inputs for DNDC simulations replacing the default ones, such as - site specific background information on atmospheric inputs like atmospheric concentration of $NH_3$ and carbon dioxide ($CO_2$), N concentration in rainfall, rate of annual increase in atmospheric $CO_2$ concentration etc. (Gilhespy *et al*., 2014). Further information on the required and optional site-specific inputs can be found in the guidelines by ISEOS, UNH (2012) and the work by Gilhespy *et al*. (2014).

The potential impact of implementing the current spatially uniform N application recommendations under spatially diverse soil and weather conditions can be explored using DNDC simulations, if the performance of the model is found to be reliable through validation - and the key inputs regulating the reliability of model performance are known. Such studies can highlight the gaps and scope for geographical refinement of such policies for improved NUE (Giltrap *et al*., 2010; Patil, 2009; Wall and Plunkett (eds.), 2020). However, there remains a challenge - the requirement for detailed site-specific input data as well as data required for model validation, thereby limiting the application of the model to a small number of sites where such information is available. To address this, we sought to identify the minimum site-specific inputs required for the model to generate reliable information that could support policy implementation. This would help to underpin a relevant database focused on collecting the minimum suite of site-specific variable information depending on the targeted scale of application of DNDC. Another option can be developing a simplified model that makes assumptions on complex biogeochemical processes associated with N dynamics, accounting for the key variables – identified through analysing sensitivity of targeted output through sensitivity analysis (Kardynska *et al*., 2022; Sweetapple *et al*., 2014; Wang *et al*., 2016) that regulate N use efficiency by grass in the Irish context. This would also reduce the details for input data required at a site-specific level for decision making on sustainable N management (Byrne and Kiely, 2008; Giltrap *et al*., 2010; Haraldsson and Sverdrup, 2013; Patil, 2009).

This study analyses the potential scope of producing reliable DNDC simulations, with parameterisation for crop phenology and local atmospheric conditions. The use of the simulated outcomes for identifying the key regulators of grass yield and N loss at field level and the variables that explain the variation of the yield and N loss in different forms across the studied site, that need be accounted for towards geographical refinement of N management strategies - was investigated (Kardynska *et al*., 2022; Wang *et al*., 2016). Further, the impact of data availability (Gilhespy *et al*., 2014; Haraldsson and Sverdrup, 2013; Patil, 2009; Shirato, 2005), as site versus generalised (soil and management) and as default (optional soil and meteorology variables) versus site-specific, impact on the model outcomes was explored. The scope of future research and developing simplified modelling for sustainable N management in Irish grasslands has also been discussed. The work represents a potential research framework (Figure 8.1) for using DNDC to spatialise N management advice for Irish grasslands. However, the framework is not limited to a particular model/crop/site/nutrient but can be replicated globally and adapted locally depending on the targeted crop and management practices, data availability and the data requirements for the model.

## 8.2. Key findings of the study

The outcomes of this study highlight the scope for using the DNDC model to support more geographically refined N management strategies for Irish grasslands managed under dairy farming. From a modelling point of view, the study identified the optimum spatial and temporal scale of reliable model performance, the spatial resolution of required detailing of model input and scope for robust application. The study also identified the key regulators of variation of yield and N loss. Besides, the minimum site-specific input data for a robust application of the model was identified. The key findings of the study are outlined below.

From Experiment 1:

- DNDC, when parameterised for phenology of perennial ryegrass and background atmospheric conditions can reliably estimate growth rate and annual yield of perennial ryegrass dominated paddock for
    - paddock level simulations with paddock specific soil and management inputs
    - farm level simulations with ideal management regime based on stocking rate specific to the farm and representative soil inputs specific to soil zones in the farm
- Both paddock level and farm level simulations were considered to be more reliable when site specific soil inputs were replaced with the lead soil information for the location from the Irish Soil Information System – indicating that generalisation of soil inputs is possible
- Annual yield of perennial ryegrass is
    - sensitive to annual rainfall and soil textural class
    - potentially sensitive to
        - soil pH, bulk density (BD), soil organic carbon (SOC), clay content
        - average maximum and minimum daily temperature
        - average daily grazing hours, stocking rate and total N fertilizer applied annually

From Experiment 2:

- Inclusion of site-specific information on waterfilled pore spaces (WFPS) at field capacity (FC) and wilting point (WP) in the suite of site-specific model inputs is necessary for the reliable annual estimation of $N_2O$ emissions and $NH_3$ volatilisation on an annual basis
- The performance of reliably estimating
    - annual yield and annual $NH_3$ volatilisation using DNDC is not significantly sensitive to fertiliser type
    - the annual $N_2O$ emissions for urea treated paddocks but not for CAN treated paddocks
- Under the parameterisation of DNDC used in this study the model is suitable for the estimation of perennial ryegrass yield in permanent paddocks but not for reseeded paddocks

- DNDC estimated daily $N_2O$ emissions and $NH_3$ volatilisation correlates poorly with respect to corresponding measured values, even when site specific inputs on WFPS at FC and WP are used, even though the error in magnitude is low – thus the model is not considered suitable for decision making based on daily weather forecast
- DNDC performs more reliably in estimating $N_2O$ emissions and $NH_3$ volatilisation for the peak emissions period after fertiliser application than the entire measurement period after fertiliser application – thus confirming the model is not suitable for estimation of the background emissions or the emissions from low N input scenarios
- DNDC estimated daily soil temperature and WFPS show similar covariation when compared to corresponding available measurements, but the magnitude of daily WFPS is poor even when site-specific inputs on WFPS at FC and WP is used
- The annual emissions of $N_2O$ are:
    - sensitive to
        - initial pH and SOC of soil
        - BD of soil (depending on textural class of soil)
        - annual rainfall
        - average annual maximum and minimum temperature (depending on textural class of soil)
        - annual application of N fertiliser
    - potentially sensitive to
        - clay content
- Annual volatilisation of $NH_3$ is:
    - sensitive to annual N fertiliser application
    - potentially sensitive to
        - initial pH, BD, SOC and clay content of soil
        - annual rainfall and average annual maximum and minimum temperature

From Experiment 3 it was found that across the studied sites:

- the key regulators of variation of both yield and $N_2O$ emissions as well as of their reduction under reduced N fertiliser application are - soil sand content, soil bulk density (BD), soil organic carbon (SOC), WFPS at FC and WP, plant available water
- the key regulators of variation of $NH_3$ volatilisation as well as of its reduction under reduced N fertiliser application are - annual rainfall and average annual temperature

- significance of key environmental regulators of $NO_3^-$ leaching can vary depending on rate of N fertiliser application
- significance of key environmental regulators of reduction of $NO_3^-$ leaching under reduction of N fertiliser application are - soil sand content, soil clay content, soil pH, annual rainfall, average annual temperature

From Experiment 4 it was found that:

under the parameterisation used in this study for crop phenology, the model generates outputs using default values for optional soil and meteorological input variables ('Default' simulations)

- that have a similar spatial variation in the annual yield of perennial ryegrass and in the annual $NO_3^-$ leaching to those obtained from the more detailed 'Site-Specific' simulations performed following Experiment 1 and 2
- that do not have a similar spatial variation in the annual $N_2O$ emissions and $NH_3$ volatilisation to those obtained from the more detailed 'Site-Specific' simulations performed following Experiment 1 and 2

### *8.2.1. Answers to the research questions*

*<u>Question 1: Can a process-oriented modelling approach be reliably used for exploring spatial and temporal variations in crop response to management?</u>*

To improve nutrient use efficiency and reduce the surplus nutrients, that are susceptible to loss, it is necessary to determine the optimum nutrient requirements of a crop. This is also relevant for increasing the N use efficiency (NUE) and reducing the potential loss of N from grassland soils. Estimating potential yield for spatially diverse landscape conditions and knowing grass growth phases can be helpful for determining site-specific N fertiliser requirements in terms of rate and timing of applications to achieve a targeted yield through developing management zones at field level within a farm or at national scale (e.g. Colaço *et al*, 2024; Franzen *et al*., 2002; Patil, 2009; Sharma and Bali, 2017; Wu and Ma, 2015). Using process-oriented models that can replicate the processes of N biogeochemistry, accounting for soil physicochemical properties, meteorological factors and management conditions, can facilitate the identification of the key drivers and factors regulating the response of grass growth to management, influenced by environmental conditions. However, as with all models, the performance can vary depending on the spatial and temporal scale of analysis (Bell *et al*., 2011; Giltrap *et al*., 2010; Patil, 2009; Shan *et al*., 2021; Zimmermann *et al*., 2018).

