

Mapping and monitoring Artisanal and Small-scale Mining (ASM) in the tropics from Sentinel-1 imagery using change detection and deep learning approaches

by

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Declaration

I declare that this thesis has not been submitted either in whole or in part for any degree or qualification to this or any other university. The contents of the thesis are entirely my own work, and all other sources of information and literature used have been sufficiently acknowledged in the text and in the bibliography.

Signed:

A handwritten signature in black ink, appearing to read 'Obour', written over a light gray rectangular background.

Isaac Obour Mensah, February 2026

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Abstract

Artisanal and Small-scale Mining (ASM) is on the rise in the Global South, providing a primary source of income for many communities, especially among the rural poor. However, many ASMs are often operated illegally or informally, leading to major social and environmental problems such as water pollution, low worker safety, and deforestation. Despite these problems, the informal nature of the sector currently presents serious challenges related to accurately locating ASM activities in a timely manner to support their sustainable development. Remote sensing methods are therefore suitable for regular monitoring, although the use of optical images has faced challenges such as spatial resolution and persistent cloud cover, which limit their capabilities for regular ASM monitoring in cloudy regions like southern Ghana. Synthetic Aperture Radar (SAR) offers a solution for regular ASM monitoring in cloudy regions due to its ability to penetrate clouds. However, the use of freely available Sentinel-1 (S1) C-band imagery can be affected by several factors, such as speckle noise, atmospheric effects from active rainfall events, and topography, leading to a greater or lesser degree of high false alerts and measurement uncertainties. These constraints have resulted in a lack of research to date that has explored the timely detection of ASM to facilitate rapid response. This thesis first investigates an optimal SAR processing methodology in addressing these constraints to subsequently develop a new scalable SAR-based method, the first to leverage Change Point Detection (CPD) and Deep Learning (DL) techniques for timely and reliable ASM monitoring using C-band S1 imagery in persistently cloudy regions. In this thesis, the use of S1 radiometric terrain-normalised γ^0 backscatter products processed using Copernicus 30 m digital elevation model (DEM) is demonstrated to be superior to conventional σ^0 backscatter products in mitigating terrain-induced effects to improve the timely detection of ASM. This thesis makes an important contribution by proposing time series smoothing as an essential additional SAR preprocessing step and as a robust, practical approach for effectively smoothing S1 data with outliers caused by high-intensity rainfall and seasonality, enabling timely and reliable ASM detection, particularly during rainy seasons. CPD is a powerful statistical technique for analysing smoothed S1 SAR imagery to generate ASM-induced forest disturbance alerts in mining landscapes, reducing the delays in locating ASM from several months using traditional methods to within a few days, with possible delays of up to 18 days. In this thesis, the potential of DL to overcome the speckled effect associated with traditional pixel-based Machine Learning (ML) methods is demonstrated to improve the accuracy of distinguishing mining from other forest disturbances from S1 SAR imagery promptly, with a *mean IoU* of 0.82 and an overall *F1-score* of 89%. The methods tested in this thesis are a step towards achieving operational ASM early warning systems, as this will be crucial for mitigating their social and environmental impacts and providing emergency aid to protect lives and the natural environment globally.

Acronyms

ARD	Analysis-Ready Data
ASM	Artisanal and Small-scale Mining
ALOS	Advanced Earth Observation Satellite
ATLAS	Advanced Topographic Laser Altimeter System
AW3D	Alos World 3D
BCD	Binary Change Detection
BinSeg	Binary Segmentation
BOA	Bottom-Of-Atmosphere
CEOS	Committee on Earth Observation Satellites
CERGIS	Centre for Remote Sensing and Geographic Information Services
CD	Change Detection
CPD	Change Point Detection
CNN	Convolutional Neural Network
CM	Change Map
CRS	Coordinate Reference System
CuSuM	Cumulative SuM
DC	Direct Classification
DEM	Digital Elevation Model
DI	Difference Image
DSD	RainDrop Size Distribution
DL	Deep Learning
ESA	European Space Agency
FAO	Food and Agriculture Organisation
GEE	Google Earth Engine

GDP	Gross Domestic Product
GRD	Ground Range Detected
GDAL	Geospatial Data Abstraction Library
GMet	Ghana Meteorological Agency
HFZ	High Forest Zones
ICESat-2	Ice, Cloud, and Land Elevation Satellite-2
InSAR	Interferometric Synthetic Aperture Radar
ITCZ	InterTropical Convergence Zone
JAXA	Japan Aerospace Exploration Agency
JT	Joss-Thunderstorm
KF	Kalman Filter
LIA	Look Incidence Angle
LSM	Large-Scale industrial Mining
LOESS	LOcally Estimated Scatterplot Smoothing
SLC	Simple Look Complex
SDG	Sustainable Development Goal
SAR	Synthetic Aperture Radar
SRTM	Shuttle Radar Topography Mission
SG	Savitzky-Golay
SVM	Support Vector Machine
MCD	Multi-class Change Detection
MSI	Multi-Spectral Instrument
ML	Machine Learning
MP	Marshall-Palmer
NRT	Near Real-Time
NDI	Normalised Difference Index
NDVI	Normalised Difference Vegetation Index
NRCS	Normalised Radar Cross-Section
OBIA	Object-Based Image Analysis
OHS	Occupational Health and Safety

PA	Protected Areas
PCA	Principal Component Analysis
PELT	Pruned Exact Linear Time
PCC	Post-Classification Comparison
RTC	Radiometric Terrain Correction
RTF	Radiometric Terrain Flattening
RF	Random Forest
RS	Remote Sensing
TOA	Top-Of-Atmosphere
TOF	Trees Outside Forest
VH	Vertical transmit Horizontal receive
VV	Vertical transmit Vertical receive
XGBoost	eXtreme Gradient Boosting

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Chapter 1

Introduction

Artisanal and Small-scale Mining (ASM) is the primary source of livelihood for many communities in the Global South, particularly among the rural poor, and is expanding significantly (Nunfam et al., 2020; Ofosu et al., 2020; Pokorny et al., 2019). These mines are rarely regulated or monitored, culminating in significant social and environmental problems for these communities (Bansah et al., 2018; Fritz et al., 2018). The most pressing problem is therefore to locate these sites in a timely manner, and although remote sensing (RS) techniques have been widely used to detect ASM, they have encountered significant challenges. In tropical regions where ASM is generally most prevalent, image cost, spatial resolution, and persistent cloud cover restrict the use of optical imagery (Gallwey et al., 2020; Snapir et al., 2017). The advent of freely available Sentinel-1 (S1) C-band Synthetic Aperture Radar (SAR) data from the Copernicus programme has opened new possibilities to explore the development of a novel ASM monitoring methodology, however, atmospheric effects from heavy rainfall events and SAR speckle noise have been shown to reduce the effectiveness of C-band SAR imagery for complex regions such as the tropics (Forkuor et al., 2020; Janse van Rensburg and Kemp, 2022). Constraints such as these have held back the development of effective early warning systems for timely and reliable ASM monitoring in the tropics. In this thesis, a new scalable, SAR-based method is developed and validated, the first to leverage change detection and deep learning (DL) techniques for timely and reliable ASM monitoring using C-band S1 imagery in persistently cloudy regions, such as the rainforest of Ghana.

This chapter introduces the motivation behind this research and offers a thorough overview of the knowledge gap concerning the use of RS and DL techniques for ASM monitoring in tropical regions. It then presents the first comprehensive overview of the i) ASM sector from a global perspective and subsequently focusing on the Ghanaian context, together with the problems that arise from ASM operations, ii) the role of RS and DL in ASM monitoring in the tropics, and iii) the current research gaps/challenges that restrict these methods being used

for timely detection of ASM in the tropics. The research objectives are presented, and the significance of the study is outlined. This introductory chapter then concludes by outlining the structure of the thesis, along with a concise summary of the content covered in each subsequent chapter.

1.1 Overview of Artisanal and Small-scale Mining

The definition of ASM varies across countries and reflects diverse international regulatory frameworks and institutional contexts. Broadly, however, ASM is recognised as a labour-intensive method of mineral extraction and processing, typically employing rudimentary tools and techniques ([Moyo et al., 2022](#); [Zvarivadza, 2018](#)), and targeting deposits that are considered not to be economically viable for exploitation by Large-Scale industrial Mining (LSM) operations. ASM is generally undertaken by small groups of individuals or cooperatives, relying predominantly on basic tools such as picks, shovels, wheelbarrows, and panning dishes ([Zvarivadza, 2018](#)), but in some instances, operations may extend to the limited use of mechanised machinery, including heavy machinery such as excavators on a small scale ([Figure 1.1](#)). ASM is practiced across a wide range of geographic regions, with the greatest concentration occurring in the Global South, encompassing Africa, Asia, Oceania, Central America, and South America ([Fritz et al., 2018](#)).



Figure 1.1: Typical ASM operations. (a) Artisanal coltan mining, ground sluicing using simple tools such as picks and shovels in Rwanda (source: [Dorner et al., 2012](#)). (b) Artisanal gold mining employing heavy machinery such as an excavator in the wet tropical forest in Ghana (source: [Bansah et al., 2018](#)).

Depending on the type of mineral being mined, ASM operations typically involve prospecting, excavation, and mineral processing to enhance the concentration of the desired metal. In addition, where technological resources permit, these operations involve the simultaneous extraction and recovery of the mineral ([Moyo et al., 2022](#)). The most common ASM activity that can be observed from space is surface mining, often alluvial (i.e. minerals found in loose

deposits such as riverbeds and sand) in nature, and can appear as single, corridor, or ribbon-like clusters of pits ([Gallwey et al., 2020](#); [Snapir et al., 2017](#)), as shown in [Figure 1.2](#). These types of ASM are generally performed because they are in close proximity to rivers or other water bodies, characterized by the presence of dugouts or pools of water, and bare-earth waste piles evincing a high evaporation rate ([Gallwey et al., 2020](#); [Owusu-Nimo et al., 2018](#)). Their size and distribution vary considerably, ranging from less than 0.5 hectares for small operations to several hundred hectares in the case of larger mining clusters (see [Figure 1.2](#)). Water becomes the dominant type of land cover after vegetation removal and manual flooding, and there is often bare soil or vegetation in between ([Forkuor et al., 2020](#)). The various land cover features of a typical ASM site are illustrated in [Figure 1.2](#).

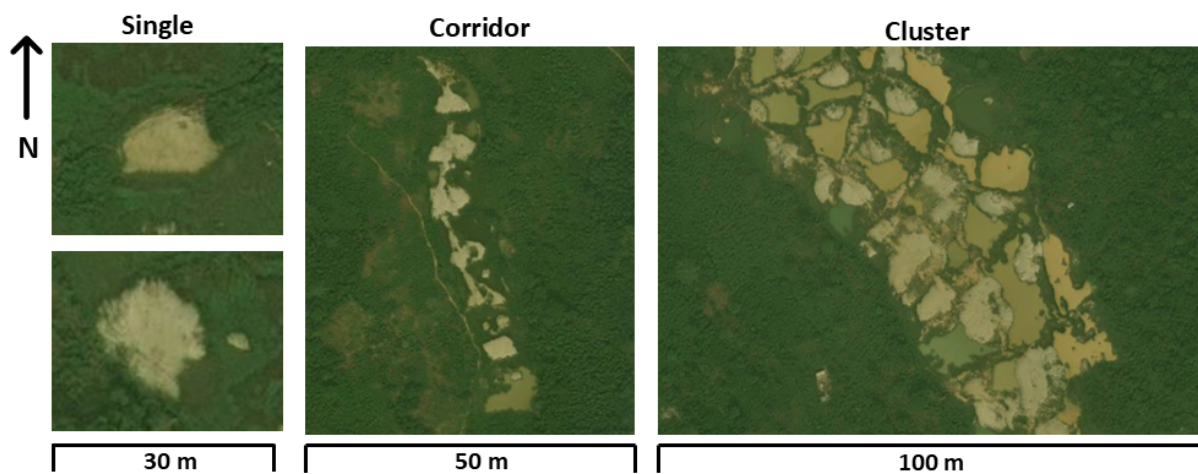


Figure 1.2: The distinct structure and features of ASM in the tropical rainforest of Ghana, which can exist as single, corridor, or ribbons of cluster pits, including various land cover types. Water is generally the dominant land cover after vegetation removal because it is introduced during the mining process; however, there may also be bare soil or vegetation in between.

In the Ghanaian context, ASM exhibits significant diversity in its operational forms. [Mantey et al. \(2017\)](#), in their comprehensive study of ASM practices in Ghana, classify the sector into five principal categories: alluvial mining, underground mining, surface mining, mill-house operations, and pilfering or selective extraction. The most common ASM methods practised in Ghana are surface and alluvial mining, which involve simultaneous mining and extraction of the mineral deposit. Surface mining refers to ASM activities generally performed in forests and prohibited areas, while alluvial mining is mostly concentrated along the floodplains and riverbeds of major rivers in Ghana, such as the Ankobra, Tano, Pra, Birim, and Offin ([Mantey et al., 2017](#)). Unlike surface ASM, which can be done in the centre of towns and villages, alluvial ASM is usually confined to remote, vegetated, and well-drained areas with no or limited monitoring ([Owusu-Nimo et al., 2018](#); [Mantey et al., 2017](#)). Other ASM practices in Ghana, such as underground ASM, involve mining solely from abandoned underground shafts after LSM operations or from manually dug pits/holes. The ores mined through these underground ASM operations are processed at the mill-house ASM operations sites, where house

structures are specifically assembled for extraction and processing. The 'pilfering' or 'selection' ASM operators also use these mill-house structures for processing ore, which are usually stolen from stockpiles or pit dump sites of LSM (Mantey et al., 2017). Within each of these categories, further distinction is possible based on the technology or hardware employed. These sub-categories of ASM include the use of washing plants, washing boards, dig-and-wash techniques, abandoned underground shafts, chamfi operations, and river or stream dredging (Mantey et al., 2017). In Ghana, the focus of ASM is largely on gold extraction, with gold deposits constituting the majority of reported mineral production from this sector (Owusu-Nimo et al., 2018).

1.1.1 Socioeconomic benefits of ASM

The estimates of the number of ASM operators by region and country are based on data on ASM compiled from various global baseline ASM studies published within the last two decades and can be accessed from the ASM Knowledge Sharing Archive (2025) database (ASM Inventory, 2025) and World Bank Group (World Bank Group, 2025). The data retrieved from the ASM Knowledge Sharing Archive (2025) database was subsequently mapped using ArcGIS Pro software to support the analysis throughout this section. Alongside this, the state of the ASM sector data published in literature was used to review the growth of the sector over the past two decades. The number of people working in the ASM sector globally has increased significantly in recent years (see Figure 1.3), and ASM is estimated to provide a livelihood to approximately 49.5 million people across 86 countries worldwide. In addition, a further 270 million is estimated to depend on ASM indirectly (World Bank Group, 2025). The ASM sector continues to experience substantial growth, with global employment rising from approximately 13 million people in 1999 to 30 million in 2014, and more recently to over 49.5 million people (ASM Inventory, 2025; Delve Database, 2022; Fritz et al., 2018), as shown in Figure 1.3.

The increase in activity in the ASM sector is driven by higher prices and demand for precious minerals (Hirlekar et al., 2025), as well as the growing challenges of earning a living through alternative activities such as agriculture (Fritz et al., 2018). In Ghana, ASM offers significantly higher daily earnings than agriculture, with a recent study by Azumah et al. (2021) revealing that ASM miners earn at least 10 times the national minimum wage per day. Around 20% to 25% of the world's annual production of gold, diamonds, cobalt, tin, and tantalum comes from ASM operations, with roughly two-thirds sourced from countries in South America, South Asia, and Sub-Saharan Africa (Schwartz et al., 2021). ASM therefore contributes 20% of the global gold supply, and countries such as Ghana and Zimbabwe generate significant portions of their gold output through ASM (Fritz et al., 2018). Ghana, over the years, has been recognised as one of the leading gold producers in Africa and in the world, and the majority of the country's gold production comes from ASM (Adu-Baffour et al., 2021). Over the past few decades, ASM has seen a significant increase, rising from approximately 2 thousand ounces in

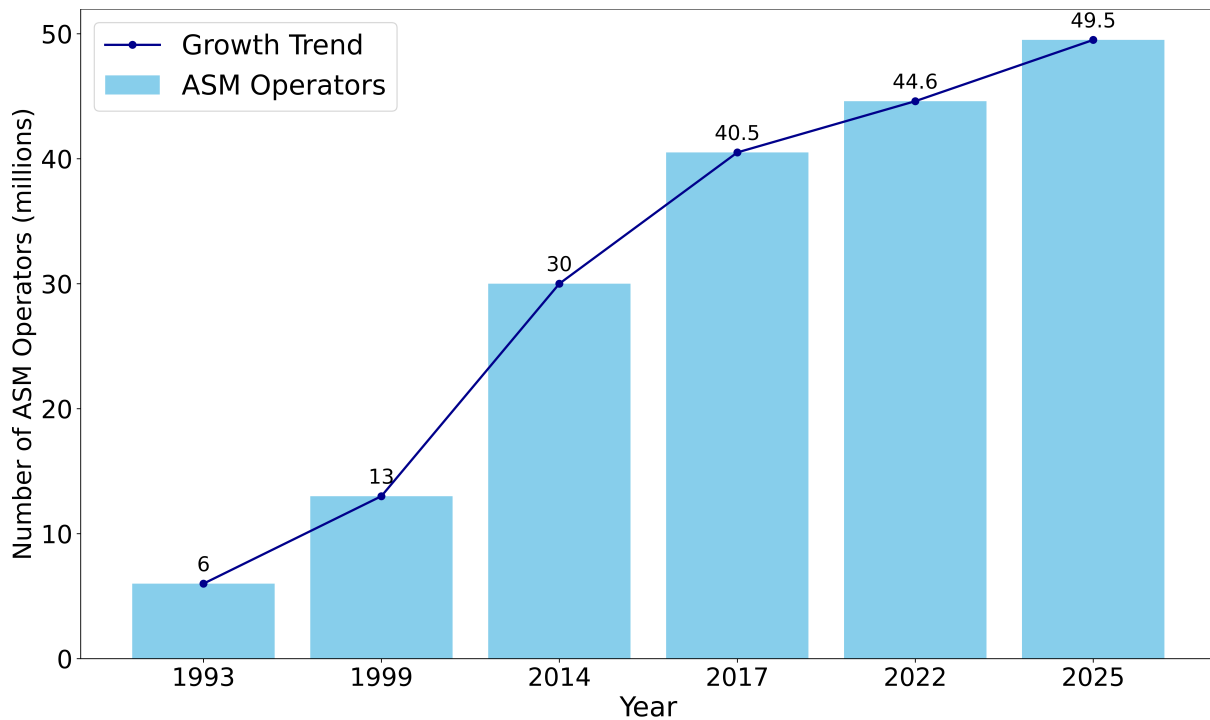


Figure 1.3: Growth in the number of ASM operators worldwide (1993–2025). The ASM sector has experienced substantial growth, with global employment rising from approximately 13 million people in 1999 to 30 million in 2014, and more recently to over 49.5 million people. Sources: ([ASM Inventory, 2025](#); [Delve Database, 2022](#); [Fritz et al., 2018](#)).

2000 to about 2 million ounces in 2018, accounting for approximately 43% of total gold output in Ghana in 2018 ([Adu-Baffour et al., 2021](#); [Adranyi et al., 2024](#)) (see [Figure 1.4](#)). Due to the large quantities, the data presented in [Figure 1.4](#) is based on the Indian numbering system, where 10 lakh (10,00,000) represents 1 million (1,000,000) in the international system.

Additionally, as depicted in [Figure 1.5](#), the percentage of population per country involved in ASM varies considerably across Africa, Latin America, and Asia ([ASM Inventory, 2025](#)). According to recent data from the ASM Knowledge Sharing Archive (2025) database and estimates based on 2020 world population data from the World Bank, exploring the state of the ASM sector ([ASM Inventory, 2025](#)), it is estimated that up to 9.3% of the population in many African countries can depend directly on ASM for their subsistence and income. In contrast, dependence on ASM is considerably lower in other regions, approximately 0.1–3% of the population in Latin America and 0.1–1.5% in Asia. In Africa, eight countries have at least 2.7% of their populations directly working in ASM: the Central African Republic, Zimbabwe, Burkina Faso, Sierra Leone, Liberia, Ghana, Sudan, and Zambia. In contrast, only two countries in Latin America (Suriname and Guyana) meet this threshold, and there are no countries in Asia that have such a high percentage of their population dependent on ASM. However, the high percentages observed in Latin America and some African countries are often due to lower-population countries such as Suriname and the Central African Republic, with a large number

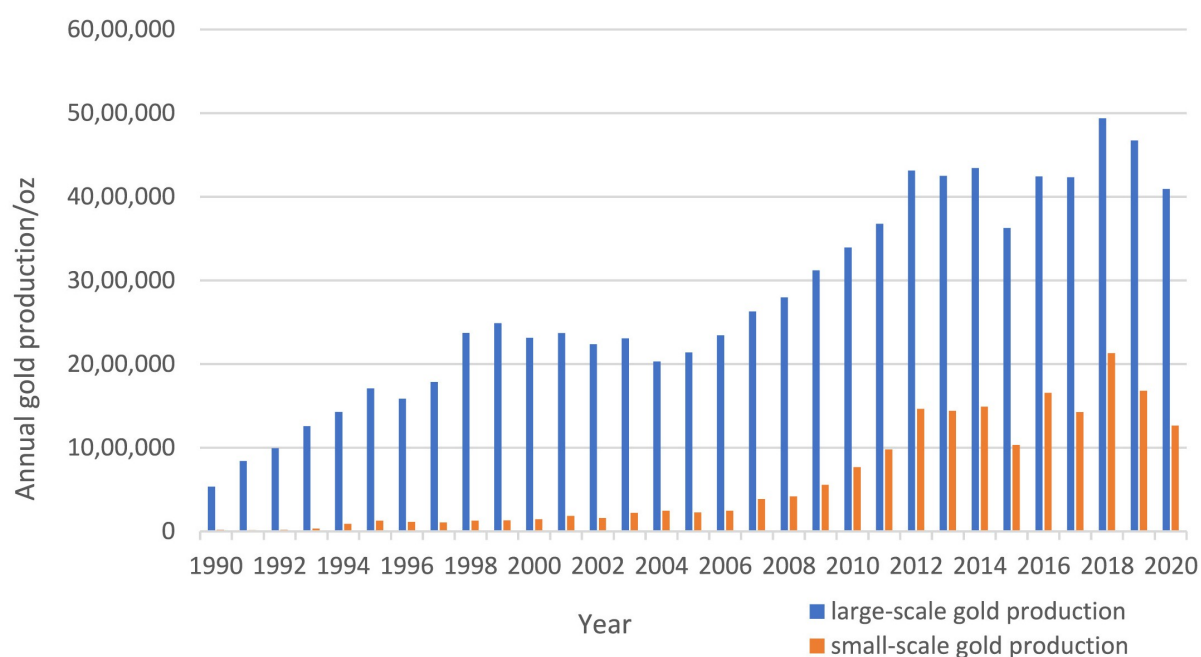


Figure 1.4: The trend in gold production in Ghana between 1990 and 2020. ASM has contributed significantly to the total gold production in Ghana over the years, accounting for approximately 43% of total gold output in Ghana in 2018. Due to the large values, the data presented is based on the Indian numbering system, where 10 lakh (10,00,000) represents 1 million (1,000,000) in the international system. Source: (Adranyi et al., 2024).

of people involved in ASM, while larger populated countries in Asia, such as China, account for the percentage estimates (see Table 1.1).

In Africa, ASM is much more concentrated in Sub-Saharan Africa (Figure 1.5), with most of the world's top ten countries with high percentages of their populations directly engaged in ASM for their subsistence located in this region (ASM Inventory, 2025), as shown in Table 1.1. In West Africa, at least 5 million people work directly in the ASM sector in 10 countries (Hilson, 2016), Ghana among the countries having a high percentage of their population employed by ASM, involving at least 3.86% of the total population (see Table 1.1), highlighting its importance but also its significant impact on local communities and the economy (ASM Inventory, 2025). In the DRC and Ghana, for example, mining (i.e. both LSM and ASM) significantly contributes to economic growth, making up about 13% and 9.8% of their Gross Domestic Product (GDP) in 2016 and 2013, respectively (Ericsson and Löf, 2019; Ghana Statistical Service, 2014).

Despite ASMs clear contribution to local livelihoods and national economies, ASMs remain largely informal, with approximately 70 – 80% of miners globally operating informally or illegally (Fritz et al., 2018). ASM operations are increasingly understood to operate along a continuum of formality (McQuilken and Gavin, 2016), ranging from highly informal and often illegal practices, including extraction within protected areas such as wildlife preserves

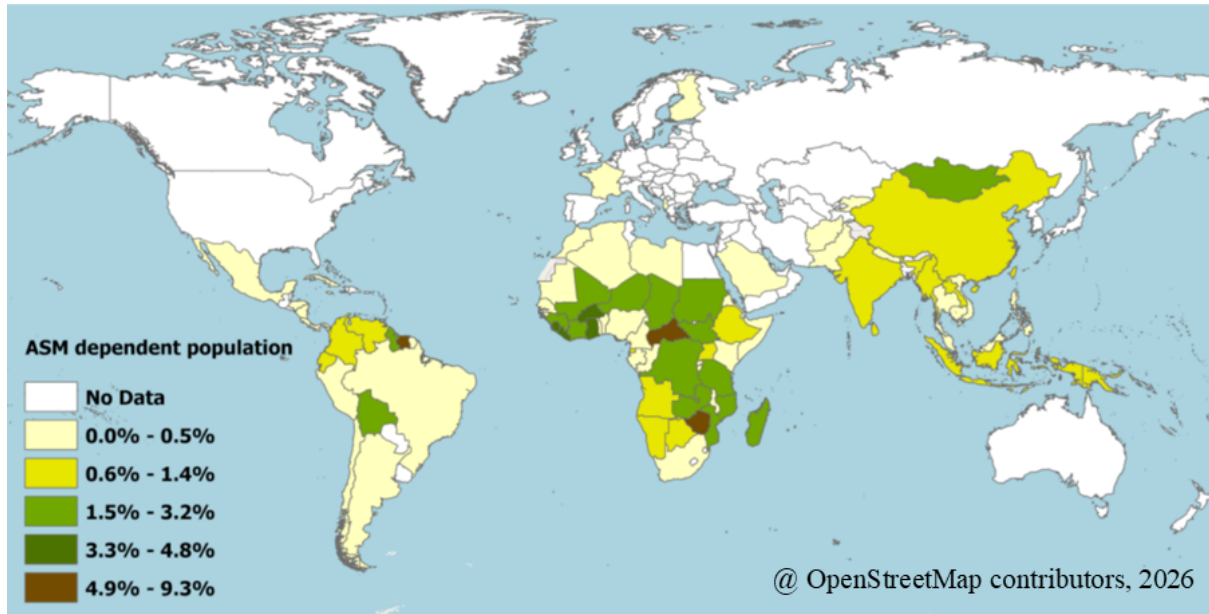


Figure 1.5: Global geographic distribution of the percentage of the population dependent on ASM by regions and country, based on World Bank 2020 population data and data on the current state of the ASM sector from the ASM Knowledge Sharing Archive (2025) database ([ASM Inventory, 2025](#); [OpenStreetMap contributors, 2026](#)). ASM operators are more concentrated in the Global South, with Africa accounting for the majority of the population engaged in ASM operations.

Table 1.1: The top 10 countries in the world with the highest percentage of the total population directly dependent on ASM. Estimates are based on the current state of ASM sector data from the ASM Knowledge Sharing Archive (2025) database and 2020 World Bank population data. Source: ([ASM Inventory, 2025](#))

Region	Country	% population working in ASM (%)
Sub-Saharan Africa	Central African Republic	9.32
Sub-Saharan Africa	Zimbabwe	6.73
South America	Suriname	5.97
Sub-Saharan Africa	Burkina Faso	4.78
Sub-Saharan Africa	Sierra Leone	4.39
Sub-Saharan Africa	Liberia	3.95
Sub-Saharan Africa	Ghana	3.86
Sub-Saharan Africa	Sudan	3.19
South America	Guyana	2.92
Sub-Saharan Africa	Zambia	2.72

or heritage sites ([Boadi et al., 2016](#)), to fully licensed and formalized activities that operate in compliance with environmental regulations and governance frameworks ([Hilson, 2002](#)). However, in Ghana, the vast majority of ASMs (about 85%) are often operated illegally (known colloquially as 'galamsey'), driven by an influx of heavy earth-moving equipment such as ex-

cavators, mostly brought in illegally by foreign investors ([Adu-Baffour et al., 2021](#); [Hilson and Gatsinzi, 2014](#); [Ndubuisi, 2024](#)). Galamsey operations are therefore the cause of numerous social and environmental problems for local communities and the country at large, and have been a significant and growing national concern in Ghana for many years ([Baffour-Kyei et al., 2021](#); [Ndubuisi, 2024](#)).

1.1.2 Environmental, Social, Safety, and Health challenges associated with ASM

While each ASM site possesses distinct characteristics, certain common factors underscore the broader health and safety risks arising from ASM activities ([Fritz et al., 2018](#)). These include a lack of mechanisation, reliance on rudimentary mining methods, inadequate implementation of occupational health and safety (OHS) practices, and lack of skilled labour ([Fritz et al., 2018](#)). In terms of safety, ASM pits are often constructed without proper planning and monitoring, which increases the risk of rockfalls, cave-ins, and poor ventilation and air-circulation ([Hilson, 2002](#)). Additionally, explosives, despite being banned for many ASM areas by various governments, are used recklessly, frequently leading to injuries and fatalities ([Bansah et al., 2018](#); [Hilson, 2002](#)). These safety concerns can largely be traced back to a lack of government monitoring, inadequate training of ASM personnel, and non-compliance with regulations ([Adu-Baffour et al., 2021](#); [Nunfam et al., 2020](#)). In addition, ASM is associated with increased occurrences of prostitution, conflicts, alcohol abuse, and the spread of diseases such as HIV/AIDS within host communities ([Bansah et al., 2018](#); [Fritz et al., 2018](#); [Hilson, 2002](#)). HIV/AIDS has become particularly prevalent across Africa, spreading rapidly in numerous ASM hotspots in Western Africa (Ghana, Nigeria, etc.), Zimbabwe, and South Africa, where awareness of contraception remains critically low. The exploitation of women and the involvement of children in the ASM sector are also ongoing concerns, contributing to truancy and poor educational performance ([Bansah et al., 2018](#)).

Aside from the issues mentioned above, several environmental problems are associated with ASM. The reliance on hazardous substances poses significant risks to the health of miners and surrounding communities, who may be exposed to mercury, zinc vapour, cyanide, or other acids ([Fobi et al., 2025](#)). This is a particular concern in artisanal and small-scale gold mining, where mercury is often used, and the use of cyanide is increasing across all African, Latin American, and Asian countries ([Fritz et al., 2018](#)). For example, Indonesia, along with Ecuador, Mongolia, and Peru, is identified as one of the countries facing significant mercury-related health issues from ASM, with each country having between 70,000 and 150,000 individuals exposed to mercury contamination ([Fritz et al., 2018](#)). The impacts of informal ASM on water bodies encompass contamination from suspended solids, heavy metals, mercury, and oil and grease ([Bansah et al., 2018](#)). The dredging and washing of alluvial gold in rivers (see

Figure 1.6c and Figure 1.6d) has polluted many streams and rivers in regions where mining activities occur and this has been linked to health problems such as skin infections including rashes and ringworm, particularly among individuals who rely on river water for bathing, drinking, cooking, and other daily activities (Bansah et al., 2018). Ghana's major rivers, such as the Ankobra, Pra, Oda, and Offin, have recorded high suspended sediment levels due to galamsey operations, resulting in increased water treatment costs and fish migration from these affected rivers (Kusimi et al., 2014; Bansah et al., 2018).



Figure 1.6: Mercury-related problems from ASM. (a – b) Children in Nigeria involved in gold amalgamation processes and occupational exposure to toxic mercury fumes released during the burning of amalgams. Source: (Veiga et al., 2025). (c – d) Informal ASM workers dredge river beds for gold in Ghana. Source: (Bansah et al., 2018).

Mercury can enter the body through inhalation, ingestion, or skin contact, but its health effects are typically not immediate (Armah et al., 2016; Veiga et al., 2025). Major mercury-

related health risks associated with ASM include exposure to dust and fine particles from blasting and drilling, as well as toxic mercury fumes released during the burning of amalgams, often done in open fires with miners' noses close to the source (see [Figure 1.6a](#) and [Figure 1.6b](#)) ([Armah et al., 2016](#); [Veiga et al., 2025](#)). Such practices can cause respiratory diseases, including silicosis, mesothelioma, and pneumoconiosis, among miners and in children who often accompany their parents ([Armah et al., 2016](#); [Fritz et al., 2018](#)). In sub-Saharan Africa, studies indicate that women bear most OHS risks due to the gendered division of mining tasks, making them particularly vulnerable to mercury exposure, which can severely compromise foetal development ([Armah et al., 2016](#); [Fritz et al., 2018](#); [Hinton et al., 2003](#)).

Another significant environmental issue associated with the sector is deforestation and forest degradation. As shown in [Figure 1.7](#), informal ASM sites often result in landscapes scarred by abandoned, unstable piles of soil and rock, excavated pits, and widespread deforestation ([Bansah et al., 2018](#)). These ASM operations often leave behind abandoned flooded pits, which pose risks to livestock, the environment, and local communities, in addition to creating breeding grounds for malaria-carrying mosquitoes ([Bansah et al., 2018](#)). Much of the excavated land is not properly reclaimed subsequently, exhibiting the distinctive uneven, 'potholed' landscape ([Hilson, 2002](#)). For clarity, the terms deforestation and forest degradation used throughout this thesis are defined based on the Food and Agriculture Organization's (FAO) definition of deforestation and forest degradation ([FAO, 2022](#)). **Deforestation** is the complete removal of forest from its natural, unused state to a different forest land use, such as mining, agriculture, and urban development. **Forest degradation** refers to a process of thinning of the forest canopy, such as a reduction in tree density in the area, but without a complete removal of trees or a move to another land use. Degradation, on the other hand, can be caused by human activities such as selective logging and is an indicator of an early stage of mining activity. **Forest disturbance** is a term that can encompass both deforestation and forest degradation. In this thesis, we refer henceforth to degradation only, due to its usefulness as an early-warning indicator.

To address the many problems associated with ASM, the government of Ghana established a National Task Force in 2013 to curb these operations. As part of this initiative, a nationwide ban on all ASM operations was introduced in March 2017, with the ban partially lifted in December 2018 to facilitate the formalization of the sector and to redefine how ASM might be facilitated across the country ([Botchwey et al., 2019](#)). Although the government of Ghana has made ongoing efforts to streamline the ASM sector since 2017, illegal ASM operations remain a livelihood for many Ghanaians in rural areas ([Baddianaah et al., 2022](#); [Baffour-Kyei et al., 2021](#); [ASM Inventory, 2025](#)). Although the causes are not always clear, this is most likely due to several factors, most noticeably a lack of or limited monitoring capability for ASM activities due to their remote locations ([Baddianaah et al., 2022](#); [Baffour-Kyei et al., 2021](#)). Attempts to deploy military task forces to enforce this policy led to conflict and violations of human rights,



Figure 1.7: Artisanal gold mining in the Amazon forest causes widespread deforestation, leading to excessive vegetation removal and soil disturbance. The land is left barren and abandoned for several years, with an additional risk arising from the creation of breeding grounds for malaria-carrying mosquitoes. Source: ([Kalamandeen and Galbraith, 2020](#)).

financial losses, and increased public dissatisfaction ([Bansah et al., 2018](#)).

Any new methodologies that support effective management of the ASM sector are therefore of great value to help governments in the Global South meet several targets (e.g. reduce poverty, promote good health and well-being of miners, decent work and economic growth, better life on land, peace and justice) with benefits directly linked to 9 of the 17 United Nations Sustainable Development Goals (SDGs) ([Hilson and Maconachie, 2020](#)). However, faced with the immediate challenge of simply locating these ASM sites, a critical need is to minimize delays in locating ASM activities in near real-time and delineate their spatial distribution and dynamics. Achieving this goal will be crucial for mitigating their social and environmental impacts and providing emergency aid to protect lives and the natural environment.

1.2 The ASM monitoring challenge in the tropics

This section reviews the current frameworks for monitoring ASM activities in the tropics, highlighting the advantages and challenges that restrict their use for timely and reliable ASM monitoring in the tropics.

1.2.1 Limitations of conventional methods for ASM monitoring

Traditional efforts to monitor ASM operations, support their formalisation, and reclaim many abandoned wastelands in tropical regions have traditionally depended on field-based surveys to document their spatial distribution, dynamics, and hotspots ([Jiménez et al., 2024](#); [Mantey et al., 2017](#); [Owusu-Nimo et al., 2018](#)). Field-based surveys are important for obtaining detailed information on ASM, and may also include its social aspects and any site-specific characteristics. However, obvious limits on scalability and high resource demands of any field-based method highlight the need for complementary methods, such as remote sensing, to enable a synoptic, timely, safer, and more reliable method for reliable ASM monitoring ([Owusu-Nimo et al., 2018](#)).

1.2.2 Role of remote sensing and machine learning for ASM monitoring

This section outlines the recent advances in the use of RS and machine learning (ML) technologies for monitoring ASM activities in the tropics and identifies the knowledge gaps that will be addressed in this study.

1.2.2.1 Optical data

The use of high-resolution aerial imagery has long been acknowledged as valuable for mapping and monitoring ASM activities, offering the required detail and higher accuracy for site-specific studies ([Asner et al., 2013](#); [Chirico and Dewitt, 2017](#)), although it is acknowledged that this method is too expensive and therefore does not lend itself to the high frequency of image updates required for regular monitoring. Satellite RS has therefore clear potential for enabling regular monitoring, though the use of optical satellite imagery can be limited by cloud cover, a significant challenge for countries in the tropical regions of the Global South ([Coulter et al., 2016](#); [Dogbey et al., 2022](#)).

In recent years, the use of optical imagery for mapping ASM activities has been explored, but results vary according to a number of factors, such as the resolution of the sensor, the degree of persistent cloud cover, and the accuracy of the method used to identify ASM in the images ([Asner et al., 2013](#)). Several studies have explored the suitability of Landsat images and traditional pixel-based ML classifiers for time series analysis to map ASM activities in Brazil ([de Lucia Lobo et al., 2018a](#); [Lobo et al., 2016](#)), Burkina Faso ([Leroux et al., 2018](#)), Suriname ([Quash et al., 2024](#)), Tanzania ([Pancrace et al., 2022](#)), and Ghana ([Boakye et al., 2020](#); [Obodai et al., 2019](#); [Snapir et al., 2017](#); [Barenblitt et al., 2021](#)) and incorporated land use/land cover changes to infer the presence of ASM activities. These studies reported errors of omission/commission ranging from 8 to 40% for the ‘mining’ class, indicating mixed success in the accuracy of this method for ASM mapping due to image resolution problems ([Boakye et al., 2020](#); [Obodai et al., 2019](#)). A significant challenge encountered in these investigations occurred

in regions where bare soil and vegetation were mixed with mining dugouts, presenting a challenge in detecting small ASM sites at 30 m Landsat resolution ([Snapir et al., 2017](#); [Barenblitt et al., 2021](#)).

A specific group of pixel-based techniques, mainly applied in deforestation research, utilises spectral mixture analysis to identify changes at the subpixel level. This approach has been employed in numerous studies for Landsat images to detect deforestation associated with ASM ([Asner et al., 2013](#); [Asner and Tupayachi, 2017](#); [Espejo et al., 2018](#)). These methods usually present omission and commission errors for the mining class, ranging from 10% to 25% ([Asner and Tupayachi, 2017](#); [Espejo et al., 2018](#)), with challenges often arising in accurately distinguishing water pools within alluvial mining areas ([Espejo et al., 2018](#)). The primary limitation of these pixel-based classifiers is their lack of spatial context, as each pixel is analysed in isolation. One consequence of this is that it results in a 'speckled' appearance in the classification maps ([Blaschke et al., 2014](#)), which can be somewhat reduced through postprocessing, though not entirely eliminated ([Kelly et al., 2011](#)).

In recent years, advances in satellite imaging systems such as the European Space Agency's (ESA) Sentinel-2 platform now provide multispectral imagery under an open-access license with a 10 m resolution, which has greatly contributed to the monitoring of the Earth's surface ([Phiri et al., 2020](#)). Researchers have leveraged this new data, exploring methods for mapping ASM using Sentinel-2 time series and traditional pixel-based ML classifiers ([Ngom et al., 2020, 2022](#); [Nyamekye et al., 2021](#); [Pereira et al., 2023](#); [de Lucia Lobo et al., 2018b](#); [Tamfuh et al., 2024](#)). These approaches typically achieved commission and omission errors for the mining class from roughly 10% to 20%. The main limitations faced included cloud cover issues during the rainy season and challenges in distinguishing mining from other land use classes, reinforcing the 'speckled' appearance in the classification maps encountered using Landsat images.

Object-Based Image Analysis (OBIA) techniques aim to incorporate the spatial component by segmenting the image into regions based on spectral similarity (i.e. shape, texture, etc.) and then classifying these regions instead of individual pixels ([Blaschke et al., 2014](#); [Stoll et al., 2022](#)). These techniques have proven effective for mapping small ASM sites (< 5 ha), though they are primarily suited for high-resolution images, site-specific or localized studies, achieving an average accuracy of 90% with high-resolution PlanetScope imagery in Guyana ([Stoll et al., 2022](#)). Nonetheless, this approach is expensive (cost of image purchase) and does not provide the frequency updates of images to facilitate regular ASM monitoring. Additionally, determining suitable parameters for the initial object segmentation can be time-consuming and demands substantial domain expertise ([Nuijten et al., 2019](#)).

The general trend towards DL in many applications in earth observation also presents an opportunity to improve accuracy over the traditional ML methods ([Liu et al., 2022](#); [Vali et al.,](#)

2020). DL has been utilised for mapping surface ASM in Peru, achieving an accuracy of up to 95.8% using Sentinel-2 imagery (Camalan et al., 2022). In Ghana, the southern regions have a hot and wet climate, are prone to cloud cover and haze, and are particularly affected by this during the rainy season that lasts from early March to October (Snapir et al., 2017; Forkuor et al., 2020). A recent study by Gallwey et al. (2020) built on the findings of earlier Landsat studies and developed a DL-based approach to map the extent of ASM activities in a large area of southern Ghana using Sentinel-2 images only. This method achieved less than 8% omission and commission errors; however, cloud cover was identified as the critical weakness, as the study was not able to identify a single, suitable, cloud-free image throughout the rainy seasons, despite the weekly satellite revisit times that could allow timely and reliable continuous ASM monitoring. According to Snapir et al. (2017), analysis of the MODIS cloud fraction product (Platnick et al., 2003) in 2015 revealed that southern Ghana has an average cloud cover of 83%, with a minimum of 53% even during the dry season, i.e. the month of December. Figure 1.8 illustrates the persistent cloud cover problem in southern Ghana for one of the test sites in this thesis, with all available Sentinel-2 images over a mining area during the major and minor rainy periods between April and December 2022 affected by cloud cover. A fundamental justification for the methods in this thesis is that while improved accuracies can be achieved with optical imagery and DL techniques for ASM monitoring, the problem of cloud cover limits its use for early warning ASM applications.