Here we explored the potential for using the DNDC model (version 9.5) (Source: http://www.dndc.sr.unh.edu/) to estimate annual grass yield and grass growth rate at paddock and farm level (Tang *et al*., 2024). From the results of Experiment 1 (Chapter 4) and 2 (Chapter 5) it can be concluded that DNDC can reliably estimate the temporal patterns of the growth rate and the annual yield of perennial ryegrass, at both paddock and farm level, for intensively managed permanent grasslands. Parameterisation of the phenological inputs for the selected crop type, perennial ryegrass, is required to reliably estimate yield and grass growth rate. The model performed well for both site-specific soils inputs on texture, clay content, bulk density (BD), soil organic carbon (SOC), pH and corresponding, and more generalised inputs from Irish Soil Information System (O'Sullivan *et al*., 2018). Site-specific inputs for WFPS at field capacity FC and WP were optional.

In Experiment 1 (Chapter 4), when default inputs on crop phenology and atmospheric conditions were employed at farm level, the model was able to estimate the temporal pattern of grass growth rate over the course of the year but was less reliable in the estimation of the magnitude of growth at a daily and annual scale. This was reflected in terms of the metrics of mean absolute error (MAE) and root mean square error (RMSE) as well as at annual scale in terms absolute relative deviation (|RD %|). The performance significantly improved at both paddock and farm level at both daily and annual scale, when the crop phenological parameters (biomass fraction, biomass C:N ratio, thermal degree days, water demand, N fixation index) were modified for perennial ryegrass, and meteorological parameters (atmospheric concentration of ammonia ($NH_3$) and carbon dioxide ($CO_2$), concentration of N in rainfall and annual rate of increase in atmospheric concentration of $CO_2$) were set according to local/regional conditions (Gilhespy *et al*., 2014). The model's ability to reliably estimate grass yield and growth rate was evident even when soil inputs specific to farm or paddock were replaced with corresponding information on series leader soil from Irish Soil Information System (Irish SIS) database. This indicated that there might be scope for application of the DNDC with more generalised soil inputs than site-specific ones. However, further studies are required to explore the scope for using of the Irish SIS database to simulate DNDC reliably for other grassland locations across Ireland (Haraldsson and Sverdrup, 2013; Patil, 2009). The performance of farm-specific simulations of DNDC (based on the weighted average of grass growth rate and yield across individual soil types within farm) was found to be more accurate than the paddock-specific simulations, irrespective of specificity of soil and management inputs. This indicates that DNDC can reliably estimate grass growth rate and yield for a farm using more generalised soil information (Franzen *et al*., 2002; Patil, 2009).

In Experiment 2 (Chapter 5) it was found that the parameterisations performed in Experiment 1 (Chapter 4) were suitable for annual grass yield estimation in permanent paddocks but less suitable for reseeded paddocks, in terms of |RD %|, irrespective of inclusion of site-specific WFPS at FC and WP as inputs. A possible explanation for this is that reseeded paddocks generally show higher grass yield than permanent paddocks under similar treatments and conditions (Creighton *et al*., 2016). Thus, the model's applicability is restricted to permanent paddocks under the parameterisation used in Experiment 1 (Chapter 4). However, future research could focus on the model's performance when modification of crop phenology parameters is performed according to the phenology of perennial ryegrass in reseeded paddocks. Abdalla *et al*. (2009) found that the performance of DNDC was not reliable for low to medium N input scenario (<140kg N/ha/year). In our study, the experiments performed were limited to intensively managed paddocks (>140kg N/ha/year). Thus, outcomes of this study are more relevant for intensively managed paddocks and may not be suitable for paddocks receiving annual N input below 140kg N/ha. However, the model's performance to estimate yield was found to be reliable for both grazed paddocks in Experiment 1 (Chapter 4) and ungrazed Paddocks in Experiment 2 (Chapter 5), both intensively managed.

*<u>Question 2: Can a process-oriented modelling approach be reliably used for exploring spatial and temporal diversity of major pathways of N loss from intensively managed grasslands under local conditions of soil, climate and weather in Irish dairy farms?</u>*

As highlighted in Experiment 1 (Chapter 4) and 2 (Chapter 5), the grass growth estimation by DNDC was reliably simulated for permanent paddocks, and so it can be assumed that the surplus N determined by DNDC is reliable (Zhang *et al*., 2015). In terms of |RD %| (Abdalla *et al*., 2020; Babu *et al*., 2006; Cai *et al*., 2003), in Experiment 2 (Chapter 5) it was found that, when parameterised for crop phenology of perennial ryegrass and provided with the input information on farm's soil texture-specific inputs on WFPS at FC and WP along with the site-specific inputs on - soil texture, BD, SOC, pH and clay, DNDC can more reliably estimate N loss, specifically annual $NH_3$ volatilisation. Whereas for reliable estimates of annual $N_2O$ emissions, site-specific inputs on WFPS at FC and WP are a requirement. This limits the potential scope for applying DNDC to estimate N dynamics when yield and $NH_3$ are not the only targeted outputs. The reliability of annual $NH_3$ volatilisation estimation was not significantly affected by fertiliser type, whereas the estimation of annual $N_2O$ emissions were sensitive to fertiliser type. For annual estimation of $N_2O$ emissions it was found suitable for the urea treated site but not for the CAN fertiliser treated site, even when using site-specific input on WFPS at FC and WP. This also limits the scope of using DNDC, even when information on site-specific WFPS at FC and WP is available, for sites that are treated by N fertilisers other than urea, especially for CAN. The reliable estimate of annual $NH_3$ volatilisation was for the reseeded paddocks in Experiment 2 (Chapter 5), where the reliability of estimated yield was relatively poorer. This potentially indicates that the estimated loss of N through $NH_3$ volatilisation from surface applied N fertilisers is less dependent on N uptake in field condition. This was similar to the observation by Bussink (1994), who had shown that $NH_3$ volatilisation in grasslands is mainly dependent on the rate of N supply from fertiliser or animal excreta. Bussink (1994) was unable to find a clear relation between herbage yield and $NH_3$ volatilisation and gave the indication of potential masking effect of other drivers of $NH_3$ volatilisation. However, it may not be applicable for estimation of $N_2O$ emissions from reseeded paddocks, as $N_2O$ emissions are highly dependent on surplus N after uptake (Smith *et al*., 2012).

From experiment 2, DNDC did not produce reliable estimates of the temporal pattern of $NH_3$ volatilisation and $N_2O$ emissions at daily scale. Model performance was poor even when site-specific inputs of WFPS at FC and WP were used; likely driven by temporally incoherent estimation of peaks (Yadav and Wang, 2021). However, the errors in estimated daily $NH_3$ volatilisation and $N_2O$ emissions, seen with site-specific inputs of WFPS at FC and WP, were lower in terms of RMSE (Abdalla *et al*., 2011). For daily $N_2O$ emissions, the RMSE of DNDC estimations were lower than the existing reports on studies performed using DNDC Irish grassland that were reviewed during this research (Abdalla *et al*., 2010; Khalil *et al*. 2016; Zimmermann *et al*., 2018). An improvement from the estimations of daily $NH_3$ volatilisation was also seen when compared to results from a similar study performed on spring barley and spring wheat fields by Dutta *et al*. (2016). It also aligns with the annual reliable estimations of $NH_3$ volatilisation and $N_2O$ emissions. Although annual $NO_3^-$ leaching estimated by DNDC was not validated in this study, it was assumed to be reliable at annual scale for permanent paddocks when soil inputs are provided according to Experiment 2 (Chapter 5), since the estimated annual yield (that determines the surplus N) and annual estimated N loss through $NH_3$ volatilisation and $N_2O$ emissions were reliable, that are two of the major three N loss pathways in grasslands (Hoekstra *et al*., 2020; van Beek *et al*., 2008; Woodmansee *et al*., 1981).

*<u>Question 3: What are the key regulators of grass growth and N loss in intensively managed grasslands under Irish dairy farming and how they may support geographical refinement of N management?</u>*

From the OFAT sensitivity test at paddock level in Experiment 1 (Chapter 4) (Kardynska *et al*., 2022; Wang *et al*., 2016) it was found that the annual yield of perennial ryegrass at site-specific level is most sensitive to annual rainfall and soil texture. The experiment also showed annual yield to be sensitive to soil variables - pH, SOC, BD, clay content, to weather variables - average daily maximum and minimum temperature and to the management variables – average daily grazing hours, stocking rate and total N fertiliser applied. From the OFAT sensitivity test at paddock scale in Experiment 2 (Chapter 5) (Kardynska *et al*., 2022; Wang *et al*., 2016) it was found that the annual $N_2O$ emissions at site-specific level are sensitive to soil pH, SOC, BD, annual N fertiliser application, annual rainfall and average air temperature and potentially sensitive to soil clay content. Whereas the annual $NH_3$ volatilisation was found to be sensitive to annual N fertiliser application and potentially sensitive to all of the remaining variables tested for in the same experiment. The outcomes indicate that for paddock level sustainable N management to achieve optimum yield of perennial ryegrass and reduced N loss, the relevant variables that need to be accounted for are - soil texture, clay content, SOC, BD, pH and weather variables (like average daily temperature and average annual rainfall) for their interaction with N application and grazing management. To determine the *right rate* of N fertiliser application at the *right place* to meet 4RNS objectives for a farm through paddock level management based on estimation of their potential impact on the N dynamics, these variables can be particularly important (Fixen, 2020; Kardynska *et al*., 2022; Patil, 2019; Sharma and Bali, 2017; Wu and Ma, 2015).

In Experiment 3 (Chapter 6), the basis for management zones to be developed nationally or within farm for more targeted N management, based on indicator variables (e.g. sand), was established (Nabati *et al*., 2020; Patil, 2009). In Experiment 3 it was found that sand content, was a common indicator and suitable for national level zoning (Nabati *et al*., 2020; Patil, 2009) for yield of perennial ryegrass and annual N loss through $N_2O$ emissions. Whereas it was also shown that the yield of perennial ryegrass itself is also an indicator of susceptibility of surplus N to $N_2O$ emissions loss, and vice versa. Other relevant indicators of both yield and $N_2O$ emissions were – soil BD, SOC, WFPS at FC and WP and plant available water. Among them BD and SOC, in combination due to their interdependence (Fornara and Higgins, 2022; Libohova *et al*., 2018; Minasny and McBratney, 2017), are more suitable to develop management zones due to their potential stabilisation if the land use practice was consistent for a time period that is long enough to reach their equilibrium (Bauer and Black, 1981; Evans et al., 2012). While for $NH_3$ volatilisation average annual temperature and annual rainfall were identified to be suitable indictors, the option of developing management zones based on long term climate averages that might not be suitable to represent annual weather variations remains a challenge

(Krishnamurthy, 2019; Patil, 2009; Walsh, 2012). It was seen from Experiment 3 (Chapter 6) that significance of environmental variables as indicators of $NO_3^-$ leaching may change depending on the rate of N fertiliser application. Thus, for each N fertiliser application strategy there may be a need to identify unique set of indicators to determine vulnerability of a site to $NO_3^-$ leaching.

It was found that N management strategies, even if tailored for zone-specific implementation, nationally or at farm level, could offer greater geographical refinement for sustainability by considering the impact of key regulators of N dynamics and efficiency of implemented strategies. Such refinement for improved N management strategies can reduce the uncertainties of downscaled application of national level strategies, while improved yield and reduced N loss through management at higher spatial resolution locally, can in turn shift towards meeting the national targets at an upscaled effect (Milne *et al*., 2020; Schipanski *et al*., 2009; Shirmohammadi *et al*., 2008). For effective strategies to maintain yield of perennial ryegrass and reducing $N_2O$ emissions sustainably, such variables of concern, as determined in Experiment 3 (Chapter 6), were - soil sand content, soil BD, SOC, WFPS at FC and WP and plant available water. For reduction of $NH_3$ volatilisation accounting for annual rainfall and average annual temperature was found to be important. The reduction of $NO_3^-$ leaching was found to be associated with - soil sand and clay content, soil pH, annual rainfall and average annual temperature. Among these factors soil texture, BD and SOC (that represents by soil organic matter) reduces the requirement of accountability to WFPS at FC and WP and thus the plant available water, being their key regulators (Carter, 2002; Pragg *et al*., 2024; Pribyl, 2010). In summary, soil sand and clay content, soil BD, SOC, pH, annual rainfall and average annual temperature were the key variables regulating the effect of a reduction in rate of N fertiliser application on yield and N loss. Such variables can be particularly important to accounted for to improve the efficiency of implemented strategies to maintain yield and reduce N loss depending on local conditions (Schipanski *et al*., 2009; Shirmohammadi *et al*., 2008; Zhang *et al*., 2020a).

*Question 4: Is there potential to improve the robustness of the modelling approach?*

The robustness of DNDC can be described as the applicability of the DNDC model to reliably estimate grass yield and N loss for spatially diverse sites with minimum requirements of parameterisation and site-specific input data (Haraldsson and Sverdrup, 2013; Patil, 2009). It was observed from Experiment 4 (Chapter 7) that DNDC - parameterised for phenology of perennial ryegrass, is able to produce the same spatial variation for annual yield and $NO_3^-$ leaching using default inputs for optional input variables for soil and meteorological conditions

(‘Default’ simulations) (Gilhespy *et al*., 2014) when compared to simulations that are more ‘Site-Specific’ following Experiment 1 (Chapter 4) and 2 (Chapter 5). These conditions are applicable to simulate the scenario of a management regime to estimate yield and $NO_3^-$ leaching where limited data is available on the optional inputs on soil and meteorological conditions (Gilhespy *et al*., 2014). Thus, ‘Default’ simulations of DNDC, with phenological parameterisation as used in this study, can be directly employed to estimate variation of yield and $NO_3^-$ leaching across sites that can help inform and improve N use efficiency to reduce N loss (Bryla, 2020; Fixen, 2020) and determining potential vulnerable sites according to the EU Nitrates Directives or for determining requirement of action plans (EPC, 1991), respectively. However, the model failed to produce the same spatial variations, as obtained from ‘Site-Specific’ simulations, for $N_2O$ emissions and $NH_3$ volatilisation by ‘Default’ simulations. Hence, DNDC is directly not suitable for robust application to estimate vulnerability of sites to $N_2O$ emissions and $NH_3$ volatilisation. However, the simulated variation of yield under ‘Default’ simulations can be an indicator of variation of $N_2O$ emissions, as seen from Experiment 3 (Chapter 6), which may inform the requirement to consider applicable measures to reduce $N_2O$ emissions.