1.2.2.2 Synthetic Aperture Radar data

SAR is an active RS technique that operates at longer wavelengths, ranging from millimetres to centimetres. SAR satellites possess the capability to penetrate cloud cover using these longer wavelengths and active imaging techniques, thereby offering a solution for regular monitoring in areas prone to cloud cover or a rainy season, operational during nighttime and during adverse weather conditions (Pulella et al., 2020; Ruiz-Ramos et al., 2020). The potential of SAR to identify ASM has been shown in previous studies utilising remote sensing techniques such as image classification and change detection (Forkuor et al., 2020; Janse van Rensburg and Kemp, 2022; Kimijima et al., 2022b); however, SAR has many limitations that must be addressed before it can be employed in ASM near real-time (NRT) approaches. For example, previous studies in Ghana (Forkuor et al., 2020), Nigeria (Chike and Balz, 2024), and Indonesia (Kimijima et al., 2022b) have faced challenges such as adverse atmospheric effects from heavy rainfall, leading to increased measurement uncertainty and reduced accuracy, especially during the rainy season using C-band SAR S1 imagery. The atmospheric effects from active rainfall often cause a darkening effect or local decrease in backscatter that is unrelated to surface conditions (see Figure 1.9). These challenges significantly hinder the timely detection of ASM activities using S1 SAR imagery in the wet tropics.

In addition to adverse atmospheric effects, the inherent speckle noise of the SAR data

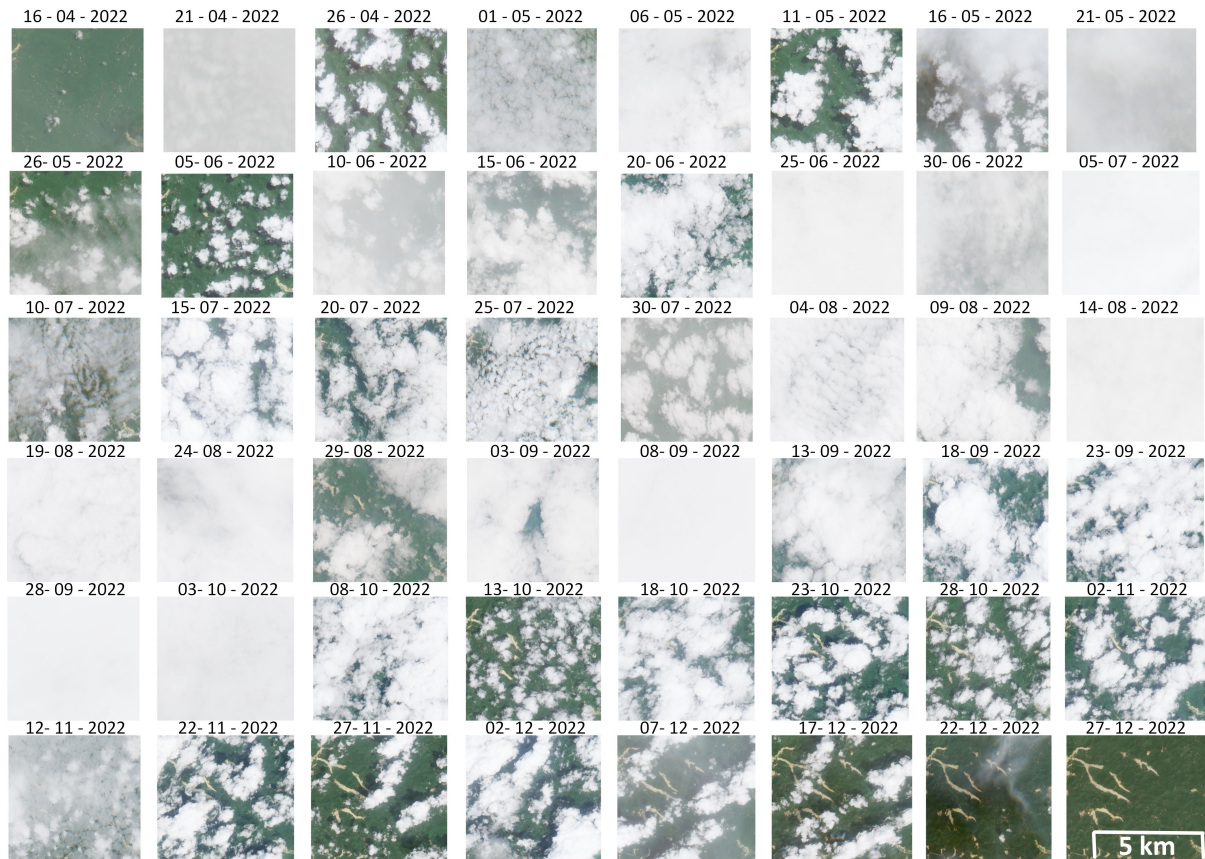


Figure 1.8: The typical persistent cloud cover problem in southern Ghana affecting all available Sentinel-2 images over a mining area during the major and minor rainy periods between April and December 2022, which is typical for any other year in the region. This rules out the use of optical imagery for regular ASM monitoring.

has also affected the accuracy of timely detection of ASM using SAR imagery in the tropics (Janse van Rensburg and Kemp, 2022). SAR images are inherently influenced by signal-dependent noise, referred to as speckle, which results in a random granular ‘salt and pepper’ pattern present in images that significantly affects their appearance and quality, as illustrated in Figure 1.10 (Singh and Shree, 2016; Sivaranjani et al., 2019; ESA, n.d.). Therefore, effectively reducing speckle noise is an important pre-processing step in SAR image classification applications to achieve reliable results (Sivaranjani et al., 2019). Speckle noise problems have been encountered in previous studies in detecting and mapping ASM sites using SAR time series and traditional pixel-based ML classifiers, and incorporating land use/land cover changes to infer the presence of ASM activities in Ghana (Janse van Rensburg and Kemp, 2022). This resulted in challenges in accurately discriminating ASM-related disturbances from other forest changes, limiting the broader application of the approach for timely and reliable ASM monitoring.

Another study by Kimijima et al. (2022a) using SAR time series for detecting and characterising ASM activities in Indonesia reported limitations caused by rugged topography, which affected the accuracy of detecting ASM sites in the tropics. The uneven topography causes SAR

geometric distortions in mountainous regions due to the SAR side-looking imaging geometry, which strongly affects the backscatter coefficient (Kimijima et al., 2022a).

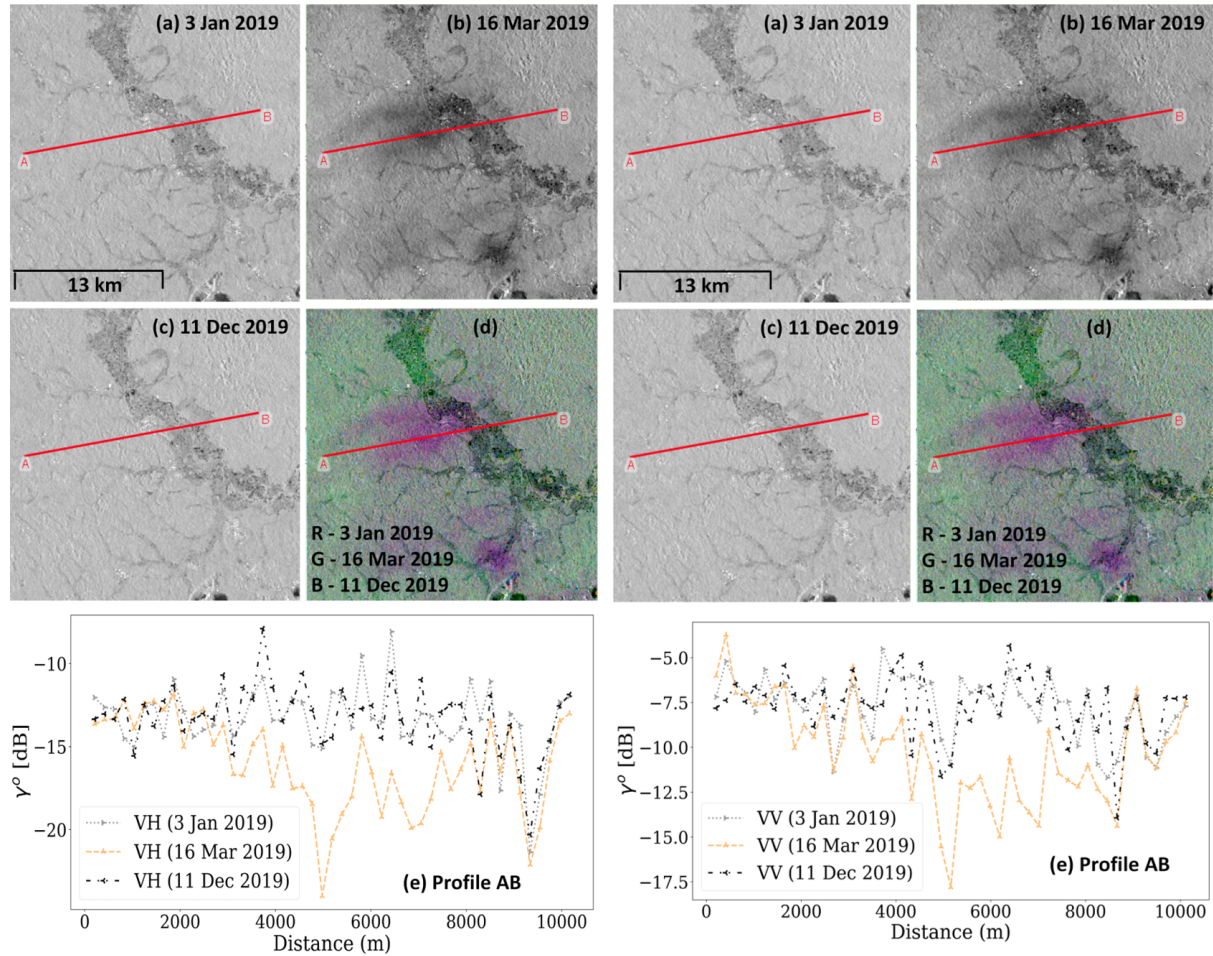


Figure 1.9: Sentinel-1 C-band SAR example of atmospheric effects from active rainfall on backscatter showing darkening effects or a strong local decrease in backscatter during the rainy season in March 2019. (a) VH and VV backscatter image acquired on 3 January 2019, (b) VH and VV backscatter image acquired on 16 March 2019, (c) VH and VV backscatter image acquired on 11 December 2019, (d) The S1 false colour composite image comprised of the red channel (3 January 2019), green channel (16 March 2019), and blue channel (11 December 2019), (e) VH and VV backscatter values along the profile AB over the mining site in southern Ghana.

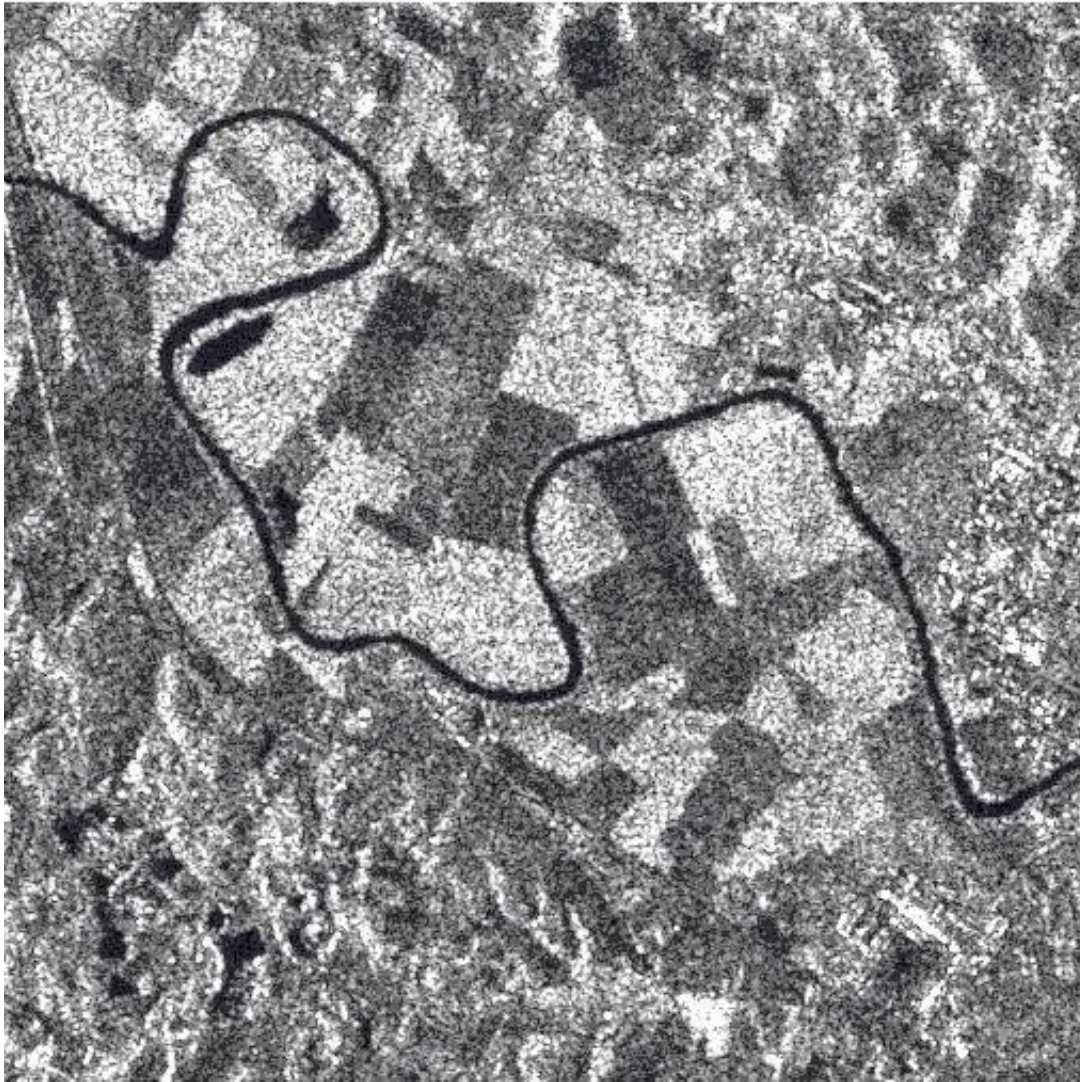


Figure 1.10: Example of SAR speckle noise affecting the appearance and quality of radar images, often resulting in a 'speckled' appearance in the classification maps using traditional ML classifiers. SAR speckle noise affects the backscatter values in the agricultural fields, resulting in a grainy image that degrades the appearance and quality of the radar image. Source: ([ESA](#), [n.d.](#)).

1.3 Knowledge gaps

Despite the interest in the use of SAR for monitoring ASM activities in wet tropical regions, the literature review conducted as part of this thesis revealed several significant research gaps that can be unaddressed.

1.3.1 Enhancing SAR data quality to improve the accuracy of ASM detection

Existing studies have primarily focused on developing workflows for creating SAR backscatter analysis-ready data (ARD) to support ASM mapping in tropical regions. These workflows were typically utilised to create geometric terrain-corrected backscatter coefficient ARD products processed in sigma naught (σ^0) (Kimijima et al., 2022b; Janse van Rensburg and Kemp, 2022), or radiometric terrain-corrected ARD products in gamma naught (γ^0) (Forkuor et al., 2020). Although these ARD preparation approaches have demonstrated effectiveness for ASM detection under optimal conditions, they tend to be less reliable for images acquired during the rainy seasons, particularly for S1 C-band SAR. This limitation highlights the essential need for further investigation into robust SAR backscatter ARD frameworks specifically designed for the environmental and seasonal complexities of wet tropical regions. Border noise removal is an essential SAR processing step that has been demonstrated to be an effective method for removing outliers caused by active rainfall in SAR images and improving forest disturbance monitoring in the wet tropics using S1 imagery (Reiche et al., 2021). However, its effectiveness in reducing the atmospheric effects from heavy rainfall to improve ASM monitoring has not been explored. Additionally, the influence of varying topographic conditions on the performance of S1 σ^0 and γ^0 backscatter products for ASM mapping has not been systematically assessed. Studies have shown that the selection of DEM options for generating the γ^0 radiometric terrain normalisation product is a crucial step for effectively reducing topographic distortions, including effects such as foreshortening (Truckenbrodt et al., 2019). The choice of DEMs for creating γ^0 backscatter radiometric terrain-corrected ARD products also remains unexplored, despite its potential impact on terrain normalisation accuracy and the reliability of subsequent ASM detection.

1.3.2 Timeliness of ASM detection

Beyond those ARD challenges, there also appear to be no remote sensing studies, using either optical or SAR imagery, that have explored the potential of early detection of ASM activities in the tropics to facilitate rapid intervention. ASM usually progresses through several stages, starting with vegetation clearance before ore extraction and processing, typically done using water (see Figure 1.11). Hence, detecting ASM during the early stages is essential to minimise damage to the natural environment. The use of S1 C-band SAR therefore presents opportunities due to its reliability and open-data policies, but also challenges for detecting small ASM sites, as these sites are typically around 20m in diameter, which challenges the limits of what can be detected in an S1 image (see Figure 1.2). Existing studies utilising multi-temporal data have been shown to be effective in identifying ASM rather than relying on imagery from a single date (Asner et al., 2013); however, the use of SAR time-series for ASM studies has faced several

challenges, such as speckle noise, adverse atmospheric effects from active rainfall, and effects of topography described in section 1.2.2.2, which have limited its early warning capabilities. Addressing this research gap is particularly crucial due to the significant impact that variations in forest structure and biomass have on SAR backscatter responses (Vreugdenhil et al., 2018), which makes early detection of ASM activity with SAR time series more challenging. Therefore, there is a critical need to develop a monitoring method that provides timely alerts, allows rapid response, and supports informed decision-making in dynamic and environmentally sensitive tropical landscapes. This is one of the major unresolved challenges that this thesis aims to address.

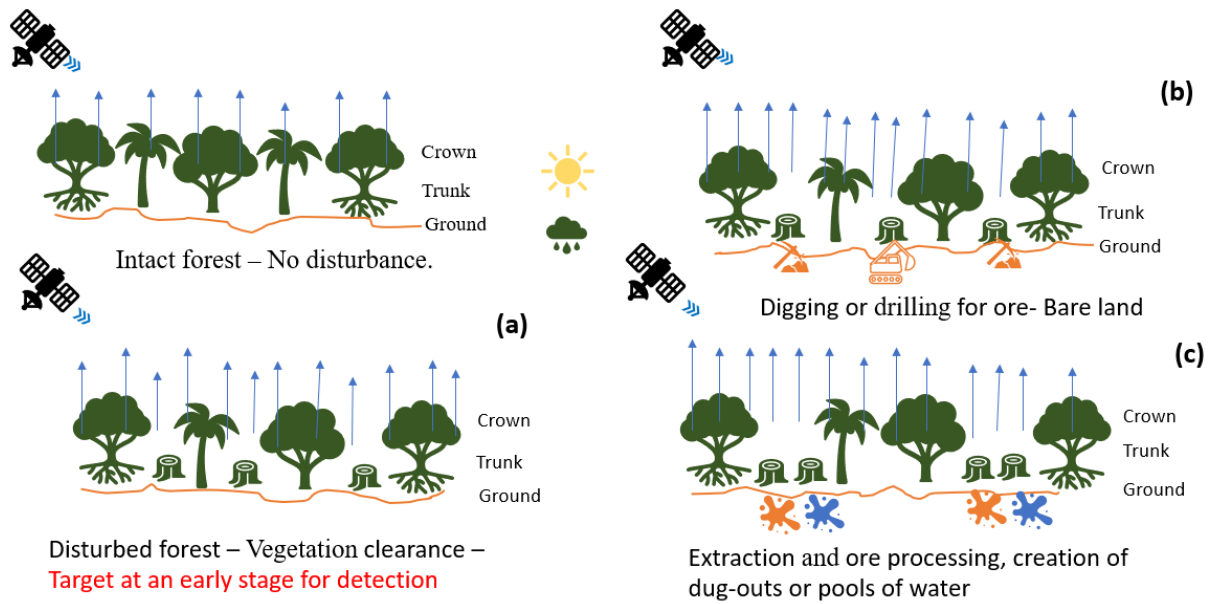


Figure 1.11: Schematic diagram showing the interaction of S1 C-band (5.6cm) signals with forest canopy and considerations for detecting the different ASM stages: (a) vegetation removal/thinning, usually removing small lines of trees or thinning (b) bare land after vegetation removal, (c) mining commences and formation of pools of water interspersed with bare soil or vegetation. One of the goals of this thesis is to identify early ASM activity as soon as possible after stage 1 begins, which is an unresolved challenge from the literature.

1.3.3 Scaling

Despite the demonstrated potential of DL for accurately detecting ASM in complex tropical environments on a large scale using optical imagery (Gallwey et al., 2020), a significant gap remains in exploring the suitability of DL for timely ASM mapping using S1 SAR imagery. Existing SAR-based ASM studies have primarily relied on traditional ML classifiers, which are essentially limited in their ability to model complex contextual patterns in SAR images and to suppress speckle-induced ambiguity (Janse van Rensburg and Kemp, 2022). As a result, SAR approaches have encountered challenges in distinguishing ASM-related disturbances from other forest changes, particularly in heterogeneous tropical environments where multiple disturbance drivers coexist. While recent advances in DL have significantly improved SAR-based

change detection in other domains (Gao et al., 2023; Zhao et al., 2023; Zheng et al., 2017), these methodological developments have not yet been extended to ASM mapping. To date, no studies have applied DL techniques to SAR images for ASM detection, especially in differentiating ASM-induced disturbances from other forest changes in complex tropical regions. Addressing this knowledge gap is essential to advancing the understanding of how DL methods can improve the detection and characterization of ASM activity in the tropics and reduce the effects of SAR noise. As data volumes increase to enable a rapid detection methodology, the processing requirement also increases proportionately, and therefore, this thesis explores a cloud-based processing platform, Google Earth Engine (GEE), suitable for a wide range of land applications at a large scale.

1.4 Aim and objectives

The overarching aim of this thesis is to develop a scalable, SAR-based methodology that leverages cloud computing, change detection, and DL methods for timely and reliable ASM monitoring in persistently cloudy regions. To accomplish this, five objectives were developed:

Objective 1 – establish evidence-based guidelines for optimizing the choice of backscatter normalisation approaches (σ^0 vs γ^0) for generating S1 ARD products within the GEE environment. This will thereby enable a more robust, reliable, and operationally scalable SAR-based monitoring framework for detecting ASM-induced forest disturbance across heterogeneous tropical landscapes.

Objective 2 – investigate the analysis readiness of open-source global DEMs for generating S1 radiometric terrain normalization γ^0 products for timely and reliable ASM monitoring in the tropics across different forest types and varied topography, including mountainous areas, during both wet and dry seasons.

Objective 3 – develop a novel methodology to model backscatter variations caused by (i) seasonality and (ii) outliers from adverse atmospheric conditions to improve the accuracy of ASM detection using S1 SAR data in the wet tropics, particularly during the rainy seasons.

Objective 4 – develop a robust approach to automatically detect the early stage of ASM activity using S1 time series data across different geographical areas in the tropics. This will allow rapid detection to facilitate timely interventions to prevent further extensive damage to the natural environment.

Objective 5 – design a novel, scalable SAR-based DL model for NRT ASM monitoring capable of reliably and accurately distinguishing ASM-related disturbances from other forest land use changes in complex tropical environments.

1.5 Study significance

This thesis makes five major contributions to addressing the challenges in mapping ASM activities in cloud-prone tropical environments using SAR imagery. The findings of the thesis will help establish guidelines for processing S1 SAR data to improve its effectiveness for timely and reliable ASM monitoring in the tropics, particularly during the rainy seasons. One of the significant contributions of this thesis lies in developing a novel, cost-effective methodology that can be scaled for large-area, continuous ASM monitoring from S1 SAR imagery by utilising change detection and DL techniques in the dynamic and environmentally sensitive tropical landscapes. More importantly, the findings will offer valuable insights for guiding and informing stakeholders on sustainable forest management, promoting action against illegal ASM activities, and enforcing legislation on climate change globally.

1.6 Thesis structure

The thesis is organised into six chapters, each structured as follows:

Chapter 2 provides a state-of-the-art review of SAR and image processing methods for ASM mapping and monitoring in the tropics, along with a theoretical background to justify the approaches presented in this thesis. First, a review of existing studies incorporating SAR and backscatter properties of SAR for forest mapping is discussed. Next, the acknowledged challenges of using SAR for ASM monitoring and the importance of SAR image preprocessing for ASM monitoring are discussed. Then, remote sensing change detection and image classification methods that have been used in ASM studies are presented and explained. The change detection methods focused on related works using time-series statistical change detection approaches for ASM mapping in the tropics, highlighting the potential and challenges of utilising S1 imagery. In terms of image classification, previous studies using machine learning classifiers and SAR for forest land use classification to detect ASM are reviewed. The review emphasizes the reported accuracy of these approaches and relates these to the methodological challenges associated with distinguishing mining activities from other forest disturbance drivers. Chapter 2 concludes with a synthesized summary of the literature.

Chapter 3 introduces the datasets used and created in this study and the rationale for selecting Ghana as the case study area to evaluate the methods developed in the thesis. The datasets, including the S1 SAR data, the optical data used in the later validation, and the DEMs used in pre-processing, are presented and described. Additionally, an overview of the regions within the study area chosen as case study locations is provided, covering natural resources, vegetation, climatic conditions, and topography.

Chapter 4 presents the first SAR preprocessing methodology for preparing S1 ARD backscatter data in GEE capable of addressing challenges of using SAR for timely ASM monitoring in the dynamic and environmentally sensitive tropical landscapes. This chapter first establishes evidence-based guidelines for optimizing the choice of backscatter normalization approaches (σ^0 vs γ^0) for generating S1 ARD products, enabling more robust and reliable ASM monitoring (**Objective 1**), with a focus on overall usability and the backscatter data quality. This was peer-reviewed and published in the IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2024) proceedings (DOI: [10.1109/IGARSS53475.2024.10640528](https://doi.org/10.1109/IGARSS53475.2024.10640528)). Secondly, Chapter 4 investigates the analysis readiness of four openly available DEMs for creating S1 γ^0 radiometric terrain normalization products for detecting ASM-induced deforestation stages in the tropics across different forest types and varied topography, including mountainous areas, during both wet and dry seasons (**Objective 2**). This was also peer-reviewed and published in the IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2024) proceedings (DOI: [10.1109/IGARSS53475.2024.10641014](https://doi.org/10.1109/IGARSS53475.2024.10641014)). Finally, the first investigation into the suitability of time series smoothing techniques to model backscatter variations caused by (i) seasonality and (ii) outliers from adverse atmospheric conditions is presented, aiming to enhance the effectiveness of S1 data for timely and reliable ASM monitoring in the tropics, particularly during the rainy seasons (**Objective 3**). This was presented as part of the European Space Agency (ESA) Living Planet Symposium 2025 proceedings, available at <https://lps25.esa.int/>.

Chapter 5 presents a novel, robust methodology to automatically detect early stage ASM activity using S1 time series data across different geographical areas in the tropics (**Objective 4**). Chapter 5 compares different state-of-the-art statistical CPD algorithms belonging to structurally different approaches in identifying change points in univariate time-series data to develop a robust method for the timely detection of ASM activity in the wet tropics, enabling rapid response based on the optimal integrated SAR backscatter ARD preparation framework proposed in Chapter 4. Chapter 5 was published in the *International Journal of Applied Earth Observation and Geoinformation* (DOI: doi.org/10.1016/j.jag.2025.104525).

Chapter 6 builds on the methods developed in Chapter 5 by designing a novel SAR-based DL model to classify the alerts identified from the CPD algorithm in Chapter 5, and is the first method to distinguish mining from other forest disturbances, allowing timely ASM mapping in the tropics (**Objective 5**). Alongside this, several pixel-based ML classifiers were utilised to benchmark the performance of the proposed DL model against current best practices. Chapter 6 has been submitted to the *International Journal of Applied Earth Observation and Geoinformation* and is currently under review.

Chapter 7 provides a synthesis of the results and findings. It also discusses the limitations of the data, models, and methods used in this study. The implications of the results for stake-

holders and local communities, as well as how the evaluated methods could be operationalised for NRT monitoring of ASM in the tropics, are discussed. Chapter 7 includes the conclusions drawn and the recommendations made for further improvement or research.

Chapter 2

Artisanal and Small-scale Mining monitoring

2.1 Introduction

This chapter outlines recent advances in the use of SAR and remote sensing techniques, encompassing both image classification and change detection, for detecting and mapping ASM activities in tropical regions, along with a review of SAR backscatter characteristics most relevant for forest applications and those used to develop and justify the methodology in this study. This chapter is structured according to the relevant objectives outlined in Section 1.4 that will be addressed in this study. Section 2.2 will review SAR imaging concepts relevant to achieving **Objectives 1 & 2** (i.e. impact of using σ^0 or γ^0 and DEM options for processing SAR data ASM monitoring). This section begins with a discussion of SAR imaging concepts, highlighting the influence of both incidence angle and topography on the backscatter response from forested areas. It will further review the backscatter normalisation approaches developed in the literature and used in ASM monitoring, identifying the limitations that will be addressed in this study. The third objective is introduced in Section 2.3 by discussing the current challenges that limit the application of SAR for the development of ASM early warning systems in the tropics, building on what is presented in Section 1.2.2.2. The influence of adverse atmospheric conditions on the imaging capabilities of SAR and signal variability caused by forest canopy seasonality effects on SAR backscatter are also introduced in this section. The most relevant sensor parameters, including frequency and polarisation, as well as target factors such as vegetation type, soil moisture content, and their contribution to SAR backscatter responses from forest, are discussed in this section. Section 2.4 establishes the current body of knowledge by collating all relevant studies that have utilised SAR time-series statistical change detection methods for ASM monitoring in the tropics, highlighting the advantages and challenges

in these approaches for SAR imagery acquired at different wavelengths (e.g C- and L-Band) relevant to achieving **Objective 4**, and plays a key role in justifying the S1 C-Band approach proposed in this thesis. Section 2.5 highlights the trend in previous studies that employ traditional ML classifiers or SAR time series, incorporating forest land use/cover changes to infer the presence of ASM activities. Specifically, the review critically examines the methodological challenges encountered in accurately discriminating ASM-related disturbances from other forest land use/cover changes from SAR imagery relevant to achieving **Objective 5**. The key knowledge gaps identified throughout the review are then summarised in Section 2.6.

2.2 Objectives 1 & 2 – Impact of backscatter normalisation approaches and choice of DEM for SAR ASM monitoring

The first two objectives of this thesis are to help establish guidelines for the choice of SAR backscatter normalisation approaches and DEM options for creating SAR ARD products, thereby enabling timely and reliable ASM monitoring across different forest types and varied topography. This section begins with a brief discussion of the SAR imaging concepts, along with a detailed discussion of backscatter normalisation approaches introduced in the literature for SAR data processing. It also reviews the backscatter normalisation approaches used in ASM monitoring applications, highlighting the influence of topography on the backscatter response from the forested area, identifying the gaps that will be addressed in this study.

2.2.1 SAR – background and advantages for forest applications

SAR is an active remote sensing technology that operates by transmitting microwave signals with wavelengths ranging from millimetres to centimetres, measuring the intensity of the energy reflected from the Earth's surface (Alessi et al., 2023). These returned SAR signals, generally known as backscatter, will vary significantly in intensity depending on the biophysical and structural properties of the target. SAR satellites pass over the earth in both descending or ascending orbital paths, traveling from north to south or south to north, respectively, to facilitate observations from different viewing angles. The angle of sight of the sensor, referred to as the slant range, varies across the ground extent of the SAR scene, which is commonly called the swath width (Figure 2.1) (Alessi et al., 2023). While optical sensors typically use the frame-based or push-broom scanning geometry, SAR employs a side-looking imaging geometry, with the radar antenna faced nearly perpendicular to the direction of the sensor's flight path and emitting an arcuate waveform (see Figure 2.1).

As an active remote sensing system, operating at much longer wavelengths than optical

sensors, SAR offers the advantage of being independent of daylight and weather conditions, making it particularly valuable in regions where persistent cloud cover limits the availability of optical imagery for regular monitoring (Pulella et al., 2020) and ties into the ascending and descending orbit capability above. The majority of spaceborne radar systems operate within the microwave region of the electromagnetic spectrum (i.e. wavelengths between 1 m and 1 mm) (see Figure 2.2) (Chaturvedi, 2019). The use of these longer wavelengths has also been proven to enable SAR to penetrate certain surface features, such as dry soil and forest canopies, thereby providing information on understory structures that optical sensors cannot capture (Alessi et al., 2023).

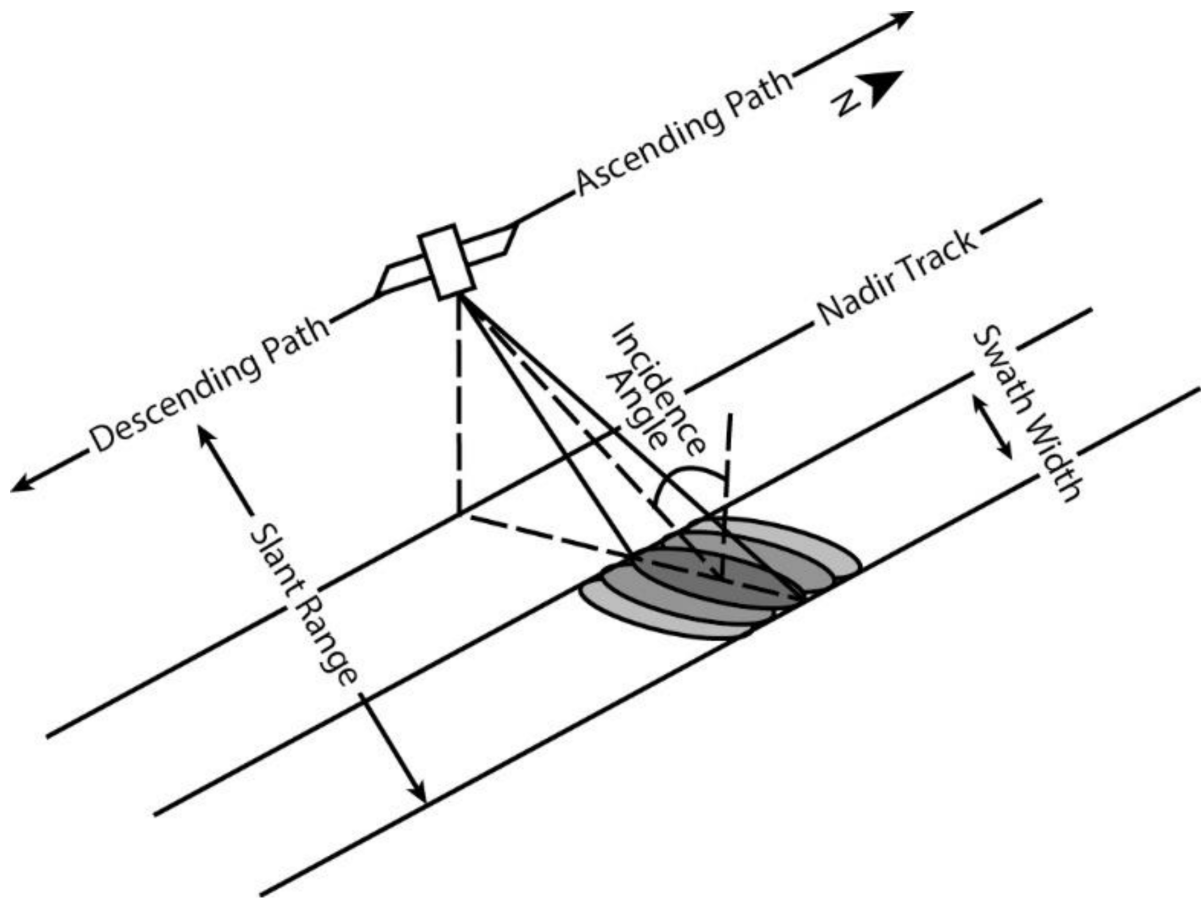


Figure 2.1: The typical observation geometry of a side-looking SAR system characterized by the spacecraft flying along a straight flight path while imaging the Earth's surface at an oblique look angle (θ), commonly expressed as the incidence angle ($90^\circ - \theta$). Image formation is achieved through the forward motion of the platform, which synthesises a large antenna aperture and enables high-resolution imaging. Source: (Alessi et al., 2023).

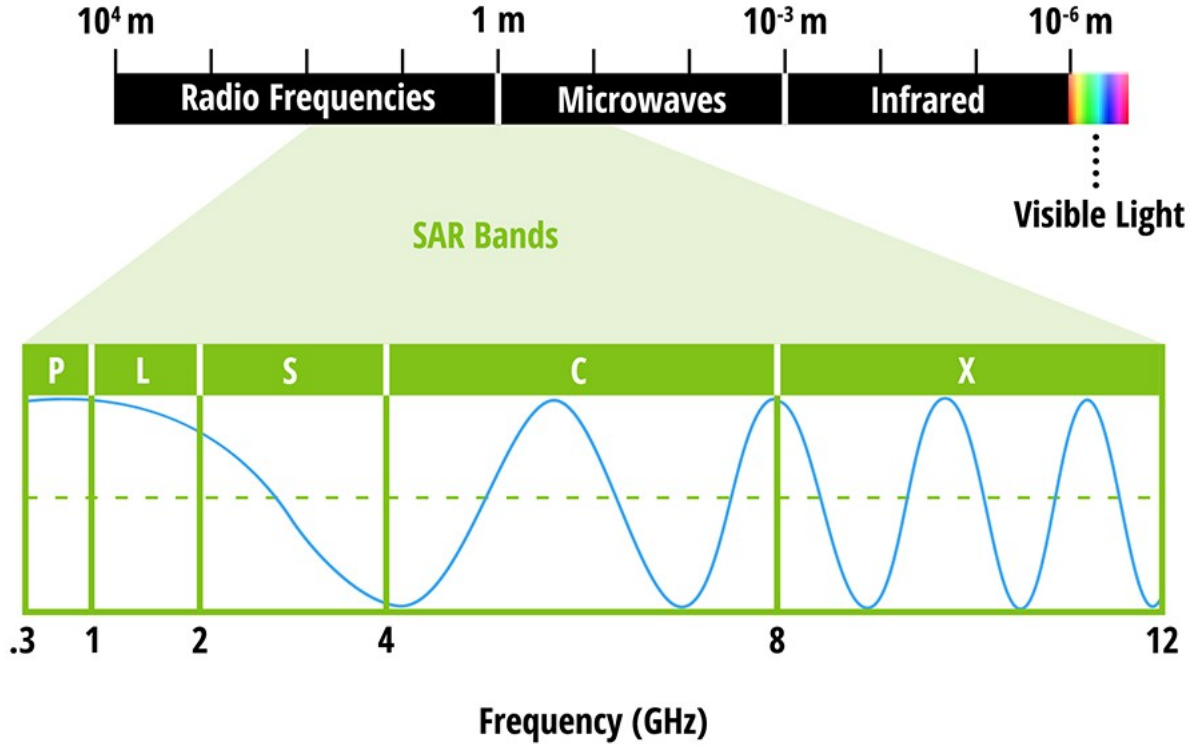


Figure 2.2: The most commonly utilised frequency bands for SAR, along with their corresponding wavelength representations within the electromagnetic spectrum. Radar systems operate in the microwave region, typically characterised by wavelengths ranging between approximately 1 m and 1 mm. Source: (NASA EarthData, n.d.).

2.2.2 Impact of local topography on SAR backscatter normalisation approaches

SAR imagery supports a broad range of change detection and classification applications that rely on the normalised radar cross-section (NRCS), expressed in terms of the backscatter coefficient. This is an estimate of the return signal normalised to a defined reference area (Dostalova et al., 2022). This allows images acquired with varying viewing angles and at different times in the same area to be compared or analysed for changes (Atwood et al., 2012). The reference areas utilised in these backscatter conversions are illustrated in Figure 2.3. Each conversion approach uses its own interpretation of the backscatter reference area, which can further be placed into (i) the slant range plane itself, known as β^0 backscatter and denoted as A_β (delineated by the solid rectangle in the image), (ii) the ground reference area modeled by an ellipsoidal Earth, referred to as the σ^0 backscatter and represented as A_σ (dashed rectangle), and (iii) the plane that is perpendicular to the local look direction, known as γ^0 backscatter and denoted as A_γ (dotted rectangle) (Atwood et al., 2012; Small, 2011).

Due to the side-looking imaging configuration of radar systems and the arcuate waveform of the pulse as it travels, terrain features showing significant topographic variation (e.g. steep slopes) can cause significant geometric distortions in the image acquired. These distortions are

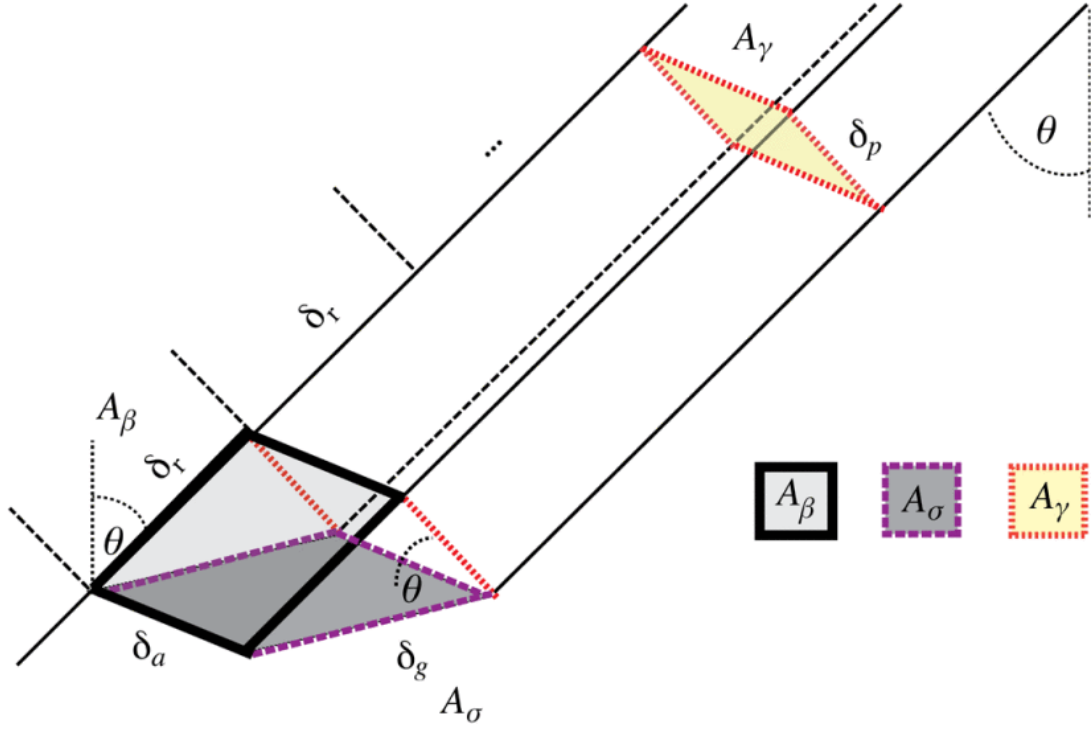


Figure 2.3: Illustration of the various reference areas for the three different SAR backscatter conversions. (i) β^0 backscatter reference area is denoted as A_β (solid rectangle), (ii) the σ^0 backscatter is represented as A_σ (dashed rectangle), and (iii) the γ^0 backscatter is denoted as A_γ (dotted rectangle). Source: (Atwood et al., 2012; Small, 2011).

often observed in images acquired in rugged terrains and are defined as layover, foreshortening, and shadow (Meyer, 2019). Foreshortening occurs when slopes facing the sensor appear compacted, such that relief features like mountains are shortened and appear in the SAR image as if leaning towards the sensor. As shown in Figure 2.4a, the slope between image acquisition points A and B has been foreshortened to form the image area A'B'. The degree of distortions caused by foreshortening is dependent on both the sensor's look angle (i.e. incident angle) and the slope angle.