### *8.2.2. Policy relevance of the findings*

Overall, we found from these experiments that the DNDC model, when suitably parameterised (e.g. phenology of perennial ryegrass; meteorological conditions etc), could be used as a potential tool to estimate grass yield under intensively managed paddocks and farms under Irish dairy farming (Giltrap *et al*., 2010; Patil, 2009). Thus, DNDC can be used to geographically refine the N management strategies for improved NUE in Irish grasslands from farm to paddock level through exploring the key drivers of growth of perennial ryegrass (Callaghan, 2023; DAFM, 2023a; Milne *et al*., 2020; Nabati *et al*., 2020; Wall and Plunkett (eds.), 2020; Kardynska *et al*., 2022). It can be useful to determine phases of grass growth and making decisions on the *right time* and the *right rate* of N fertiliser application for meeting the requirement of grass growth according to the 4RNS objectives, but its success with forecasted weather conditions needs to be tested prior to that (Fixen, 2020; McDonnell *et al*.,2019). It might also help to develop management zones based on the estimation of potential yield or its drivers across representative farms, or for paddocks within a farm, that may further support the requirements to meet the 4RNS objectives of identifying the *right place* and *right rate* of N fertiliser application (Bryla, 2020; Fixen, 2020; Patil, 2009). Similar to previous field-based experiments (Harty *et al*., 2017), the DNDC model in both Experiment 1 (Chapter 4) and 2 (Chapter 5) did not show a significant impact of fertiliser type on estimated yield of perennial ryegrass. Thus, it enables the model to simulate potential yield under diverse fertiliser types to determine the *right rate* of N fertiliser application for meeting the demand of grass, especially for the commonly used N fertilisers in Ireland- urea and calcium ammonium nitrate (CAN) (Fixen, 2020; Gebremichael *et al*., 2022). As the impact of using site-specific inputs on WFPS at FC and WP on estimated yield and growth rate of perennial ryegrass was not significant, the DNDC model can be used reliably to estimate grass growth rate and yield even for sites where information on WFPS at FC and WP is not available, even though WFPS at FC and WP regulate the water stress and N uptake simulation by DNDC (Kröbel *et al*., 2011; Li *et al*., 2014).

The outcomes show that DNDC, parameterised for phenology of perennial ryegrass and provided with inputs on the set of variables according to Experiment 2 (Chapter 5), including site-specific WFPS at FC and WP, has limited applicability for determining the *right time* of N fertiliser application at a daily scale to meet 4RNS objectives through considering the susceptibility of N loss driven by daily weather conditions (Fixen, 2020; McDonnell *et al*., 2019). Future research can be performed for improving its capacity to timely estimate peaks and drops of N loss at daily scale. On the other hand, DNDC simulations can be reliably used for simulating scenarios of annual grass yield, annual N loss through $NH_3$ volatilisation and $N_2O$ emissions for permanent grasslands dominated by perennial ryegrass (Giltrap *et al*., 2010) – under the use of parameterisation and inputs identified from Experiment 1 (Chapter 4) and 2 (Chapter 5). This implies scope to apply DNDC to estimate potential N loss at paddock scale, which can help in within-farm, field level assessment to achieve the 4RNS objectives by classifying susceptible places of higher N loss through $NH_3$ volatilisation and $N_2O$ emissions as management zones that would help in determining *right place* of N fertiliser application, coupled with *right rate* determined from the potential yield (Fixen, 2020; Franzen *et al*., 2002; Patil, 2009; Rattalino Edreira *et al*., 2017). Identifying the potential N loss at field scale can help to determine the *right product* and *right time* of N fertiliser application based on empirical evidence of weather driven N loss through $NH_3$ volatilisation and $N_2O$ emissions, that could not be identified directly from DNDC simulations at daily scale (Craswell, 1978; Di and Cameron, 2002; Fixen, 2020; Hargrove, 1988; Hess *et al*., 2020; Schwenke and Haigh, 2016).

At national scale, the DNDC model can be applied to estimate the susceptibility of grassland soils to N loss and potential yield under diverse environmental conditions and various policy scenarios and to identify potential drivers at a national scale, when suitable parameterisation is performed and data is available for identified key input variables. This is directly relevant for the development of national level management zones as well as to test the impact of potential N management policy (national) to progress towards geographical refinement in comparison to uniform N fertiliser application to reduce the associated uncertainties (Franzen *et al*., 2002; Milne *et al*., 2020; Rattalino Edreira *et al*., 2017; Shirmohammadi *et al*., 2008; van Wart *et al*., 2013). The identification of national management zones and within zone variability of N loss can help in the geographical refinement of national level policies to meet the 4RNS objectives and improving NUE through determining the *right place* of N fertiliser application at *right time* and at a *right rate* from a *right source* (Colaço *et al*, 2024; Fixen, 2020; Patil, 2009; Sharma and Bali, 2017; Wu and Ma, 2015). Zoning at field level can also support farm level sustainable management options as an improvement from the currently aspatial NMP-Online (Patil, 2009; Wall and Plunkett (eds.), 2020). Besides supporting the endeavour to adapt 4RNS for sustainable N management based on estimated impact of an applied strategy, such zoning, whether at national level or within farm, can be utilised for monitoring the actual impact of a management plan on yield and N loss, particularly focusing on vulnerability of a site to specific forms of N loss (EPC, 1991; IPCC, 2000; Patil, 2009).

Based on the findings from Experiment 4, when the model is parameterised for the correct phenology (e.g. perennial ryegrass) it has potential to be effectively used for geographical refinement of N management strategies, allowing for a comparison between sites in terms of potential yield and $NO_3^-$ leaching, using the 'Default' inputs for soil and atmospheric conditions. Thus, DNDC is suitable for a wider application to estimate potential yield and $NO_3^-$ leaching, to develop corresponding management zones or relative susceptibility of sites to $NO_3^-$ leaching for focused N management, overriding the limitation posed by data availability for model parameterisation (Higgins *et al*., 2017; Patil, 2009; Schellberg *et al*., 2008). The model could contribute to identifying the relative vulnerability of different sites to $NO_3^-$ leaching to establish good agricultural practices (GAP) (EPC, 1991). At the same time DNDC can support zoning or decision making based on identifying $N_2O$ emissions inventories from grassland management, using estimated yield as an indicator, according to Tier 3 approach of IPCC (Intergovernmental Panel on Climate Change) at national level (Buendia *et al*., 2019; IPCC, 2000), in such sites.

Based on the current data availability in Ireland, in combination with findings from empirical studies, there is scope to use the findings from this study to inform N management strategies in Ireland, through the development of management zones (e.g. timing, rate and form of N fertiliser application) and supported by monitoring, to meet the 4RNS objectives (Fixen, 2020).

A potential strategy for 4RNS that can be explored is described below. There is scope of further refinement of such strategies at locations where the required site-specific measured datasets are available. Currently available datasets for Ireland and their potential use for 4RNS, aimed at sustainable N management, can be performed by:

- National level zoning to refine national guidelines and policies (Nabati *et al*., 2020; Patil, 2009), directed to meet targeted productivity (O'Donovan *et al*., 2021) by improving N use efficiency while reducing N loss, like - Green Book, Climate Action Plan 2023 and the Fifth Nitrates Action Programme 2022-2025 (DECC, 2023; DHLGH and DAFM, 2022; Wall and Plunkett, (eds.), 2020), focusing on susceptibility of a particular landscape to N loss and reducing overapplication of N fertiliser (Ritchie, 2021), using –
    - Measured Sand, SOC, BD data for sites across Ireland from Irish Soil Information System database (O'Sullivan *et al*., 2018) as indicators of potential grass yield and $N_2O$ emissions
    - Climatic zones using national database on annual rainfall and average annual temperature across Ireland (e.g. Curley *et al*., 2023; Walsh, 2012) as indicators of potential $NH_3$ volatilisation

\- and employing methods like clustering for landscape classification (e.g. Carlier et al., 2021)

- A similar approach can be applied for landscape classification to identify susceptibility of $NO_3^-$ leaching. However, the indicator variables need to be identified for each policy to be implemented and those would be valid for the duration of the applied policy. This may either enable the existing datasets (e.g. Curley *et al*., 2023; O'Sullivan *et al*., 2018; Walsh, 2012) to be useful for developing management zones (e.g. Nabati *et al*., 2020; Patil, 2009) or may require the development of additional databases/new measurements depending on the identified indicator. However, as shown in this study, DNDC can be useful to identify such indicators by comparing the variation of estimated $NO_3^-$ leaching with variation of environmental factors under a targeted N management strategy.
- While such soil and climate maps can be used individually to identify potential yield and N loss in different forms for a site based on its position within a landscape, intersection of soil and climate can also be used to develop landscape classification maps at a higher resolution, combining the overall potential impact of management on N dynamics (e.g.

Black, et al., 2008), to be used for refinement of the N management plans for at a higher resolution.

- National classification of landscape based on the potential outcomes of N dynamics on yield and different forms of N loss would help in –
    - Finding the balance between targeted yield and susceptibility to specific forms of N loss based on soil and climate conditions, to determine the optimum rate of N fertiliser application rather than only focusing on stocking rate, feed requirement and N from excreta (e.g. DHLGH and DAFM, 2022; Wall and Plunkett, (eds.), 2020). Sites identified to be less susceptible to N loss may be considered to have a higher rate of N fertiliser application, while reducing the upper limit of N fertiliser application in sites with higher vulnerability. This would reduce the N loss at a targeted rate at national scale cumulatively (e.g. DECC, 2023) and enable more sustainable national grass yield production. Whereas, increasing the upper limit of N fertiliser application in sites that are less vulnerable to N loss can support production of excess silage for supply to farms the that may face reduced yield under policy constrains. This would enable a stocking rate to maintain productivity while reducing input cost and feed import, ultimately supporting the productivity goals of Food Wise 2025 (DAFM, 2021).
    - Identifying zones as indicator of potential yield and susceptibility to different forms of N loss, can also support weather driven decision making on appropriate type and time of N fertilizer application to improve NUE and reduce vulnerability of applied N to loss (e.g. Craswell, 1978; Fixen, 2020; Forrestal *et al*., 2015a; Hargrove, 1988; Harty *et al*., 2017; Rahman and Forrestal, 2021; Schwenke and Haigh, 2016; Woodward *et al*., 2021).
- Such zones can be subdivided into higher resolution if key drivers of efficiency of new N management strategy on N loss and its impact on yield, in comparison to existing ones are considered, using –
    - Soil sand content, as indicator of changes in yield and efficiency of reduction in annual $N_2O$ emissions, annual $NO_3^-$ leaching, from Irish Soil Information System database (O'Sullivan *et al*., 2018)
    - Soil clay and initial pH as indicators of efficiency in reducing annual $NO_3^-$ leaching from Irish Soil Information System database (O'Sullivan *et al*., 2018)

- Soil BD and SOC as indicators of efficiency in reducing annual $N_2O$ emissions from Irish Soil Information System database (O'Sullivan *et al*., 2018)
- Annual rainfall and average annual temperature as indicators of efficiency in reducing annual $NH_3$ volatilisation and $NO_3^-$ leaching from national climate database (e.g. Curley *et al.*, 2023; Walsh, 2012)

\- where all variables other than soil clay and initial pH, that are already shown to the indicators of overall N dynamics relevant at national scale, would not be required if already considered in a national level classification of zones (e.g. Carlier *et al*., 2021)

- Such zoning of national landscape into classes, based in potential impact of yield and N loss, is not only relevant for targeted N management are also relevant for monitoring as they would lead to identification of representative sites for empirical studies on identifying real-time impact of different N management strategies on N dynamics and choosing the most optimum alternative. This is in line with the objectives of EU Nitrates Directive (EPC, 1991) and such representative sites can also be used for validation studies prior to implementing modelling approach to understand the N-dynamics in line with the Tier 3 approach of IPCC (Buendia *et al*., 2019).
- The concept of zoning and monitoring is not limited only to the national landscape, but also can be applied for classifying zones, especially for soil zones indicating potential grass yield and N loss in different forms, within farm using the indicator variables. Such soil zoning can be relevant for improving the farm level management advice provided through NMP Online (Wall and Plunkett, (eds.), 2020) by identifying the site-specific N requirement and choosing appropriate timing and its form of application, as discussed earlier.

## 8.3. Limitations of the study and future research opportunities

The limitations of the study were primarily generated due to limited availability of relevant detailed datasets from records or empirical works for model simulations and validation in the context of Irish grasslands. This is a common challenge faced by other researchers working with DNDC as indicated by Byrne and Kiely (2008) in the context of Ireland and by Giltrap *et al*. (2010) in a global context. However, this challenge can be reduced in the future if datasets can be created through monitoring or measurement of targeted output variables and site-specific input details, particularly accounting for the diversity of soil and management in grasslands across Ireland. A detailed description of limitations of this study is discussed further in this section.

All simulations performed for this study were for grasslands under intensive management, i.e. > 140 kg N/ha of N fertiliser application (Abdalla *et al*., 2009). Thus, a gap that remains in all four experiments is how the DNDC model may perform for estimating grass yield and N loss for low to medium intensity of N fertiliser application (< 140 kg N/ha), when parameterised for crop phenology of perennial ryegrass and site-specific soil inputs including WFPS at FC and WP are used. This can be important for refining N management strategies for grasslands under a lower stocking rate and bands on milk production by herd, where the recommended N fertiliser applications can be much lower than 140 kg N/ha (DAFM, 2023a).

The other major gap that remains to be explored beyond this study was the performance of DNDC with different chemical N fertilisers other than urea and CAN. This includes N fertiliser applied with urease, and nitrification inhibitors and exclusive analysis of performance for N input through organic fertilisers as well as impact of other nutrients (Harty *et al*., 2017). Li *et al*. (2011) indicated that DNDC performs poorly for organic N inputs like slurry, thus the ammonium ($NH_4^+$) contents in the slurry (Teagasc, 2022) were used in fertiliser inputs section in Experiment 1 (Chapter 4) for corresponding application events, that gave reliable simulation of grass growth. However, the same scenario could not be tested in Experiment 2 (Chapter 5) due to data unavailability, that could have broadened the scope of utility of the model. Though DNDC is primarily dedicated to simulating the N and carbon (C) dynamics in soil and plant (Gilhespy *et al*., 2014), it also generates some outputs on the phosphorus (P) dynamics in soil, while accepts inputs on the sulphate and phosphate content in fertiliser (ISEOS, UNH, 2012). Inputs of P and sulphur (S) have not been included in this study, for which future research can be performed that may improve the accuracy of estimated yield and N loss. Besides P and S, there are other soil nutrients that do not have direct input options in DNDC, such as potassium, calcium etc (Gilhespy *et al*., 2014; ISEOS, UNH, 2012). However, for paddocks under treatments with nutrients other than N, studies can be performed to evaluate performance of DNDC by parameterising the crop phenological inputs based on empirical results and validated - to improve the scope of using DNDC for simulating more diverse grassland management scenarios. The same could be performed for reseeded paddocks for which DNDC showed lower reliability of estimated annual yield in comparison to permanent paddocks in the Experiment 2 (Chapter 5).

In this study, the simulations were performed for years with typical Irish weather conditions. However, drought conditions, though relatively rare, do occur in Ireland, as was seen in 2018

(Falzoi *et al*., 2019; Hurtado-Uria *et al*., 2013). It could be useful to explore the capability of DNDC to simulate scenarios of drought in Ireland through validation studies, which if found to be reliable, could be used for determining required modification of management strategies to maintain productivity of dairy farms under drought conditions. Such investigations may become more important for developing adaptation strategies in Ireland, given the future projections of climate change (Holden and Brereton, 2002; Meresa et al., 2023). Future research could also be performed to improve the estimation of daily WFPS by DNDC, that has been seen in Experiment 2 (Chapter 5) to be underestimated for most parts of the year, even when site-specific inputs of WFPS at FC and WP are used. This can be important since WFPS simulation in DNDC is a key driver of estimated yield and N loss through different pathways (Beheydt *et al*., 2007; Uzoma *et al*., 2015).