In areas of steep slopes and steeper incidence angles, for example, foreshortening turns into layover (see Figure 2.4b). In the case of a layover, the signal returns from the top of the mountains and those from the base are received at the same time, which results in the area in the front of the slope appearing to be projected onto the back side in the image of the slant range (Meyer, 2019). Both layover and foreshortening effects can be significantly reduced by increasing the look angle or incident angle; however, a larger look angle leads to more shadow in the acquired radar image (see Figure 2.4c), which is the complete absence of data, not an area of reduced illumination more typical of an optical system. Shadow occurs when the back slope (i.e. the slope facing away from the radar sensor) is extremely steep, and so there are no signal returns received by the sensor. Therefore, geometric terrain correction is an important preprocessing step in SAR applications to achieve reliable results. While areas affected by

foreshortening can be corrected using DEMs, areas affected by layover and shadow effects do not produce any return data, leading to difficulties in correcting these effects (Meyer, 2019).

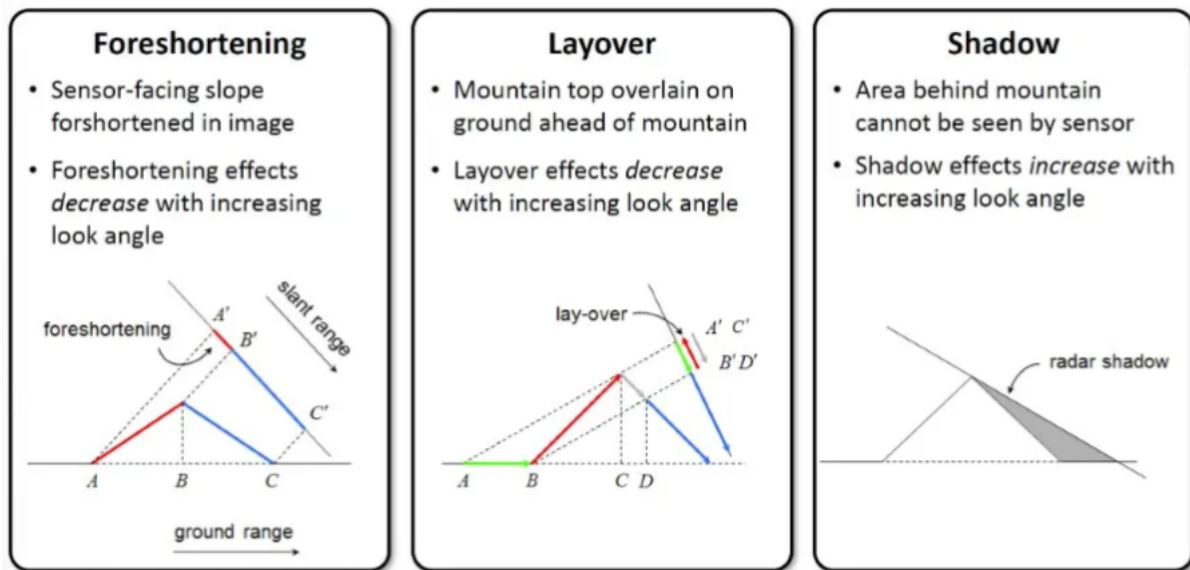


Figure 2.4: The relevant geometric distortions in SAR images cause terrain features such as slope. (a) foreshortening, (b) layover, and (c) shadow. Source: (NASA EarthData, n.d.).

In addition to geometric distortions, terrain features like slopes significantly influence the brightness values that are returned in any radar images (i.e. radiometric distortions). The recorded radar brightness values at an image pixel in rugged terrains are significantly affected by changes in scattering mechanisms due to varied incident angles, as well as changes in the local scattering region (Loew and Mauser, 2007). This results in features facing the sensor appearing brighter and those facing away appearing darker in the image, despite being the same land cover type. The SAR backscatter normalised to σ^0 and γ^0 are typically derived using an ellipsoidal reference area estimation (see Figure 2.3), and in this instance, can result in significant limitations. Their radiometric properties are strongly influenced by topographic variations, even in slightly uneven terrain. These topographically induced variations in SAR backscatter are often much larger than changes in backscatter associated with observed geophysical parameters of interest (Dostalova et al., 2022). Radiometric terrain correction (RTC) is therefore an essential SAR preprocessing step to retrieve surface properties such as surface roughness (Loew et al., 2006), ensuring that any changes in the forest cover (like degradation) can be detected (Reiche et al., 2021).

2.2.3 Addressing the impact of topography on SAR backscatter for accurate ASM monitoring

This section reviews the geometric and radiometric terrain correction approaches developed and used in ASM monitoring applications, identifying the gaps relevant to addressing **Objectives 1**

& 2.

2.2.3.1 Geometric terrain normalisation

To overcome the limitation of topographic variations on SAR backscatter, several methods for geometric terrain correction of the backscatter coefficient have been introduced in the literature. Geometric terrain correction compensates for the geometric distortions (e.g. foreshortening) that reduce the quality of SAR due to side-looking geometry employed in SAR systems. This procedure uses a digital elevation model (DEM) to correct SAR geometric distortions caused by topography and modify the position of each pixel in the SAR image (Filipponi, 2019), as illustrated in Figure 2.5.

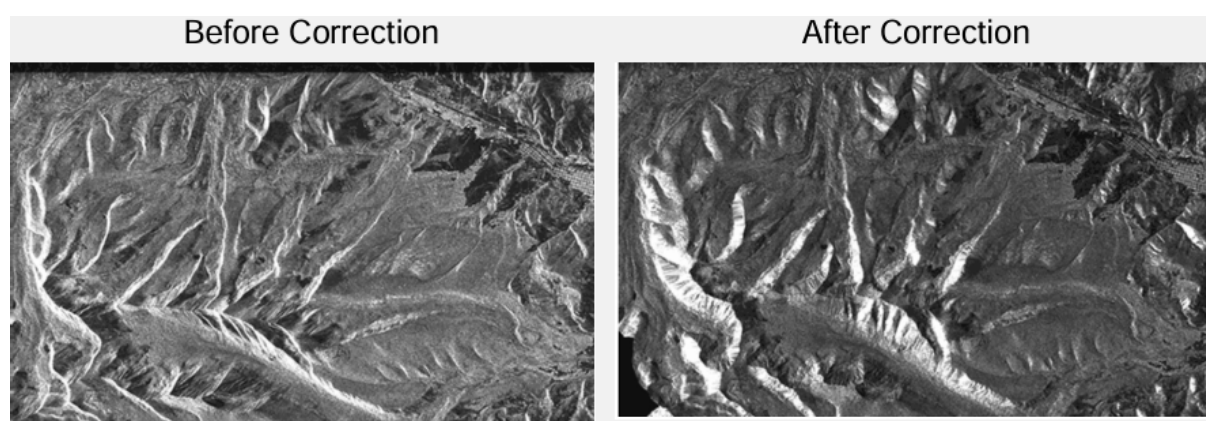


Figure 2.5: Example of Range Doppler Terrain Correction correcting for the effects of geometric distortions caused by topography, such as foreshortening (left) before applying geometric terrain correction and after correcting for foreshortening (right). Source: (NASA ARSET, 2017)

2.2.3.2 Terrain geocoding

Geocoding transforms the raw image coordinates into a map projection product, and it is a crucial step for an accurate radiometric terrain correction of the SAR data (Filipponi, 2019; Loew and Mauser, 2007). Geocoding utilises the scene orbit state vector information from the metadata to convert the scene from ground range geometry or slant range to a map coordinate system. There are generally two main approaches to geocoding a pixel value in an image, namely forward and backward geocoding (Loew and Mauser, 2007). The position of each pixel value in an image on the Earth's surface is estimated independently in the forward geocoding method using a range-Doppler equation. In contrast, the calculation steps required in the backward geocoding approach are reduced significantly, focusing only on the image pixel relating to the nearest range-Doppler coordinate for each DEM element instead of every image pixel (Loew and Mauser, 2007). The key processing steps are summarised in Figure 2.6, where:

- A) Conversion of coordinates to a common reference system.

- B) Incorporating appropriate orbit state vector information.
- C) Performing an iteration using a range-Doppler equation to identify suitable image and DEM pairs.
- D) Performing estimations of local imaging geometry to map image pixels onto the DEM product.
- E) In instances of ground range products, reconstructing the slant range.

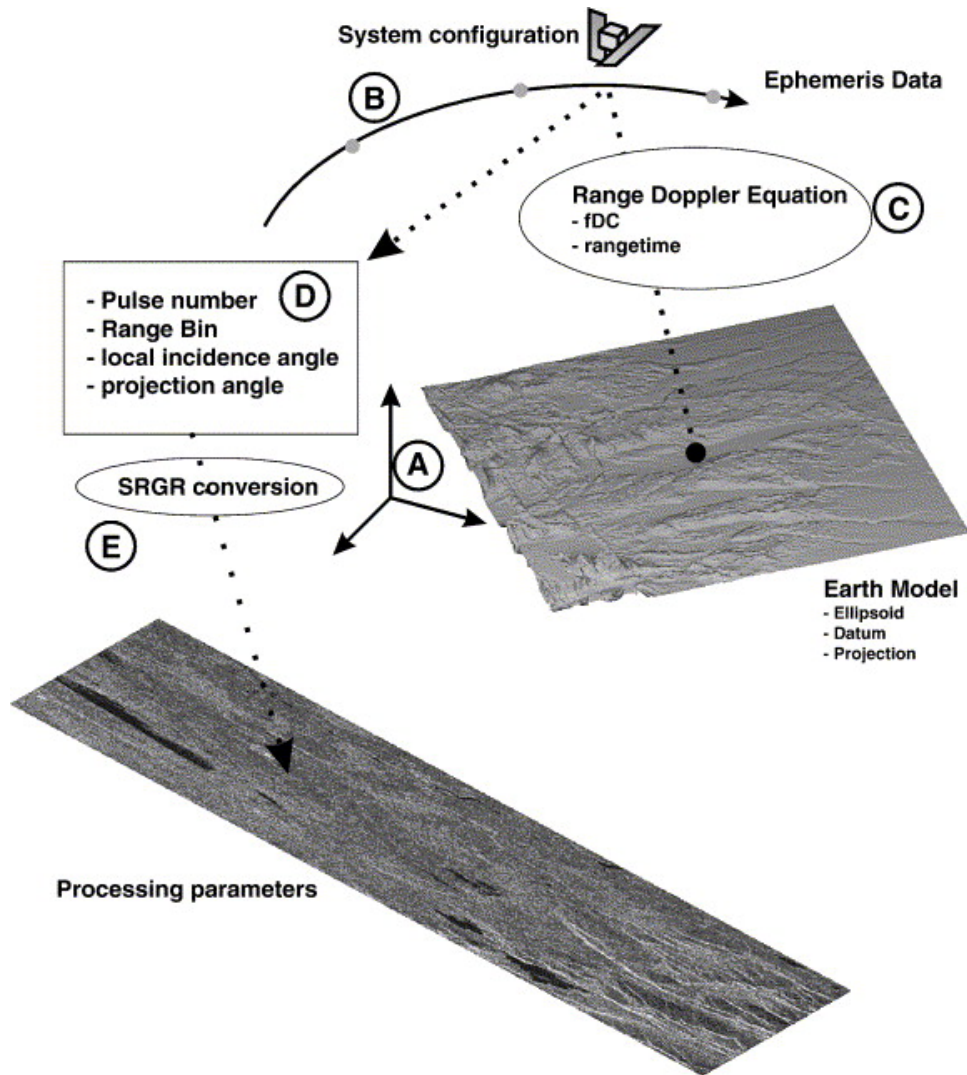


Figure 2.6: The main steps in the backward geocoding method. The orbit state vector information and the DEM coordinates are transformed into a common reference system, allowing for the estimation of corresponding image pixels for each DEM element. Source: (Loew and Mauser, 2007)

The target Coordinate Reference System (CRS) can optionally be chosen to match the area's UTM zone for better geocoding precision (Filipponi, 2019). The majority of studies to map ASM activities in tropical regions have used geocoded geometrically terrain-corrected ARD products normalised to the σ^0 backscatter coefficient (Janse van Rensburg and Kemp,

2022; Kimijima et al., 2022a; Alessi et al., 2023; Chike and Balz, 2024). These studies have reported reliable accuracies in detecting ASM activities in the tropics. However, a significant limitation encountered was backscatter variations due to topographic variations, leading to low accuracy in mountainous areas (Kimijima et al., 2022a). This presents a challenge in using the σ^0 geometrically terrain-corrected ARD products for timely and reliable ASM monitoring on a large scale.

2.2.3.3 Radiometric terrain correction

To effectively address the challenge of backscatter variability due to topographic variations, radiometric terrain normalisation methods have been introduced as best practice. Radiometric terrain normalisation is an important SAR preprocessing step recommended by the Committee on Earth Observation Satellites (CEOS) (CEOS, 2021) for a wide range of terrestrial applications to mitigate the impact of topography on backscatter and is crucial to retrieve useful information in SAR images, such as forest disturbances caused by ASM. In radiometric terrain normalisation, the image pixel brightness or backscatter is adjusted using a DEM to remove topographic effects such as layover, shadow, and foreshortening, ensuring accurate retrieval of changes in surface properties, for example, changes in forest cover caused by ASM activity. In relatively flat areas, the relationship between the backscatter coefficient (σ^0) and the recorded radar brightness (β^0) at an image pixel is defined as (Equation 2.1) (Loew and Mauser, 2007). For radiometric normalisation, the relationship between the backscattering coefficient (σ^0) and the scattering area A (m^2) is given as (Equation 2.2) (Loew and Mauser, 2007):

$$\sigma^0 = \frac{\beta^0}{A} \quad \text{Equation 2.1}$$

$$\sigma^0 = \beta^0 \cdot \sin(\theta) \quad \text{Equation 2.2}$$

where θ denotes the incidence angle. The sine function is used for local approximations of scattering area estimation, accounting for changes in scattering from close to distant range regions (see Figure 2.1).

Different methods for radiometric normalisation of SAR backscatter have been developed in the literature. A conventional approach to perform radiometric normalisation assumes a flat terrain, where each image pixel's scattering area is approximated as described in Equation 2.2. This technique is commonly applied to generate radiometric normalised standard products across various SAR sensors (e.g. European Remote-sensing Satellite (ERS) and Advanced Synthetic Aperture Radar (ASAR) calibrated products) (Rosich and Meadows, 2004; Laur et al., 1998). However, this approach does not adequately mitigate terrain-induced vari-

ations in the scattering area, introducing significant errors in backscatter-normalised products, particularly for rugged terrains. To address this limitation, other radiometric normalisation methods were subsequently developed. Depending on the technique used to approximate the scattering area, these methods include slope-normalisation approaches based on the local incidence angle (LIA) (Hoekman and Reiche, 2015; Ulander, 1996; Vollrath et al., 2020) or radiometric terrain flattening (RTF), which takes into account the visible ground area to the imaging radar sensor (Small, 2011). The RTF proposed by Small (2011) adopts a triangular facet-based area approximation from the radar imaging geometry using a DEM of the imaged area to model the impact of topographic distortions on the independent estimation of each image pixel's scattering area Figure 2.7. Each estimated triangular DEM facet is projected into the image space (i.e. the plane perpendicular to the radar line of sight) to compute its projected area contribution to each radar pixel (Small, 2011). Since the mapping relationship between terrain (map geometry) and radar slant-range geometry is non-homomorphic in rugged terrain, as illustrated in Figure 2.8, the projected facet areas are accumulated in radar geometry using a suitable bilinear distribution method, for instance, nearest neighbour (Small, 2011). This is to ensure that terrain-induced effects, such as layover and foreshortening, are adequately mitigated. Once the scattering area is determined, the terrain-flattened γ^0 normalisation is then performed, defined as:

$$\gamma^0(\tau, \alpha) = K_\gamma \cdot \frac{\beta^0(\tau, \alpha)}{A_\gamma(\tau, \alpha)} \quad \text{Equation 2.3}$$

where:

- β^0 is the measured or recorded radar brightness,
- A_γ is the terrain-corrected local illuminated or scattering area,
- K_γ is a calibration constant,
- τ is the range image coordinate,
- α is the azimuth image coordinate.

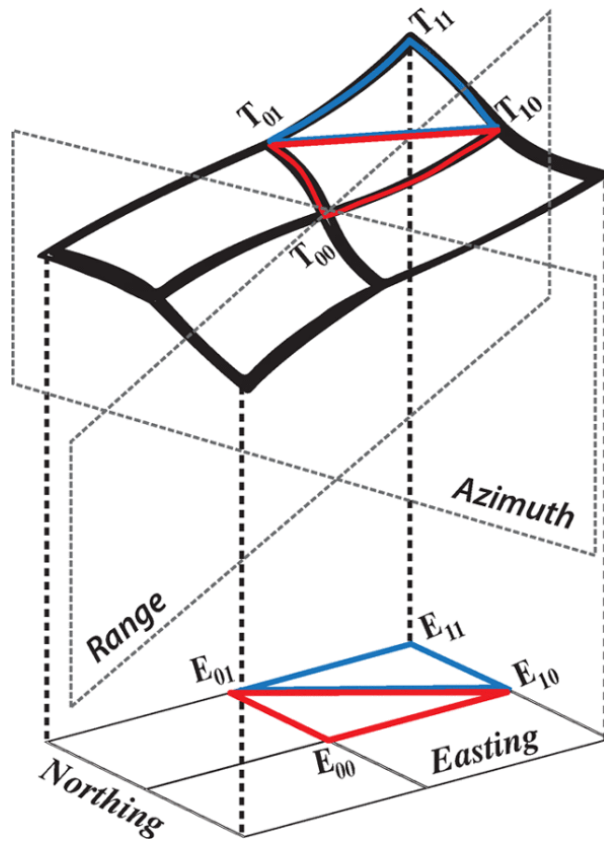


Figure 2.7: Each triangular DEM facet projected into the image space to estimate its projected area contributions to each radar pixel. Source: (Small, 2011)

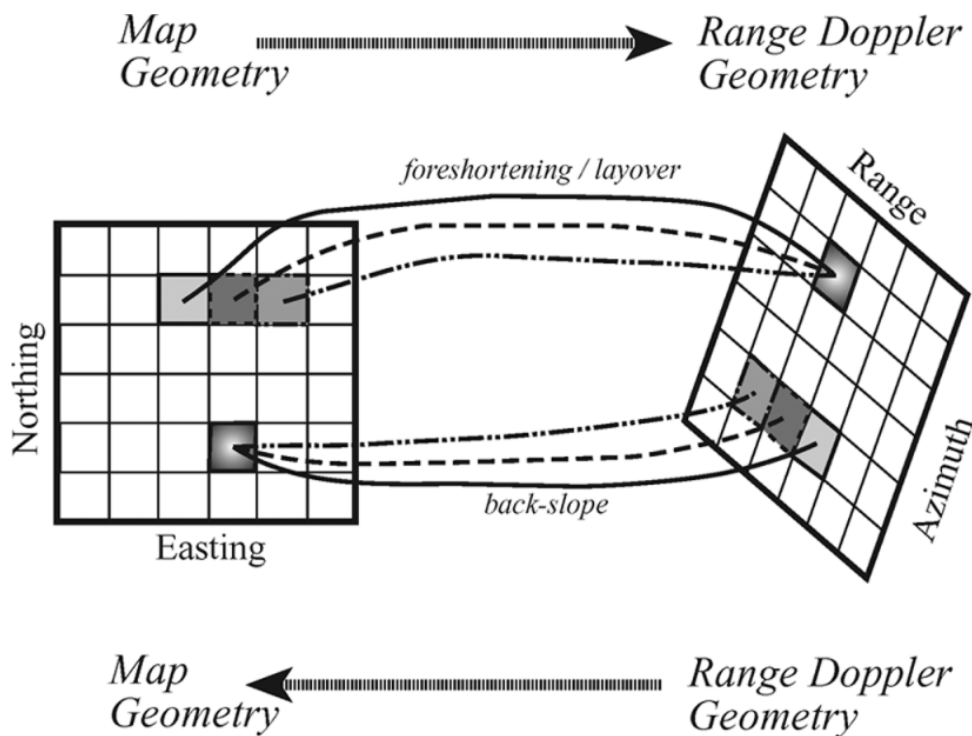


Figure 2.8: The non-homomorphic mapping relationship between the terrain and radar geometry in rugged terrain. Source: (Small, 2011)

The RTF is a common approach for various SAR applications, and it is implemented in the ESA 'SNAP' SAR toolbox for generating SAR γ^0 RTF ARD products. Forkuor et al. (2020) applied S1 γ^0 RTF ARD products to map ASM activities in the tropics, and they reported an improvement in the SAR data quality, yielding high accuracies in detecting changes in backscatter caused by ASM activities. However, to fully realise the potential of this additional SAR preprocessing step for ASM monitoring, validating the derived products with and without this step across different topographies and vegetation types is essential (**Objective 1**). Moreover, the RTF technique is computationally expensive because it requires converting from map to radar geometry (Small, 2011), making it ineffective for processing SAR data for large-scale applications. A recent study by Vollrath et al. (2020) proposed an alternative radiometric slope-normalisation approach based on the LIA for S1 SAR imagery within the GEE platform. This method employs an angular relationship rather than pixel-based area approximations to compensate for the terrain-induced effects. The radiometric slope-normalisation approach proposed by Vollrath et al. (2020) has shown potential in rapidly creating γ^0 radiometric terrain-normalised products for NRT forest disturbances monitoring in the wet tropics from S1 SAR imagery (Reiche et al., 2021). Despite the advances in the SAR ARD processing, no studies have explored the potential of these approaches (i.e. radiometric slope-normalisation approaches) to create γ^0 radiometric terrain normalised ARD products for ASM monitoring. This approach is computationally efficient (Vollrath et al., 2020) and offers the potential for timely ASM monitoring on a large scale. This will be explored in this study, and details of the approach are discussed in Chapter 4.

Ideally, to achieve optimal results in creating SAR γ^0 radiometric terrain-normalised ARD products, the **DEM resolution** should be higher than that of the SAR image resolution, but no open data options exist to compare any global DEMs to S1 data. Hence, the DEM is often over-sampled to match the resolution of the image with existing ASM studies relying on the 30m Shuttle Radar Topography Mission (SRTM) DEM to process SAR data for ASM monitoring. The influence of the **choice of DEM** options for creating γ^0 radiometric terrain-normalised ARD products, assessing the effectiveness of newer DEMs for timely and reliable ASM monitoring, has never been explored (**Objective 2**). See Chapter 4 for further details.

2.3 Objective 3 — Modelling backscatter signal variability to enable NRT ASM monitoring in the wet tropics

In the context of ASM monitoring in the tropics, in addition to the topographic variations problems affecting backscatter, shorter-wavelength SAR, such as S1 C-band SAR, faces several other challenges that limit its effectiveness for ASM early warning systems, as described in Section 1.2.2.2. This section explores these challenges in greater detail, focusing on their impact on backscatter for continuous ASM monitoring, and helping to identify the gaps that were addressed in this study.

2.3.1 Impact of adverse atmospheric effects from active rainfall on SAR backscatter for ASM monitoring

Despite the advantages of SAR, i.e. operations independent of daylight and generally unhindered by weather conditions, precipitation-related artefacts caused by adverse atmospheric conditions significantly affect the appearance and quality of SAR images [Danklmayer et al. \(2009\)](#). A significant challenge faced by spaceborne radar systems operating in the microwave regions is the notable signal attenuation (i.e. a decrease in backscatter value unrelated to surface changes) from rain ([Danklmayer et al., 2009](#)). Radar signal attenuation is dependent on several factors, including the frequency of the imaging sensor and the rainfall rate, one of the widely used approaches to describe rain intensity, often expressed in millimetres per hour, which measures the quantity (i.e. rain intensity) of rain reaching the surface of the Earth. Generally, the rain intensity is considered moderate when the rain rate is approximately 4 mm/h ([Danklmayer et al., 2009](#)).

[Table 2.1](#) provides a summary of typical values of specific attenuation (i.e. for a propagation path of 1 km) at a given rainfall rate across different SAR frequencies ([Danklmayer, 2009](#); [Olsen et al., 1978](#)). The relationship between specific attenuation, $\gamma(x, t)$, and rain rate (R) can be empirically defined as ([Equation 2.4](#)) ([Danklmayer et al., 2009](#); [Olsen et al., 1978](#)):

$$\gamma(x, t) = aR^b \quad \text{Equation 2.4}$$

where a and b are dependent on the frequency of the radar sensor, the RainDrop Size Distribution (DSD), and other factors.

As shown in [Table 2.1](#), the performance of shorter wavelengths (i.e. higher frequency) SAR is more impacted by attenuation caused by heavy rainfall compared to longer wavelengths SAR. For example, under conditions of intense tropical convective rainfall of approximately 80 mm/h or more, a path-integrated attenuation (i.e. a two-way attenuation of microwave

Table 2.1: Relationship between rainfall rate and specific attenuation for different SAR frequencies. The DSDs were estimated based on the Marshall-Palmer (MP) and the Joss-Thunderstorm (JT). Source: (Danklmayer et al., 2009; Olsen et al., 1978).

Rain rate [mm/hr]	DSD	Specific Attenuation [dB/km]		
		L-band (1.5 GHz)	C-band (6 GHz)	X-band (10 GHz)
2.5	MP	< 0.01	< 0.01	0.032
12.5	MP	< 0.01	0.032	0.24
50	J-T	< 0.01	0.36	1.29
80	J-T	< 0.01	0.82	2.14
150	J-T	< 0.01	1.5	4.23

signals due to scattering by precipitation particles and absorption by atmospheric gases) exceeding 30dB can be observed at shorter wavelength X-band SAR, making it ineffective for timely ASM detection applications. This effect has been confirmed through empirical measurements from TerraSAR-X of a wavelength of roughly 3.1 cm over tropical rainforest (Danklmayer et al., 2009). A study by Danklmayer et al. (2009) investigating the imaging capabilities of different SAR frequencies to detect and penetrate heavy rainstorms over tropical forests in Brazil revealed that shorter-wavelength SAR (i.e. wavelength of roughly 3.1 cm) can be significantly affected by intense rainfall cells, but this effect is significantly reduced at L-band radar with longer wavelength (Figure 2.9).

For ASM monitoring in the tropics, several studies using S1 C-band SAR in Ghana (Forkuor et al., 2020), Nigeria (Chike and Balz, 2024), and Indonesia (Kimijima et al., 2022b) have faced problems caused by heavy rainfall, particularly during the rainy season. This active rainfall effect usually causes a darkening effect in the affected area in the acquired image, unrelated to the surface conditions (Figure 2.10). In the case of southern Ghana, this may lead to a local decrease in backscatter at the affected area in the order greater than -10dB compared to the long-term mean backscatter (Figure 2.10), impacting the effectiveness of the SAR data for continuous monitoring (Forkuor et al., 2020). Forkuor et al. (2020) pointed out that 25% of the total S1 images (i.e. 155) acquired between 2015 and 2019 in their study area in southern Ghana were significantly affected by atmospheric effects from heavy rainfall events. The S1 images acquired during the rainy season between March and October were mostly affected by this effect. Modelling this effect to improve the effectiveness of S1 imagery acquired during the rainy season is crucial for developing new methodologies for the timely and reliable ASM monitoring in the wet tropics (**Objective 3**). However, no studies have investigated methodologies to reduce the rainfall effects on SAR to allow continuous ASM monitoring in the tropics. This study will make a significant contribution to addressing this limitation to enhance the early detection of ASM activities in the wet tropics. The details of the approach proposed in this study

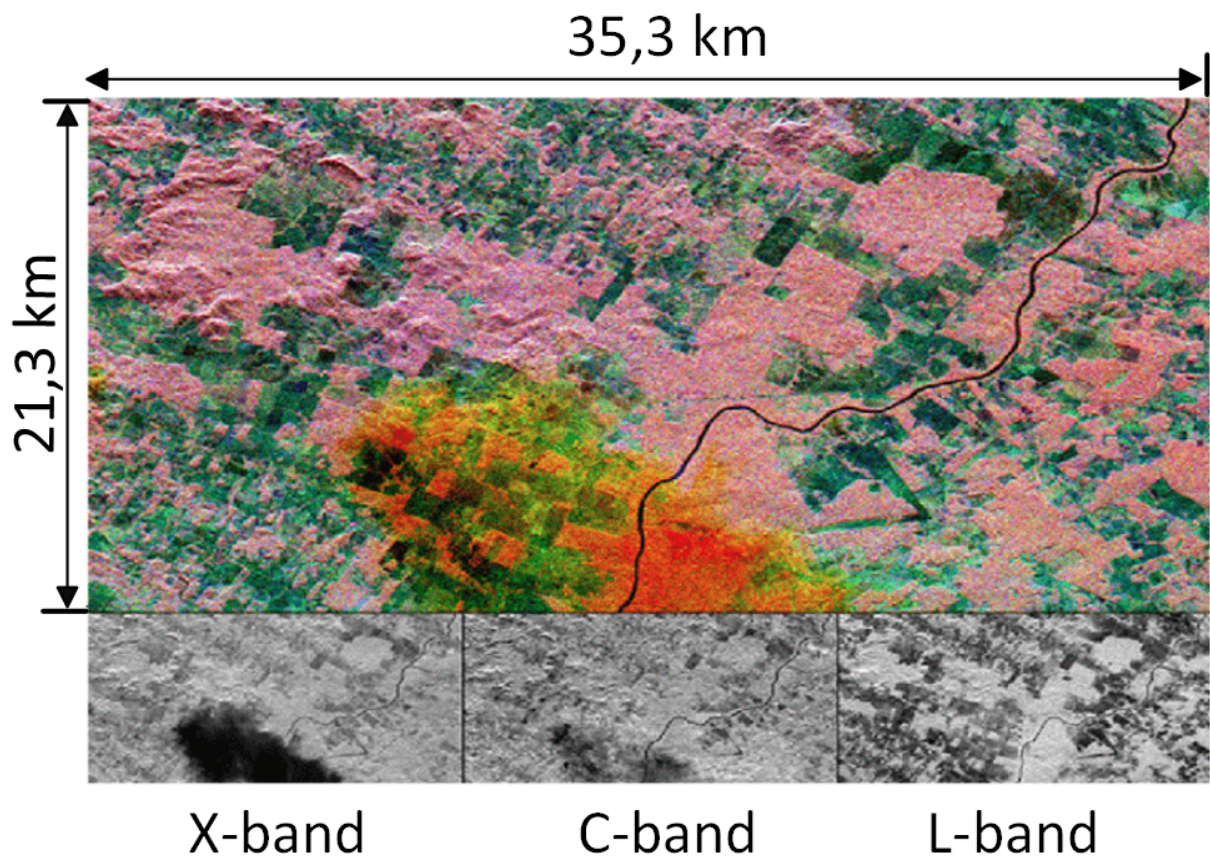


Figure 2.9: Example of the influence of rainfall on the imaging capabilities of SAR at different frequencies, along with an RGB composite corresponding to R – X-band, B – C-band, and G – L-band over a tropical rainforest in Brazil. The active rainfall-induced effect is more pronounced in X-band and appears to decrease in L-band. The rainforest is shown in pink, and the green and blue patches represent areas cleared for agricultural purposes. The rain cells appear in the RGB image as red and yellow. Source: ([Danklmayer et al., 2009](#)).

will be presented in Chapter 4 of this thesis.

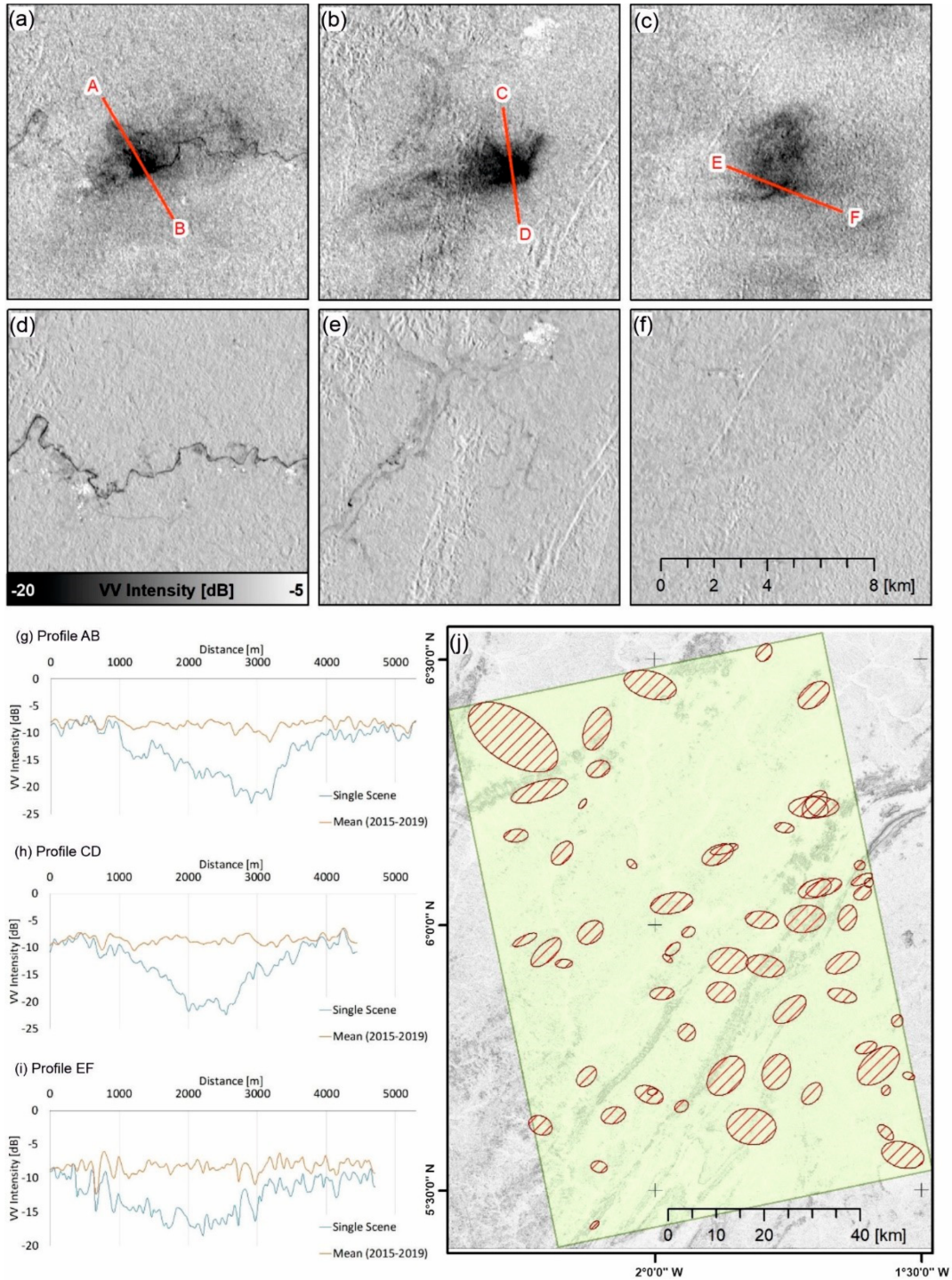


Figure 2.10: Examples of atmospheric effect from high-intensity rainfall affecting the timely and accurate detection of ASM activities using S1 C-band imagery acquired between 2015 and 2019 in southern Ghana. (a) VV image acquired on 2 March 2017, (b) VV image acquired on 23 October 2018, (c) VV image acquired on 8 February 2019, (d-f) Mean VV image (2015-2019), (g-i) backscatter values along profiles AB, CD, and EF, and (j) background map in southern Ghana and locations where acquired scenes were degraded by active rainfall effects. Source: (Forkuor et al., 2020).

2.3.2 Variations of SAR backscatter due to seasonality

For SAR-based NRT forest disturbance monitoring, signal variability caused by seasonal variations in forest structure presents significant limitations in accurately detecting sudden forest loss caused by forest degradation (Bottani et al., 2024), such as the early stage of ASM activity (Figure 2.11). Additionally, existing NRT forest disturbance methods that rely on threshold-based approaches to identify subtle changes in forest cover (Doblas et al., 2022; Ruiz-Ramos et al., 2020; Ygorra et al., 2024) often fail to adequately address the complexities of forest dynamics, particularly in the wet tropics, where seasonal variations can have a significant influence. These seasonal variations in forest structure cause a decrease in backscatter intensity, frequently of a degree comparable to a decrease in backscatter caused by forest degradation, often mistaken as loss in forest cover (Figure 2.11), leading to high false alert rates (Bottani et al., 2024). This further presents a challenge when using S1 imagery for early ASM detection in seasonality-sensitive regions such as the wet tropics. To date, no studies have explored methods to address this limitation to enhance S1 data quality and effectiveness for NRT ASM monitoring in the tropics. One of the objectives of this thesis is therefore to contribute to addressing this limitation by facilitating the timely monitoring of ASM activities in the wet tropics (**Objective 3**). The details of the approach proposed in this study will be presented in Chapter 4 of this thesis.

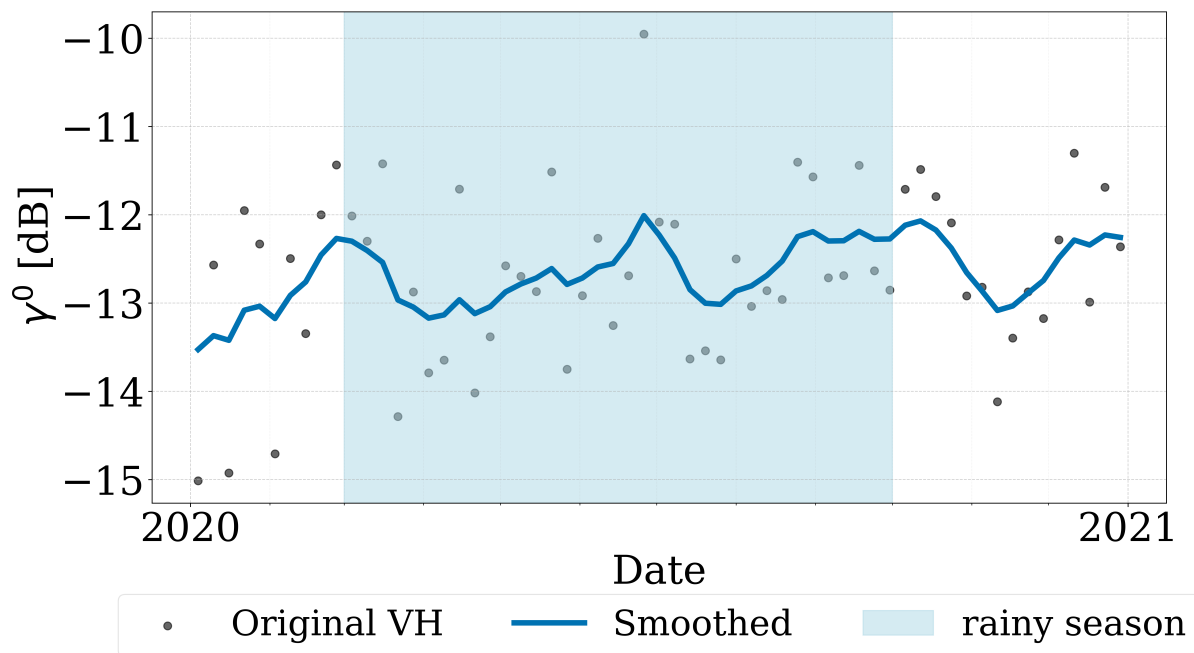


Figure 2.11: Example of S1 VH backscatter profile over rainforest in southern Ghana showing signal variability due to seasonal variations in forest structure presents significant limitations in accurately detecting sudden forest loss related to forest degradation, such as the early stage of ASM activity, leading to high false alert rates.

2.3.3 Influence of surface characteristics, moisture content, polarisation, and vegetation density on SAR Backscatter

In addition to these seasonal variations in leaf-on/off conditions, fluctuations in soil and vegetation moisture content also strongly affect SAR backscatter and are directly proportional to the wavelength of the SAR sensor (Sabir et al., 2024). These introduce ambiguity in identifying the exact point of change in the forest cover caused by forest disturbances using SAR time series, especially using shorter wavelength SAR such as S1, in these dynamic and environmentally sensitive tropical landscapes. As illustrated in Figure 2.12, there is often a direct reflection of the signal from surface water content in the disturbed area due to the introduction of water in the ASM process, which significantly impacts the detection of forest canopy loss. For example, the presence of high moisture content in the forest canopy during wet seasons often increases volume scattering, thereby increasing backscatter and obscuring underlying changes in backscatter related to early ASM activity.

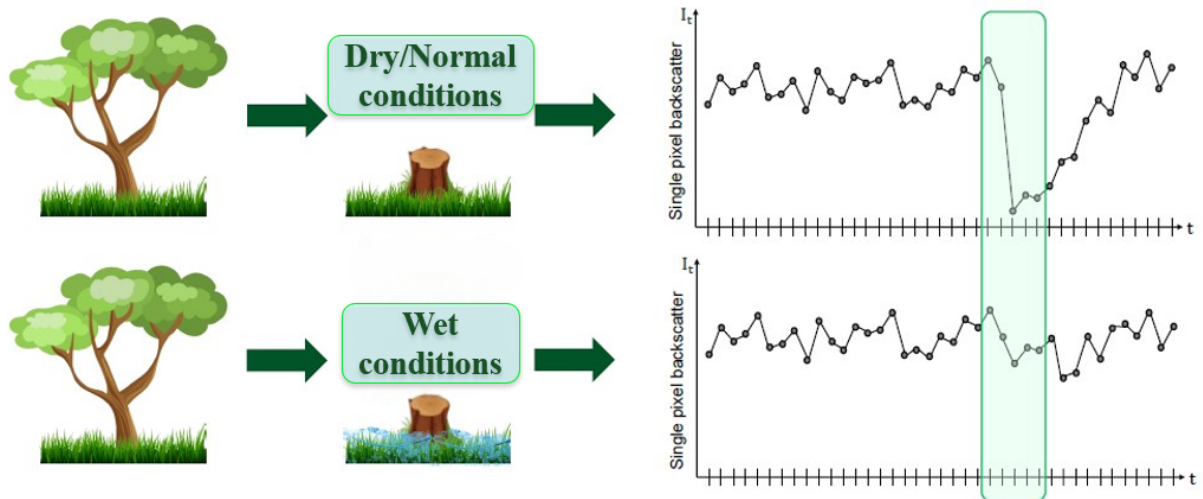


Figure 2.12: The radar signal variability caused by changes in soil and vegetation moisture content, which significantly impacts the fine-grained forest disturbance detection, particularly using shorter wavelength SAR, such as S1 C-band. Wet soil has a high dielectric constant, leading to stronger backscatter returns, whereas high vegetation moisture content increases volume scattering, thereby increasing backscatter and obscuring underlying changes in backscatter. Source: Adapted from (Bottani et al., 2025).

SAR signals interact differently with various surfaces, which greatly impacts the signal strength and subsequently the appearance of these surfaces in the SAR image. Flat or smooth surfaces, such as water bodies, produce a very low backscatter signal because of specular reflection (Alessi et al., 2023) from the water surface. This occurs because the signals are reflected away from the receiving sensor (see Figure 2.13). In urban areas with many vertical structures, double-bounce or corner reflection will often occur, leading to greatly increased backscatter as the signals are reflected directly back to the sensor (Alessi et al., 2023). In vegetative areas, volumetric scattering will also occur, where microwave signals are reflected off vegetation

branches and wet leaves, resulting in a brighter signature (see [Figure 2.13](#)). Dense forests with high tree density and greater foliage will further exacerbate this effect, resulting in an increase in both scattering and absorption of microwave signals, leading to greater overall signal attenuation ([Ma et al., 2024](#)). The vegetation type and the structure of the forest canopy will also contribute significantly to this effect. Forest disturbances caused by the early stage of ASM are characterized by a transition from volume scattering to increased surface scattering, often resulting in a decrease in backscatter intensity, especially in VH polarisation (see [Figure 2.13](#)).

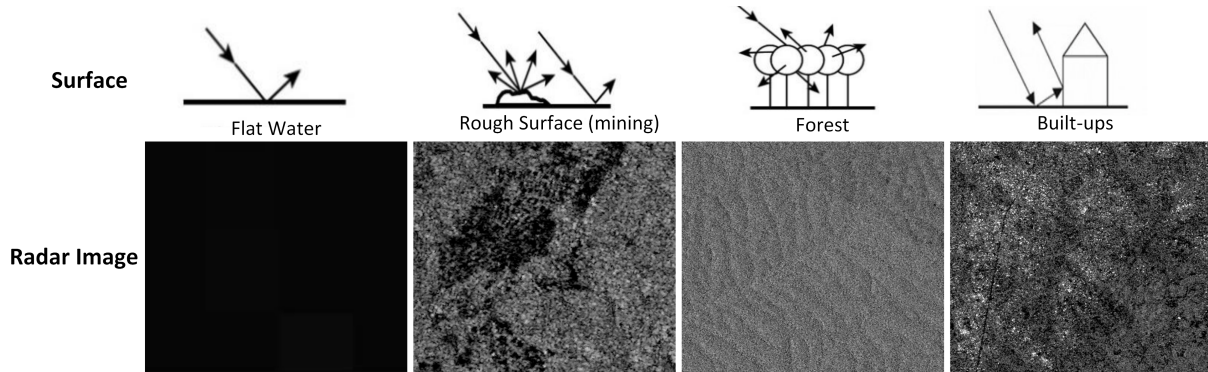


Figure 2.13: SAR signal interactions with different surfaces and the appearance of the SAR image resulting from the scattering mechanism. Sentinel-1 C-band γ^0 orthorectified VH image from the Copernicus browser acquired in 2015 in southern Ghana.

Another factor that significantly affects the strength of the radar signal is the dielectric constant (or relative permittivity, ϵ_r) of the surface. The dielectric constant measures the ability of a material to reflect and conduct electrical energy ([Salas et al., 1994](#)). The dielectric property of vegetation is strongly influenced by moisture content, as water has a high dielectric constant (approximately 80), and the remaining components, such as the vegetation, are poor conductors, exhibiting a near unity relative permittivity ([Salas et al., 1994](#)). As a result, the presence of water in vegetation or soil will often increase the backscatter ([Kellndorfer, 2019](#)). However, in forest wetlands, studies have shown a significant backscatter variability (and often a reduction) when C-band SAR radar signals interact with different vegetation types due to different vegetation density, as well as moisture content and radar polarisation ([Kasischke et al., 2003](#); [Lang and Kasischke, 2008](#); [Zhang et al., 2022](#)). A study by [Zhang et al. \(2022\)](#) explored the role of vegetation density and water depth (i.e. the distance between the ground level and the water surface) on S1 C-band SAR VV and VH backscatter responses in sparse woody, dense herbaceous, and sparse herbaceous vegetative wetland areas. They found that an increase in water content causes a significant variation in backscatter response from tall, dense vegetation due to double-bounce scattering, whereas a low backscatter response is observed from short, sparse vegetation due to specular reflection. This effect is most pronounced in the co-polarised (i.e. VV) polarisation due to less or no depolarisation ([Zhang et al., 2022](#)). These effects will be investigated across different forest types in this thesis and further discussed in detail in Chapter 5.

Microwave signals are influenced by the polarity of the energy. Polarisation explains how microwave signals are oriented when they are transmitted and/or received by the sensor. A key advantage of radar sensors is that their signal polarisation can be effectively filtered for both transmit and receive. Typically, a radar sensor can emit a vertically polarised signal (V) and receive a horizontally polarised signal (H), often denoted as VH. Conversely, if a signal is both transmitted and received in vertical polarisation (V), it is indicated as VV, for example (NASA EarthData, n.d.) (Figure 2.14). If the radar waves are transmitted and received in the same polarisations (i.e. VV or HH), the data is termed co-polarised. On the other hand, if the transmitted and received radar waves are in different polarisations (i.e. VH or HV), the data is described as cross-polarised (NASA EarthData, n.d.). Dual-polarised SAR systems, such as the S1 SAR used in this thesis features both VH and VV polarisation data.

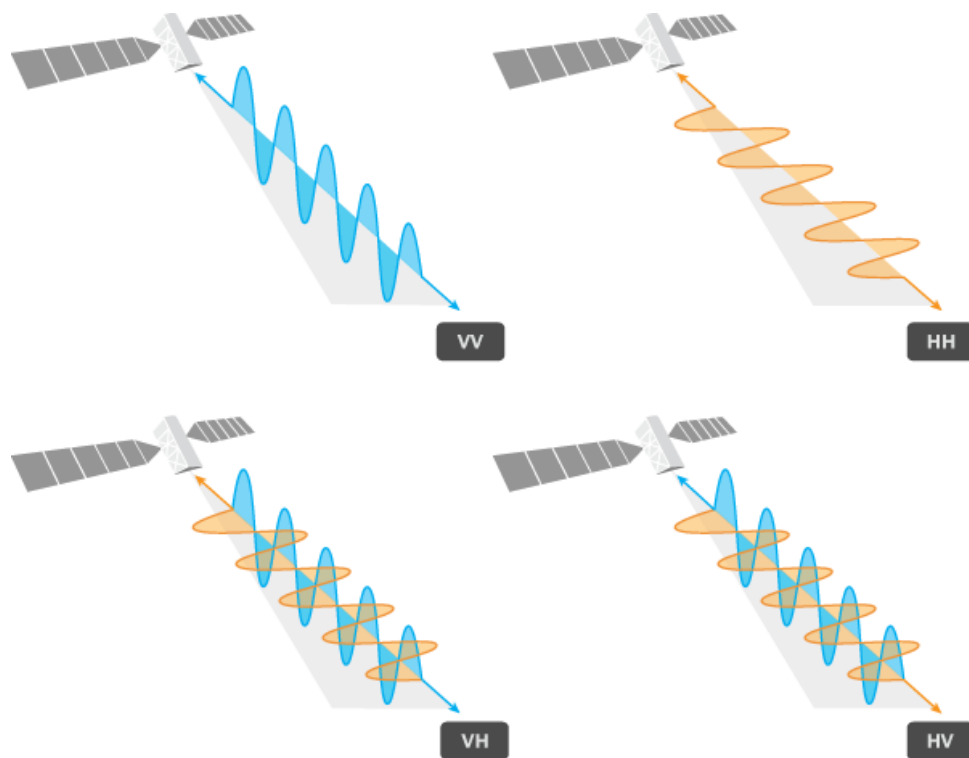


Figure 2.14: Examples of the different polarisations used in radar imaging systems. Source: (Esri, 2025).

The polarisation characteristics of the microwave signal interaction with forests are strongly influenced by the frequency or wavelength of the radar sensor. By examining the signal strength across these polarisations, useful information about the forest structure of the imaged surface can be uncovered. For shorter wavelength SAR, such as S1 C-band SAR, co-polarised signals interact strongly with surface scattering components, such as broad leaves, whereas radar signals from the cross-polarised interact strongly with the vertical structures like crowns and branches due to volumetric scattering. To track changes in forest structure caused by forest degradation, such as those early stages of mining activity which lead to a decrease in volume scattering, leveraging a satellite capable of cross-polarized measurements is crucial (Meyer,

2019). The timeliness of ASM detection using both S1 VV and VH polarisations will be investigated in this study. The details of polarisation characteristics of S1 C-band microwave signal interactions with the tropical forest are discussed in more detail in Chapter 5.

The frequency of SAR determines the wavelength of the electromagnetic signal (also referred to as bands) and significantly influences how it interacts with different targets, such as forest canopies (Alessi et al., 2023). In simple terms, longer wavelengths (i.e. lower frequencies) can penetrate deeper into forest canopies, enabling the timely detection of subtle forest canopy loss due to early ASM activity. For instance, X-band SAR data with a wavelength of roughly 3 cm has proven to be effective in agricultural studies in low vegetated areas (Fontanelli et al., 2022; Villa et al., 2015). Nonetheless, the X-band SAR tends to be unreliable in detecting ASM-related deforestation in the tropical rainforest due to its limited penetration abilities into the larger volume of the forest canopy (Janse van Rensburg and Kemp, 2022). In contrast, the S1 C-band SAR has the potential for ASM early warning applications, with a better penetration wavelength of approximately 5.6 cm compared to X-band of roughly 3.1 cm. This results in C-band having higher penetration ability compared to X-band SAR, allowing it to better detect differences in roughness among various forest land cover classes (Janse van Rensburg and Kemp, 2022). However, the limits on C-band SAR have traditionally arisen from significant saturation problems due to its limited penetration into the larger volume of the forest canopy (Huang et al., 2018). As a result, C-band SAR data is not recommended for accurate biomass estimation. Therefore, in vegetated areas, X-band (3 cm) SAR is primarily chosen when necessary to measure or interacts with the upper layers of the canopy, while C- (6 cm), L- (24 cm), and P-band (65 cm) signals increasingly penetrate further into the vegetation structure (see Figure 2.15).

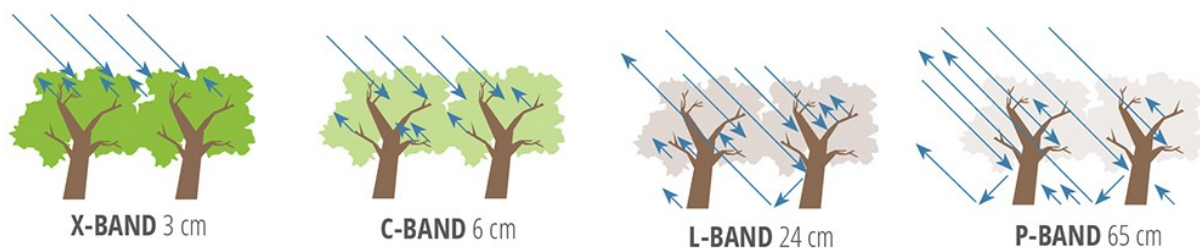


Figure 2.15: SAR forest canopy penetration capabilities at various wavelengths. X-band (3 cm) SAR primarily interacts with the upper layers of the canopy, while C- (6 cm), L- (24 cm), and P-band (65 cm) signals increasingly penetrate further into the vegetation structure. Source: (NASA EarthData, n.d.).

2.4 Objective 4 – Change detection for SAR-based ASM-induced forest disturbance alerts

This section outlines the current state-of-the-art literature on statistical change detection methods for detecting ASM, highlighting the limitations that restrict the early-warning capabilities of these methods, which will be addressed in this study. It also reviews key theory on SAR change detection using time-series data to understand the model developed in Chapter 5. It also explains SAR speckle noise reduction that is crucial in achieving optimal results in SAR-based change detection applications.

2.4.1 SAR time series change detection

In the field of remote sensing, change detection generally refers to the application of multi-temporal data to identify differences in an area or object by observing that target across different dates or times (Singh, 1989). For forest disturbance mapping with SAR data, bi-temporal (i.e. two dates only) or multi-temporal (i.e. many dates) data can be utilised. Change detection applications to identify changes for a short-term study, such as flood mapping, are often carried out using bi-temporal data (Soltanian et al., 2019). However, long-term trend analysis, such as continuous ASM monitoring, requires multi-temporal data. Time series change detection in remote sensing can be classified into Binary Change Detection (BCD) or Multi-class Change Detection (MCD). BCD only identifies changed and unchanged areas, but MCD methods can improve on this and classify different kinds of changes (Paul et al., 2023). As shown in Figure 2.16, MCD is a more complex task compared to BCD, as it potentially can distinguish different classes of change (Zhu et al., 2024).

Traditional change detection (CD) methods can be broadly classified into supervised and unsupervised methods. The supervised approaches require labelled samples to train a classifier, whereas unsupervised approaches produce the difference image directly from SAR time series data (Zheng et al., 2013). This study aims to improve existing methods to develop new SAR-based methodologies for timely monitoring of ASM activities by leveraging unsupervised and supervised CD methods. The unsupervised methods are discussed in detail in this section, and the supervised methods will be discussed in later sections. Unsupervised SAR image CD processes generally include three main phases: (1) image pre-processing; (2) generation of the difference images (DI); and (3) analysis of the DI to generate the change map (CM) (Gao et al., 2016, 2019; Qu et al., 2022; Zheng et al., 2013). In contrast to optical sensors, automatic detection of changes in SAR images remains a challenging task (Gao et al., 2016, 2019), largely due to speckle or other sources of noise in the image. SAR change detection algorithms therefore first aim to reduce speckle when creating change maps from DI.

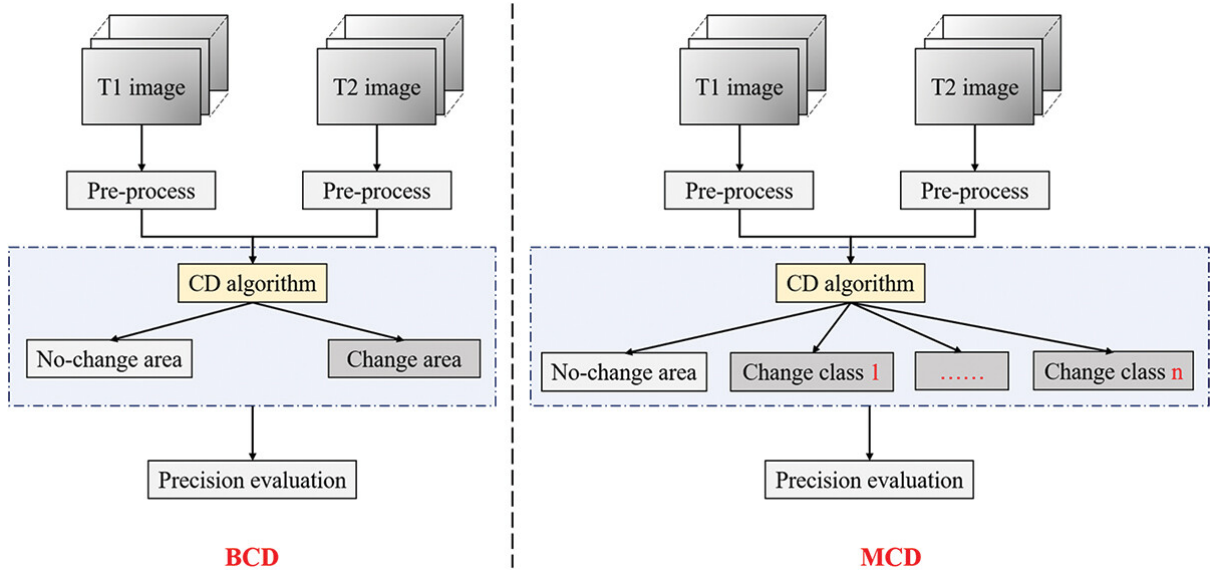


Figure 2.16: The general methodological processes of BCD and MCD applications. The MCD introduces more complexities compared to the BCD, as it distinguishes different classes of change. Source: (Zhu et al., 2024)

2.4.1.1 Speckle noise reduction to improve SAR CD

Speckle noise, appearing in SAR images as random granular ‘salt and pepper’ patterns, degrades the quality of radar images as explained in Section 1.2.2.2. Speckle filtering is a technique to reduce the noise in SAR images, thereby improving image quality (Filipponi, 2019). The choice of a suitable filtering method depends on several factors, such as the requirements of the application, the degree of noise, the data type, and its spatial resolution (Rana and Suryanarayana, 2019). For example, according to Filipponi (2019), speckle noise reduction is not recommended for applications that require identifying small changes in an image, as it compromises the spatial and radiometric resolutions of the resulting images. However, Rana and Suryanarayana (2019) pointed out that choosing filter techniques that balance SAR noise suppression while preserving subtle structures and fine details in an image is crucial for fine-grained change detection applications. Reducing speckle noise in SAR images can be achieved in two main ways: (i) multi-looking and (ii) spatial filtering techniques.

Multi-looking is a procedure that involves taking multiple measurements of the same target and averaging over the range and/or azimuth resolution cells to smooth out the noise in the SAR image (NASA ARSET, 2017). The azimuth beam is carefully divided into several narrower sub-beams, known as ‘looks’, which are subsequently summed and averaged, significantly reducing noise in the resulting image (NASA ARSET, 2017). Multi-looking appears to preserve the radiometric resolution but tends to degrade the spatial resolution of the final image, as illustrated in Figure 2.17a, where 5 looks are employed. Therefore, the choice of an appropriate speckle reduction approach is key to achieving reliable results. The S1 imagery used in this study has already been multilooked as part of the pre-processing steps prior to being

ingested into the GEE.

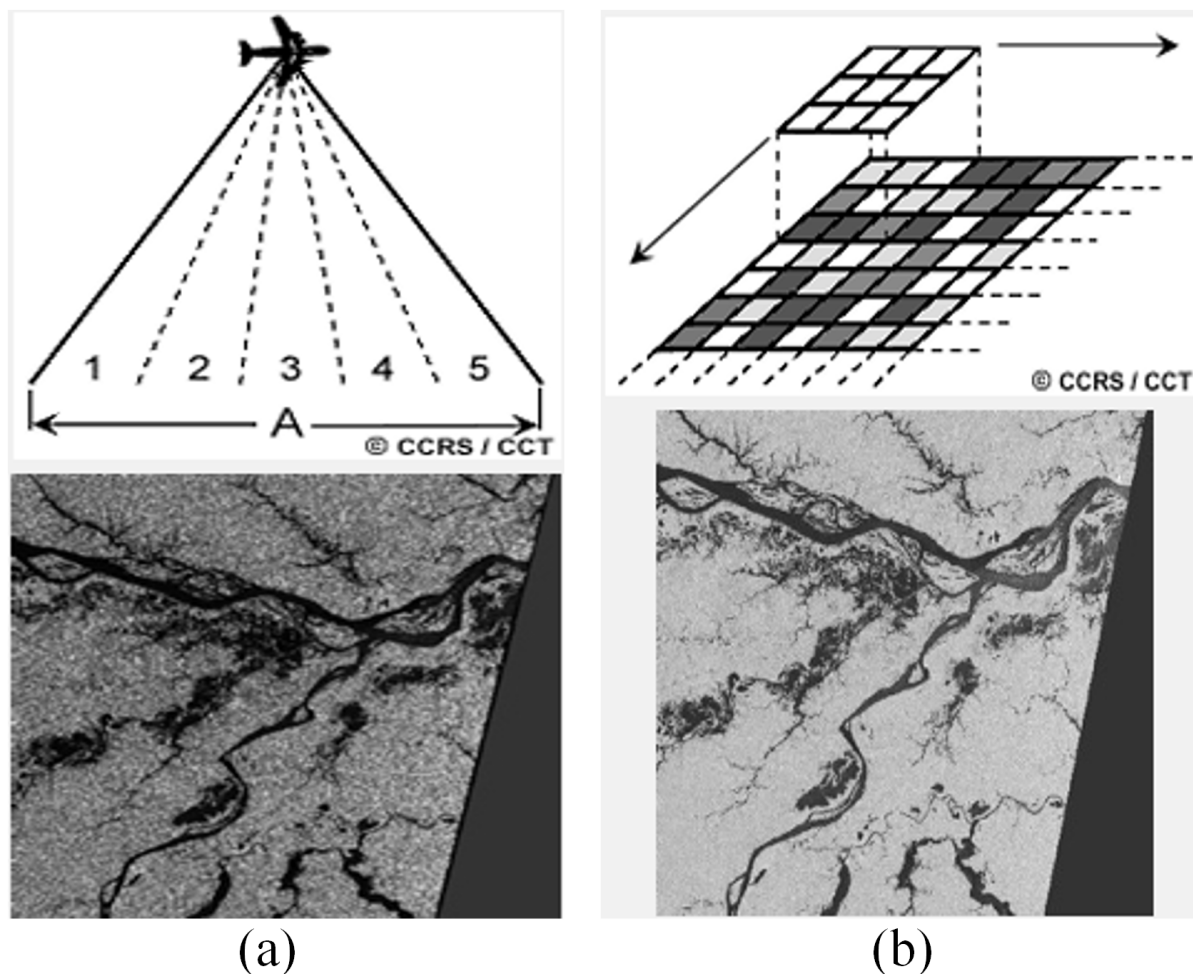


Figure 2.17: SAR speckle reduction techniques (a) Multi-looking processing using 5 looks and (b) Spatial filtering using a moving window filter to smooth out noise in the SAR image and improve the visual appearance of the final image. Source: (NASA ARSET, 2017)

Spatial filtering is the process of applying a moving window filter over each pixel in the image to smooth out noise and improve image quality by reducing the visual appearance of the image (NASA ARSET, 2017), as shown in Figure 2.17b. An appropriate and effective filter depends on its ability to average values across areas that maintain relative homogeneity and not across boundaries. This is to ensure that averaging is applied over targets exhibiting similar radar cross-sections (Woodhouse, 2006). Reducing speckle noise in SAR images has long relied on the use of single-scene speckle filter techniques (Frost et al., 1982; Lee, 1980). In the last decade, multi-temporal speckle filtering has been developed, utilising a time series image stack to achieve better results (Quegan and Yu, 2001). Multi-temporal speckle filtering has been proven effective compared to single-scene filtering in reducing noise and improving the quality of SAR data for ASM mapping in the tropics (Janse van Rensburg and Kemp, 2022). This will be further explored to identify the appropriate speckle filter to improve the fine-grained forest disturbance detection related to ASM in Chapter 4. Table 2.2 presents a detailed summary of

the most relevant speckle filters along with their characteristics (Meyer, 2019).

Table 2.2: Summary of the most relevant speckle filters along with their description and related publications. Source: (Meyer, 2019).

Speckle filter	Description	Related publication(s)
Change-preserving multi-temporal filter	Applied to SAR time-series image stacks with the ability to reduce noise while retaining changes in the temporal domain, for example, due to forest disturbance.	(Quegan and Yu, 2001)
Lee filter	Sigma (standard deviation-based) filter that applies local statistics to smooth noise while preserving image sharpness and fine detail, unlike simple filters such as Boxcar and Gaussian.	(Lee, 1980)
Enhanced Lee filter	Adaptive filter that reduces noise while preserving texture information by placing pixels into: • Homogeneous: pixel replaced by the local mean in the window. • Heterogeneous: pixel replaced by a weighted local average. • Point target: pixel value remains unchanged.	(Lee et al., 2009; Lopes et al., 1990)
Frost and improved Frost filters	Exponentially damped circularly symmetric filters leveraging local statistics to improve image quality; the enhanced version introduces adaptive filtering techniques for pixel classification	(Frost et al., 1982; Lopes et al., 1990)
Non-local means filters	Improve SAR image quality by averaging similar pixel values identified through patch-based similarity searches, enabling denoising while preserving spatial resolution.	(Buades et al., 2005; Chen et al., 2014; Martino et al., 2015)

2.4.1.2 DI generation and analysis methods for SAR-BCD applications

In traditional SAR-BCD, several methods for detecting changes from DI have been introduced in the literature, including threshold-based approaches (Otsu, 1979; Bazi et al., 2005; Yen et al., 1995) and clustering methods (Zheng et al., 2017; Zhang et al., 2018; Li et al., 2015). Threshold-based approaches, such as Kittler–Illingworth (KI) (Bazi et al., 2005) and Otsu (Otsu, 1979), use decision thresholds to classify pixels into changed and unchanged classes. Several unsupervised algorithms have been developed to determine the optimal threshold, some of which have been tested and validated in SAR-BCD applications (Gao et al., 2019; Tucker et al., 2022; Zhao et al., 2023; Zhang et al., 2018). While these conventional threshold-based approaches are computationally efficient, they produce unreliable accuracies due to their high susceptibility to speckle noise. Clustering methods such as principal component analysis

(PCA) (Zheng et al., 2017), the fuzzy c-means (FCM) algorithm, the fuzzy local-information c-means clustering model (FLICM) (Li et al., 2015), and the conditional spatial and kernel fuzzy C-means (CSKFCM) algorithm (Zhang et al., 2018) have also been applied to DI to produce the CM for unsupervised SAR-BCD. These methods identify changed and unchanged areas based on grouping similar pixels. These methods can effectively suppress speckle noise and improve detection accuracy when spatial domain information is integrated (Zhang et al., 2018). However, FCM and conventional PCA clustering methods ignore spatial domain information, making them particularly susceptible to speckle noise (Zhang et al., 2018). In recent times, advances in BCD methods, such as the statistical cumulative sum (CuSuM) method (Kellndorfer, 2019; Sabir et al., 2024; Ygorra et al., 2021) and DL methods (Li et al., 2021; Wang et al., 2022; Gong et al., 2017), have been applied for SAR-BCD applications, showing promising results in effectively suppressing speckle noise and improving detection accuracy.

2.4.2 Change detection for monitoring ASM activities

In the context of ASM mapping, the majority of studies have relied on BCD methods to detect changes in forest cover caused by ASM. Almeida-Filho and Shimabukuro (2000) demonstrated the potential of SAR for mapping ASM by utilising three L-band (wavelength of 23.5 cm) JERS-1 SAR images acquired from 1993 (dry season), 1994 (wet season), and 1996 (wet season) to detect deforestation caused by gold mining activities in the Brazilian Amazon. They generated a normalised difference index (NDI) image for BCD to infer the presence of ASM activities using Equation 2.5. The results demonstrated that at L-band SAR, land cover changes caused by mining can be detected even in areas with low tonal contrast between the changed and unchanged areas in the tropics. Another study by Telmer and Stapper (2007) utilised L-band (wavelength of 23.5 cm) ALOS PALSAR SAR imagery to detect changes in forest cover caused by ASM, again in Brazil and Indonesia. Their approach showed promising results in identifying changes in the landscape associated with ASM across the study period from June to December 2006. The changes identified from SAR were subsequently validated using high-resolution aerial photographs, reinforcing the potential for achieving reliable results in mapping ASM with L-band SAR data in the tropics. Although these studies demonstrated the potential of detecting ASM activity using SAR data, they focused on generating DI to infer the presence of ASM activities without performing further analysis to produce thematic maps (i.e. nature of the various changes). Moreover, the no-open-access policy of these L-band satellites limits their use in developing early warning ASM systems.

$$NDI = \frac{Date_1 - Date_2}{Date_1 + Date_2} \quad \text{Equation 2.5}$$

In the last decade, the growing availability of SAR data from the ESA Copernicus pro-

gramme, which provides freely available C-band (wavelength of 5.5 cm) SAR imagery at an unprecedented temporal and spatial resolution (i.e. using both S1-A and S1-B or now S1-C), allows for continuous forest disturbance mapping using radar data, particularly in the tropics (Ruiz-Ramos et al., 2020). More recently, studies have utilised remotely sensed data, including S1 C-band SAR time-series, global surface water, and world land cover datasets to identify long-term ASM-induced hotspot areas in Indonesia (Kimijima et al., 2022a), using S1 data normalised to σ^0 backscatter and employing unsupervised thresholding-based and binary supervised classification (histogram intersection) approaches to identify the mining-induced areas. The BCD threshold was first determined using a supervised technique to establish the intensity value where the two histograms intersect, producing the changed and unchanged classes. Subsequently, the result was optimised employing several automatic global thresholding methods, including the Otsu (Otsu, 1979), Maximum Entropy (Kapur et al., 1985), IJ_Isodata (Ridler and Calvard, 1978), Percentile (Doyle, 1962), and Yen (Yen et al., 1995). Among the thresholding algorithms evaluated, the IJ_Isodata was observed to be more sensitive to changes in backscatter due to ASM activities in both VV and VH polarisations. The VH polarisation was found to be more sensitive than VV, achieving producer and user accuracies ranging from 78% to 82.1%, compared to the VV polarisation with an accuracy ranging from 73.3% to 76.7%. However, the study encountered some significant limitations, such as precipitation and foreshortening and layover in mountainous areas, which cause a significant decrease in the backscatter, leading to typical commission/omission errors up to 24% and challenges in identifying small ASM areas. This limits the early warning capabilities of their approach for NRT ASM in the tropics.

In West Africa, Forkuor et al. (2020) mapped and monitored changes in land cover caused by ASM from S1 C-band SAR time-series data in the wet tropical regions of Ghana. They employed a γ^0 radiometric terrain-corrected backscatter product using unsupervised threshold-based (Otsu algorithm) and binary supervised classification (histogram intersection) techniques. The change detection technique employed three change indicators (i.e. mean, minimum, and maximum) to estimate the backscatter threshold suitable for identifying changed and unchanged areas. The minimum change indicator or feature was found to be more sensitive to changes in backscatter caused by ASM activities than the mean and maximum in both VV and VH polarisations. However, the study identified that the VH was more suitable compared to VV in detecting ASM activities with a backscatter threshold value of +1.65 dB. The reported Producers and Users accuracy ranged from 68% to 84%, reflecting the considerable variability in the repeatability of their approach. Additionally, a significant challenge encountered in their approach was a decrease in backscatter caused by heavy rainfall, especially in many images acquired during rainy seasons, which limits the early warning capabilities of their approach for continuous ASM monitoring in the tropics.

SAR interferometry (InSAR) is an alternative to the exclusive use of SAR backscatter

intensities to detect changes. In the context of InSAR, multitemporal coherence maps have proven to be highly sensitive to subtle changes and can provide better results that outperform SAR backscatter intensity for SAR change detection (SAR-CD) mapping (Mestre-Quereda et al., 2020; Papila et al., 2020)). The coherence between a pair of SAR images can be used as an indicator of the phase stability of the imaged scene over time, and their temporal changes can be tracked and correlated with the physical properties of the imaged scene (Mastro et al., 2022). The degree of coherence between the images can be used as a classification tool for various land surfaces (Mastro et al., 2022). The combination of time-series backscatter and InSAR coherence maps has the potential to track disturbances in vegetation cover and has been used in several applications (Mastro et al., 2022). This approach has proven successful in urban mapping, crop mapping, forest and land cover mapping, and selective logging (Carstairs et al., 2022; Elmezoughi et al., 2009; Engdahl and Hyypä, 2003; Lei et al., 2018; Mestre-Quereda et al., 2020; Washaya and Balz, 2018; Papila et al., 2020). A recent study by Chike and Balz (2024) applied interferometric coherence from S1 C-band SAR and backscatter intensity for time series analysis to identify ASM in Nigeria. They employed InSAR coherence change detection and the PCA unsupervised learning technique to infer the presence of ASM activities. The results showed a high correlation between the detected mining areas and the high-resolution Google Earth images used for validation. However, a major limitation of their approach is that the sensitivity of interferometry to temporal decorrelation results in lower coherence maps (decoherence) with reduced accuracy, particularly during rainy seasons (Chike and Balz, 2024). The impact of precipitation on backscatter, resulting in a local decrease in backscatter problems, was also reinforced in this study. The traditional PCA unsupervised change detection method used in this study ignores spatial domain information, making it susceptible to speckle noise and further complicating the early warning capabilities of their approach.

2.5 Objective 5 – Deep learning for the timely mapping of ASM activities

This section reviews the literature on SAR-based studies that employ machine learning approaches for land use/cover classification to detect and, most importantly, characterise ASM activities, highlighting key challenges in accurately distinguishing ASM from other forest disturbances. It also reviews key theory on image classification using SAR time series to understand the model developed in Chapter 6.

2.5.1 SAR time series image classification

Image classification is an image processing technique that involves assigning image pixels to a particular thematic class (Ponnusamy et al., 2017). Image classification techniques can be

grouped into two main categories, namely unsupervised and supervised techniques. The unsupervised classification techniques automatically assign classes to image pixels based on their characteristics. This process is referred to as clustering, where pixels with similar characteristics are assigned the same group, known as a cluster. The advantage of the unsupervised classification approach is that no prior information is required, it is fully automated, and it does not require human annotation or labels for classification (Ponnusamy et al., 2017). The most commonly used unsupervised classification techniques for SAR-CD applications were described in the previous section.

In contrast, for supervised classification, each image pixel is assigned a class based on labelled datasets through a process known as classifier training (Ponnusamy et al., 2017). The training process requires pre-existing information or human-annotated labels for different classes, which the analyst must collect. The trained classifier is then used to classify other images. The benefit of the supervised learning methods is that the analyst has more control over the classification output and also achieves high accuracies compared to the unsupervised learning techniques due to the use of labeled datasets for classifier training (Ponnusamy et al., 2017). In SAR-CD, the most widely used ML classifiers for supervised classification include support vector machine (SVM), random forest (RF), extreme gradient boosting (XGBoost), and decision trees (DT).

Any SAR MCD task can be regarded as an image classification where the different kinds of changes are classified into the various change classes. MCD methods can be broadly categorised into two main classes, namely the Post-Classification Comparison (PCC) methods and Direct Classification (DC) methods (see Figure 2.18) (Zhu et al., 2024). In the PCC approach, images are classified separately and then compared on a per-pixel basis to produce the resultant map. Many studies have applied the PCC method for SAR change detection applications (Qi and Yeh, 2012; Wan et al., 2019; Liu et al., 2019). While this method is easy to implement, the accuracy of the change detection depends on the accuracy of the two classified inputs. This can result in the introduction of errors into the final map, leading to poor detection (Zhu et al., 2024). In contrast, the error accumulation effect is significantly reduced in the DC method, where images are first stacked together or superimposed to be used to perform direct classification. The DC method will be explored in this study, and details are further provided in Chapter 6 of this thesis.

In the context of SAR-CD, the MCD has seen fewer applications compared to the BCD due to several limitations, such as the inherent speckle noise present in SAR images and spectral variability between the same surface features. For instance, these limitations pose a challenge in detecting subtle changes in forest cover that occur during the early stage of ASM activity. Additionally, the presence of class imbalance also makes the SAR-based MCD task more challenging (Zhu et al., 2024). This study will investigate an effective approach to deal with class

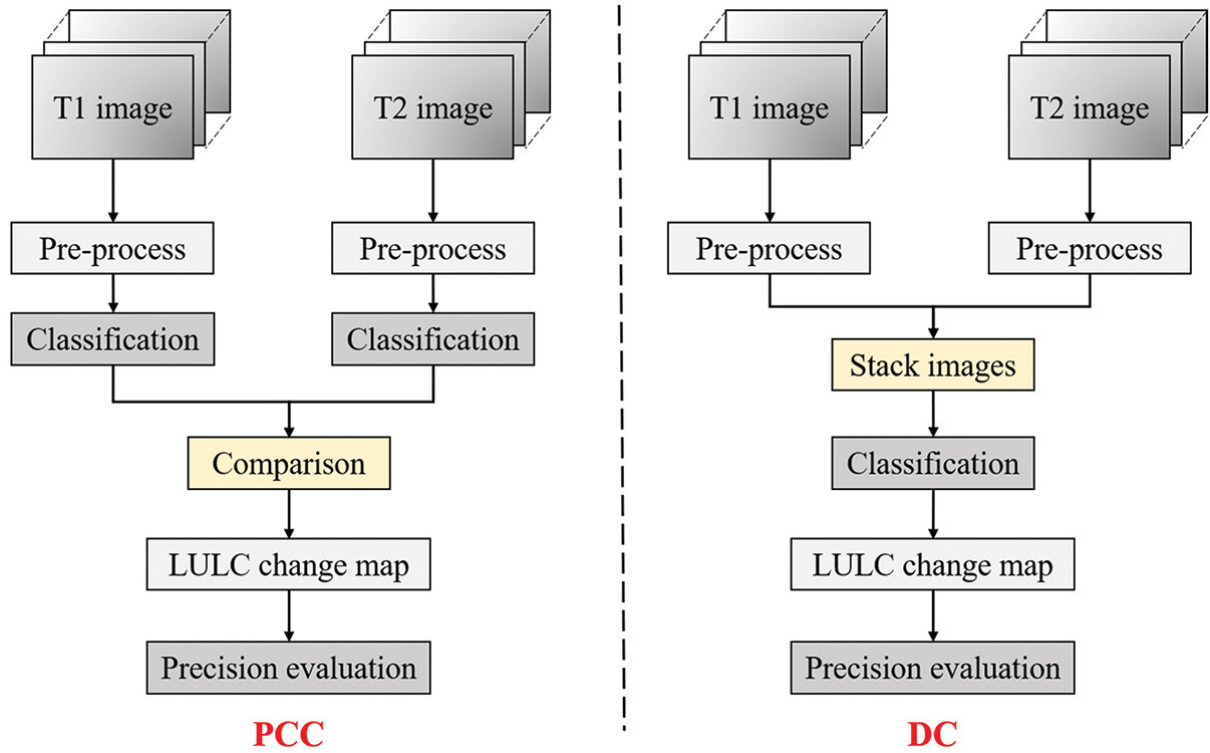


Figure 2.18: The comparison of the methodological processes of DC and PCC approaches for SAR MCD applications. Source: (Zhu et al., 2024)

imbalance problems to improve the accuracy of ASM detection. This will be discussed further in Chapter 6 of this thesis.

2.5.2 SAR-based land use/cover classification for detecting ASM

In contrast to optical methods, only one study has explored the detection of ASM using SAR imagery and incorporated land use/cover changes to distinguish ASM from other forest disturbances (Janse van Rensburg and Kemp, 2022). This is largely due to the several challenges with SAR MCD applications discussed in the previous section, which makes MCD using SAR imagery a difficult task. Exploiting the advantages of ML over traditional statistical BCD methods, Janse van Rensburg and Kemp (2022) applied different ML classifiers for both BCD (binary-water) and MCD (multi-class) schemes using ‘water’ related to ASM as a proxy to infer the presence of ASM activities from both S1 C-band SAR images and KompSAT-5 X-band (wavelength of approximately 3.1 cm) SAR images in wet tropical regions of Ghana. The study compared single-date and multi-temporal filtered datasets using textural features computed from the Gray-Level Co-Occurrence Matrix (GLCM) to enhance the discrimination of ASM from other forest land use changes. The results showed that the X-band achieved lower accuracies compared to the C-band SAR data due to its inability to penetrate deeper into the forest canopy, making it less sensitive to changes in backscatter caused by ASM activities. Additionally, the multi-temporal filtered compared to the single date demonstrated reliable results,

achieving a kappa coefficient of 0.65 (MCD) and 0.82 (BCD). The lower performance achieved using the MCD is largely due to issues with speckle or signal noise, leading to inconsistent accuracy in distinguishing ASM-related changes from other forest land use changes. This limitation further hinders the capability of the approach for reliable and timely ASM monitoring on a large scale in the tropics, where different kinds of forest disturbances coexist.

Based on the findings from [Janse van Rensburg and Kemp \(2022\)](#), it is therefore clear that further studies to develop new SAR-based methods using advanced techniques, such as DL, which have shown improved accuracy for ASM detection using optical imagery as described in Section 1.2.2.1 is crucial.

2.6 Summary

The literature review in this chapter has demonstrated the potential of SAR for monitoring ASM activities in persistent cloud cover regions in the tropics. However, further research to address the limitations of shorter wavelength SAR, such as S1 C-band, to enhance its effectiveness for timely ASM monitoring in the tropics is essential.

The SAR backscatter can be represented in three ways, depending on the reference area conversion used for normalisation, namely i) β^0 , ii) σ^0 , and iii) γ^0 , as explained in Section 2.2.2. The commonly used backscatter, σ^0 and γ^0 , are typically normalised based on ellipsoidal reference area conversion, which often results in a significant limitation. Their radiometric properties are strongly influenced by variations in topography, even in slightly uneven terrain ([Dostalova et al., 2022](#)). The variations in SAR backscatter caused by topographic distortions, such as foreshortening, are often greater than the observed backscatter changes due to ASM activities. As a result, this has led to poor performance in detecting ASM in mountainous areas in Indonesia ([Kimijima et al., 2022a](#)). To address this limitation, several methods for radiometric terrain normalisation have been developed in the literature, including i) slope-normalisation approaches based on LIA, ii) RTF, which considers the visible ground area to the imaging radar sensor, as described in Section 2.2.3.

Previous SAR-based ASM mapping studies have relied on conventional σ^0 backscatter ([Kimijima et al., 2022b](#); [Janse van Rensburg and Kemp, 2022](#); [Alessi et al., 2023](#)), except for [Forkuor et al. \(2020\)](#), who used the γ^0 RTF product processed using the SRTM DEM. However, to fully establish the contribution of this additional SAR preprocessing step for ASM mapping, validating the derived products with and without this step across different topographies and vegetation types is essential (**Objective 1**). This will be further discussed in Chapter 4. Furthermore, the choice of DEM in creating radiometric terrain corrected products is crucial to achieving optimal results ([Truckenbrodt et al., 2019](#)). Recent studies have shown that the Copernicus 30m DEM performs best among freely available global DEMs in mapping tectonic

activity in mountainous regions (González-Moradas et al., 2023). So far, no studies have investigated the influence of the choice of freely available global DEMs in creating radiometric terrain-corrected products for ASM monitoring (**Objective 2**). The details of the DEMs used in this study are further discussed in Chapter 3.

Additionally, SAR is significantly impacted by heavy rainfall, which affects the quality of the images, and seasonal variations in forest structure also significantly affect SAR backscatter. Regardless of the backscatter used in previous studies (conventional σ^0 or γ^0 RTF) for ASM mapping, they appear unreliable during rainy seasons using S1 C-band imagery, which limits the early warning capabilities of these approaches. To address this limitation, this study will be the first to investigate an approach to model these effects to improve the effectiveness of using S1 C-band SAR, allowing timely ASM monitoring in the wet tropics, particularly during the rainy season (**Objective 3**). This will be discussed in detail in Chapter 4.