Uncertainty in DNDC simulation can arise from environmental and management factors. Hastings *et al.* (2010) indicated that uncertainty in soil parameters, especially SOC as well as clay content, BD and their impact on soil hydrology can significantly affect the simulation of $N_2O$ emissions by DNDC, whereas uncertainty in precipitation has more significant impact on estimated $N_2O$ emissions in comparison to temperature. Whereas they found precipitation has least impact on uncertainty of estimated yield. They further indicated that N fertiliser application rate and its partitioning has least impact on yield unless the N application rate is low enough to create N stress for crops. Besides, estimated $NH_3$ volatilisation can be driven by uncertainties in soil clay fraction, SOC, field capacity, rate and time of fertiliser application, precipitation (Balasubramanian *et al*., 2017; Dubache *et al.*, 2019). Considering of such potential uncertainties needs further validation to improve the confidence in the model prior to a nationwide application as Irish soil and climate is diverse and can intersect into identifiable scenarios of diverse combination of soil and climate (e.g. Curley *et al*. 2023; McDonald *et al*., 2014; Walsh, 2012). This study is focused on perennial ryegrass paddocks whereas for more efficient N use there is increasing trend of research on application of multispecies and grass-clover swards (Egan, 2022; Egan *et al.,* 2022; Gilliland, 2022) – that may give rise to uncertainty for the applicability of the DNDC with the parameterisation used in this study beyond perennial ryegrass paddocks. While DNDC is sensitive to fertiliser type (Abdalla et al., 2009), the Experiment 1 does not explicitly account for the impact of individual fertiliser types, that include Ca content of CAN, urease inhibitor in KaN, S content in UAS 38% and urease and nitrification inhibitor content in Alzon urea or nutrients other than N content in slurry (Cantarella *et al*., 2018; Chatterjee, 2018; Forrestal *et al*., 2015; Kirschke *et al*., 2019; Murphy *et al*., 2002).

Whereas the Experiment 2 particularly evaluates the model for CAN and urea, even though impact of Ca in CAN is not accounted for. Considering uncertainty of model performance for different fertiliser type becomes important for Ireland since alternative to traditional use of urea or CAN are being searched and applied to improve sustainability of N fertiliser use efficiency. Besides the aforementioned fertilisers, alternatives available in Ireland include - urea ammonium nitrate (UAN), liquid N, protected urea, use of urease inhibitor with urea (Hackett, 2022; Maher and Hennessy, 2022). Whereas focus has been given on application of low emission slurry for N supply in grasslands, that is also a source of nutrients other than N (Teagasc, 2022), at a right zone (groups of counties) at a right time (Teagasc, 2025). Considering these factors, it can be said that the findings of our study, that also indicated that parameterisation of DNDC is important for improving model estimated grass growth rate and yield, is ideally applicable for sites, where-

- N application is intensive and in form of urea.
- Yield from both grazed and ungrazed paddocks, while N loss primarily from ungrazed paddocks (though results of Experiment 2 will be valid for grazed paddocks as explained in Section 6.1).
- The paddock is permanent, and reseeding did not occur prior to experimentation.
- The paddock is predominantly under perennial ryegrass monoculture.
- The weather year represents typical Irish weather conditions, but not extreme weather events (e.g. drought, frost etc.).
- The weather is typical of the prevalent climatic conditions in southern part of Ireland.
- The soil of the paddock is mineral soil (i.e. not organic soil in nature).

However, future studies can be performed to identify the scope of using DNDC, with relevant parameterisation and model calibration, for scenarios of

- Low intensity N management (e.g. < 140kg N/ha: Abdalla *et al*., 2009)
- Diverse set of N fertiliser type beyond urea while improving performance of DNDC for N loss estimation from CAN treated paddocks
- N loss from grazed grasslands, typical of Irish grasslands under dairy farming (Bourke *et al*., 2007; Läpple *et al*., 2012).
- Reseeded paddocks, as reseeding occurs for around 2 % paddocks are reseeded annually in Ireland (Creighton *et al*., 2011).
- Mixed species and grass-clover paddock – that are being propagating in Ireland (e.g. Egan *et al.*, 2022; Gilliland, 2022).Projected future increase in frequency of drought (Holden and Brereton, 2002; Meresa et al., 2023).

- Diverse climatic conditions seen across Ireland (e.g. Curley *et al*. 2023; Walsh, 2012)
- Organic soils, i.e., soils with >20 % SOC (e.g. the soil sample collected by McDonald et al. (2014) from Corduff in County Monaghan) (Renou-Wilson *et al*., 2015) and textures beyond sandy loam and loam.

## 8.4. Developing a conceptual framework for studying crop growth and nitrogen loss and their key drivers – based on the context of grasslands under Irish dairy farming

*Step 1: Considering data availability*

The current version of DNDC (9.5) requires some atmospheric inputs that are default but can be modified to local conditions. Detailed inputs on daily weather, soil physicochemical properties, crop phenology and management are required to simulate the crop and N dynamics using DNDC. The outputs are generated in both daily and annual timescales (ISEOS, UNH, 2012). For Ireland, generalised non-mandatory atmospheric inputs - such as atmospheric $NH_3$ concentration and N concentration in rainfall are available for multiple locations across the nation in the works by Doyle *et al*. (2017) and Jordan (1997) respectively. Atmospheric concentration of $CO_2$ and its annual rate of increase can be set at current global level, e.g. 409.8 ppm and 2.3 ppm/year respectively (Prasad *et al*., 2021; Ullas Krishnan and Jakka, 2022). Measured and recorded information on management and grass growth at paddock and farm scale can be obtained from farm data records of Teagasc research farms and can be used for model simulation and validation (Teagasc, 2017a) and PastureBase Ireland (PBI) (Hanrahan *et al*., 2017). Site-specific weather data for multiple locations within each county in Ireland is available from Met Éireann, including many of the Teagasc monitored grassland sites (Met Éireann, n.d.; Met Éireann, n.d.a.). For paddock level studies, besides the option of field studies and laboratory analysis, site-specific measured soil data for model inputs can be used from publications and farm records of empirical works performed in such Teagasc research farms and also for external sites used in such studies (O'Donovan *et al*., 2022). Under the current scenario where perennial ryegrass is dominant in Irish grassland sites, crop phenological inputs can be parameterised accordingly for more general use of DNDC, which was originally developed for grass-clover sites. However, for mixed species swards or variety of cultivars, the phenological inputs can also be modified using empirical data, based on requirement (DAFM, 2020; O'Donovan *et al*., 2021; Saggar *et al*., 2007; Shirato, 2005).

As of now, based on the limitations identified in the of performance DNDC, it should not be employed to explore crop and N dynamics for grassland under dairy farms that are treated with annual N fertiliser input below 140 kg N/ha (Abdalla *et al*., 2009). To simulate scenarios for research on exploring potential yield and N loss under different management options in Irish grasslands, the optimum spatial resolution for inputs and scope of utilisation of DNDC requires identification (Haraldsson and Sverdrup, 2013; Patil, 2009; Wu and Ma, 2015). Simulation of farm level scenarios, under idealised generalised advice for N fertiliser application for corresponding stocking rates of the farms (Wall and Plunkett (eds.), 2020; Callaghan, 2023), can be performed for validation and to analyse the potential impacts of downscaling of the national level policies and for identifying the requirement and scope of geographical refinement of the policies to meet the 4RNS objectives (Fixen, 2020; Shirmohammadi *et al*., 2008; Wu and Ma, 2015). To overcome the challenge of limited site-specific soil information, more generalised soil data can be employed from the Irish Soils Information System (Irish SIS) (Byrne and Kiely, 2008; Giltrap *et al*., 2010; O'Sullivan *et al*., 2018). However, site-specific performance of DNDC under such generalisation needs to be tested.

*Step 2: Model validation for grass growth and nitrogen loss*

The first step that needs to be performed prior to the application of DNDC is assessing its performance in estimating annual grass growth rate and yield. This is essential as this aspect determines the model estimated surplus N, susceptible to loss (Zhang *et al*., 2015). Such studies can be performed from paddock to farm scales, with corresponding levels of generalised soil and management inputs, to find the most robust use of the model (Patil, 2009). If DNDC is found to produce reliable simulations at a particular temporal and spatial scale, the same spatial and temporal scale can then be used to simulate and validate performance of DNDC for a management scenario against corresponding measured N loss, especially through the major pathways relevant for grassland - $NH_3$ volatilisation, $N_2O$ emissions and $NO_3^-$ leaching (Hoekstra *et al*., 2020; van Beek *et al*., 2008; Woodmansee *et al*., 1981). Tests can be performed to examine the performance of DNDC at various temporal scale to identify the optimal temporal scale of simultaneous reliable performance in estimating grass growth and N dynamics (Giltrap *et al*., 2010). The performance at daily level can be analysed using methods including correlation analysis, MAE and RMSE- with respect to the types of available data from corresponding measured records. The performance at annual level can be based on relative deviation in percentage (RD %) (Abdalla *et al*., 2011; Abdalla *et al*., 2020; Gogolou *et al*., 2019; Moriasi *et al*., 2007).