Existing SAR change detection approaches for ASM mapping in the tropics have faced several challenges as described above, which have limited the early warning capabilities of these approaches. In addition, these studies have relied on traditional BCD approaches, which are often sensitive to speckle noise and complicate the detection of small ASMs. To date, there appear to be no remote sensing studies, using optical or SAR, that have explored the early detection of ASM activity to facilitate rapid intervention. This study will therefore be the first to explore a methodology capable of overcoming these challenges with shorter wavelength C-band SAR from S1, facilitating early detection of ASM, especially during the rainy seasons (**Objective 4**). This methodology is further discussed in detail in Chapter 5.

Studies that have explored traditional ML classifiers for ASM mapping yielded inconsistent accuracy in distinguishing ASM from other forest land use changes due to speckle noise, as discussed in Section 2.5.2. In recent years, the use of DL has shown promising results in mapping and monitoring ASM in the tropics using optical imagery on a large scale, achieving commission/omission errors of less than 8% as described in Section 1.2.2.1. The DL approach has found extensive application in the field of SAR image CD because of its excellent characteristics and feature extraction capabilities, which benefit from a reduction of the speckle noise (Gao et al., 2019; Zhao et al., 2023). To date, no studies have explored the DL technique using SAR imagery for ASM studies. This study seeks to extend the application of DL to SAR for timely ASM monitoring in the tropics (**Objective 5**). This approach is further discussed in detail in Chapter 6.

Chapter 3

Study area and datasets

3.1 Introduction

This chapter provides important contextual information for the study location and the datasets used to develop and validate the proposed ASM monitoring methodology. Section 3.2 outlines a brief description of the study area used to evaluate the methods developed in the thesis. An overview of the regions chosen for each case study location is provided, covering the relevant natural resources, vegetation, climatic conditions, and topography. Section 3.3 presents a comprehensive overview of the datasets, including the different DEMs used in SAR preprocessing, the S1 SAR data, the optical data, and the spaceborne LiDAR used in the later validation. The specific applications and details of these datasets and case study areas are provided in the relevant methodological chapters.

3.2 Study area - Ghana

3.2.1 Climate of Ghana

The choice of Ghana as the case study area was informed by its wet tropical climate, and it being one of the countries in West Africa that is at the frontline of the fight against ongoing illegal ASM activities. Ghana is situated on the west coast of Africa, between latitudes 5°N and 11°N and longitudes of approximately 3°15'W and 1°15'E, as shown in [Figure 3.1](#). It is located on the Gulf of Guinea and the Atlantic Ocean and shares boundaries with Burkina Faso to the north, the Ivory Coast to the west, and Togo to the east ([Obuobie and Barry, 2012](#)). Ghana's climate is described as tropical and humid, characterised by seasonal rainfall patterns and consistently high temperatures influenced by the movement of the Inter-Tropical Convergence Zone (ITCZ), which controls the climate in the whole West Africa region ([Bagiliko et al., 2025](#); [Obuobie and](#)

Barry, 2012). The movement of the ITCZ across the country significantly influences the amount and duration of rainfall across the country, resulting in two distinct rainfall regimes in Ghana. In areas where the ITCZ crosses once a year, a mono-modal rainfall pattern is observed, whereas regions affected twice a year experience a bimodal rainfall regime (Obuobie and Barry, 2012).

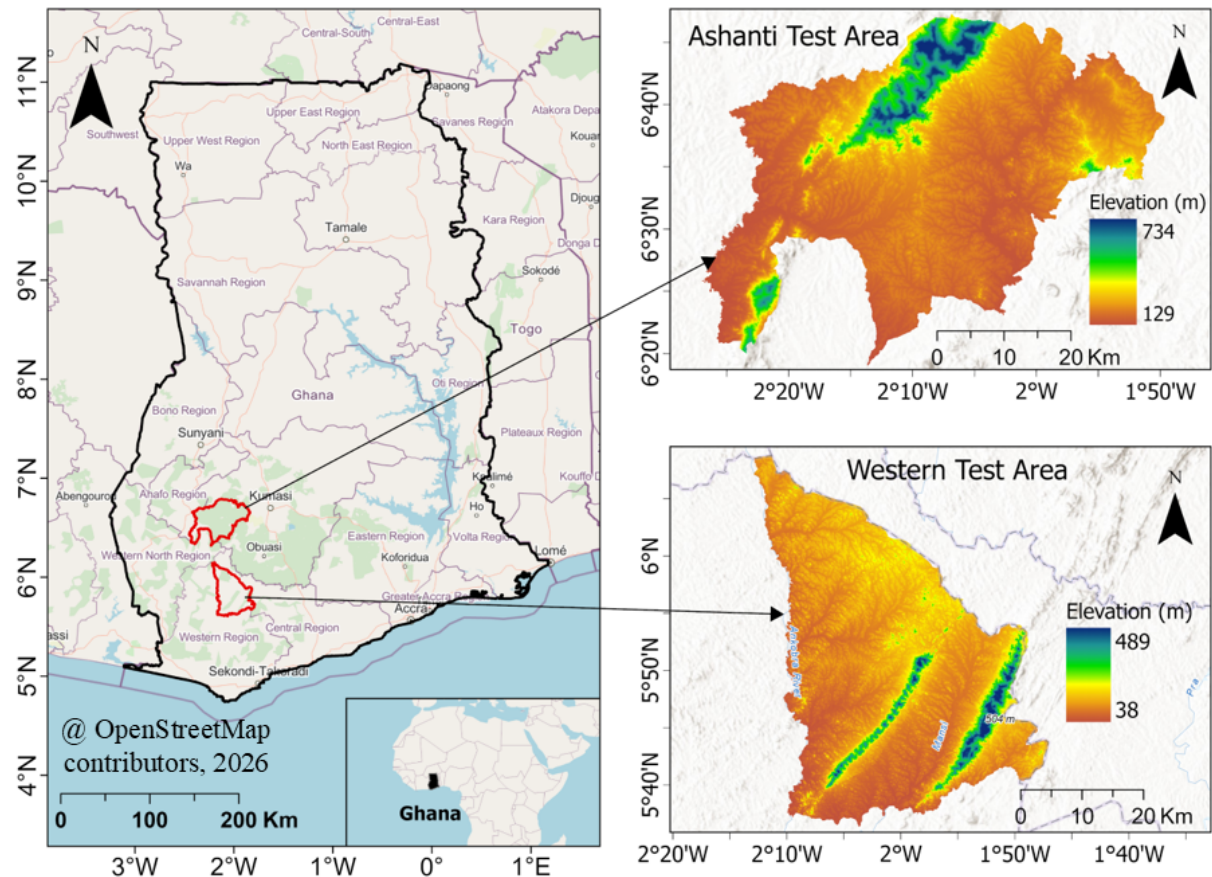


Figure 3.1: Location of Ghana in West Africa, delineating the two case study areas in the wet Ashanti and Western regions of Ghana.

The southern regions of Ghana, where ASM is mostly prevalent, tend to be impacted twice annually by the ITCZ, leading to two main rainfall seasons (Obuobie and Barry, 2012), as illustrated in Figure 3.2. The northern parts of the country experience one rainfall season, often occurring from April to October (Figure 3.2d – j), with peaks around August (Figure 3.2h) and September (Figure 3.2i), receiving a mean monthly rainfall that ranges from 150 to 250mm during this period (Bagiliko et al., 2025; Obuobie and Barry, 2012; Kyei-Manuh et al., 2025). In contrast, two rainy seasons are experienced in the south and can be expected to significantly impact any satellite monitoring approach, with the primary and major season occurring from March (Figure 3.2c) to July (Figure 3.2g). Notably, June is the wettest month (Figure 3.2f), with a mean monthly rainfall of at least 240mm. The minor rainy season typically begins in August (Figure 3.2h) or September (Figure 3.2i) and extends through to November (Figure 3.2k), peaking in September with a mean monthly rainfall from 80 to 160mm. The driest months are generally observed from December (Figure 3.2l) through to February (Figure 3.2b)

every year (Bagiliko et al., 2025; Kyei-Manuh et al., 2025).

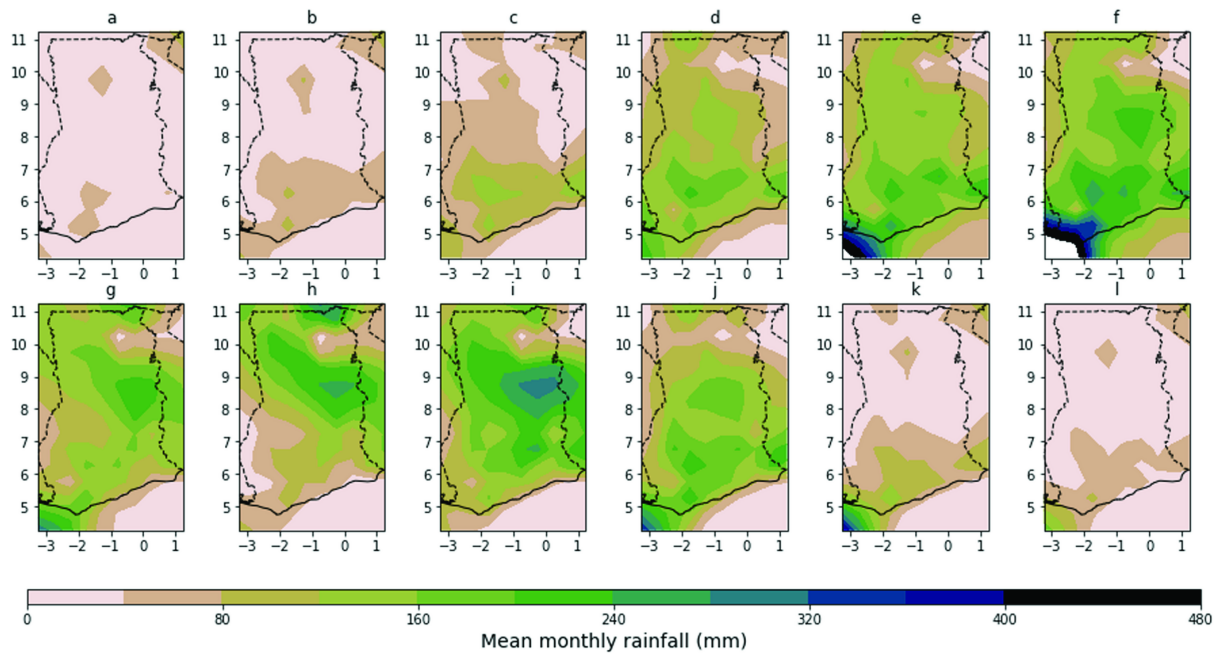


Figure 3.2: Mean monthly rainfall over Ghana between 1998 and 2012. The two main rainy seasons in southern Ghana, where ASM is most concentrated, typically begin in March to November (c – k), peaking in June (f) and September (i) with mean monthly rainfall between 160 and 320 mm during this time. Source: (Kyei-Manuh et al., 2025).

3.2.2 Forest disturbance in Ghana

Generally, Ghana features distinct tropical climatic zones, as shown in Figure 3.3 and broadly categorised by the Ghana Meteorological Agency (GMet) (Yamba et al., 2023) into (i) savannah zones that feature both Sudan and Guinea savannahs, (ii) forest zones, which include the semi-deciduous and the transition, and (iii) coastal zones. These forest zones receive the highest amounts of rainfall in the country, recording total annual rainfall ranging from about 1200 to 1900 mm. In southern Ghana, persistent cloud is observed in the forest zones during the rainy seasons (Forkuor et al., 2020; Snapir et al., 2017). The forest zones in Ghana are estimated to cover 9.17 Mha, representing approximately 40% of the total land area of the country (FAO, 2021). Ghana's forest cover has experienced a significant rate of forest disturbances over the years, with estimated annual forest loss of approximately 135,000 ha (Ankomah et al., 2020; Kyere-Boateng and Marek, 2021).

More recently, a study by Kusi (2025) assessed the state of trees outside forest reserves (TOF) in southern Ghana, revealing a significant decline in the total land area of TOF from about 38.2% to 33.8% from 2017 to 2023. According to Kusi (2025), this decline in TOF in southern Ghana is expected to continue at an annual rate of 0.79% by 2030 (see Figure 3.4). Recent reports confirm that forest reserves or protected areas (PAs) in Ghana have experienced a significantly higher rate of forest disturbance than the historical rate (Dong et al., 2025). The

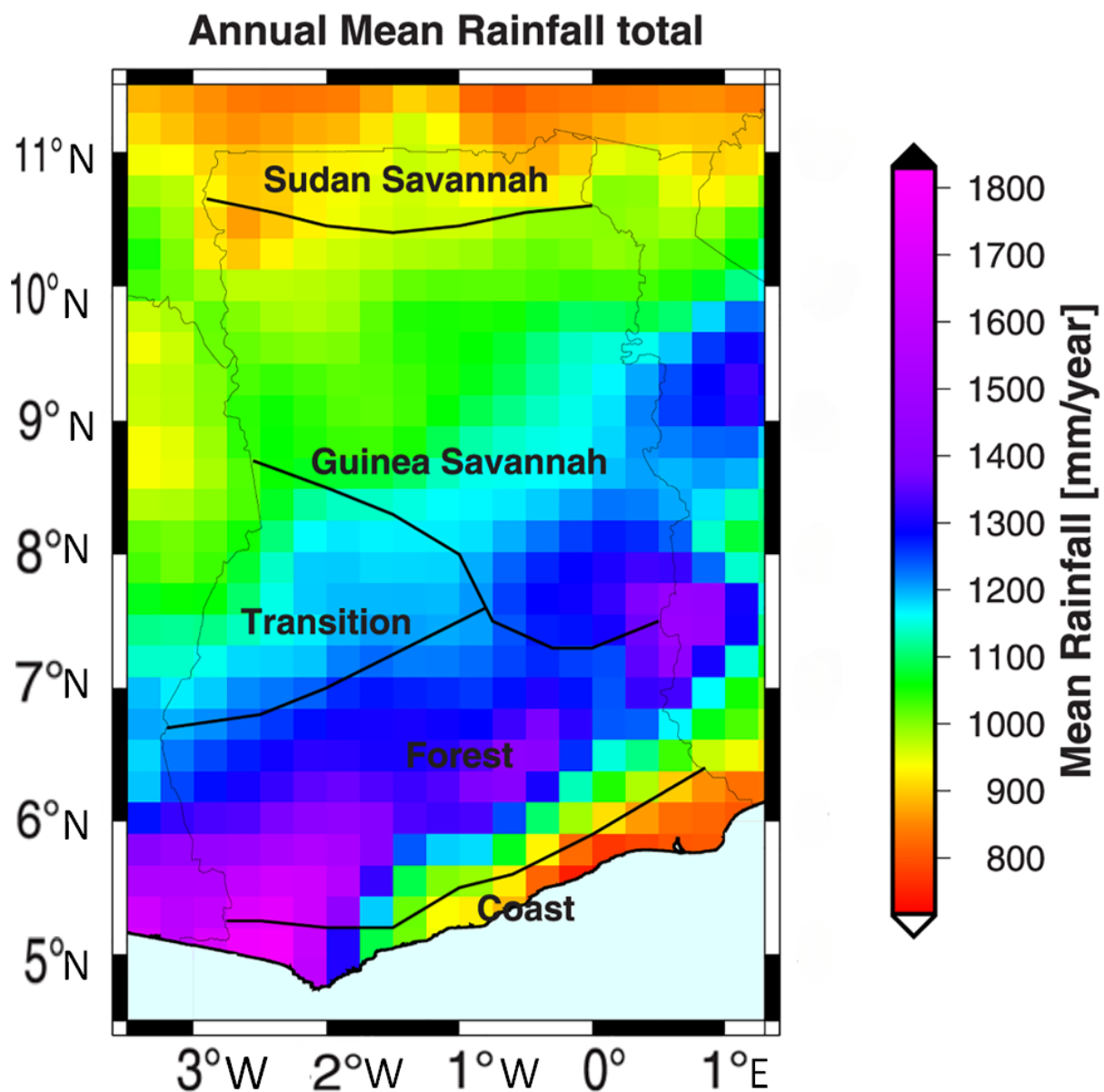


Figure 3.3: Map of Ghana showing the distinct tropical climatic zones along with the annual total rainfall recorded in these zones. Annual total rainfall is computed from the Global Precipitation Climatology Center (GPCC) data for the years 1981 to 2010. Source: (Yamba et al., 2023).

reported forest loss in 2024 (46200 ± 11600 ha) in PAs was estimated to be 91% more than that of 2023 (24200 ± 6000 ha). Most significant forest cover loss in Ghana is primarily driven by anthropogenic activities such as mining, agricultural expansion, and logging, while hazards such as fires and droughts also contribute to this issue (Ankomah et al., 2020; Boadi et al., 2016; Dong et al., 2025). In recent years, mining is reported to contribute to about 7.07% of forest loss in Ghana annually between 2022 and 2024 (Dong et al., 2025).

In Ghana, the top three regions with increasing rates of forest cover loss between 2017 and 2023 are Ashanti, Western, and Eastern regions (Kusi, 2025), as shown in Figure 3.4.

Ashanti had the most tree-cover lost, contributing an average rate of 18% of the total loss per year, followed by the Eastern region at an average rate of about 14%, and then the Western region at an average rate of roughly 13% over the period (Figure 3.4). These regions have also been reported as where illegal ASM operations are most prevalent (Gallwey et al., 2020; Owusu-Nimo et al., 2018). Consequently, the Ashanti and Western regions were selected as case study areas in this research (Figure 3.1). A more detailed analysis of these case study areas is presented in Section 3.2.3.

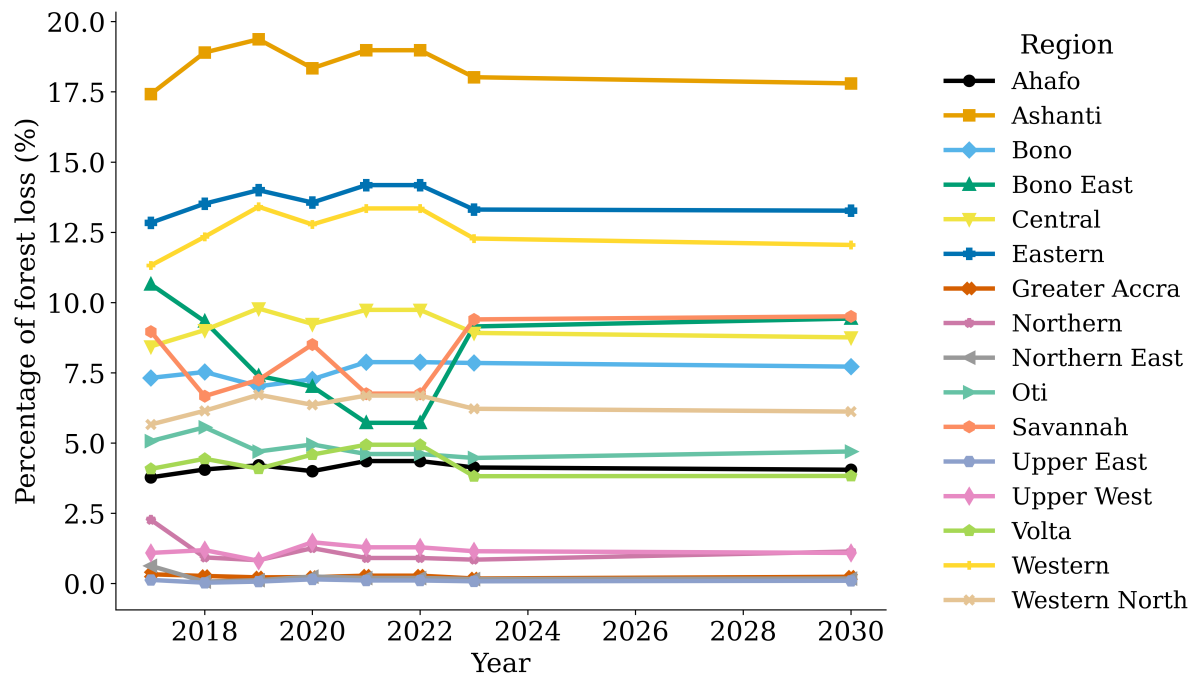


Figure 3.4: Regions in Ghana with increasing forest disturbance rates for the period of 2017 to 2023 and future disturbance projections. The selected case study regions, Western and Ashanti, are among the top 3 regions that have lost the most tree cover, partly due to increasing mining activities in these areas. Adapted from: (Kusi, 2025).

3.2.3 Overview of Ashanti and Western case study regions

Two primary case study regions located in the wet semi-equatorial forest zone, particularly in the Ashanti and Western regions in southern Ghana, were selected to develop and validate the ASM monitoring methodology proposed in this study (Figure 3.1). However, other regions were included for the investigation of the optimal SAR data preparation methodology in Chapter 4. Previous studies highlighted that high-intensity rainfall events significantly affected several S1 C-band SAR scenes acquired between 2015 and 2019 in these regions (Figure 3.5) (Forkuor et al., 2020). The study areas also fall within boundaries used in existing studies employing optical imagery and DL to detect and map ASM activities in Ghana (Gallwey et al., 2020). Although the scales are not directly comparable, the test sites overlap with existing studies, allowing for direct comparison and validation of the new methods developed in this study.

and against established benchmarks. Notably, the S1 images collected at the beginning and end of the rainy season in March and October appear to be most often affected by the atmospheric effects from heavy rainfall than other months (Forkuor et al., 2020). For example, at least fifty S1 images acquired in the months of March and October between 2015 and 2019 were significantly impacted by adverse atmospheric conditions, which limit their effectiveness for early ASM detections. The findings from these existing studies also offer valuable additional insights for developing and interpreting the results of our model in these regions.

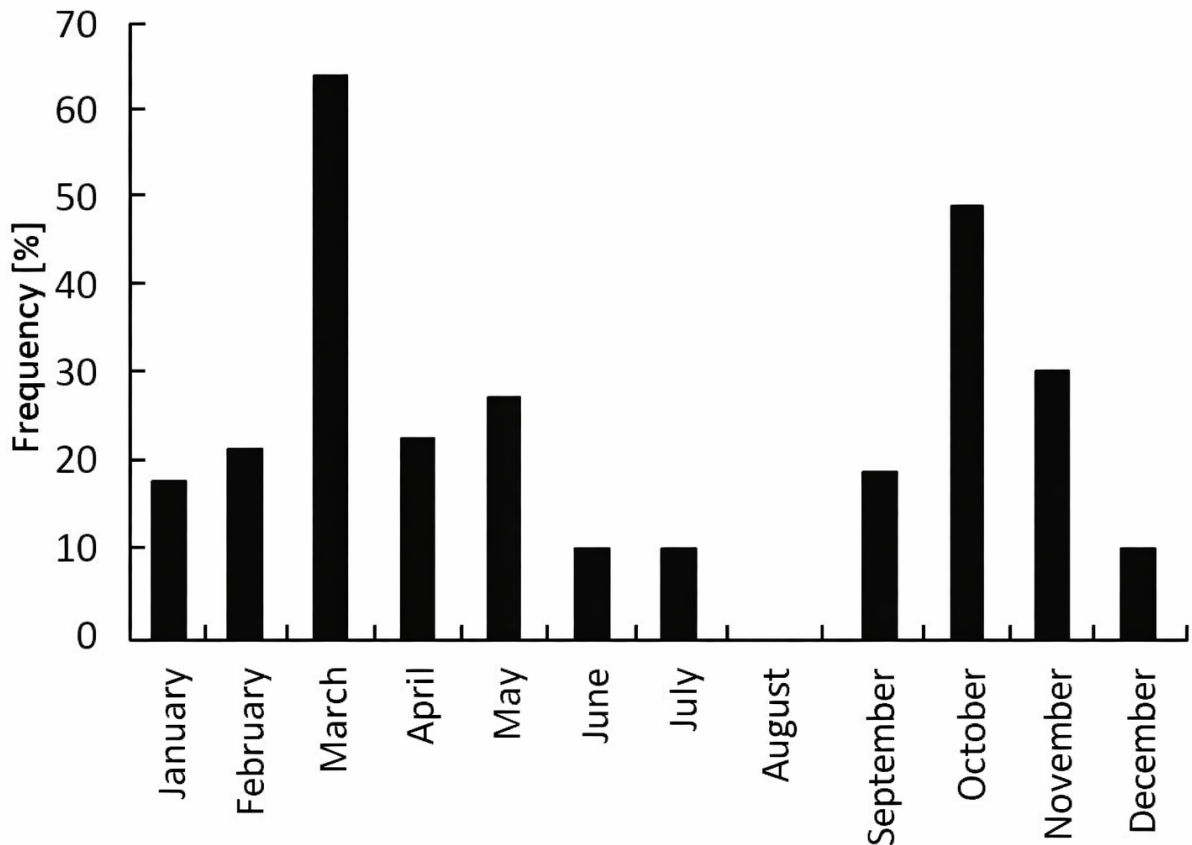


Figure 3.5: The summary of the total number of S1 scenes affected by atmospheric effects from rainfall in these areas between 2015 and 2019. The total number of S1 images affected by rain cells is expressed as the percentage of all available images per month, with images acquired in March and October (i.e. at least 50 scenes) during the rainy season most impacted. Adapted from: (Forkuor et al., 2020).

These areas also lie within the primary gold belts in Ghana, featuring major gold-bearing rock types such as Tarkwaian and Birimian, which have contributed to an increase in illegal ASM activities in these areas (Mantey et al., 2017; Owusu-Nimo et al., 2018). Although further details of these sites are provided in the respective methodological chapters, a brief description of the topography and vegetation types in these areas is presented here using data obtained from the Advanced Topographic Laser Altimeter System (ATLAS) of Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2). Ground elevation and vegetation canopy height profile data were obtained for the respective case study areas from the ICESat-2 ATL08 product

in February 2020. The ICESat-2 onboard ATLAS instrument uses three pairs of beams, each 3 km apart, with a pair spacing of 90 m (Markus et al., 2017). Each pair consists of a strong (high-energy) and a weak (low-energy) beam, typically in a 4 (strong) : 1 (weak) energy ratio, to measure surface elevation (Neuenschwander et al., 2022). Strong beams penetrate vegetation better, improving estimates of forest canopy height compared to weak beams (Zhu et al., 2020). Therefore, we used strong beams (high-energy) to estimate forest canopy height and ground elevation in this thesis. The ICESat-2 beam transects over the Ashanti and Western case study areas are shown in Figure 3.6 and Figure 3.7, respectively, considering only the higher-energy-emitting strong beams gt1r (gold), gt2r (purple), and gt3r (pink-red). The respective test area boundary of 10 x 10km is shown in red. As shown in Figure 3.6 and Figure 3.7, a significant gap in signal photons is observed along the track of beams, especially for the gt2r beam, implying that ICESat-2 datasets acquired over southern Ghana are unsuitable for validating the models developed in this study. This measurement gap is less affected by the gt3r beam, and it was therefore used for analysing vegetation canopy height and ground elevations in both test areas.

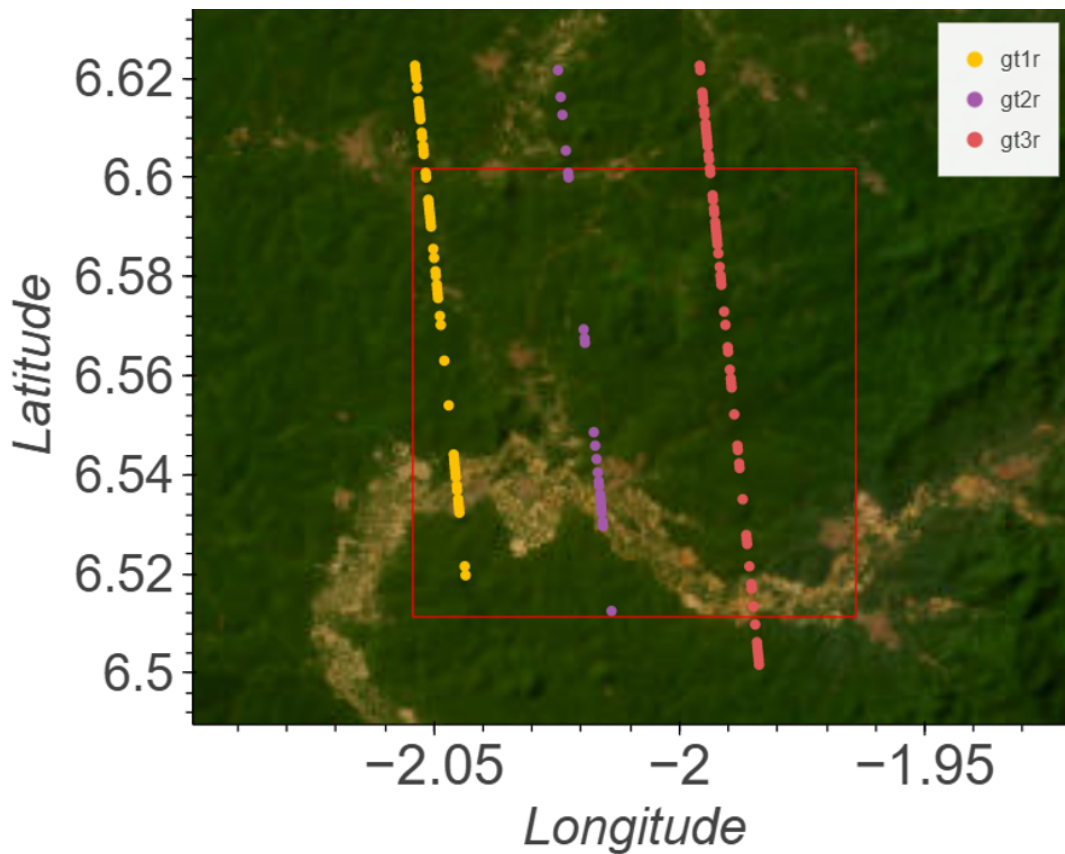


Figure 3.6: ICESat-2 ATL08 beam transects over the Ashanti case study area in southern Ghana. The data were acquired in February 2020 at the respective sites, showing photons from high-energy emitting beams of gt1r (gold), gt2r (purple), and gt3r (pink-red). The test area boundary (10 x 10km) is shown in red. Measurement gaps are observed along the track distance of beams, restricting the use of ICESat-2 as a validation dataset in this study.

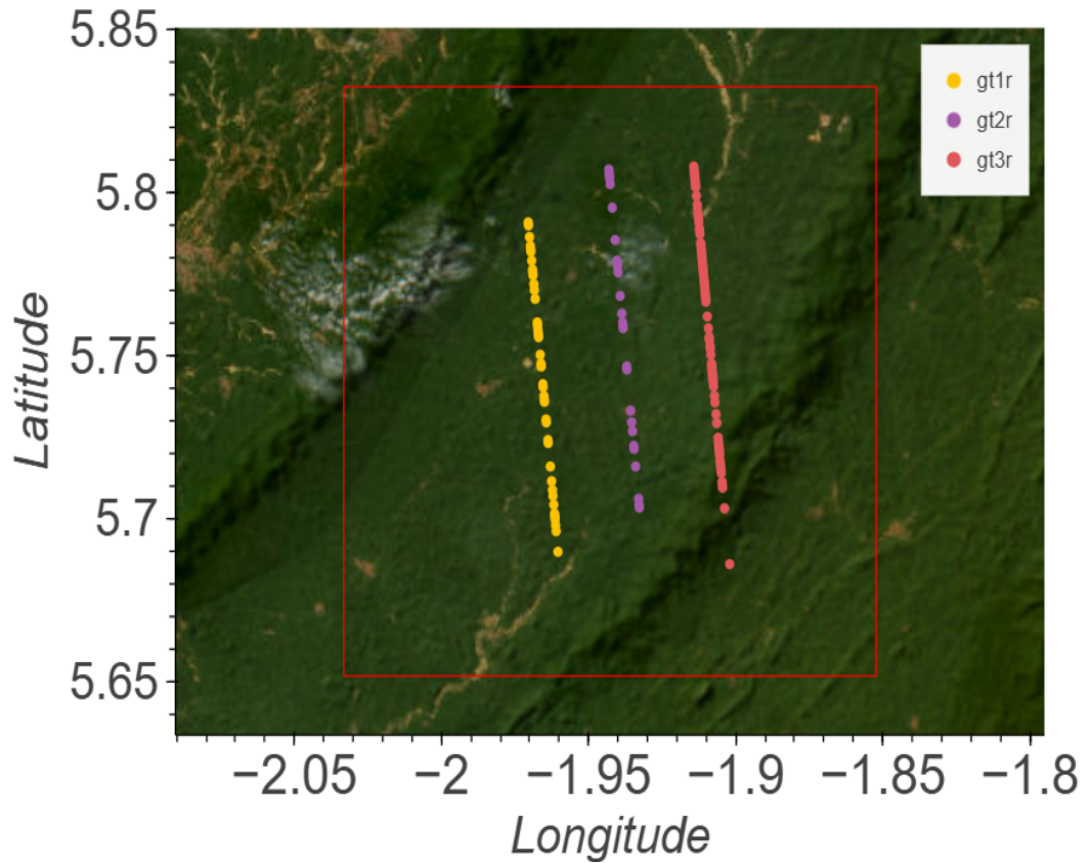


Figure 3.7: ICESat-2 ATL08 beam transects over the Western case study area in southern Ghana. The data were acquired in February 2020 at the respective sites, showing photons from high-energy emitting beams of gt1r (gold), gt2r (purple), and gt3r (pink-red). The test area boundary (10 x 10km) is shown in red. Measurement gaps are observed along the track distance of beams, restricting the use of ICESat-2 as a validation dataset in this study.

The along-track highest elevation and the top-of-canopy were estimated using a maximum filter with a 3 x 3 window size (see [Figure 3.8](#) – [Figure 3.11](#)). Major water bodies such as the Rivers Offin, Pra, and Tano flow through the Ashanti test area, which has experienced extreme pollution due to increased illegal ASM activities and unstable farming practices in the area over the years ([Atwima Mponua District Assembly, 2018](#)). The Ashanti area features an undulating terrain ranging from a ground elevation of about 150m to 220m ([Figure 3.8](#)). Three major rivers run through the Western site, including the Ankobra, Ashire, and Manse, which are crucial water supplies for illegal ASM activities in the area ([Wassa Amenfi East Municipal Assembly, 2018](#)). In the Western site, a varied topography can be observed, with regions of relatively low ground elevation less than 150m and uneven landscapes ranging from 200m to 400m ([Figure 3.9](#)). The vegetation canopy heights in these areas vary considerably by forest type and conditions, ranging from an average canopy height of lower than 10m in secondary forests to over 40m for trees in tropical primary forests in both test areas ([Figure 3.10](#) and [Figure 3.11](#)).

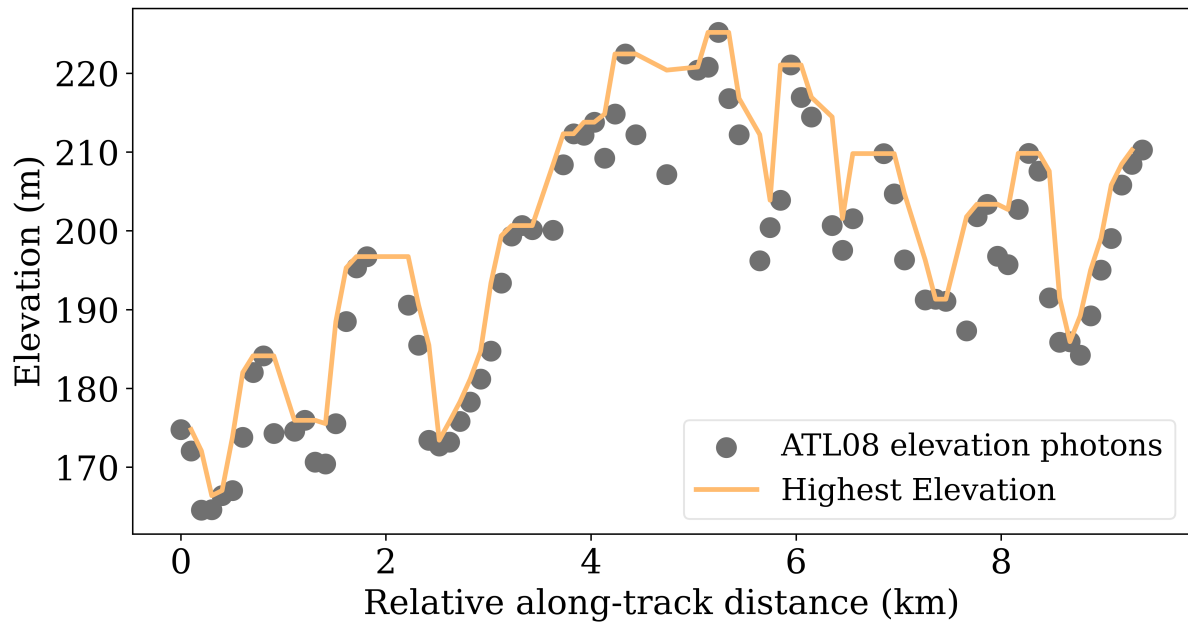


Figure 3.8: Ground elevation profile of 10km profile measured by ICESat-2 ATL08 photons from a strong beam (gt3r) over the Ashanti case study area in the forest zones in southern Ghana. The data were acquired in February 2020, showing the elevation profile (gray) and a rolling maximum of a 3 x 3 window size to estimate the along-track highest elevation (gold).

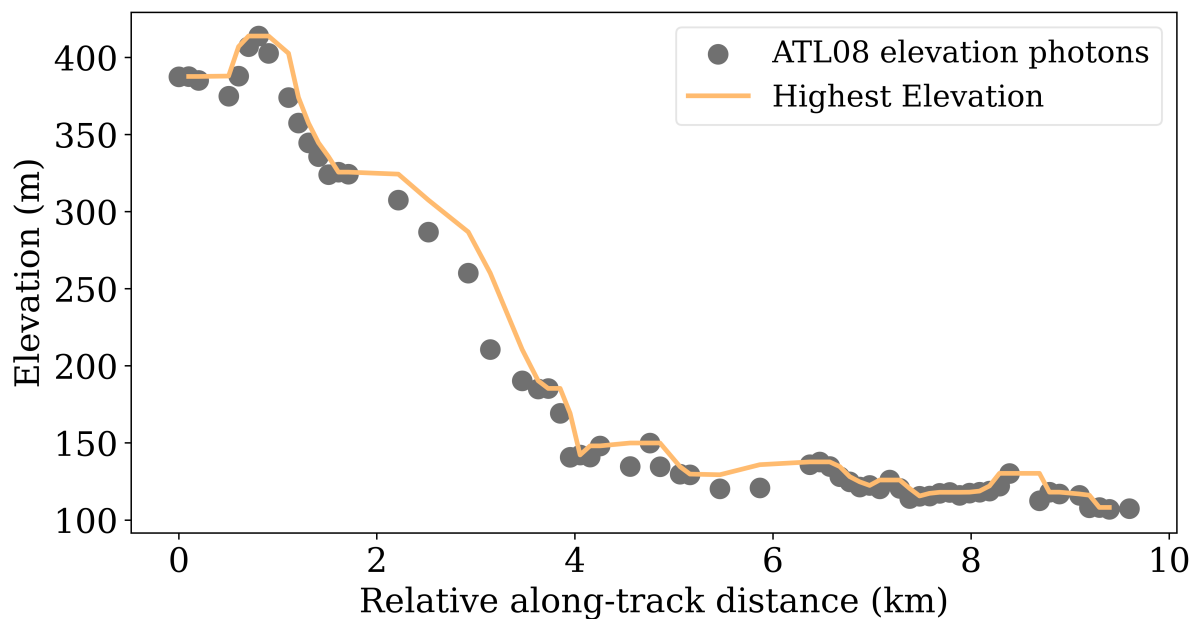


Figure 3.9: Ground elevation profile of 10km profile measured by ICESat-2 ATL08 photons from a strong beam (gt3r) over the Western case study area in the forest zones in southern Ghana. The data were acquired in February 2020, showing the elevation profile (gray) and a rolling maximum of a 3 x 3 window size to estimate the along-track highest elevation (gold).

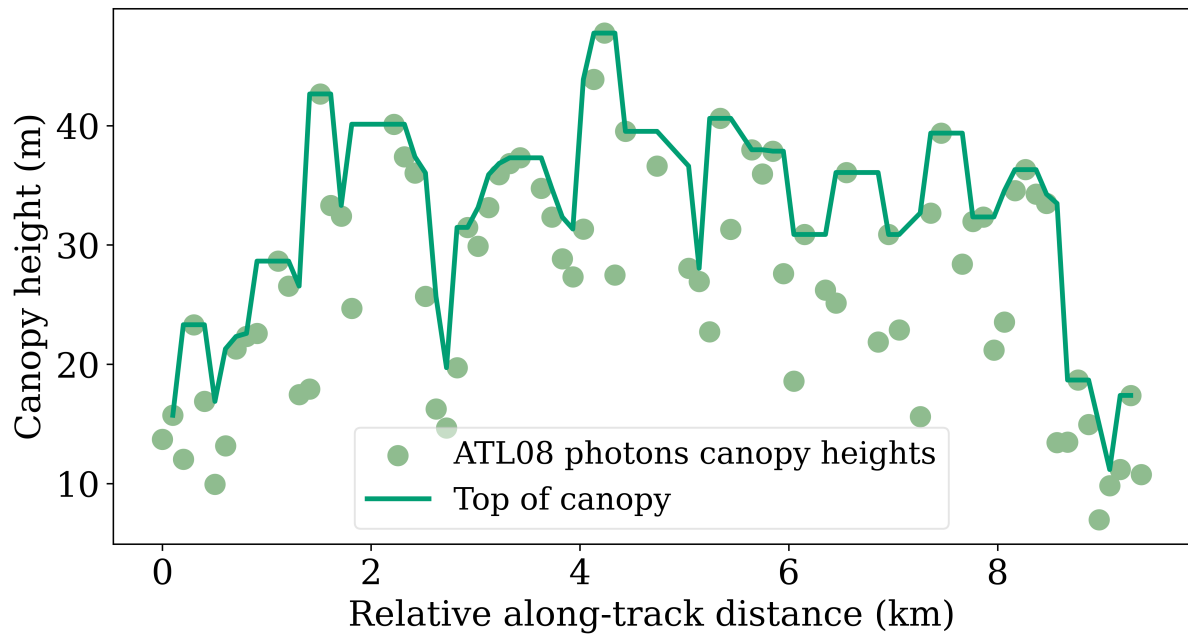


Figure 3.10: Vegetation canopy height profile of 10km profile of ICESat-2 ATL08 photons from a strong beam (gt3r) over the Ashanti case study area in the forest zones in southern Ghana. The data were acquired in February 2020, showing the vegetation canopy height profile (teal) and a rolling maximum of a 3 x 3 window size to estimate the along-track top of the canopy (green).

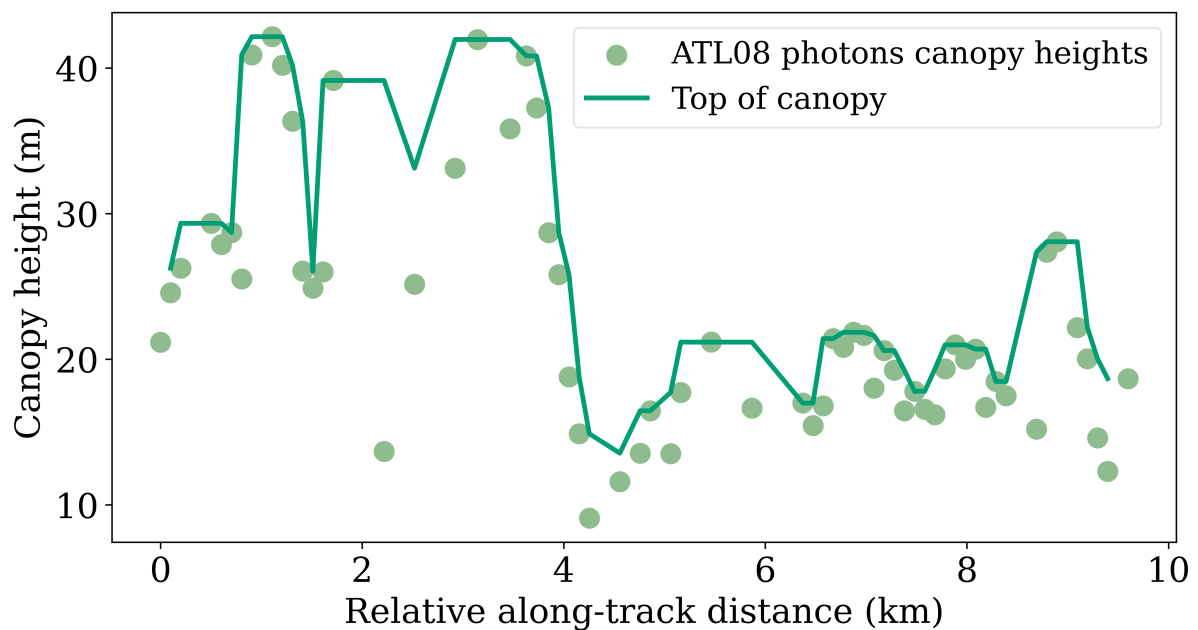


Figure 3.11: Vegetation canopy height profile of 10km profile of ICESat-2 ATL08 photons from a strong beam (gt3r) over the Western case study area in the forest zones in southern Ghana. The data were acquired in February 2020, showing the vegetation canopy height profile (teal) and a rolling maximum of a 3 x 3 window size to estimate the along-track top of the canopy (green).

3.3 Datasets

3.3.1 Digital Elevation Models (DEMs)

In this thesis, the suitability of different DEM options for creating radiometric terrain normalised products was investigated, assessing the analysis readiness of the newer DEMs for processing SAR imagery for ASM monitoring in varied topography across Ghana. Four widely-used, open-source global DEMs for processing SAR data were tested, which were created from different techniques, namely the 30m ALOS World DEM (AW3D30) ([Japan Aerospace Exploration Agency, 2024](#)), 30m SRTM DEM ([Farr et al., 2007](#)), 30m NASADEM ([Buckley et al., 2020](#)), and the Copernicus 30m DEM (COP30) ([Fahrland et al., 2022](#)) available in Google Earth Engine (GEE). It is important to note that the DEMs used in this study represent the best approximation of the underlying bare ground terrain rather than the top of the forest canopy.

3.3.1.1 Shuttle Radar Topography Mission (SRTM) DEM v 3.0

The Shuttle Radar Topography Mission (SRTM) DEM is the most commonly used DEM for processing SAR for ASM monitoring ([Forkuor et al., 2020](#); [Janse van Rensburg and Kemp, 2022](#); [Kimijima et al., 2022a](#)). The SRTM is an international collaboration initiative between the National Aeronautics and Space Administration (NASA), the National Geospatial-Intelligence Agency (NGA) of the United States, the Italian Space Agency (ASI), and the German Space Agency (DLR) ([González-Moradas et al., 2023](#); [Farr et al., 2007](#)). The SRTM collected DEM data on a near-global scale, covering latitudes from 56° south to 60° north, creating the most comprehensive high-resolution digital topographic data of the Earth's surface at the time. It utilised interferometric SAR (InSAR) techniques to create a DEM from radar images acquired by Spaceborne Imaging Radar-C/X-band SAR (SIR-C/X-SAR). The radar system was deployed with two antennas flown onboard the Space Shuttle Endeavour during an 11-day operation in February 2000 ([González-Moradas et al., 2023](#); [Farr et al., 2007](#)). The SRTM version 3 DEM used in this thesis was released in September 2014, with updates addressing data voids present in older versions using data from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global DEM v. 2.0 (GDEM2), United States Geological Survey (USGS) national elevation datasets, and USGS Global Multi-resolution Terrain Elevation Data (GMTED2010). The SRTM v. 3.0 DEM is provided in 1 arc second spacing (approximately 30m) with a reported global vertical RMSE of 7.5 m ([Tadono et al., 2016](#)).

3.3.1.2 NASADEM

The NASADEM is an initiative that aims to derive a new, high-quality, and open-source global DEM from SRTM data and other sources ([Buckley et al., 2020](#)). The NASADEM was produced by reprocessing the original SRTM data (i.e. raw data) for improved accuracy, incorporating additional data from ICESat Geoscience Laser Altimeter System (GLAS) and ASTER. These data upgrades aimed to reduce the voids and anomalies present in the original data through enhanced phase unwrapping approaches and by leveraging ICESat GLAS for precise data control ([Buckley et al., 2020](#)). NASADEM was published in February 2020 and is also available at a 1 arc second spacing (roughly 30m spatial resolution). In forested areas, the NASADEM has been found to provide the most robust performance compared to other freely available global DEMs ([Okolie et al., 2024](#)), and it was therefore particularly important that this was included in this study for processing SAR data covering tropical forests.

3.3.1.3 ALOS World 3D (AW3D30) DEM

The Japan Aerospace Exploration Agency (JAXA) developed the ALOS World 3D (AW3D) DEM at a resolution of approximately 5 m (about 0.15 arc seconds) from imagery captured by the Panchromatic Optical Sensor (POS) onboard the Advanced Earth Observation Satellite (ALOS) ([Japan Aerospace Exploration Agency, 2024](#)). The satellite operated at 3 viewing angles (i.e. nadir, forward, and backward), allowing three-dimensional representations of landscapes to be captured ([Japan Aerospace Exploration Agency, 2024](#); [González-Moradas et al., 2023](#)). The satellite orbited the Earth from January 2006 to May 2011, capturing images globally between 80° south and 80° north latitude ([Tadono et al., 2016](#)). The Japan Aerospace Exploration Agency first released the (AW3D30) DEM in May 2016, which is a resampled version of the 5m AW3D with a horizontal resolution of about 30m (1 arcsec mesh) and a global vertical RMSE of 4.4m ([González-Moradas et al., 2023](#); [Tadono et al., 2016](#)). The 30m AW3D30 DEM product, since its first release, has continuously received data updates, with newer versions addressing void-filling and anomaly problems present in older versions ([Japan Aerospace Exploration Agency, 2024](#)). The AW3D30 DEM has proven to outperform other freely available DEMs as the most robust DEM, providing reliable performance on a wide range of landscapes worldwide ([Florinsky et al., 2018](#); [Grohmann, 2018](#); [Uuemaa et al., 2020](#)). The AW3D30 version 4.0 product, published in April 2023, was used in this study.

3.3.1.4 Copernicus DEM

The Copernicus DEM is an improved version of the World DEM, which includes flattening of water bodies, correction of implausible terrain structures and hydrological networks, while ensuring accurate representation of coastlines and man-made features ([Fahrland et al., 2022](#)). The data were created from radar satellite images collected during the TanDEM-X mission between 2011 and 2015 and were gap-filled using information from other DEMs, including AW3D30,

SRTM30, and various national DEMs (Fahrland et al., 2022). Copernicus DEM is provided in three variations in terms of the spatial resolution and coverage: (i) the EEA-10 of grid cell size of 0.3 arc second (approximately 10m) that covers only European zones, (ii) GLO-30 in 1 arc second mesh (approximately 30m) with a global coverage between 90° south and 90° north latitude, and (iii) GLO-90 with 3 arc second spacing (approximately 90m) covering the surface of the Earth from 90° south and 90° north latitude (González-Moradas et al., 2023). The Copernicus DEM was first published in December 2019 with updates planned to maintain and improve data quality until December 2026. The global DEM products have a vertical RMSE of 1.68m (Leister-Taylor et al., 2020; Fahrland et al., 2022). A recent study by González-Moradas et al. (2023) assessing the performance of different global DEMs for geomorphological mapping demonstrated that the Copernicus 30m (COP30) DEM outperforms other open-source global 30m DEMs in rugged terrain. Another study evaluating the performance of global DEMs for terrain morphological analysis in mountainous regions revealed that the COP30 is, on average, better than other DEMs, especially in undulating landscapes (Trevisani et al., 2023). We therefore used the COP30 DEM in this study.

3.3.2 Microwave remote sensing data

This section describes the microwave remote sensing datasets used in this study for model development and during data exploration. It explains the rationale for focusing on Sentinel-1 C-band SAR for developing the models in this study.

3.3.2.1 Sentinel-1 SAR imagery

S1 is an ESA-funded C-band SAR mission and part of the Copernicus programme, providing all-weather, day and night imaging capabilities of the Earth's surface. S1 delivers SAR data from a dual-polarisation C-band satellite operating at 5.405GHz (approximately 5.6cm wavelength). The S1 Level 1 products are provided either as Simple Look Complex (SLC), which retains both amplitude and phase information, or as Ground Range Detected (GRD), which contains only the amplitude information (Schmidt et al., 2023). The S1 GRD datasets used in this study are freely available from October 2014 to the present with global coverage. The datasets were collected in interferometric wide-swath (IW) mode with an azimuth resolution of approximately 20m and a ground range resolution of roughly 5m, leveraging a maximum swath width of 250km. Depending on the S1 satellite acquisition geometry, images are acquired with incidence angles ranging from 31° to 46° in both ascending and descending orbits. The S1 dual-polarisation datasets used in this study feature both VV and VH bands available in GEE at a pixel spacing of 10 × 10m, although the S1 IW product has a range-azimuth spatial resolution of approximately 5 × 20m. The dataset included both S1-A and S1-B GRD products collected in both ascending and descending orbits with a revisit frequency of 6 days. Although the S1-B satellite data used in this study was decommissioned in December 2021 due to an

unexpected anomaly with the instrument power supply (ESA, 2022), S1-A remains fully operational, as well as the recent launch of S1-C in September 2024 (ESA, 2024), delivering radar data at a global revisit time of 6 days.

3.3.2.2 ALOS-2 ScanSAR imagery

L-band SAR has improved penetration capabilities of vegetation canopies and is less affected by atmospheric effects from high precipitation when compared to C-band, as described in Chapter 2 of this thesis. In 2023, the L-band ALOS-2 ScanSAR dual-polarised (i.e. HH and HV) data, with a wavelength of 23.5cm and a spatial resolution of 100m, were made freely available. The ALOS-2 ScanSAR Level-2 data is provided in GEE as orthorectified and radiometrically corrected for normalised backscatter data using the AW3D30 DEM. The ALOS-2 data is available at a pixel spacing of 25×25 m, although ALOS-2 SAR has a resolution of approximately 100m with a potential revisit interval of 14 days and a swath width of 350km (Balling et al., 2024).

3.3.2.3 Justification for using S1 C-band data for developing the models in this study

Although the L-band ALOS-2 ScanSAR data were not freely available at the start of this study, their potential for early detection of ASM was later assessed upon their release as Open Data in 2023, comparing their suitability with the S1 C-band data. Figure 3.12 compares the timeliness of detecting forest or vegetation clearance caused by the early stage of ASM activity in the tropics in southern Ghana. The ALOS-2 ASM-induced forest disturbance detections were observed to significantly lag behind the S1-based detections in the study area, with possible delays up to 21 days. The findings here align with the study by Balling et al. (2024), which reported that ALOS-2 detections experienced significant delays of up to 17.8 days compared with S1-based detections for timely tropical forest disturbance mapping in Indonesia. Despite the ALOS-2 ScanSAR's potential 14-day global repeat orbit, no data were available in the ascending orbit in our study area, and there were 12 to 25 observations per year in the descending orbit, resulting in these significant delays in ALOS-2 L-based ASM detections in the study area. There is potential for a fused approach, but this is outside the scope of this thesis, and may be explored for future work.

Additionally, while L-band ALOS-2 data has advantages in large-sized forest disturbances detections (Balling et al., 2024), its medium resolution provided at a pixel spacing of 25×25 m presents a challenge in detecting small scale ASM activity compared to the S1 C-band SAR at a pixel spacing of 10×10 m in both test areas Figure 3.13. This further limits the capability of using L-band ALOS-2 ScanSAR imagery for large-scale NRT ASM monitoring applications. The capability of using S1 C-band SAR for detecting subtle changes in forest cover caused by ASM is further discussed in Chapter 6. The justification for utilising S1 C-band SAR in this

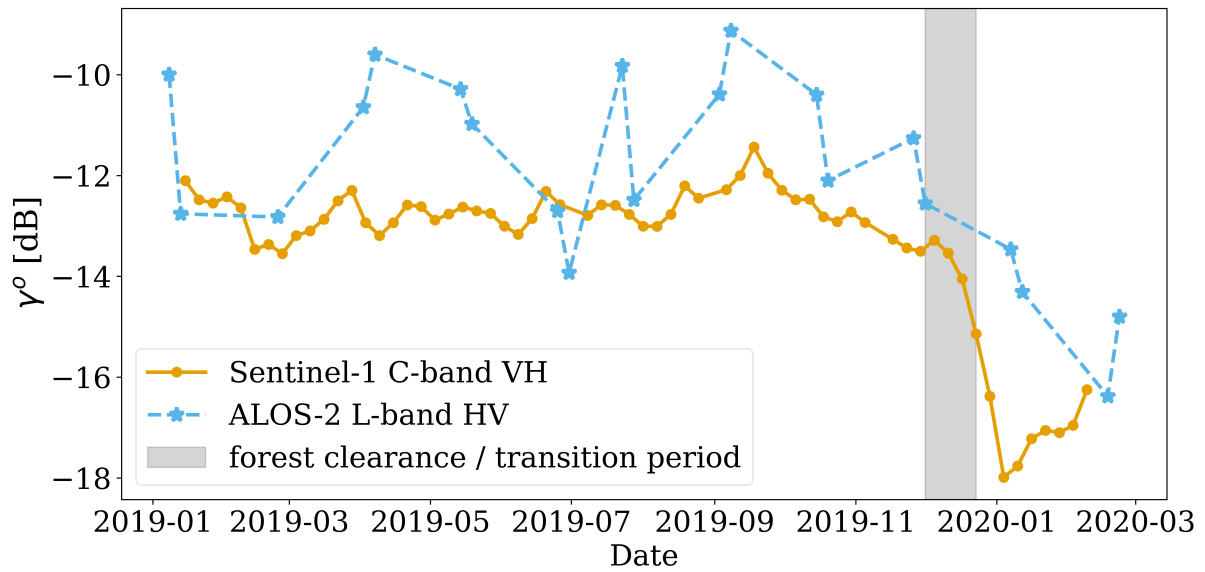


Figure 3.12: Comparing S1 C-band SAR imagery and ALOS-2 L-band SAR data timeliness of detecting ASM activity in the tropics in southern Ghana. ALOS-2 ASM detections significantly lag behind the S1-based detections, with possible delays up to 21 days.

study can be summarised as follows:

- While S1 data were freely available at no cost and at an unprecedented spatial and temporal resolution, there was no open-source L-band SAR equivalent at the start of this study. Other SAR datasets captured using X-band SAR with wavelengths of approximately 3.1 cm have proven to be unreliable for ASM monitoring, due to their low penetration capabilities and high sensitivity to adverse atmospheric effects ([Danklmayer et al., 2009](#); [Janse van Rensburg and Kemp, 2022](#)) and hence were not utilised in this study. Moreover, there are no freely available X-band SAR data for academic research with global coverage.
- Due to the medium spatial resolution of the released L-band ALOS-2 SAR data compared to S1 C-data, this introduces a challenge for detecting small-scale changes in forest cover, leading to a high rate of missed detections ([Balling et al., 2024](#)). As ASM activity generally begins with vegetation clearance/thinning (i.e. the early stage of ASM activity), this limits the effectiveness of L-band ALOS-2 SAR for timely and reliable monitoring of ASM activities on a large scale. S1 SAR, on the other hand, has the potential to overcome the limitations of the ALOS-2 L-band to improve the detection of small ASMs.
- The high temporal resolution of the S1 data compared to the L-band ALOS-2 also presents an advantage in improving the ASM detection timeliness to enable rapid interventions. The ASM timeliness analysis using different SAR polarisations (i.e. co-polarised and cross-polarised) is further discussed in Chapter 5.

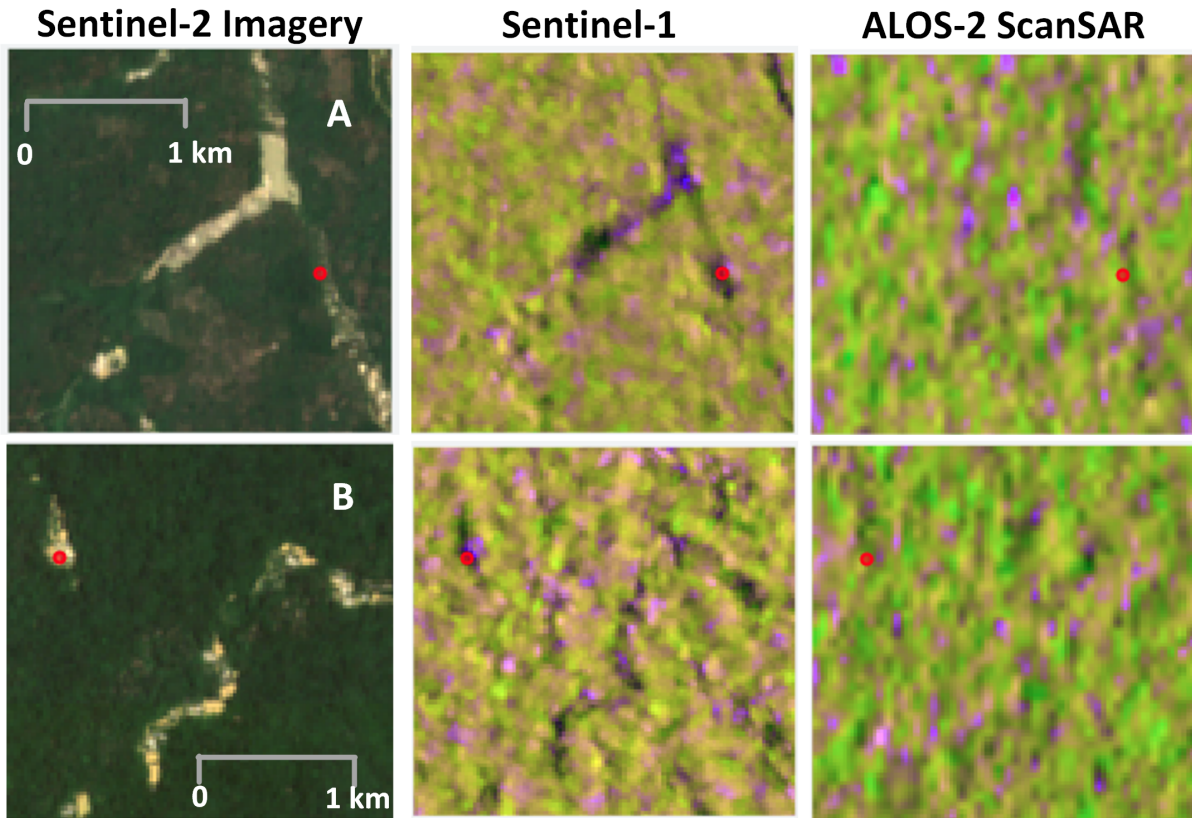


Figure 3.13: Comparing Sentinel-1 and ALOS-2 ScanSAR backscatter for detecting subtle forest disturbance caused by ASM activities in the tropical regions. The medium resolution of the L-band ALOS-2 data available at a pixel spacing of 25 x 25m presents a challenge in detecting small ASM activity compared to the S1 C-band SAR at a pixel spacing of 10 x 10m in both test areas. **A** – Ashanti test site and **B** – Western test site.

3.4 Reference datasets for validation and identification of ASM sites

Optical imagery, including Sentinel-2 and PlanetScope imagery, was used to validate the SAR-based ASM detection methods developed in this study. A yearly ASM footprint dataset collected across southern Ghana for independent validation ([Abramowitz et al., 2023](#)) was also used during validation. This dataset was collected as part of an international collaboration project between NASA SERVIR West Africa and the Centre for Remote Sensing and Geographic Information Services (CERSGIS) at the University of Ghana to map ASM activities in the country.

As described in Section 3.2, southern Ghana is among the cloudiest regions globally, leading to significant variability in satellite remote sensing data density ([Dong et al., 2025](#)). A recent study by [Dong et al. \(2025\)](#) compared the data density of Landsat (LST), Sentinel-2 (S2), and Sentinel-1 (S1) quality observations available in southern Ghana from 2020 to 2024 [Figure 3.14](#). The frequency of usable observations (i.e. scenes or images that are less or not

impacted by atmospheric effects such as cloud, haze, and rain cells) from the three sensors (i.e. LST, S2, and S1) was compared during the major rainy season from April to July, represented as hatched bars, and in any other season (see Figure 3.14). Due to the significant reduction of usable optical imagery during the rainy season, as shown in Figure 3.14, ASM operations that occurred outside the rainy season were used to assess the timeliness of ASM detections using the models developed in this study. Details of this validation are discussed in detail in Chapter 5. However, the capability of using the S1 SAR-based approach proposed in this study for monitoring of ASM activities during both rainy and dry seasons is evaluated in Chapter 6.

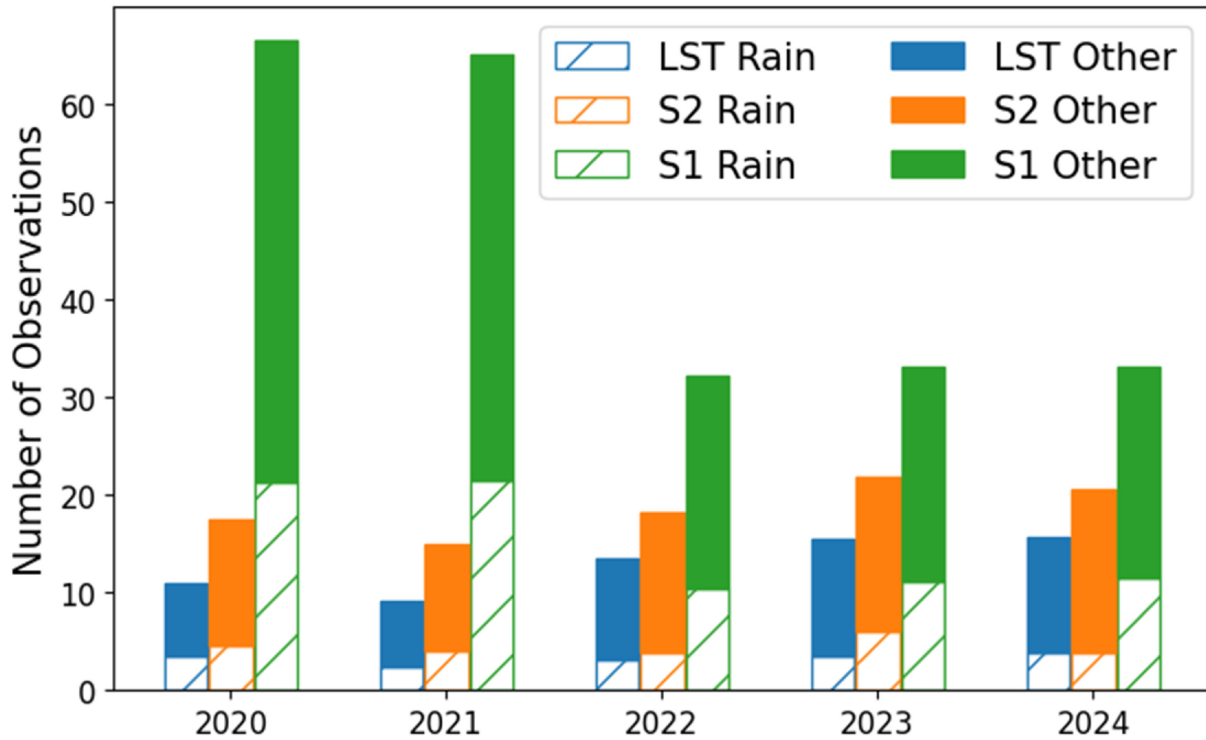


Figure 3.14: The frequency of usable observations (i.e., scenes less or not impacted by atmospheric effects such as cloud, haze, and rain cells) from Landsat (LST), Sentinel-2 (S2), and Sentinel-1 (S1) during the major rainy season from April to July, represented as hatched bars, and any other season in southern Ghana from 2020 to 2024. Source: (Dong et al., 2025).

3.4.1 Sentinel-2 optical imagery

Sentinel-2 (S2) is a multispectral optical imaging mission within the ESA Copernicus program, based on a constellation of three satellites (S-2A, S-2B, and S-2C) operating in a sun-synchronous orbit at an altitude of 784km providing high-resolution optical data for terrestrial and coastal applications (Lima et al., 2025; Phiri et al., 2020). S2 offers a high revisit frequency of 5 days, which can be more frequent at higher altitudes, with an orbital swath width of 290 km (Phiri et al., 2020). All three S2 satellites are equipped with a Multi-Spectral Instrument (MSI) sensor, which contains 13 spectral bands, including four visible and near-infrared (NIR) bands at a spatial resolution of 10m, six bands in the Red Edge, short-wave infrared (SWIR) and

narrow NIR regions at 20m spatial resolution, and three atmospheric correction bands at spatial resolution of 60m (Lima et al., 2025), as described in Table 3.1. The datasets are generally available at varying processing levels, including: (i) Level-1C Top-Of-Atmosphere (TOA) reflectance images, which have undergone geometric and radiometric corrections to produce orthorectified products available in 100 x 100km image tiles and projected to UTM/WGS84 and (ii) Level-2A Bottom-Of-Atmosphere (BOA) surface reflectance images, which have undergone atmospheric and topographic corrections using the Sen2Cor processor, and often used for forest land use/cover applications (Phiri et al., 2020). The Normalised Difference Vegetation Index (NDVI), as a popular and relatively straightforward measure of 'greenness', was included in a time-series profile computed from S2 Level-2A products and used in this study, as defined in Equation 3.1. This was calculated for mining sites to confirm the early stage of ASM activity. Optical images acquired within +/- 8 days of the S1 detection dates were utilised to verify the occurrence and timing of change events and to distinguish mining activities from other forest disturbances. An example of the NDVI profile over a mining site for visual inspection to determine the start of ASM activity is illustrated in Figure 3.15. Further details are provided in the respective methodological Chapters 5 and 6.

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad \text{Equation 3.1}$$

Table 3.1: Sentinel-2 and PlanetScope spectral bands and sensor specifications. Source: (Frazier and Hemingway, 2021; Lima et al., 2025).

Sentinel-2A/B MSI				PlanetScope Dove			
Band	Band Name	Wavelength (nm)	Res. (m)	Band	Band Name	Wavelength (nm)	Res. (m)
B1	Coastal Aerosol	433–453	60	B1	Blue	455–515	3
B2	Blue	458–523	10	B2	Green	500–590	3
B3	Green	543–578	10	B3	Red	590–670	3
B4	Red	650–680	10	B4	NIR	780–890	3
B5	Red Edge 1	698–713	20				
B6	Red Edge 2	733–748	20				
B7	Red Edge 3	773–793	20				
B8	NIR	785–899	10				
B8A	Vegetation RE	855–875	20				
B9	Water Vapour	935–955	60				
B10	SWIR Cirrus	1360–1390	60				
B11	SWIR	1565–1655	20				
B12	SWIR	2100–2280	20				

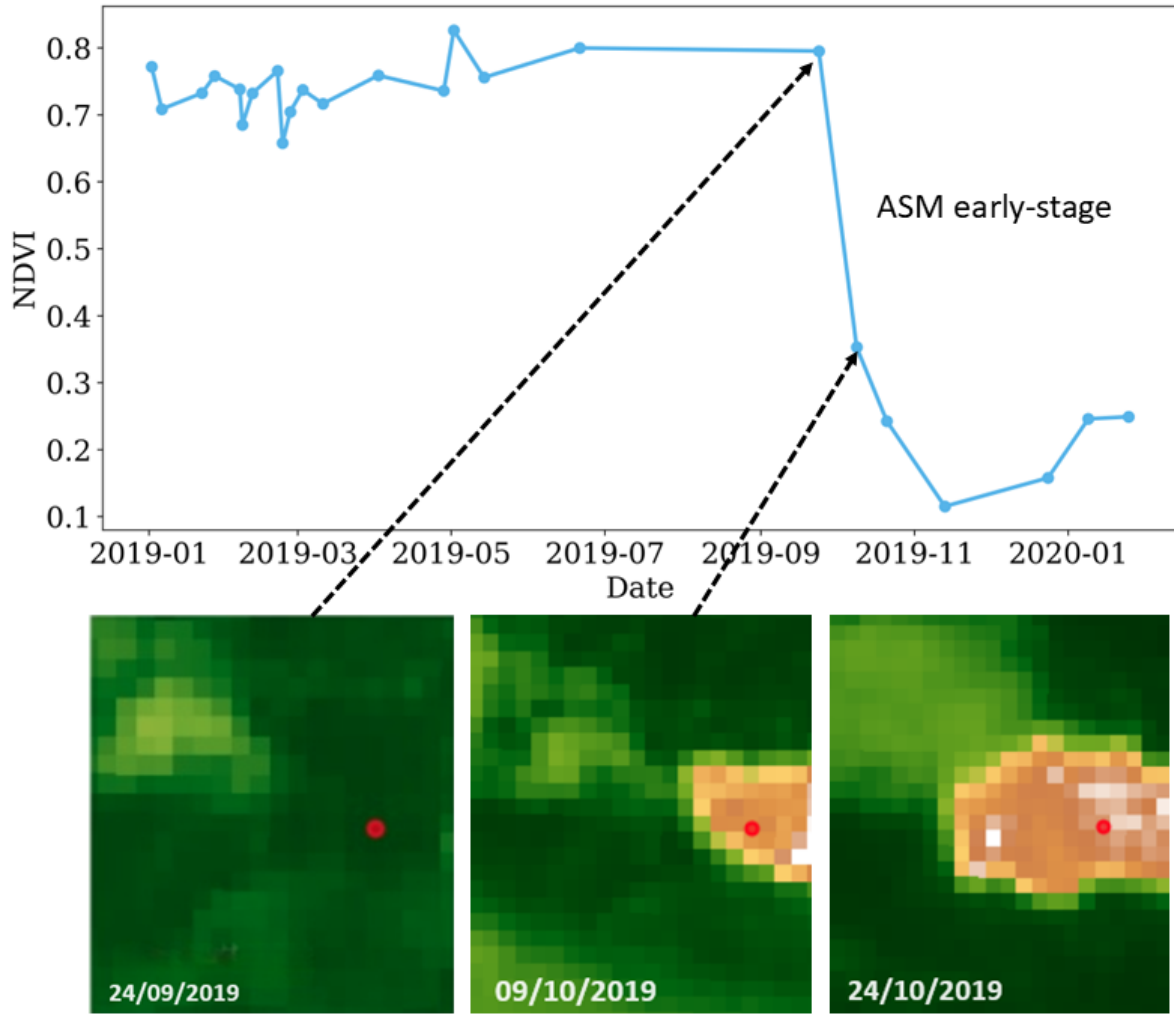


Figure 3.15: Example of visual inspection of Sentinel-2 NDVI profile over an existing ASM site in southern Ghana to identify the time of the start of mining.

3.4.2 PlanetScope optical imagery

The PlanetScope (PS) optical commercial imaging mission comprises a constellation of multiple satellites (i.e. doves) operating in a sun-synchronous orbit at an altitude of 475 km, an orbit inclination of 98° , and acquires data within $\pm 81.5^\circ$, depending on the season (Frazier and Hemingway, 2021). PS offers a high spatial resolution optical data of 3 m and a daily revisit time with an orbital swath width of approximately 24 km x 16 km. The PS satellites are equipped with four bands (i.e. blue, green, red, and NIR) (Frazier and Hemingway, 2021), as described in Table 3.1. The PS datasets used in this study were available as Level 3A products, which were orthorectified and scaled to surface reflectance image products. This dataset was accessed through the Education and Research License. The merging of the S2 and PS optical imagery datasets provided higher revisit frequency products during the validation.

3.4.3 ASM yearly footprint datasets

Alongside the optical validation datasets, yearly ASM footprints were used for independent validation, as well as to guide the collection of training, testing, and validation datasets during model development. The dataset was created from digitised polygons of mining areas in the forest zone of southern Ghana based on satellite imagery from Planet (Norway's International Climate and Forests Initiative (NICFI) monthly mosaics), as well as S1 and S2 datasets ([Abramowitz et al., 2023](#)).

Chapter 4

An investigation into the current state of the art analysis-ready data: A novel methodology to improve Sentinel-1 data quality and analytical readiness for fine-grained forest disturbance detection in tropical regions

This chapter is based on two peer-reviewed and published papers and one in conference proceedings:

Mensah, I. O., Barrett, B., and Cahalane, C. (2024a) *Evaluating the Influence of Global Digital Elevation Models (DEMS) for Sentinel-1 Radiometric Terrain Correction (RTC) for Tropical Forest Measurements in Google Earth Engine*. In: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Greece, July 2024. Athens: Institute of Electrical and Electronics Engineers (IEEE). [doi:10.1109/igarss53475.2024.10641014](https://doi.org/10.1109/igarss53475.2024.10641014).

Mensah, I. O., Barrett, B., and Cahalane, C. (2024b) *Towards Analysis Ready Data (ARD): Assessing Sentinel-1 Backscatter Data Suitability for Detecting Artisanal and Small-Scale Mining (ASM) Induced Deforestation Stages in the Tropics*. In: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Greece, July 2024. Athens: Institute of Electrical and Electronics Engineers (IEEE). [doi:10.1109/igarss53475.2024.10640528](https://doi.org/10.1109/igarss53475.2024.10640528).

Mensah, I. O., Barrett, B., and Cahalane, C. (2025) *A Novel Approach to Reconstruct Sentinel-1 Backscatter Data to Enable Early Detection of Artisanal and Small-Scale Mining (ASM) in Humid Tropical Rainforests*. Unpublished paper presented at: Living Planet Symposium (LPS2025). Vienna, 23-27 June 2025. <https://lps25.esa.int/>

4.1 Context

This chapter lays the foundation for the rest of the thesis and is the core research upon which each of the subsequent methodological chapters is built. The aim of this chapter is to investigate the optimal SAR preprocessing framework for preparing S1 ARD backscatter data capable of addressing challenges of using SAR for ASM monitoring in the dynamic and environmentally sensitive tropical landscapes, as discussed in the literature review (Sections 2.2 and 2.3). The optimal SAR processing framework is to enable the development of the methodology in later chapters for timely and reliable ASM monitoring in the wet tropics on a large scale. This chapter, therefore, first establishes evidence-based guidelines for optimizing the choice of various freely available global DEMs and backscatter normalisation approaches (σ^0 vs γ^0) for generating S1 ARD products, with a focus on overall usability and the backscatter data quality. The evaluation of S1 ARD products was performed using the cloud-based GEE platform across various landscapes and seasons, ensuring that the preprocessing framework can be applied to other study areas for extensive ASM monitoring during both wet and dry seasons.

More importantly, this is the first study to specifically address seasonal vegetation variations and key uncertainties in using C-band SAR for ASM monitoring, and this chapter illustrates a novel SAR time series reconstruction technique to do this. The proposed techniques offer a chance to enhance the effectiveness of S1 data for the timely and reliable detection of subtle changes associated with ASM activities in the tropics, especially during the rainy seasons. The proposed SAR processing methodology in this chapter will serve as a benchmark framework for creating S1 backscatter ARD for subsequent experiments throughout this thesis.

4.1.1 Abstract

SAR data offers a solution for ASM monitoring by overcoming the persistent cloud cover limitations of optical imagery in the tropics. However, if not pre-processed correctly, it can lead to reduced effectiveness or failure of early detection applications. Factors such as topography, speckle noise, soil moisture, and atmospheric effects from heavy rainfall, particularly with C-band SAR during rainy seasons, have been encountered in previous studies, leading to detection uncertainties and reduced accuracy, but have not yet been explored in terms of total contribution or properly assessed, or an effort to reduce or mitigate their effects. This study developed the first integrated methodology for creating S1 ARD within the GEE platform to enhance the monitoring of ASM activities in dynamic and environmentally sensitive tropical landscapes. The study first evaluated the performance of the backscattering coefficient processed using local incident angle approximations for σ^0 normalisation and using DEM for γ^0 radiometric terrain normalisation, and their suitability for identifying deforestation stages associated with ASM. Secondly, the study examined the suitability of different freely available global DEMs, such as the SRTM, AW3D30, NASADEM, and COP30, in terms of the overall

usability as well as backscatter data quality across different forest types and varied topography, including mountainous areas, during both wet and dry seasons in Ghana. The quality and usability of the S1 ARD products were evaluated through radiometric and geometric quality assessments. Lastly, to further improve temporal signal stability and enhance S1 effectiveness for early ASM detection during rainy seasons, the study was the first to explore three time series smoothing techniques for ASM, including Kalman Filter (KF), Savitzky-Golay (SG), and Locally Estimated Scatterplot Smoothing (LOESS) for preprocessing S1 data. An important finding of this chapter is that, when selecting SAR backscatter normalisation methods for effective monitoring of ASM, both σ^0 and γ^0 exhibited similar accuracy in detecting ASM-related disturbances in relatively flat terrains. However, terrain normalisation γ^0 showed improved performance in regions with steep or uneven topography and was less influenced by seasonal variations. The findings of this chapter also offer valuable insights into the options for freely available DEMs to enhance the performance of terrain normalisation for γ^0 ARD products. While all DEMs showed consistent results in flat regions, the COP30 DEM demonstrated the most reliable terrain normalisation in steep areas and was less affected by seasonal variations. Our findings deepen the understanding of previous results, indicating that S1 σ^0 and γ^0 ARD products can be significantly affected by adverse atmospheric conditions, which introduce outliers in images acquired during the rainy season. This chapter makes an important contribution to addressing this limitation by proposing the KF as an effective method for filtering S1 data with outliers, improving the accuracy of ASM monitoring in the tropics during the rainy season. Based on the coefficient of determination (R^2) and root mean squared error (RMSE), the KF consistently outperformed both SG and LOESS algorithms with a strong correlation and lower errors ($R^2 > 0.90$; RMSE = 0.39 dB). The findings highlight the importance of using the smoothed S1 radiometric terrain normalisation γ^0 ARD product, which is processed using the COP30 DEM, for detecting fine-grained ASM-induced forest disturbances in tropical regions throughout the year.

4.2 Introduction

In the last decade, the advent of open-source satellite imagery from the Copernicus program, such as S1 SAR, has opened new possibilities for continuous monitoring in cloud-prone areas, a key advantage over optical imagery. However, to access the valuable information contained in SAR data, users are required to perform a series of complex preprocessing steps to transform the data from its unprocessed, “raw” format into ARD (Truckenbrodt et al., 2019). For example, making accurate measurements from SAR data can be challenging if insufficient care is taken when correcting for geometric distortions caused by the sensor’s orbital path over the target. Similarly, the relationship between the sensor’s viewing angle and the slope and elevation of the underlying terrain influences the SAR backscatter significantly (Small, 2011). Users are also faced with the choice of the most suitable DEM when creating terrain-corrected backscatter

data, clearly an important consideration (Flores-Anderson et al., 2023; Truckenbrodt et al., 2019). However, no studies have investigated the effects of slope, local incidence angle, and the choice of freely available global DEMs on S1 SAR backscatter in monitoring ASM.

Studies exploring SAR backscatter ARD workflows to process S1 backscatter, processed using local incident angle approximations for σ^0 geometric terrain normalisation (Kimijima et al., 2022a; Janse van Rensburg and Kemp, 2022; Alessi et al., 2023; Kimijima et al., 2022b), or using DEM for γ^0 radiometric terrain normalisation (Forkuor et al., 2020), have shown their potential to map ASM activities in the tropics. While these studies produced reliable results for accurately detecting ASM activity from S1 imagery, a significant reported limitation is precipitation or heavy rainfall events, which often cause a darkening effect in multiple images, leading to a local decrease in backscatter. It is therefore clear that further study is required to explore the S1 backscatter data preparation and develop a novel methodology capable of mitigating these effects, allowing regular ASM monitoring using S1 imagery in the wet tropics.

Time-series reconstruction techniques have proven to be an effective approach for enhancing optical time series data by removing outliers caused by cloud contamination, atmospheric perturbations, and viewing conditions geometry (Malhi et al., 2021). These methods have also been successfully applied to smooth S1 time series data to improve the monitoring of vegetation phenology (Schlund and Erasmi, 2020; Soudani et al., 2021), crop mapping (Li et al., 2024), and deforestation in temperate forests (Kellndorfer, 2019). Time series smoothing techniques have significant potential to reduce SAR speckle noise, seasonal variability in S1 backscatter signals due to fluctuations in canopy moisture content, and outliers caused by adverse atmospheric effects during active rainfall events, and thereby enhance detection accuracy. However, no studies have explored or identified the most effective time series smoothing technique to enhance S1 data for ASM mapping in tropical environments, particularly during the rainy seasons. This study is the first to test the effectiveness of these methods for ASM studies using S1 C-band SAR imagery in the wet tropics.

Currently, web-based platforms such as GEE offer global archives of earth observation ARD along with cloud processing infrastructure, thereby improving the accessibility of satellite imagery for large-scale applications (Gorelick et al., 2017). The preprocessing of S1 data available in GEE is limited to orbit files correction, thermal noise removal, radiometric calibration to σ^0 normalisation, multi-looking, and range-doppler terrain correction before being ingested into GEE (Mullissa et al., 2021). However, for ASM studies, additional preprocessing steps, including speckle noise filtering, are essential (Janse van Rensburg and Kemp, 2022). The implications of the choice of S1 backscatter coefficient normalised to either σ^0 or γ^0 for ASM monitoring in the tropics have not been explored. To benefit from cloud processing, this study developed a novel integrated methodology for creating S1 backscatter ARD within the GEE environment to enhance the timely and reliable monitoring of ASM activities in the

tropics on a large scale. The specific objectives were:

- (i) to establish evidence-based guidelines for optimising the choice of S1 σ^0 and γ^0 backscatter ARD products for detecting ASM-induced deforestation stages in the tropics,
- (ii) to investigate the analysis readiness of four openly available DEMs for creating S1 radiometric terrain normalisation γ^0 products for detecting ASM-induced deforestation stages in the tropics across different forest types and varied topography, including mountainous areas, during both wet and dry seasons, and
- (iii) to investigate a novel time series smoothing technique to model backscatter variations caused by seasonality and outliers from adverse atmospheric conditions, aiming to enhance the effectiveness of S1 data for timely and reliable ASM monitoring in the tropics, particularly during the rainy seasons.