*Step 3: Identifying the optimum spatial and temporal scale of reliable performance of DNDC*

The applicability of DNDC at a particular temporal scale depends on its performance observed at that corresponding temporal scale. DNDC has been reported to show leads and lags at daily $N_2O$ estimation, while producing reliable total $N_2O$ emissions estimations at longer time scale (Giltrap *et al*., 2010; Li *et al*., 2011). In the settings of Irish perennial ryegrass dominated paddocks or farm, the most reliable temporal scale should be identified for employing DNDC in studies. For example, a reliable estimation of annual $N_2O$ emissions by DNDC but poor estimation of $N_2O$ emissions at daily time step would make DNDC suitable for aiding development of strategies to reduce $N_2O$ emissions at annual scale - but would be unfit for similar decision making at a daily scale. The geographical refinement of the applied N management strategy focusing on the targeted output variable thus can be performed using DNDC at the corresponding temporal scale only. For example, an observation of a poor performance at daily scale would likely make DNDC unfit for management decision based on weather forecast (McDonnell *et al*., 2019).

The optimum spatial scale of input data requirement would help to determine the spatial resolution of the model's focus and would help to develop relevant databases (Haraldsson and Sverdrup, 2013; Patil, 2009). In a scenario where at least the minimum inputs for reliable DNDC simulation for grass yield and targeted forms of N loss are unavailable, either field study and data collection may be required. Otherwise, alternative sites are required to be selected where a set of minimum input data is available. For confidence in direct applicability of DNDC at a national scale as a tool for site specific estimation of grass growth rate and yield, as well as to estimate N loss, in terms of reliability of simulated annual magnitude and variability at a daily scale, increasing number of such validation studies across diverse sites representative of diverse soil type, management and climate conditions in Ireland (McDonald *et al*., 2014; Walsh, 2012) would be helpful. However, for that it is a requirement for creating additional databases on measured yield and N loss for evaluation of the model's performance, unless there are existence of validation studies that may have already been performed for a particular management scenario in a specific characteristic landscape (Haraldsson and Sverdrup, 2013) prior to using the model.

*Step 4: Identification of key variables of regulating grass growth and their use for geographical refinement of N management*

If preliminary investigations find DNDC to reliably simulate grass growth and N loss at an annual scale, it can be used to identify the key variables from field level to national level to modify the existing N management strategies geographically for sustainable yield and reduced N loss (Milne *et al*., 2020; Patil, 2009; Wu and Ma, 2015). Reliable DNDC simulations can be used to identify the potential impact of the national level policies through scenario analysis for spatially diverse grassland conditions (Giltrap *et al*., 2010), that when compared with the spatial variability of soil and meteorological conditions of the studied sites can reveal the key regulatory factors of yield and N loss. Choosing the indicator variables that are more temporally stable in nature, can be useful to develop management zones at national scale for focused N management through refinement of the existing strategies (Nabati *et al*., 2020; Patil, 2009) by accounting for the variability of N dynamics driven by interaction of management with soil and atmospheric conditions. Such zoning can be particularly important for landscape-specific refinement of national level generalised N management guidelines like that provided in Green Book (Wall and Plunkett (eds.), 2020) or the policies like Fifth Nitrates Action Programme 2022-2025 (DHLGH and DAFM, 2022) to reduce N loss as well as maintaining profitability of dairy farming. The potential impact of different policies on such diverse sites will also help to choose the most sustainable management approaches for a site and to identify the more dynamic variables, that need to be further accounted for increasing the effectiveness of implemented policies (Schipanski *et al*., 2009). The same concept can be applied at field scale within a farm, for more informed management of N and improve NUE (Wu and Ma, 2015). Whereas, at field scale, one factor at a time (OFAT) sensitivity analysis can also be employed to identify the key variables that are regulating the grass yield and N loss (Kardynska *et al*., 2022; Wang *et al*., 2016), relevant for informing the site-specific N management strategies like NMP online (Wall and Plunkett (eds.), 2020). Similar principles of research can be employed at temporal scale other than annual, if performance of DNDC is found to be reliable at that scale.

*Step 5: Developing a simplified model for yield*

For field level management, it remains important to determine the optimum N required by grass to maintain yield, so that application of surplus N can be reduced and thus reducing overall N loss potential without affecting soil fertility (Patil, 2009; Ritchie, 2021; Varallyay, 1994; Wu and Ma, 2015). Identification of the key variables that impact grass growth may assist in the development of a simplified model, that would identify the optimum N requirements to produce targeted yields with reducing surplus N supply, while accounting for the potential impact of soil and climate conditions and their interaction with management (Haraldsson and Sverdrup; 2013; Patil, 2009). A successful simplified model would also reduce the requirements for input data that usually limits the scope of application of DNDC. The development of a simplified model using the identified key variables provides the opportunity to include low to even no N input scenarios using relevant database and research reports. This would help to overcome the challenge of DNDC not being suitable for non-intensive N management in grassland (Abdalla *et al*., 2009; Byrne and Kiely, 2008; Giltrap *et al*., 2010; Haraldsson and Sverdrup, 2013; Patil, 2009).

The development of such a simplified predictive model may be created by using key variables regulating grass growth, identified by conducting a sensitivity analysis using methods such as OFAT, followed by the development of a sensitivity index (Kardynska *et al*., 2022; Wang *et al*., 2016). All identified key regulatory variables can be used as independent variables and yield as a dependent variable for a 'backwards multiple linear regression' or a 'backward multiple linear regression with interaction effects' approach (Williams and Ojuri, 2021; Zarei, 2022). Measured data from existing empirical works performed in Ireland and farm databases can be used in this process. The process can be performed by choosing the most important variables and interactions from corresponding p-values during the regression process (Williams and Ojuri, 2021; Zarei, 2022). However, such models would also need to be validated prior to use for deriving optimum N requirements (Haraldsson and Sverdrup, 2013). The same method can be applied to determine the potential N loss through different pathways from grasslands, to estimate potential impact of different management practices on N loss through interaction with their key regulators.