The study is organised as follows. Section 4.3 presents a brief description of the study area and datasets described in Chapter 3 of this thesis. The integrated methodological approach proposed in this study to enhance ASM monitoring in the tropics using C-band SAR data is presented and explained in Section 4.4. The performance metrics used to evaluate the S1 backscatter ARD products are discussed in Section 4.5. The results of the performance of the S1 backscatter products are detailed in Section 4.6, and the discussion is presented in Section 4.7. Finally, Section 4.8 concludes by summarising the relevance of the findings.

4.3 Datasets and study area

4.3.1 Description of test sites

The region of tropical forest in southern Ghana was chosen for this study. The evaluation involved a single-image assessment for a single-scene classification task to detect ASM, as well as time series analysis to evaluate the effects of seasonal variations for change detection and classification in ASM applications. For the single-scene analysis (Section 4.5.1), four mining test sites located in the Western (WT), Western North (WN), Ashanti (AS), and Eastern (ET) regions of Ghana with distinct landscapes were used in this study (see Figure 4.1). These areas were situated in the wet semi-equatorial forest zone, which features semi-deciduous and tropical rainforests that experience heavy rainfall year-round, along with a variety of terrains, including mountainous areas. Two test sites were chosen as case studies for the time series assessments (Section 4.5.2): the Western (WT) site was chosen to assess the analysis readiness of the ARD products in complex terrain, while the Western North (WN) site was selected to provide evaluations in relatively flat areas. Additionally, four known and verified mining sites located in the Western (WT) and Ashanti (AS) test sites were utilised to benchmark the

performance of the three smoothing techniques assessed in this study, aimed at enhancing the effectiveness of S1 data.

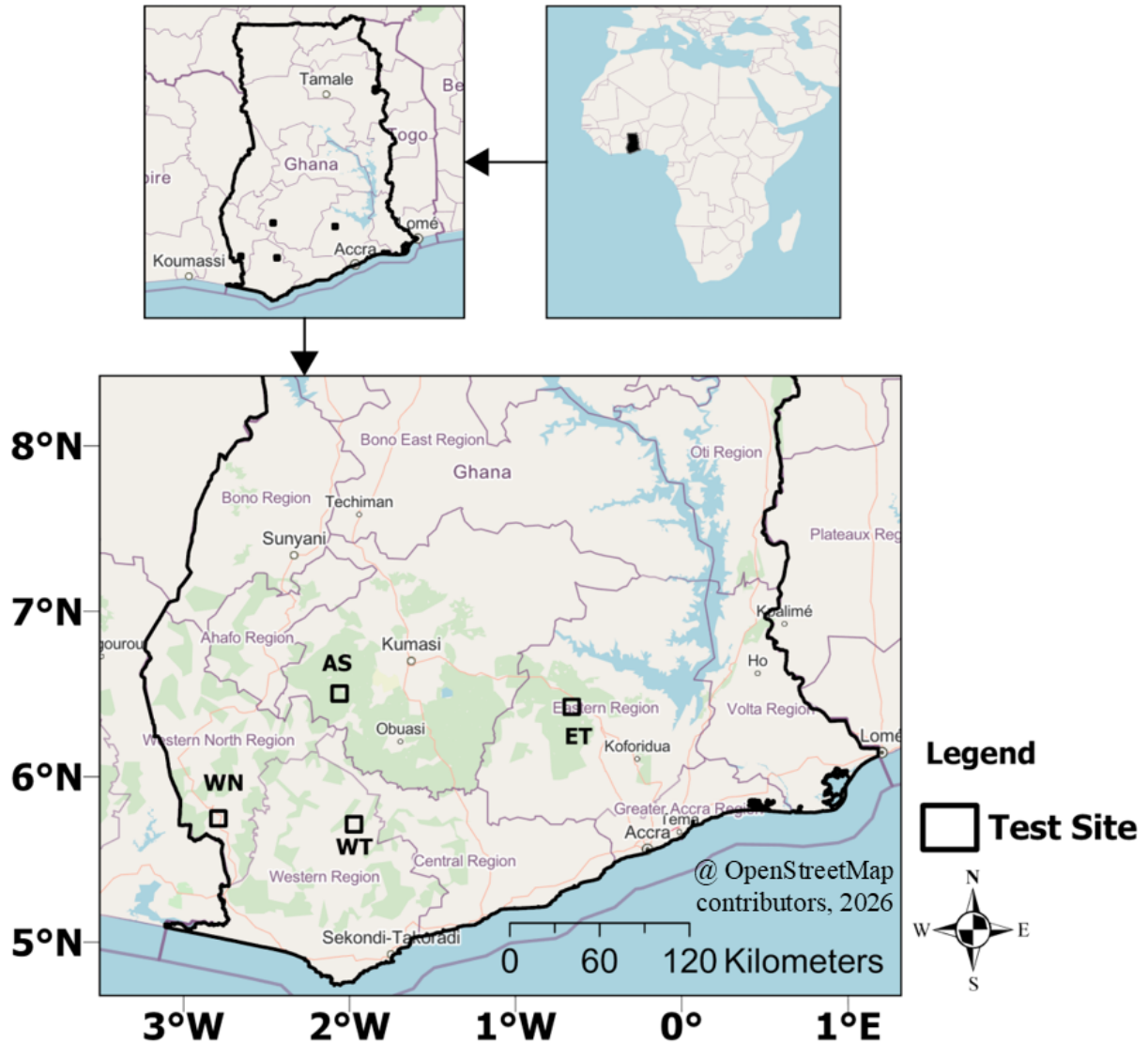


Figure 4.1: Locations of the test sites used in this study. Western (WT), Western North (WN), Ashanti (AS), and Eastern (ET) mining test sites located in the tropical rainforest region of southern Ghana. These areas were situated in the wet semi-equatorial forest zone, which features semi-deciduous and tropical rainforests that experience heavy rainfall year-round, along with a variety of terrains, including mountainous areas. The forest type and rainfall patterns are discussed in detail in Chapter 3 of this thesis.

4.3.2 SAR time series and validation data

Dual-polarised (VV and VH) S1 SAR GRD products in interferometric wide-swath (IW) mode acquired over the respective sites from January 2018 to March 2020, were selected in GEE (Gorelick et al., 2017). The S1 image catalogue includes all of the GRD S1-A and S1-B scenes acquired in both descending and ascending orbits and resampled to a pixel spacing of 10m with a revisit time of 6 days. A total of 58 images formed the time series over both WN and WT, and

120 images formed the time series over AS and WT. A normalised difference vegetation index (NDVI) created from selected cloud-free Sentinel-2 imagery available for the study period was created to independently estimate the detection accuracy of each stage of deforestation caused by ASM activities against the S1 ARD products.

4.3.3 Digital Elevation Models

The DEMs used in this study have been described in detail in Chapter 3 of this thesis. The performance of ASM detection using SRTM v. 3.0 DEM, the AW3D30, NASADEM, and COP30 DEM at mine sites was compared across the four test sites in GEE. All DEMs were resampled to match the resolution of the S1 image using a suitable bilinear resampling method (Truckenbrodt et al., 2019).

4.4 Sentinel-1 SAR backscatter ARD creation framework to enhance ASM monitoring in the tropics in GEE

This study modified the S1 backscatter ARD preparation framework established in Mullissa et al. (2021) for a wide range of terrestrial and coastal applications on a large scale in GEE, extending the analysis to include time series smoothing for robust ASM applications in the wet tropics. The integrated S1 backscatter ARD preparation framework proposed in this study is described in Figure 4.2. The S1 GRD data in GEE have already been pre-processed using the Sentinel-1 Toolbox to incorporate precise orbit files, remove thermal noise, calibrate radiometrically to σ^0 , and generate orthorectified products before being ingested into GEE (Gorelick et al., 2017).

In this study, we implemented additional preprocessing steps to enhance the S1 data. These steps included removing remaining border noise artifacts, applying multi-temporal speckle filtering, and performing radiometric terrain normalisation. These improvements facilitated a better comparison of S1 σ^0 and γ^0 backscatter ARD products in detecting stages of deforestation associated with ASM in tropical regions. Alongside this, various γ^0 products were generated using the four global DEMs to investigate the optimal DEM option for the generation of S1 γ^0 radiometric terrain normalisation (RTN) ARD products. Once the optimal backscatter coefficient data and DEM options were finalised, S1 smoothed data were created using the KF time series smoothing algorithm to further enhance the effectiveness of the S1 data for timely ASM monitoring, particularly during the rainy seasons. Subsequently, two widely used smoothing algorithms for remote sensing applications, such as the SG and LOESS, were utilised to benchmark the KF method against best practices.

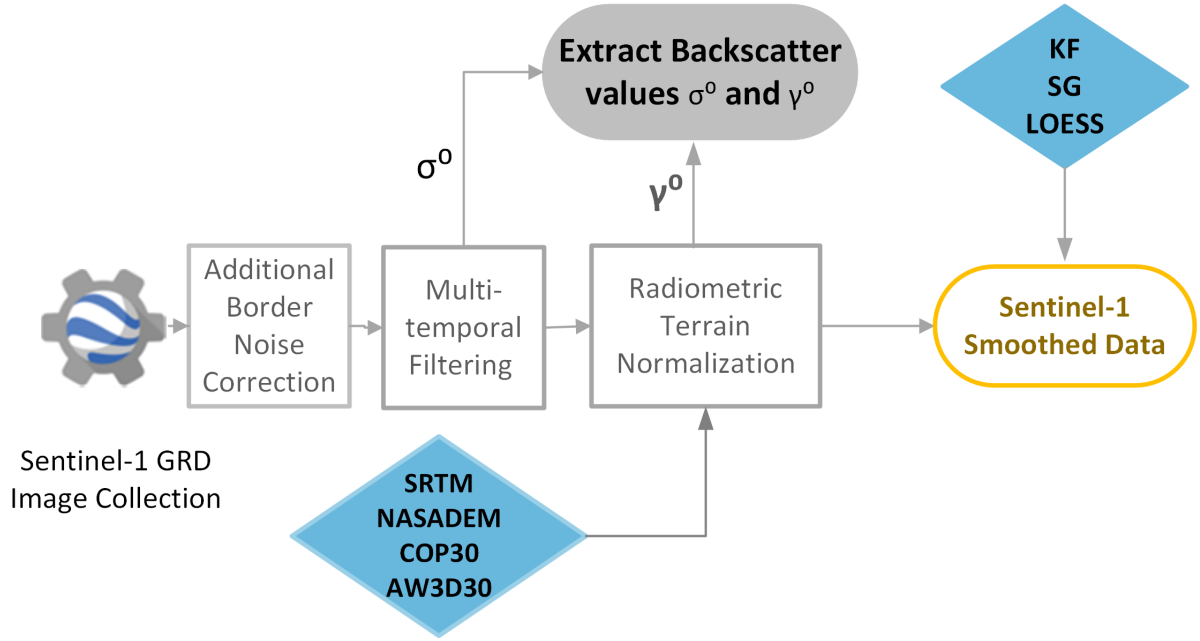


Figure 4.2: The flowchart of the proposed integrated Sentinel-1 backscatter ARD preparation methodology in GEE used in this study. Additional preprocessing steps, such as removing remaining border noise artifacts, multi-temporal speckle filtering, and radiometric terrain normalization, along with time series smoothing to further improve ASM monitoring in the tropics, particularly during the rainy season.

4.4.1 Additional border noise correction

Border noise present in S1 GRD images constitutes an unwanted artifact that should be mitigated prior to subsequent analysis (Stasolla and Neyt, 2018). Border noise artifacts were initially introduced during the conversion of raw data to level-1 products by the S1 Instrument Processing Facility (IPF) software versions 2.34 to 2.84 (Stasolla and Neyt, 2018). Specifically, the products exhibited cross-track border noise along the range direction and along-track border noise in the azimuth direction (Stasolla and Neyt, 2018). Figure 4.3a and Figure 4.3b illustrate examples of border noise (highlighted in red), while Figure 4.3c offers a closer look at border noise patterns (in red), often mixed with samples set to zero by the IPF (shown in blue) (Stasolla and Neyt, 2018). Despite the improvements in GRD border noise removal with the latest version of IPF released in March 2018, border noise artifact problems remain in some images (Mullissa et al., 2021). Additional border noise correction has not been explored for ASM studies, but it has the potential to remove the remaining border noise and rain cells due to atmospheric effects on SAR images in the tropics. This study is the first to apply additional border noise correction to improve S1 data for reliable ASM monitoring in the wet tropics.

To address any remaining border and artifacts from heavy rainfall in the S1 imagery, additional border noise correction was first applied. The additional border noise implemented in this study was modified from methods described in Hird et al. (2017). This process is based on

a threshold for incidence angles and involves removing outlier backscatter values from neighbouring pixels in the border region (Mullissa et al., 2021).

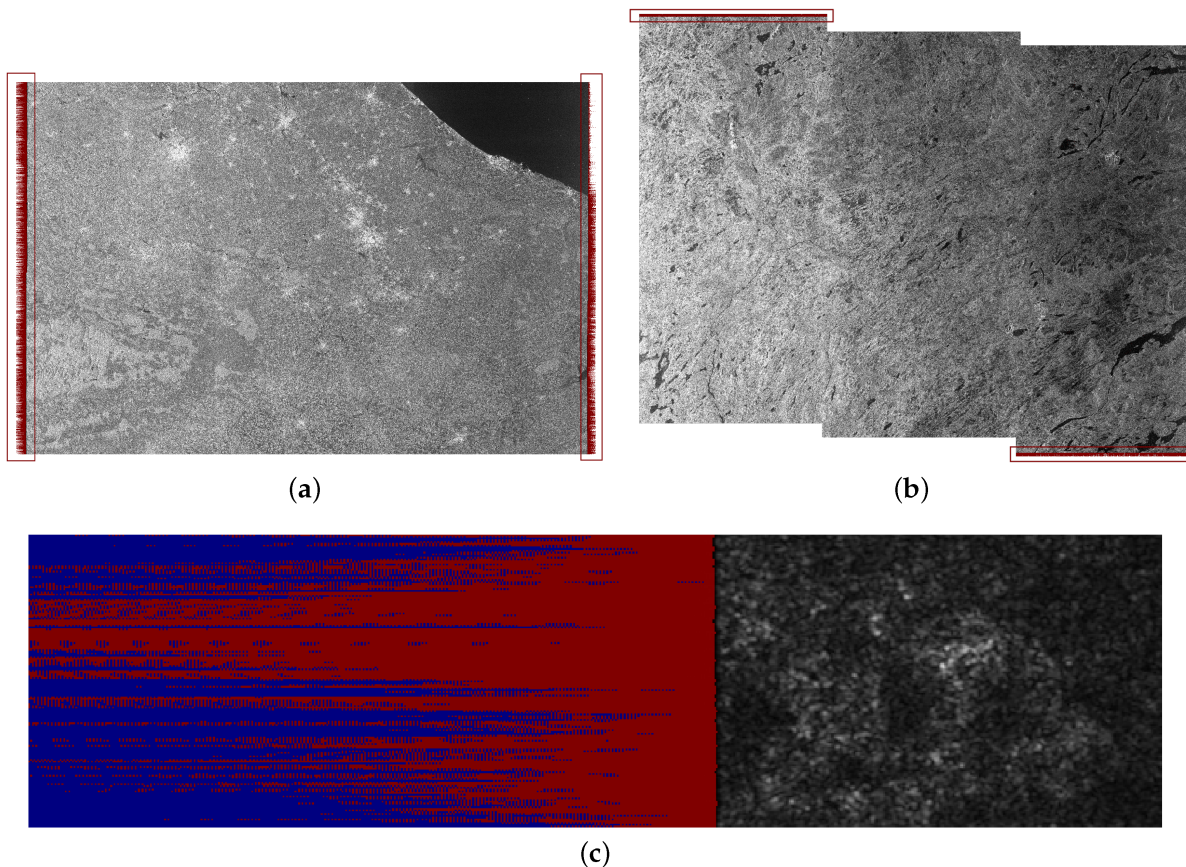


Figure 4.3: The presence of border noise (dark pixels) in S1 GRD images, highlighted in red: (a) cross-track border noise along range direction (left and right); (b) along-track border noise in the azimuth direction (top and bottom); (c) closer look at the border noise patterns (in red), often mixed with samples set to zero by the IPF (shown in blue). Source: (Stasolla and Neyt, 2018)

4.4.2 Multi-temporal speckle filtering

Subsequently, an adaptive multi-temporal speckle filtering approach identified as an effective technique for detecting ASM activities (Janse van Rensburg and Kemp, 2022), was implemented following the methodology recommended by Quegan and Yu (2001). To improve the consistency of multi-temporal filtering, additional parameters were incorporated, including the number of images used in the filtering framework. Additionally, only acquisitions with comparable imaging geometry were retained, irrespective of acquisition orbit, to prevent a reduction in the quality of the S1 speckled-filtered products. This was achieved through frame matching between images, ensuring that only fully overlapping image frames were included (Mullissa et al., 2021). For optimal results, the multi-temporal filtering employed a set of 10 restricted images in this study to create high-quality filtered products. The filtering process utilised an improved Lee Sigma filter (Lee et al., 2009) with a kernel size of 9 x 9 pixels.

4.4.3 Radiometric Terrain Normalisation (RTN)

In line with the Committee on Earth Observation Satellites (CEOS) ARD data standards (CEOS, 2021), RTN is a recommended preprocessing step for a wide range of terrestrial applications. Further, radiometric terrain normalisation was applied to obtain the S1 γ^0 RTN products using the four different open-source DEMs described in Section 4.3.3. The RTN was performed using a simplified angular-based correction approach as proposed by Hoekman and Reiche (2015). Because the S1 images available in GEE were provided in ground range formats and lacked orbital state vectors, the GEE implementation by Vollrath et al. (2020) was adopted, which incorporates the volume scattering model described by Hoekman and Reiche (2015). Both reference models rely on angular relationships between the SAR acquisition geometry and the underlying terrain. The angular-based RTN employed in GEE derives a simplified relationship between image and terrain based on angles or angular parameters. The RTN procedure generates a mask to automatically exclude pixels located within active layover and shadow regions in the image (Mullissa et al., 2021).

Following the described workflow, the S1 backscatter data were processed to γ^0 . Without applying the radiometric terrain normalisation, the data were processed in σ^0 . Figure 4.4 illustrates the S1 backscatter image over the western test site, comparing backscatter ARD products as ingested in GEE (Figure 4.4a), which has further been preprocessed to σ^0 (i.e. without RTN) (Figure 4.4b), and γ^0 (i.e. with RTN) (Figure 4.4c). The σ^0 and γ^0 values were systematically extracted from each respective test site for further performance assessment.

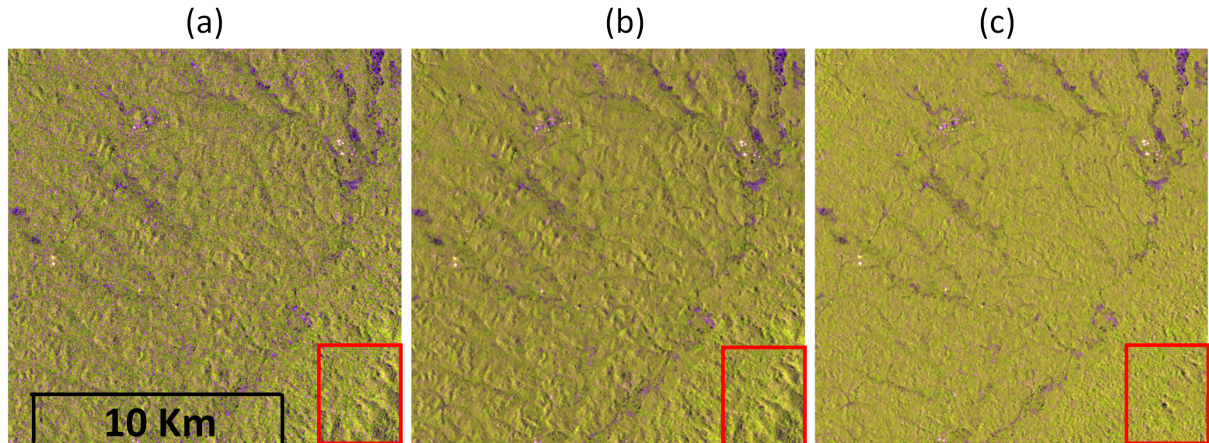


Figure 4.4: RGB visualization of a dual-polarized (R-VV, G-VH, and G-VV/VH) S1 SAR backscatter image over the Western (WN) mining test site. (a) S1 GRD image as ingested in GEE; (b) after applying border noise correction and a 9 x 9 multi-temporal improved Lee Sigma filter normalized to σ^0 ; and (c) after applying border noise removal, a 9 x 9 multi-temporal improved Lee Sigma filter, and radiometric terrain normalization normalised to γ^0 processed using Copernicus 30 m DEM. The S1 σ^0 and γ^0 ARD products better reduce noise than the raw GRD product. However, the S1 γ^0 gave improved image pixel brightness, accounting for terrain-induced effects.

4.4.4 Reconstruction of time series Sentinel-1 data

After comparing the S1 σ^0 and γ^0 ARD products, the Kalman filter (KF) smoothing technique was applied to reconstruct the S1 γ^0 , aiming to predict periods of low-quality backscatter values due to adverse atmospheric conditions and seasonal variations in forest canopy structure. The performance of the proposed KF method was assessed against two widely used smoothing algorithms for remote sensing applications: the Savitzky-Golay filter (SG) and locally estimated scatterplot smoothing (LOESS) at the wet WT and AS test sites. This reconstruction aimed to further enhance the effectiveness of the S1 backscatter ARD for reliable and timely monitoring of ASM in tropical regions.

4.4.4.1 Smoothing S1 data for accurate ASM monitoring in the tropics: KF algorithm

A Kalman filter (KF) (Kalman, 1960) was implemented to reduce the influence of SAR noise and artifacts due to atmospheric effects by smoothing the original S1 ARD data and to estimate backscatter values during periods with low-quality observations. The KF has long been considered more efficient for many data prediction tasks, as it always achieves the minimum mean square error possible (Kalman, 1960; Faragher, 2012). It can predict measurements recursively, enabling new measurements to be processed immediately as they arrive, which offers significant potential for satellite-based early warning systems. The KF has demonstrated promising results in reducing outliers in satellite-based time series observations for NRT monitoring of defoliation (Olsson et al., 2016) and forest disturbances (Ye et al., 2021) using MODIS and Landsat images, respectively.

The KF applied in this study was based on the following state space representation (Faragher, 2012) (Equation 4.1 and Equation 4.2):

$$\text{State equation: } \gamma_t^0 = A \cdot \gamma_{t-1}^0 + B \cdot u_{t-1} + w_t \quad \text{Equation 4.1}$$

$$\text{Observation equation: } Y_t = C \cdot \gamma_t^0 + z_t \quad \text{Equation 4.2}$$

where γ_t^0 is the true value of the γ^0 backscatter (i.e. the state of the system) at time t , u_{t-1} is the input to the system (or KF), Y_t is the observation of the γ^0 backscatter from the S1 SAR data at time t , w_t is the process noise of the model, and z_t is the measurement noise. The A , B , and C are the coefficient matrices that depend on the quality of the γ^0 backscatter from the S1 SAR data.

The true value of the backscatter γ_t^0 , however, cannot be observed directly with the satellite sensors due to uncertainties at the time of measurement, and therefore, KF uses Y_t , which is

the observation of the γ^0 backscatter from the S1 SAR data. The KF algorithm recursively computes γ_t^0 by integrating historical information, predictions from the system models, and noisy measurements. The KF algorithm works in two main steps: (1) first, the true value of γ_t^0 is estimated using the state equation (Equation 4.1), and (2) Equation 4.2 once a new observation Y_t is made available, γ_t^0 is updated to predict its optimal γ^0 backscatter value. The algorithm was applied using the FilterPy module (Labbe, 2015) in Python 3.7.

The KF predictions were improved through fine-tuning by visually comparing the predicted γ^0 backscatter with the time series of raw γ^0 backscatter for different coefficient parameters of A , B , and C , and varying the w_t and z_t noise. These are user-defined parameters, which are crucial for achieving accurate and reliable KF predictions depending on the quality of the raw measurements or observations. For the VH polarization, a process noise (w_t) parameter of 0.05 and a measurement noise (z_t) of 0.09 was used. Additionally, a process noise (w_t) parameter of 0.10 and a measurement noise (z_t) of 1.0 was utilised for the VV polarization. Since the γ_t^0 true backscatter value was not known, the optimisation was performed by considering temporary spikes or decreases in the raw γ^0 backscatter time series to be likely outliers, while two consecutive low backscatter values were assumed to likely be forest disturbance, which was considered to occur due to mining activities.

4.4.4.2 Smoothing S1 data for accurate ASM monitoring in the tropics: SG algorithm

The Savitzky-Golay (SG) filter is a widely used smoothing method effective for filtering time-series data with significant temporary spikes (Savitzky and Golay, 1964). The SG is considered a weighted moving average filter, where the weight is defined by a polynomial of a certain degree using the method of linear least squares convolution (Chen et al., 2004). The general equation for the simplified least-squares convolution implemented in this study for S1 time-series smoothing can be expressed as follows (Equation 4.3) (Chen et al., 2004):

$$\gamma_t^0 = \frac{\sum_{j=-m}^m C_j Y_{t+j}}{N} \quad \text{Equation 4.3}$$

where Y_t is the original backscatter at time t , γ_t^0 is the γ^0 backscatter smoothed by the SG filter, j is the distance from t , C_j is the weighting coefficient, N is the size of the moving smoothing window (equal to $2m + 1$), and m is the half-width of the smoothing window. In general, the length of the filter window (m) determines the degree of smoothing, which was set to 9 in this study. The second parameter is an integer (d) that specifies the degree of the smoothing polynomial, typically ranging from 2 to 4. Normally, lower-order polynomials lead to smoother reconstructions of time series data; therefore, the polynomial order (d) was set to 3 in this study.

4.4.4.3 Smoothing S1 data for accurate ASM monitoring in the tropics: LOESS algorithm

The locally estimated scatterplot smoothing (LOESS) method uses local polynomial regression with the weighted least squares technique to smooth time-series data (Cleveland et al., 1990). The LOESS filter implemented in this study has two key design parameters: the polynomial order and the window size. The polynomial order was set to 2, and the window size was set to 9. In this study, the weights were estimated based on the temporal proximity (i.e. date difference to the fitted value) and are defined as (Equation 4.4) (Li et al., 2024):

$$w = \left(1 - \left(\frac{d}{r} \right)^3 \right)^3 \quad \text{Equation 4.4}$$

where w is the tri-cubic weight function, r is the window size, and d is the date difference between a given value and the fitted value.

4.5 Performance evaluation of S1 backscatter ARD products

The quality and usability of the S1 backscatter ARD products were assessed through radiometric calibration, topographic normalisation, and geometric quality evaluations. These involved a single scene to ensure the assessment of the single-image S1 ARD product for forest land use/cover classification to detect ASM activity in the tropics and a time series analysis to examine the effects of seasonal variations in identifying ASM-induced deforestation stages in the wet tropics. This study replicated the evaluation metrics outlined in Flores-Anderson et al. (2023) as detailed in Figure 4.5. The factors that significantly influence SAR backscatter, such as topography, seasonality, and local incidence angle, discussed in Sections 2.2 and 2.3 of Chapter 2 in this thesis, are examined in detail in the following sections.

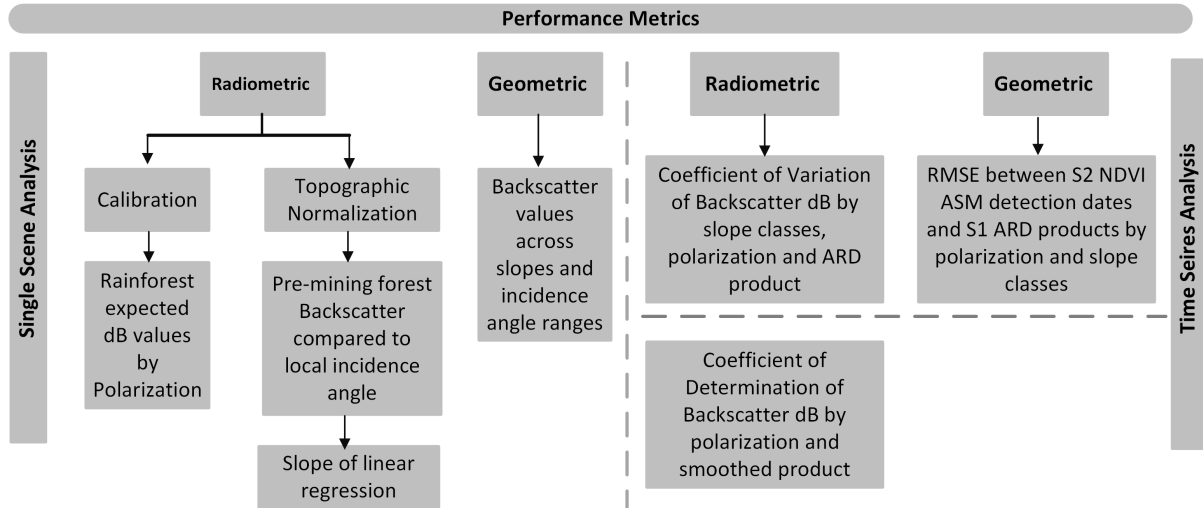


Figure 4.5: Evaluation framework for assessing the usability and quality of S1 backscatter ARD products across all sites in this study. The analysis considered radiometric calibration, topographic normalisation, and geometric quality assessments for both single scene image classification and time series analysis for change detection and classification for tropical ASM applications.

4.5.1 Single scene analysis

4.5.1.1 Radiometric calibration assessment of S1 γ^0 ARD products

Radiometric correction mitigates terrain-induced distortions to accurately represent the backscatter from intrinsic surface properties, including forest structure and moisture content (Meyer, 2019). For C-band SAR, tropical rainforests in general exhibit backscatter values of -12.5 dB for VH polarization and -6.5 dB for VV polarization (CEOS, 2018; Nicolau et al., 2021; Truckenbrodt et al., 2019). To evaluate the radiometric calibration quality of the S1 γ^0 ARD products, average backscatter values over an area of stable pre-mining, evergreen intact rainforest in the respective sites were compared with the expected C-band average backscatter values. High-resolution Google Earth imagery was first used to identify pre-mining forest areas. Subsequently, the mean backscatter values over these pre-mining forest regions were computed in GEE using the first image from 2019 for each test site.

4.5.1.2 Topographic normalisation assessment of S1 σ^0 and γ^0 normalised ARD products

It has been reported that SAR backscatter is significantly affected by the incidence angle (Kellndorfer, 2019). To assess the quality of the topographic normalisation between the different ARD products, backscatter values over pre-mining forested areas were compared to the local incidence angle at the pixel level by performing a linear regression using GEE's *ee.Reducer.linearFit()* function. To extract both the backscatter and incidence angles from each scene, 5000 random points were generated at each mining test site exclusively within forested

areas.

4.5.1.3 Geometric assessment of S1 backscatter σ^0 and γ^0 ARD products

To assess the quality of geometric distortion corrections as explained in Section 2.2.3 in Chapter 2, initial tests looked at the influence of both incidence angle and topography (ranging from flat to steep, defined as slopes below 12% and above 20% respectively (Truckenbrodt et al., 2019)) on S1 backscatter σ^0 and γ^0 ARD products in detecting ASM-induced deforestation stages. Incidence angle, slope, and backscatter values were extracted from a random sample of 5000 pre-mining forest points in each mine site. The slope was derived from the different DEMs and reclassified into two categories: flat and steep topography. An intact pre-mining forest was selected because the backscatter values were more stable compared to the mining site.

4.5.2 Time series analysis

4.5.2.1 Radiometric assessment of S1 backscatter σ^0 and γ^0 ARD products

To evaluate the radiometric performance of each time series S1 backscatter σ^0 and γ^0 ARD product, the Coefficient of Variation (CoV) was estimated for both VV and VH polarizations for pre-mining forested areas in GEE. To account for temporal variability, backscatter was extracted over 5000 randomly generated points stratified by slope (i.e. below 12% for flat terrain and above 20% for steep topography), and CoV was calculated using Equation 4.5. For the S1 σ^0 and γ^0 products comparison, the CoV was calculated on a scene-by-scene basis in GEE to assess the influence of seasonality on backscatter. The radiometric time series evaluation of the different DEMs was carried out by computing the monthly CoV for forest areas in 2019 for each test site.

$$\text{CoV} = \left(\frac{\text{std}}{\text{mean}} \right) \times 100 \quad \text{Equation 4.5}$$

4.5.2.2 Geometric assessment of S1 backscatter σ^0 and γ^0 ARD products

To analyse the geometric quality of the time series, root mean squared error (RMSE) for detecting ASM-induced deforestation stages was calculated for comparison of different ARD products using Equation 4.6. The detection dates identified using the Sentinel-2 NDVI values were considered as the true detected stage dataset. The S1 SAR ARD product datasets were used as predicted stage datasets. The RMSE was calculated as a function of time by polarization and the ASM-induced deforestation stages.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (\text{Predicted}_i - \text{Actual}_i)^2}{N}} \quad \text{Equation 4.6}$$

4.5.3 Evaluating the performance of smoothing techniques

In this study, the performance of the S1 smoothing techniques was evaluated using statistical metrics such as the coefficient of determination (R^2) and RMSE between the predicted or smoothed and actual S1 backscatter. The formula for the R^2 (Equation 4.7) is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^N (\text{Actual}_i - \text{Smoothed}_i)^2}{\sum_{i=1}^N (\text{Actual}_i - \overline{\text{Actual}})^2} \quad \text{Equation 4.7}$$

where *Actual* is the original S1 backscatter data, *Smoothed* is the backscatter predicted by the various smoothing techniques, $\overline{\text{Actual}}$ is the mean backscatter value, and N is the number of data pairs.

4.6 Results

4.6.1 Performance of S1 σ^0 and γ^0 ARD products for detecting ASM-induced deforestation stages in the tropics

4.6.1.1 Single scene analysis

The topographic normalisation results comparing S1 σ^0 and γ^0 ARD products for detecting ASM-induced deforestation stages in the tropics are shown in Figure 4.6. An optimal slope of zero in the linear regression analysis signifies complete independence from local incidence angle (Flores-Anderson et al., 2023). The linear regression analysis between the backscatter of the pre-mining intact forest and the incidence angle shows consistently low slope values in both S1 σ^0 and γ^0 products in all sites and for both VV and VH polarizations (see Figure 4.6). Importantly, this study showed that γ^0 provided better topographic normalisation results compared to σ^0 for both sloped and flat terrains. These findings suggest that γ^0 is less affected by geometric distortions than σ^0 due to its lower dependence on the angle of incidence. Figure 4.7 shows the backscatter in VH and incidence angles comparison in a mine site in uneven and relatively flat terrains. Comparing the incidence angles and backscatter values in the increasingly steep terrain, the S1 backscattering coefficient tends to decrease as the local incidence angle increases in both σ^0 and γ^0 products (see Figure 4.7). However, the σ^0 showed a significant decrease in backscatter values for high incidence angles (typically $> 43.345^\circ$). This also suggests that the σ^0 values were considered unreliable due to geometric distortions; however, comparable performance was observed in flat terrain for both S1 σ^0 and γ^0 products (see Figure 4.7).

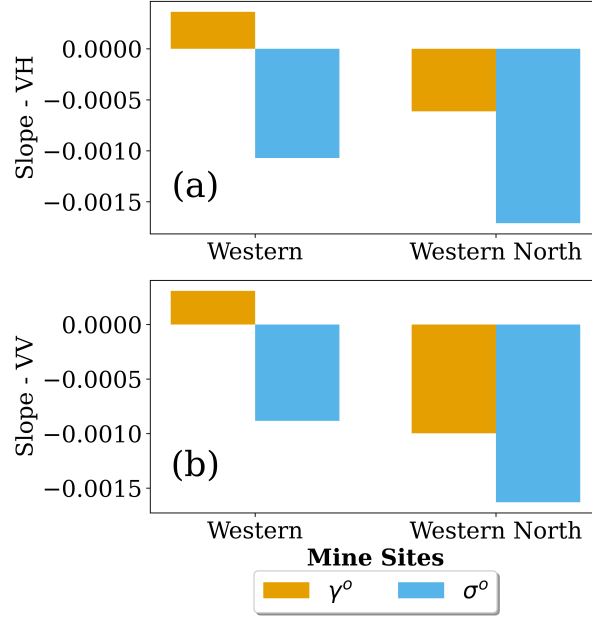


Figure 4.6: Topographic normalisation results showing the slope of the linear regression between backscatter and the local incidence angle. (a) VH polarization (b) VV polarization. A significant finding in this study is that γ^0 provided better topographic normalization results compared to σ^0 for both sloped and flat terrains, showing lower slope values closer to zero, less affected by geometric distortions, making it suitable for robust ASM monitoring applications in the tropics.

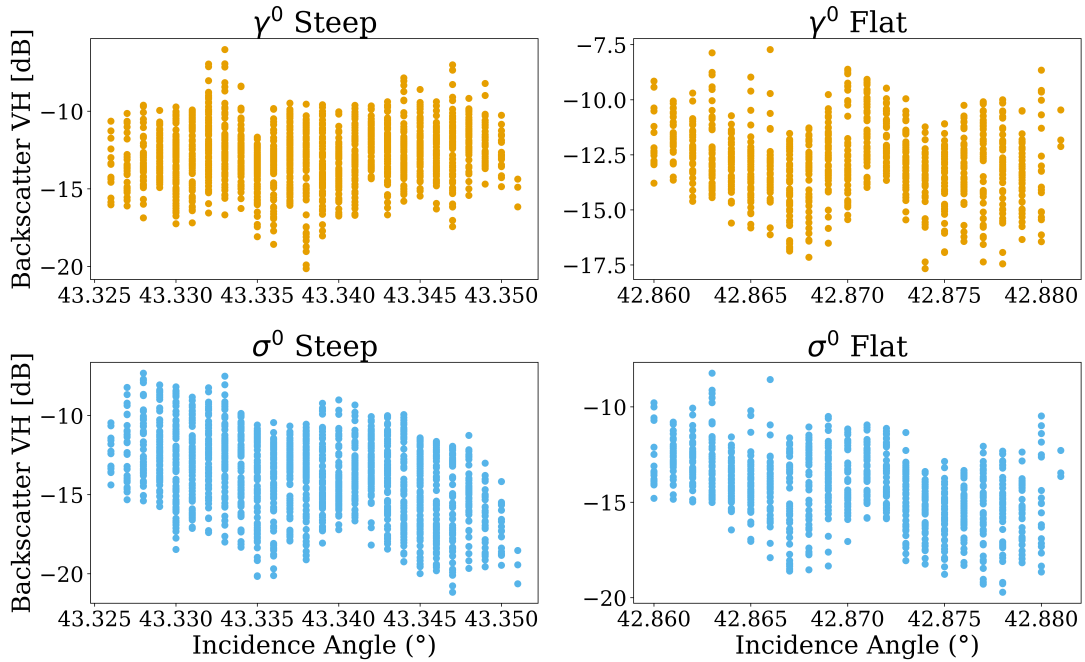


Figure 4.7: Comparison of incidence angle and backscatter (VH) in WT and WN across the S1 σ^0 and γ^0 ARD products. Comparable results can be achieved by both S1 σ^0 and γ^0 ARD products in relatively flat areas, but the S1 σ^0 ARD product appears to be unreliable in rough terrains with a local decrease in backscatter for incidence angles above 43.345 degrees.

4.6.1.2 Time series assessment

Figure 4.8 shows the results of the scene-by-scene comparison of S1 σ^0 and γ^0 ARD products over a stable pre-mining, evergreen forest in both flat and steep terrains for both VV and VH polarisations. The time series radiometric assessment indicates that both S1 σ^0 and γ^0 backscatter showed similar variations with a median CoV of about 10% for both polarizations in generally flat topography. However, over the areas of sloped terrain, the γ^0 values show an improvement over σ^0 . This is shown over steep mine sites with a median CoV of about 70% for γ^0 , but σ^0 showed a significant variability of over 130% for the VV polarisation. Notably, in areas of steep topography, the VH polarisation demonstrated superior performance, displaying lower CoV compared to the VV polarisation products (see Figure 4.8). Overall, both σ^0 and γ^0 products showed variability in the steep terrain. However, the σ^0 product has a more variable response over the intact pre-mining forest, for both polarisations. The temporal variation in backscatter appears to be consistent with the seasonal variations of the forest canopy.

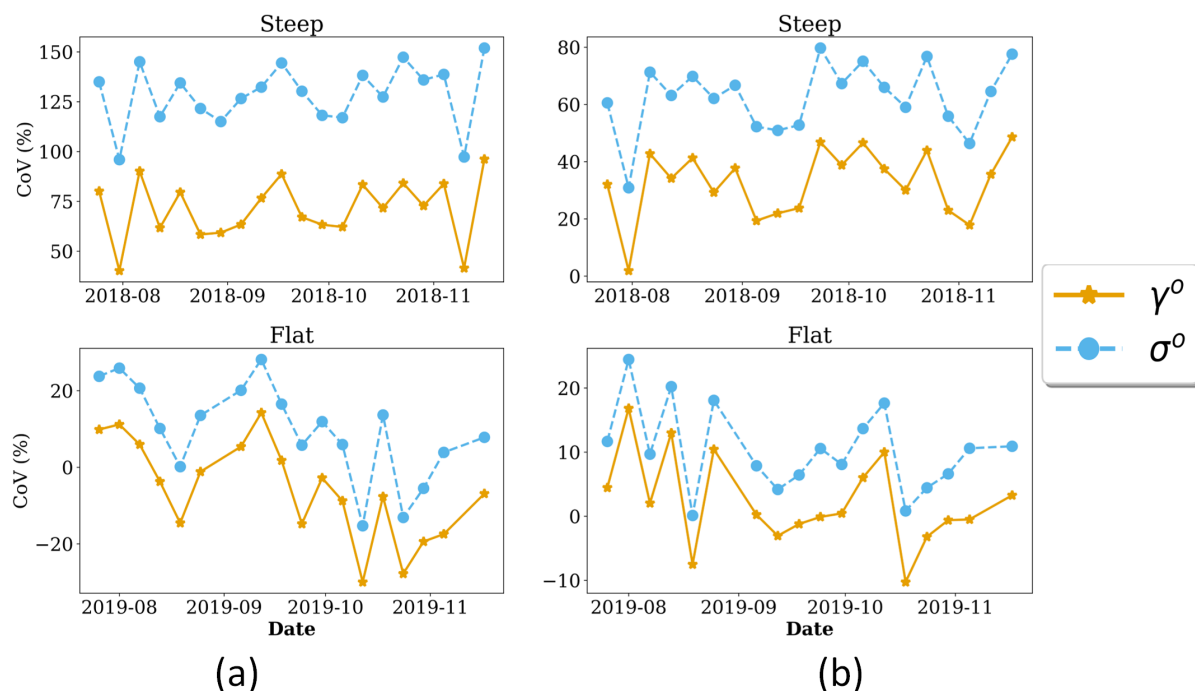


Figure 4.8: Scene-by-scene CoV for pre-mining evergreen forest in southern Ghana, steep and flat slopes for (a) VV polarisation and (b) VH polarisation over WT and WN mining sites. The S1 σ^0 product showed more variability due to seasonal fluctuations in forest structure and vegetation and moisture content in both VV and VH polarisations compared to the S1 γ^0 product, particularly in steeped areas. The σ^0 showed a significant variability of over 130% for the VV polarisation compared to about 70% for γ^0 in steeped areas.