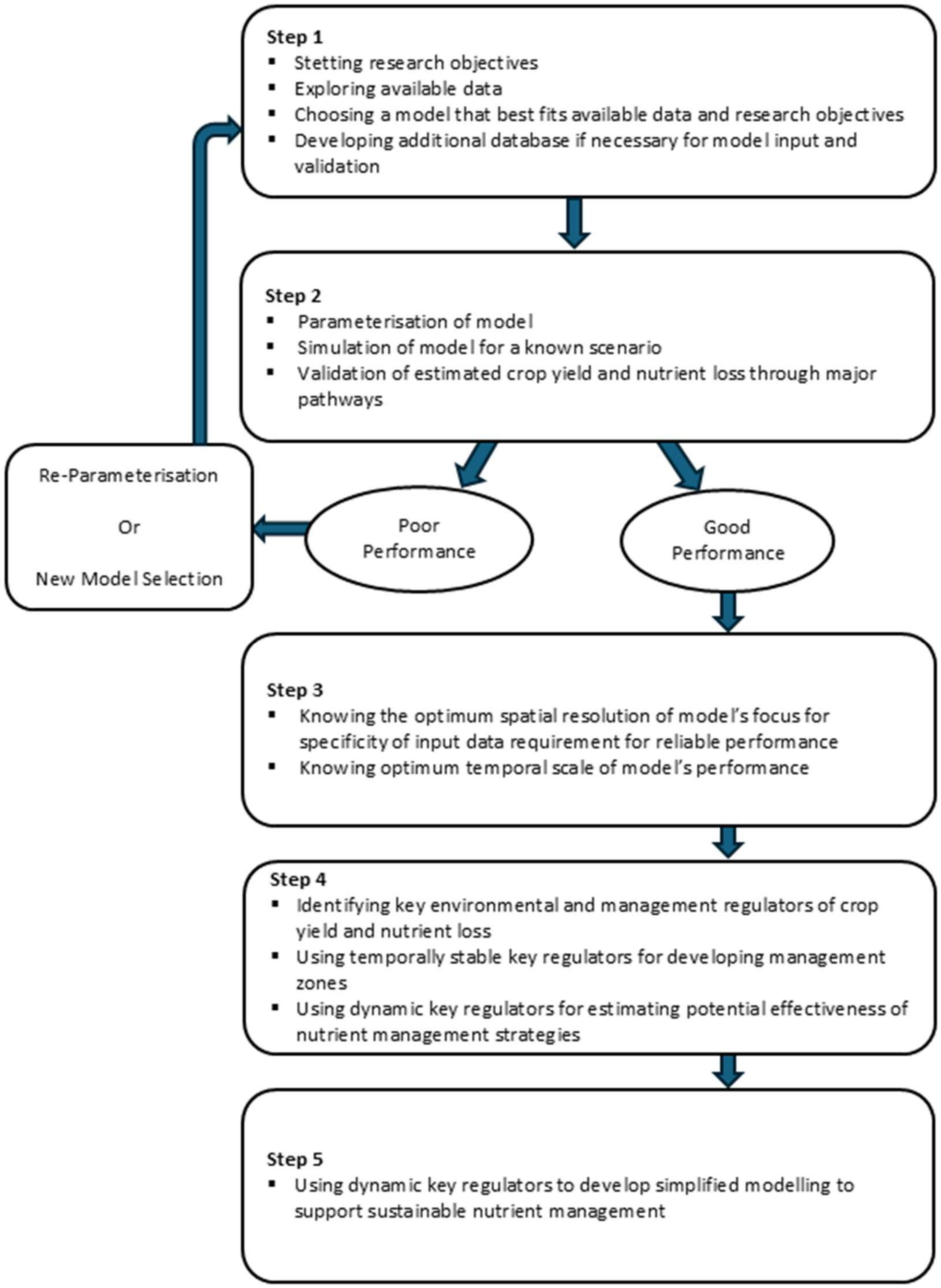


**Figure 8.1:** Flowchart of conceptual framework of using the DNDC model for deriving geographically refined nitrogen (N) fertiliser application advice

## 8.5. Scope for further use of the conceptual framework

The conceptual framework described in this work (Figure 8.1) is focused on perennial ryegrass dominated grasslands in Ireland and for use of the DNDC model. However, scope of its application is not limited to these. The DNDC model provides an opportunity to simulate yield and N dynamics for agricultural lands managed for 87 other agricultural and horticultural crops, and also provides the opportunity to create simulations for new crops (ISEOS, UNH, 2012).

Similarly, there are other existing models - APSIM, Expert-N, ECOSSE, DayCent etc. (Engel and Priesack, 1993; Keating *et al*., 2003; Zimmermann *et al*., 2018) - that can be used, depending on the targeted crop, type of land use, focused pathways of N loss, availability of data and model performance. Other relevant models may be identified or developed to investigate the dynamics and importance of N and other soil nutrients and for analysing impact of interaction of corresponding management practices with soil and weather that regulate dynamics of the soil nutrients (Giltrap *et al*., 2010; Streich *et al*., 2014). Depending on research objectives, targeted nutrient, chosen models and their focus, a necessity may arise to develop datasets for input and evaluation of the model's performance (Haraldsson and Sverdrup, 2013). Evaluation of a model's performance may not be mandatory for each application, depending on the availability of existing works that may have already validated crop growth or nutrient dynamics at a local scale. However, the framework provided here can help in such model evaluation and development studies.

The optimum spatial and temporal scale of reliable simulation by a model would determine the number of variables and their details required as inputs (Haraldsson and Sverdrup, 2013). The identification of the temporal and spatial relevance of key regulatory factors using model simulations and sensitivity, would help in identifying the key focus areas that require attention for geographic refinement of nutrient management to achieve the 4RNS objectives (Fixen, 2020) – and is embedded within this framework. The relevance of these factors would depend on the spatial homogeneity of the crop production, soil and management, and the performance of the model at various spatial scale (Mearns *et al*., 2001, van Wart *et al*., 2013a). Alternatively, the identification of relevant variables can be used to define agroclimatic zones nationally, that can further help in providing targeted nutrient management advice (van Wart *et al*., 2013a). Process-oriented models like DNDC, if they are capable of providing reliable yield and nutrient dynamics simulations, can also be helpful in determining the feasibility of international and national targets like the Farm to Fork Strategy. They may determine the appropriate spatial scale for the implementation of such strategies and in identifying requirements of local, regional and temporal modifications (EC, 2020; Milne *et al*., 2020; Shirmohammadi *et al*., 2008; Zhang *et al*., 2020a). These functions could potentially lead to the modification of nutrient management policies tailored to stakeholder requirements. For example, to allow policy makers to achieve national and international goals in reducing the agricultural pollution, and for farmers to maintain sustainable yield, soil health and reducing economic loss – through determining necessary steps to meet the 4RNS objectives of nutrient application in agricultural soils.

### 8.6. Conclusion

Overall, this study shows that DNDC, when parameterised according to crop phenology of perennial ryegrass and local atmospheric conditions, is capable of reliably simulating grass yield and N loss in permanent perennial ryegrass dominated grasslands (as the case of Ireland) – when site-specific input is provided on soil and management. Unless growth rate and yield of perennial ryegrass is the only focus, WFPS at FC and WP appeared as a key input requirement for reliable simulation of N dynamics. The performance of the model in simulating N dynamics was also dependent on fertiliser type. The scope of employing the DNDC model to explore N dynamics in grasslands sites is dependent at least on the availability of information on site-specific WFPS at FC and clay content for inputs among the suite of variables for which DNDC-default inputs are available. The study identified the potential to improve current, spatially uniform national level N management strategies in Ireland through geographical refinement, by the development of management zones based on national level regulatory factors of grass yield and N loss. The current uniform strategies may not be sufficient for optimum productivity and targeted reduction of N loss across spatially diverse Irish grasslands. The study also identified the key regulators of grass yield and N dynamics at field level that can be accounted for developing field level NMP for improved NUE and the ones that should be considered to explore the potential impact of national level policies on grass yield and N loss within management zones.

A primary framework to determine the performance and potential use of DNDC as a tool to support research on sustainable growth of perennial ryegrass, with reduction of potential N loss for perennial ryegrass dominated grasslands used for Irish dairy farming, is proposed. The template of this study can be replicated globally for other agricultural landscapes by parameterising the model to the relevant crop phenology and identifying optimum spatial resolution for providing inputs on soil conditions, weather and management for reliable DNDC simulations. The template can also be employed in case of other models with similar objectives. As was seen for DNDC, it was reliable for estimating both daily growth and annual yield of perennial ryegrass, whereas the model's ability to reliably estimate $NH_3$ volatilisation and $N_2O$ emissions was limited to annual scale. The model performed reliably for paddock scale for both grass yield and N loss through $NH_3$ volatilisation and $N_2O$ emissions, whereas its performance of estimating N dynamics at farm scale was not tested. Not only DNDC, but the applicability of any such process based model to achieve the 4RNS objectives through geographically refined N management is dependent on reliability of the model's performance and the corresponding optimum spatial and temporal scale. A reliable model simulation is important for identifying key variables that are driving the crop growth and nutrient loss – from field to national level. These variables are required for geographical refinement of N management plans through development of management zones based on potential yield and N loss – that is governed by the interaction of soil and weather with management. These variables can also lead towards simplified modelling that would have lower input data requirement in comparison to DNDC. Furthermore, the minimum input requirement for reliable model simulation helps to identify the potential impact of uniform N management policies on grass yield and N loss, that were developed targeting a lower spatial resolution like national scale, when implemented for a downscaled management at farm or field level.

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