For the time series geometric assessment, the RMSE results comparing S1 σ^0 and γ^0 ARD products for detecting ASM-induced deforestation stages are shown in Table 4.1. Similar performances were obtained in the flat terrain for both σ^0 and γ^0 products in VH and VV polarizations for detecting the early stage of deforestation, where there is less vegetation clear-

ance. However, σ^0 gave a better performance in the later stages of deforestation for both VV and VH polarisations in flatter regions, followed closely by γ^0 with RMSE of 0.3237 dB and 0.4503 dB, respectively, in VH polarisation. In steep terrain, σ^0 gave the lowest agreement with the dates observed from the Sentinel-2 NDVI values, potentially due to the higher variability in the backscatter values compared to the generally flat site. More importantly, the γ^0 is observed to perform better than σ^0 in uneven terrains in both VV and VH polarizations to detect early deforestation and later stages, where more trees have been cleared. Overall, σ^0 introduces more errors compared to γ^0 in detecting the ASM-induced deforestation stages in steeper areas, particularly in detecting later stages of deforestation for both VV and VH polarizations.

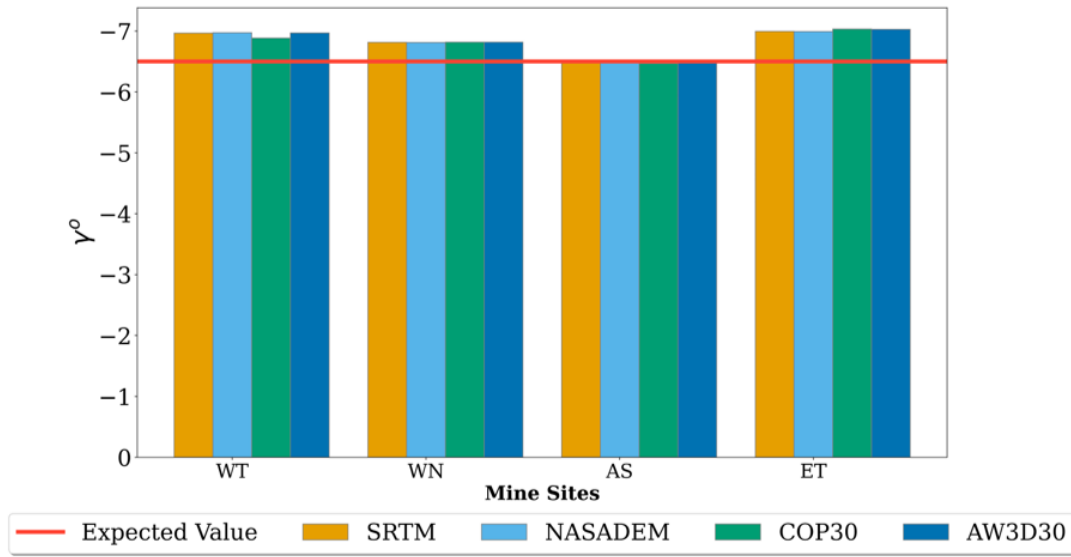
Table 4.1: RMSE (dB scale) over mine sites for steep and flat terrains to detect ASM-induced deforestation stages. The RMSE was determined using the NDVI profile value at the time when the change event was confirmed as the expected value.

ARD product	Steep terrain		Flat terrain	
	Early stage	Later stage	Early stage	Later stage
γ_{VH}^0	0.7390	0.5480	0.5440	0.4503
σ_{VH}^0	0.7580	0.8457	0.5440	0.3237
γ_{VV}^0	0.8983	0.3700	0.3555	0.4343
σ_{VV}^0	0.9173	0.7264	0.3557	0.3081

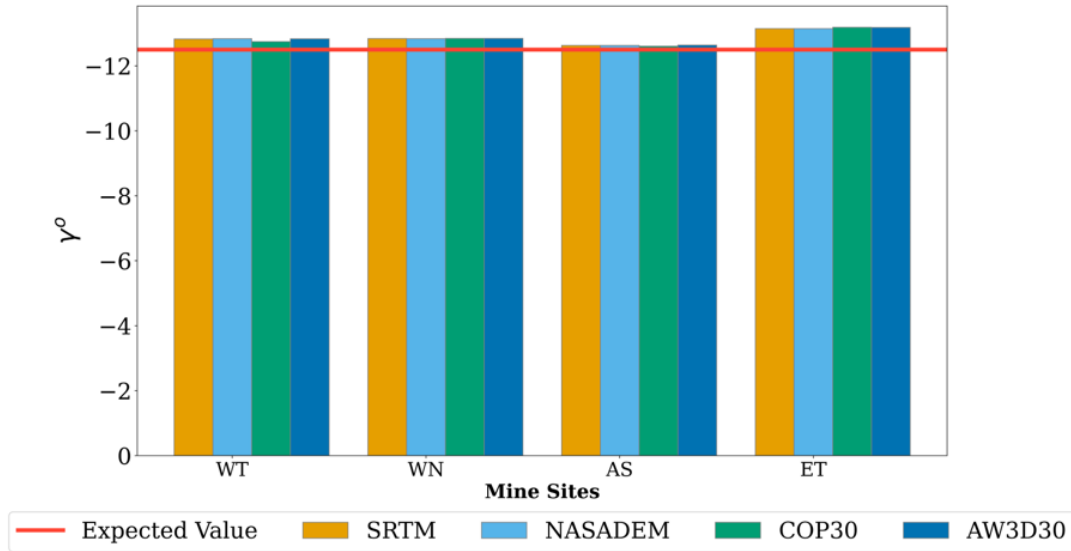
4.6.2 Performance of different DEMs for creating Sentinel-1 γ^0 RTC products for detecting ASM in the tropics

4.6.2.1 Single scene analysis

Figure 4.9 presents the mean backscatter (dB) across pre-mining forested areas for the four γ^0 RTC products. The horizontal red line represents the expected reference value for rainforest average backscatter, serving as a benchmark for comparison as described in Section 4.5.1.1. Similar performance is achieved by all DEMs in the single-scene analysis for this metric across the test sites for both VV and VH polarisations.



(a)



(b)

Figure 4.9: The average backscatter value (dB) over pre-mining forested areas within all mining test sites for each S1 γ^0 product for the (a) VV polarisation (b) VH polarisation. The mean backscatter values for both VV and VH polarizations compared to the expected (of -12.5 dB for VH polarisation and -6.5 dB for VV polarisation) showed comparable results across all S1 γ^0 ARD products.

The topographic normalisation results comparing the analysis readiness of different DEMs are shown in Figure 4.10. The linear regression analysis between the backscatter of the pre-mining intact forest and the incidence angle shows very low values in all γ^0 products, in all sites, for both VV and VH polarisations. In steep slopes in the WT, the COP30 DEM shows better topographic normalisation results compared to other DEMs for both VV and VH polarizations. However, the NASADEM performs better in generally flatter regions, ET, and WN, for VV and

VH polarisations, respectively.

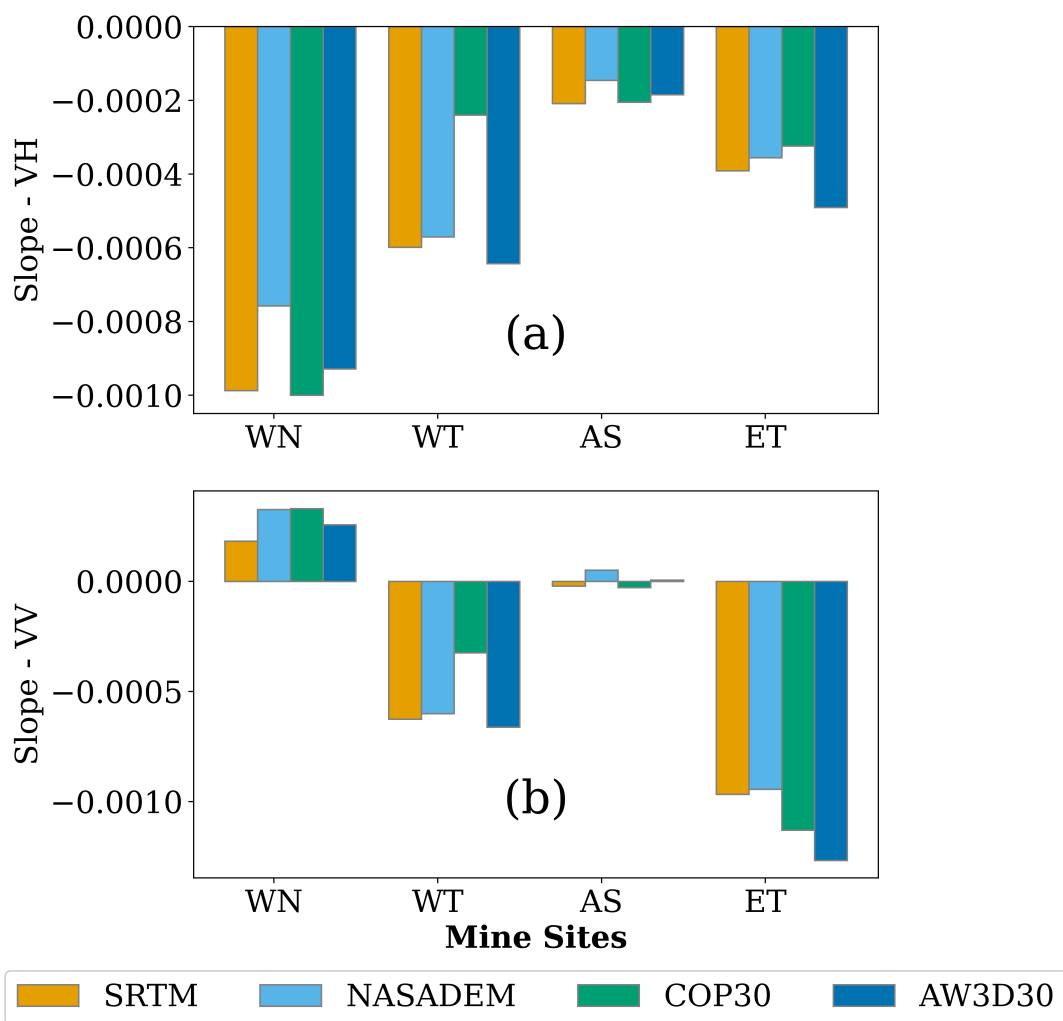


Figure 4.10: Topographic normalisation results showing the slope of the linear regression between backscatter and the local incidence angle across all S1 γ^0 products. (a) VH polarisation (b) VV polarisation. The COP30 DEM S1 γ^0 product showed better terrain normalisations in all sites that were less affected by topographic effects compared to other S1 γ^0 DEM products, especially in steep areas.

4.6.2.2 Time series assessment

For the time series radiometric analysis, Figure 4.11 shows the CoV over the intact pre-mining forest, comparing flat and steep slopes, by S1 γ^0 products for VV and VH polarisations. As expected, the flatter areas showed less backscatter variability with a median CoV typically ranging between about 1% and 8% for both VH and VV polarisations across all products (see Figure 4.11c and Figure 4.11d). The temporal variability appears to be aligned with the seasonal rainfall variations in the mine sites (March to November) (Forkuor et al., 2020). Importantly, in steeper terrain, the COP30 DEM product showed less variation in both VV and VH polarisations compared to other products (see Figure 4.11a and Figure 4.11b). The SRTM γ^0 product shows stronger temporal fluctuations in rugged terrain, which is more pronounced in

VV polarisation up to about CoV of 35% compared to NASADEM (32%), AW3D30 (30%), and COP30 (23%).

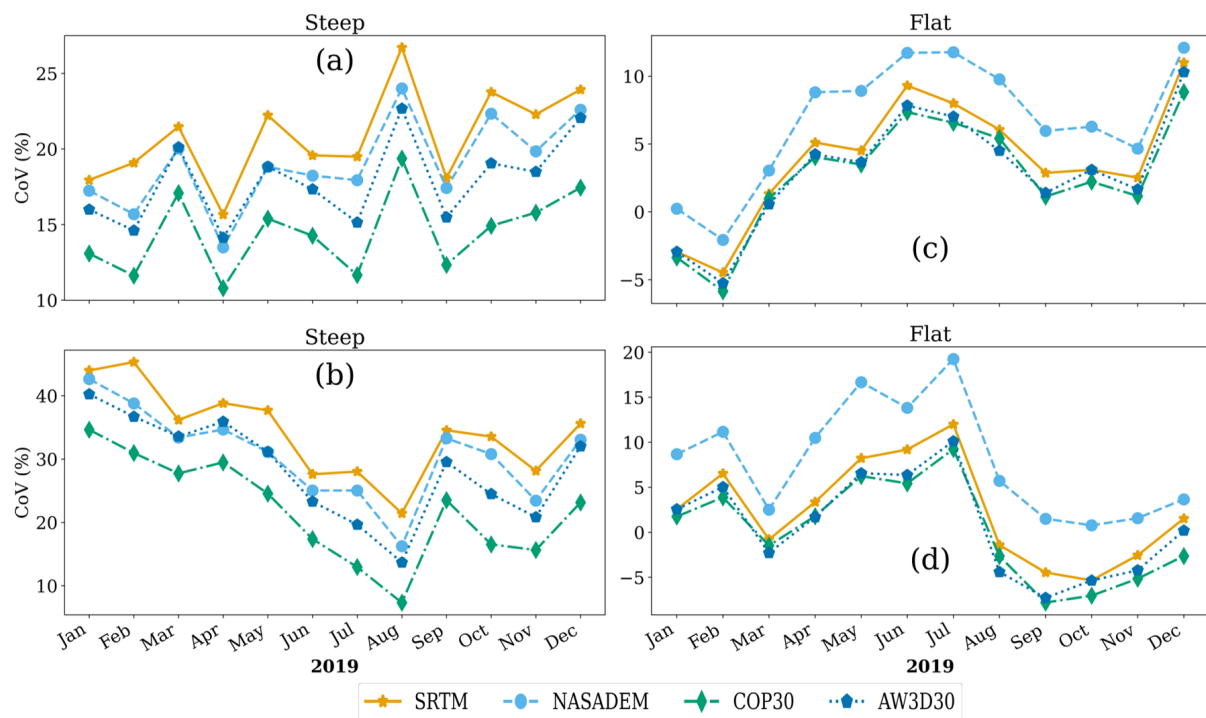


Figure 4.11: Monthly CoV for the intact evergreen forest over flat (AS site) and steep (WT) terrains in 2019 for (a and c) VH polarisation (b and d) VV polarisation. In steeper terrain, the COP30 DEM product showed less variation in both VV and VH polarisation compared to other products. The SRTM γ^0 product shows stronger temporal fluctuations in rugged terrain, which is more pronounced in VV polarisation up to about CoV of 35%.

The RMSE results for detecting the ASM-induced deforestation stages using all S1 γ^0 products are shown in Table 4.2. All γ^0 ARD products achieved similar performances in flatter terrains to detect both early and later deforestation stages. The VV polarised γ^0 RTC products gave the best results in detecting both early and later stages of deforestation caused by ASM activities in flat regions with RMSEs of 0.3555 and 0.1100, respectively. Notably, in steep landscapes, the COP30 DEM γ^0 product performed better at detecting the early stage of ASM-induced deforestation for VV and VH polarisations, where there is less vegetation clearance. However, the VV polarisation in steeper terrain had the lowest agreement with the Sentinel-2 NDVI to detect later deforested stages, in which more trees have been cleared and left on the ground. This is because the angular-based radiometric terrain normalisation employed in this study can perform poorly in increasing steep topography (Vollrath et al., 2020).

Table 4.2: RMSE (dB scale) over mine sites in steep and flat terrains for detecting ASM-induced deforestation stages. The RMSE was determined using the NDVI profile value at the time when the change event was confirmed as the expected value.

γ^0 RTC Product	Steep				Flat			
	Early stage		Later stage		Early stage		Later stage	
	VH	VV	VH	VV	VH	VV	VH	VV
SRTM	0.5326	0.4377	0.1001	1.4830	0.5440	0.3555	0.4503	0.1100
NASADEM	0.5320	0.4367	0.1005	1.4830	0.5440	0.3555	0.4503	0.1100
COP30	0.4560	0.3607	0.2020	1.5845	0.5604	0.3607	0.3127	0.1166
AW3D30	0.5683	0.4730	0.0748	1.4565	0.5440	0.3723	0.4677	0.1100

4.6.3 Performance of different smoothing techniques to enhance the effectiveness of Sentinel-1 time series data to enable early ASM detection

Figure 4.12 and Figure 4.13 show the results of both smoothed and original S1 backscatter time-series data, mitigating outliers caused by adverse atmospheric effects to improve the early detection of ASM activity at the Ashanti and Western test sites, respectively. Smoothed S1 backscatter time series at mining sites in the respective study areas, using smoothing algorithms for VH polarisation, comparing backscatter for intact forest (left) and ASM-induced deforestation (right). Additionally, the performance evaluation results for reconstructing Sentinel-1 time series data using the smoothing methods are presented in Table 4.3 at both the Ashanti and Western mining test sites, for VH polarisation.

Table 4.3: RMSE (dB) and R^2 for reconstructing S1 SAR time series using smoothing methods, comparing the predicted and original backscatter for VH polarization at the Ashanti and Western test sites.

Smoothing Method	Ashanti Test Site				Western Test Site			
	Mine 1		Mine 2		Mine 1		Mine 2	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
KF	0.6188	0.9489	0.4122	0.9207	0.7883	0.9016	0.3930	0.9641
SG	0.7039	0.9338	0.4579	0.9022	0.9828	0.8471	0.4540	0.9521
LOESS	0.8362	0.9066	0.5583	0.8546	1.1245	0.7998	0.5282	0.9352

In this section, the degree to which the three smoothing methods (KF, SG, and LOESS) improve S1 SAR time series data to allow early detection of ASM activity in the wet tropics, particularly during the rainy season, has been demonstrated. Figure 4.12 and Figure 4.13 show the fitted models (KF, SG, and LOESS) that follow the original S1 time series backscatter trajectory to reduce outliers and obtain the filtered data in both test sites. As shown in Figure 4.12

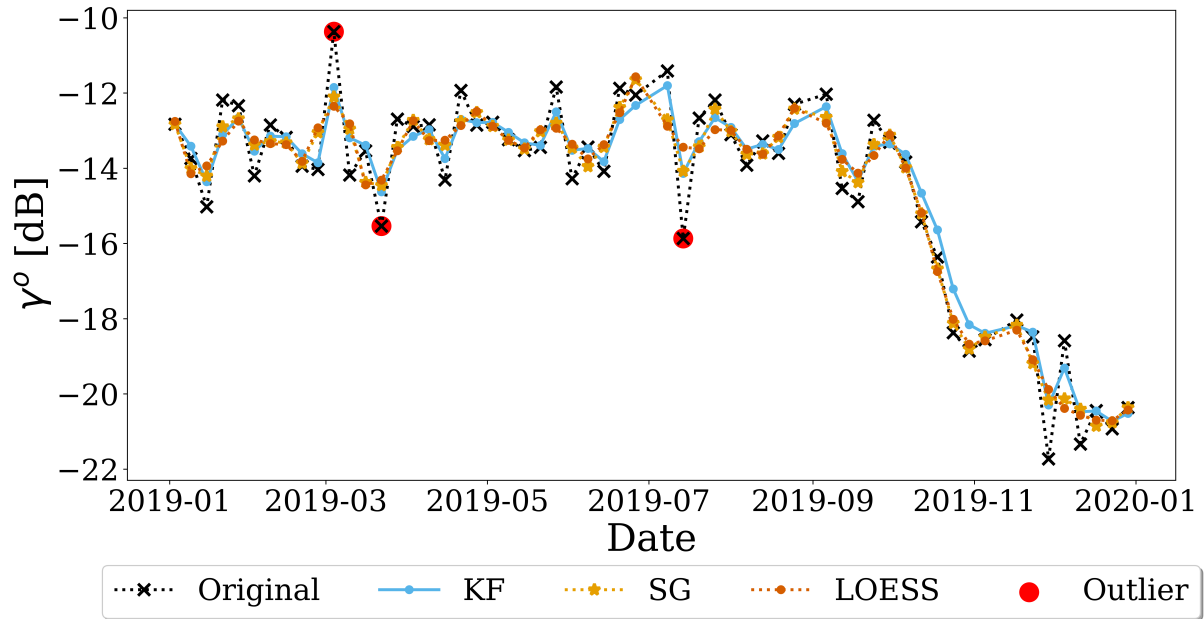


Figure 4.12: Comparison of smoothed and original S1 SAR time-series data to improve early detection of ASM activity in the humid tropical rainforest in southern Ghana. Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 1 in the Ashanti test site for VH polarisation using smoothing algorithms, mitigating outliers occurring due to adverse atmospheric effects. The rainfall season in the area reported occurs between March and October.

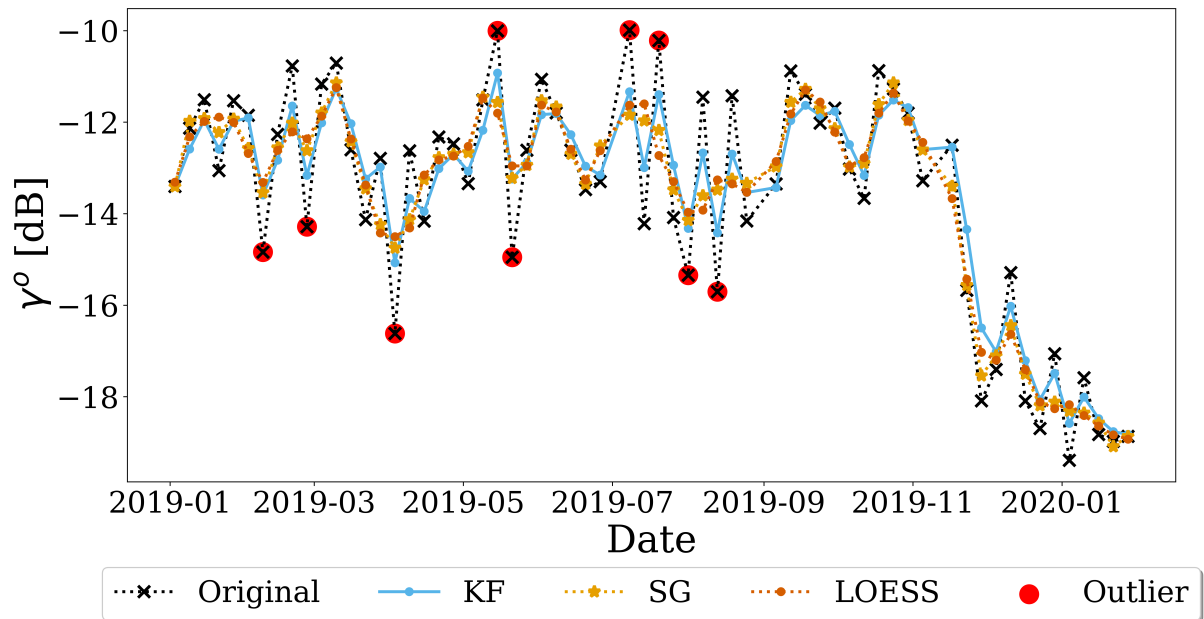


Figure 4.13: Comparison of smoothed and original S1 SAR time-series data to improve early detection of ASM activity in the humid tropical rainforest in southern Ghana. Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 1 in the Western test site for VH polarisation using smoothing algorithms, mitigating outliers occurring due to adverse atmospheric effects. The rainfall season in the area reported occurs between March and October.

and Figure 4.13, outliers are seen as temporal spikes (red) due to atmospheric effects from high-intensity rainfall events, and S1 imagery values are predicted using the smoothing algorithms. These outliers correspond with the rainy season of the region, which is reported to fall between March and October (Forkuor et al., 2020). While all filters evaluated significantly contribute to reducing SAR noise and mitigating outliers assumed caused by atmospheric effects from high-intensity rainfall events, KF provides the best performance, followed by SG and then the LOESS algorithm in both test sites.

The findings indicate that KF provided the most accurate predictions and effectively followed the original S1 time series backscatter trajectory, reducing outliers to obtain high-quality filtered data at both test sites, followed by SG and the LOESS method. In the study area, the KF showed the strongest correlation ($R^2 > 0.90$), followed by SG ($R^2 > 0.85$), and LOESS ($R^2 > 0.80$) between the predicted and original S1 backscatter across all mining sites (Table 4.3). Additionally, KF consistently achieved the lowest RMSE, which can be as low as 0.3930, followed by SG of 0.4540, and LOESS with an RMSE of 0.528.

4.7 Discussion

Objective 1 – This Chapter was the first to evaluate **the potential of S1 σ^0 and γ^0 ARD products for identifying ASM-induced deforestation stages**, and importantly incorporated and explored the suitability of four open-source global DEM options for SAR processing. It also investigated a novel approach to improve the effectiveness of C-band SAR data for rapid and reliable ASM detection in the tropics, especially during the rainy season. The findings in this chapter showed for the first time that S1 σ^0 products exhibited significant variability in sloped terrain across all similar test sites, potentially leading to more errors in detecting ASM-related deforestation stages in steeper areas, and particularly when identifying later stages of deforestation using both VV and VH polarisations. This may be because σ^0 cannot reduce the effects of topographical variations (Flores-Anderson et al., 2023). The flat regions show good geometric correction across all S1 σ^0 and γ^0 ARD products for both VV and VH polarisations across all mining sites. However, comparing the incidence angle and backscatter, this study also identified significant differences in the areas of uneven topography for the S1 σ^0 backscatter product, especially at high incidence angles above 43.345 degrees. Studies have shown that the variations in biomass and surface moisture significantly affect the SAR backscatter properties observed over vegetated surfaces (Vreugdenhil et al., 2018). The time series analysis showed that the S1 σ^0 product shows more variation in response to seasonal changes than the γ^0 product, especially in steeper terrains. Importantly, the findings in this chapter suggest that the original S1 GRD imagery as ingested in GEE, without further preprocessing, is not suitable for ASM applications in the tropics. The raw S1 GRD imagery may compromise the accuracy and effectiveness of ASM detections, making further preprocessing essential for achieving reliable

results.

Objective 2 – The choice of DEM options for generating the γ^0 product is crucial for effectively reducing topographic distortions, including effects such as foreshortening (Truckenbrodt et al., 2019). In this study, all γ^0 products demonstrated acceptable geometric and radiometric corrections across flat areas for all mining test sites for both polarisations. However, upon further analysis, we learned that the NASADEM γ^0 products showed relatively better topographic normalisation results in relatively flat terrains for both VV and VH polarisations. The topographic normalisation analysis in this Chapter revealed that all S1 γ^0 products have low incidence angle dependence for each of the four DEMs at both steep and flat area test sites. After robust testing for the time-series assessments, the results confirmed that the COP30 DEM γ^0 products outperformed other DEMs in reducing topographic distortions for uneven terrain and were more effective at detecting ASM-induced deforestation for both VV and VH polarizations. In addition, the COP30 DEM shows the lowest dispersion response to seasonal rainfall effects, followed closely by the AW3D30 DEM. The influence of seasonal rainfall is more pronounced in the VV polarisation due to its greater sensitivity to surface scattering and has a greater impact on the NASADEM product in the flat terrains and the SRTM product in the steep areas of up to CoV of 40%. Overall, the results followed similar findings reported in (González-Moradas et al., 2023), where COP30 DEM performs best among freely available global 30 m DEMs in uneven landscapes. This further suggests the potential of the proposed methodology in this chapter for processing S1 imagery for monitoring ASM and its related forest land use changes globally.

Objective 3 – The choice of local filtering, such as the SG and LOESS, replaced each data value with a combination of neighbouring values within a specified window using least-squares fitting and polynomial order, although LOESS employs a more advanced weighting system than SG. However, the importance of the results from these tests was that LOESS was not significantly better than those from SG, especially for mining sites that exhibited notable temporal spikes in the S1 time series during the rainy season (see Figure 4.12 and Figure 4.13). This resulted in LOESS having higher RMSEs of 1.1245 and 0.8362 at the Western and Ashanti sites, respectively, compared to SG, which had RMSEs of 0.9828 and 0.7039 at the Western and Ashanti sites, respectively (see Table 4.3). The SG filtering is effective for filtering time-series data with sharp and prominent peaks (Savitzky and Golay, 1964), whereas LOESS filtering is better for analysing broad signal bands with robustness (Cai et al., 2017). On the other hand, the KF was identified as consistently achieving the lowest RMSE compared to the other smoothing techniques for mining sites that exhibited notable temporal spikes with RMSE values of 0.7883 and 0.6188 at the Western and Ashanti sites, respectively (see Table 4.3). The KF employs a recursive estimation process that considers system dynamics and integrates historical information to refine its estimates, enhancing its robustness to noise and changes in the under-

lying time series data (Faragher, 2012). These findings establish the KF method as a robust and practical alternative to SG and LOESS smoothing techniques for enhancing C-band SAR data quality. The KF method's demonstrated capability can facilitate the development of early warning systems for ASM in wet tropical regions using S1 imagery for rapid interventions.

4.8 Conclusion

In this study, a novel integrated methodology for S1 SAR backscatter ARD preparation in GEE to enhance the timely and reliable monitoring of ASM activities in the wet tropical regions was investigated. To address the challenges of using S1 C-band SAR for continuous ASM monitoring in the wet tropics, the suitability of backscatter processed using local incident angle approximations for σ^0 geometric terrain normalisation (i.e. without RTN) and using DEM for γ^0 radiometric terrain normalisation was evaluated, along with the choice of freely available DEM options for processing S1 SAR data. Additionally, an additional preprocessing step was explored to enhance the effectiveness of S1 data for accurate and reliable ASM monitoring in the tropics, especially during the rainy seasons. This method was benchmarked against widely used smoothing techniques in remote sensing applications. This study has demonstrated the importance of geometric and radiometric corrections as a crucial SAR preprocessing step for accurate ASM monitoring applications in the tropics. An important finding of this chapter is that, when choosing SAR backscatter normalisation methods for effective monitoring of ASM in the dynamic and environmentally sensitive tropical regions, both σ^0 and γ^0 showed similar accuracy in detecting ASM-related disturbances in relatively flat terrains. However, the γ^0 terrain normalisation product demonstrated better performance in areas with steep or uneven topography and was less affected by seasonal variations. This chapter also provides valuable insights into the options for freely available DEMs to improve the performance of terrain normalisation for γ^0 ARD products. While all DEMs produced consistent results in flat regions, the COP30 DEM proved to be the most reliable for terrain normalisation in steep areas and was less influenced by seasonal changes. Our findings further reinforce previous results, showing that S1 σ^0 and γ^0 ARD products can be significantly impacted by adverse atmospheric conditions, which cause outliers in images acquired during the rainy season. This thesis makes an important contribution to addressing this limitation by proposing the KF as an effective method for filtering S1 data with outliers, improving the accuracy of ASM monitoring in the tropics during the rainy season. The findings suggest that KF provides the most robust description of the seasonal dynamics and is good for filtering S1 time series data with prominent outliers due to atmospheric effects during rainy seasons, providing great potential for early detection of ASM activity using S1 data in wet tropical rainforests.

Based on the analysis presented in this study, the following strategies are proposed to create C-band S1 SAR backscatter ARD, enhancing its effectiveness for ASM early warning

applications in the wet tropics:

1. It is not suitable to utilise the original S1 GRD imagery as ingested in GEE without prior preprocessing for ASM applications in the tropics.
2. It is recommended to use γ^0 backscatter ARD products over σ^0 with radiometric and geometric corrections to mitigate distortions caused by topography for continuous mapping of ASM activities on a large scale in the tropics.
3. The Copernicus 30 m DEM is proposed as the most suitable to create S1 γ^0 radiometric terrain normalization backscatter data for continuous large-scale mapping of ASM activity in tropical regions using S1 imagery.
4. Time series reconstruction is recommended as an essential additional preprocessing step to improve the effectiveness of C-band S1 SAR, reducing the atmospheric effects from high-intensity rainfall to allow regular ASM monitoring in wet tropical regions.

In the subsequent chapters, the proposed SAR data preparation methodology will be validated by applying it for timely ASM monitoring in the wet tropics from S1 imagery.

Chapter 5

Assessing change point detection methods to enable robust detection of early stage Artisanal and Small-scale Mining (ASM) in the tropics using Sentinel-1 time series data

This chapter is based on the peer-reviewed article:

Mensah, I. O., Barrett, B., and Cahalane, C. (2025) Assessing change point detection methods to enable robust detection of early stage Artisanal and Small-Scale mining (ASM) in the tropics using Sentinel-1 time series data. *International Journal of Applied Earth Observation and Geoinformation* 139. doi.org/10.1016/j.jag.2025.104525.

5.1 Context

This chapter introduces the first robust automatic SAR-based ASM early detection method capable of rapidly flagging ASM-related canopy degradation in mining landscapes, where optical data are frequently unavailable due to cloud cover. It aims to address the research objective “develop a robust approach to automatically detect the early stage of ASM activity using S1 time series data across different geographical areas in the tropics”. This chapter assesses the potential of using the optimal SAR preprocessing methodology developed in Chapter 4 of this thesis to enhance the quality of S1 C-band SAR data for the timely detection of ASM across various geographical mining landscapes and seasons. To fully understand the benefits of the

time series smoothing method proposed in this thesis (Chapter 4) as an essential additional SAR preprocessing step to effectively address the challenges of using S1 C-band SAR, such as active rainfall effects and seasonality, this study is the first to evaluate S1 ARD backscatter products with and without smoothing for timely and reliable detection of ASM activities in the tropics. In this study, three state-of-the-art statistical unsupervised change point detection (CPD) methods are introduced and compared, including cumulative sum (CuSuM), pruned exact linear time (PELT), and binary segmentation (BinSeg), for the timely detection of ASM activities in the tropics. Additionally, in this study, the effectiveness of using different S1 C-band SAR polarisations (i.e. VV and VH) for the timely detection of ASM activities in the wet tropics, particularly during the rainy seasons, is examined.

5.2 Abstract

Artisanal and Small-scale mining (ASM) provides essential livelihoods for many in developing countries, but often lacks regulation, leading to environmental issues such as water pollution and deforestation. Timely and accurate mapping of ASM activities is vital for responsible mining that benefits the environment and local communities. Synthetic Aperture Radar (SAR) is crucial for regular ASM monitoring in cloudy regions due to its ability to penetrate clouds. However, atmospheric effects can limit its effectiveness, particularly with shorter wavelengths in wet tropical areas during the rainy season. This study utilised a time series smoothing technique to improve Sentinel-1 (S1) SAR time series data, reducing SAR noise and atmospheric effects from heavy rainfall for early ASM activity detection. We tested three change point detection (CPD) methods, including cumulative sum (CuSuM), pruned exact linear time (PELT), and binary segmentation (BinSeg) in the Western and Ashanti wet regions in southern Ghana using the smoothed S1 data for early ASM detection. We observed a relatively fast response of ASM activity tracking when utilising smoothed S1 data at both sites for VV and VH polarisations during the rainy seasons. However, VH polarisation is more effective than VV polarisation during rainy seasons. While all CPD algorithms showed similar performance, CuSuM had the shortest lag time of up to 9 days, compared to 11 days for PELT and BinSeg. This method significantly reduces ambiguity caused by heavy rainfall when identifying change points due to ASM activity, making it a viable option for near real-time monitoring in wet tropical regions.

5.3 Introduction

Artisanal and small-scale mining (ASM) is a low-cost, labor-intensive method of mining (Moyo et al., 2022) that provides a primary source of income for many communities in developing countries globally, particularly among the rural poor (Nunfam et al., 2020; Pokorny et al., 2019; Ofosu et al., 2020). ASM occurs in diverse regions globally, mostly in the Global South,

comprised of Africa, Asia, Oceania, Central America, and South America (Fritz et al., 2018). It is estimated that it provides livelihood opportunities for over 150 million people worldwide through direct and indirect ASM-related activities (Fritz et al., 2018; World Bank Group, 2019), and contributes between 20% and 25% of the world's gold, diamonds, cobalt, tin, and tantalum production annually (Schwartz et al., 2021). In West Africa, there are at least 5 million people directly working in the ASM sector across 10 countries, with Ghana having the highest ASM rates of over 1 million miners (Hilson, 2016). In Guinea and Ghana, for instance, mining plays a crucial role in driving economic growth, contributing about 25% and 9.8% of their Gross Domestic Product (GDP) in 2013, respectively (Ericsson and Löf, 2019; Ghana Statistical Service, 2014).

Although ASM generates important socioeconomic benefits for communities and countries, the operations often leave behind pits flooded with water, deforested lands, and polluted water bodies (Owusu-Nimo et al., 2018; Baffour-Kyei et al., 2021) that pose a health risk to livestock, the environment, and local communities. Hence, it remains a critical concern, as the demand for precious minerals continues to rise globally (Moomen and Dewan, 2017). Monitoring ASM operations in near real-time and developing early warning systems to support the effective management of the sector is therefore crucial. However, developing methods for monitoring these sites can be extremely challenging and dangerous due to their broad geographic distribution, remote locations, and because many ASMs operate illegally (Asner et al., 2013; Owusu-Nimo et al., 2018).

A remote sensing approach has therefore clear potential for enabling regular monitoring, though the use of optical satellite imagery can be limited by cloud cover, a significant challenge for countries in the tropical regions of West Africa, such as Ghana (Coulter et al., 2016; Dogbey et al., 2022). While the use of optical imagery to map ASM activities has been explored, results vary according to the resolution of the sensor, the degree of persistent cloud cover, and the accuracy of the classification method (Asner et al., 2013), presenting a challenge in detecting small ASM sites as sites can cover less than half a pixel, even at 30 m Landsat resolution (Snapir et al., 2017). Recent studies have built on the findings of earlier Landsat studies and developed deep learning-based approaches to map the extent of ASM activities using Sentinel-2 images (e.g. (Gallwey et al., 2020; Ibrahim et al., 2020)). These methods achieved promising results, but were greatly hindered in their ability to continuously monitor ASM by persistent cloud cover, particularly during the rainy seasons. The southern regions of Ghana, where most ASM is concentrated, have a hot and wet climate, prone to cloud cover and haze, particularly during the rainy season that lasts from early March to October (Forkuor et al., 2020; Snapir et al., 2017). According to Snapir et al. (2017), an analysis of the MODIS cloud fraction product (Platnick et al., 2003) in 2015, revealed southern Ghana has an average cloud cover of 83%, with a minimum of 53% even during the dry season, i.e. the month of December.

Synthetic Aperture Radars (SAR) are active sensors operating at longer wavelengths (mm – cm) that are cloud-penetrating and can thus bridge this gap and enable regular monitoring, even at nighttime and under adverse weather conditions (Pulella et al., 2020). In the last decade, the growing availability of SAR data collected by new satellites such as the ESA Sentinel-1 (S1) mission, which provides freely available C-band SAR imagery, has permitted continuous mapping of forest disturbances such as deforestation and forest degradation (Ruiz-Ramos et al., 2020). The potential of SAR data for identifying ASM-affected areas has been demonstrated in previous studies. L-band ALOS PALSAR SAR (12.5 m resolution) data has successfully been utilized to detect changes caused by ASM in Indonesia (Telmer and Stapper, 2007), and JERS-1 SAR data to identify deforestation in mining areas in the Brazilian Amazon (Almeida-Filho and Shimabukuro, 2000). In West Africa, S1 SAR has shown promising results in detecting ASM activities in semi-arid regions in Nigeria (Chike and Balz, 2024) and in the wet tropical rainforest in southern Ghana (Forkuor et al., 2020; Janse van Rensburg and Kemp, 2022). Nevertheless, S1 was observed to be affected in the wet tropical rainforest, particularly during active rainy seasons, leading to increased false positives and compromised classification accuracy. A recent study by Nursamsi et al. (2024) efficiently applied SAR and optical fused datasets to improve the detection of ASM in wet tropical rainforests in Indonesia. However, an approach that integrates historical data analysis to allow continuous monitoring of such an informal sector has yet to be explored. Due to these issues, to date, there appear to have been no remote sensing studies using either optical or SAR images that have explored the timely detection of ASM activities to enable a rapid response.

In recent years, change point detection (CPD) methods have been proposed for satellite-based mapping and monitoring applications, with preliminary studies showing promising results in detecting precise information about the location and timing of change events using time series SAR data (Aquino et al., 2022; Kellndorfer, 2019). The pruned exact linear time (PELT) algorithm has been applied to track deforestation in heterogeneous ecosystems (Fuentes et al., 2024) and to detect changes in urban areas using SAR imagery (Li et al., 2023) with high accuracy. Montefiore et al. (2022) applied the binary segmentation (BinSeg) method to identify the years of construction for swine waste lagoons from Landsat imagery with high accuracy. Similarly, the cumulative sum (CuSuM) method has been used to track forest changes with high accuracy (Kellndorfer, 2019; Ruiz-Ramos et al., 2020; Ygorra et al., 2021). While most CPD methods have been accurate in identifying changes using satellite imagery, less attention has been paid to their suitability for early detection using S1 backscatter to handle the variations in backscatter problems due to seasonal vegetation variation and adverse atmospheric effects from active rainfall events in complex wet tropical environments. Moreover, to identify change points, CPD methods based on SAR backscatter are affected by the sensitivity of SAR data to changes in forest phenology, vegetation, soil moisture content, and seasonal variation (Masolele et al., 2024; Sabir et al., 2024).

Time series reconstruction techniques have been effectively employed to smooth optical NDVI time series data by removing outliers caused by cloud contamination, atmospheric perturbations, and viewing geometry (Geng et al., 2014; Malhi et al., 2021). These techniques have been applied to smooth S1 time series data to improve the monitoring of vegetation phenology (Schlund and Erasmi, 2020; Soudani et al., 2021), crop mapping (Li et al., 2024), and deforestation in the temperate forest (Kellndorfer, 2019). However, no studies have exploited these techniques for ASM mapping. They have great potential to suppress SAR speckle noise and outliers caused by adverse atmospheric effects from active rainfall events and improve detection accuracy.

We develop a robust approach in this study to improve the early detection of ASM activity during the active rainy season using S1 imagery in complex wet tropical rainforests in southern Ghana. Our specific objectives are:

- (i) to explore a time series smoothing technique for modeling backscatter variations influenced by seasonality and outliers caused by adverse atmospheric conditions using S1 SAR data in wet tropical rainforests,
- (ii) to develop a robust approach to automatically detect the early stage of ASM activity using smoothed S1 time series data, and
- (iii) assess the performance of three structurally different CPD algorithms for the early detection of ASM activities across different geographical landscapes in wet tropical rainforests.

The study is structured as follows. Section 5.4 presents an overview of the study area and datasets used to develop and validate the models developed in this study. Section 5.5 introduces the robust automatic SAR-based ASM early detection methodology proposed in this study, defines the S1 data preparation steps, and describes the time series reconstruction prediction model for modeling outliers in the time series data, discusses the three CPD methods for the early detection of ASM, and performance evaluations. The results of the S1-based timely ASM detections using the CPD methods are detailed in Section 5.6, and the discussion is presented in Section 5.7. Finally, Section 5.8 concludes by summarising the relevance of the findings.

5.4 Study area and datasets

5.4.1 Study sites

Ghana is one of the countries in West Africa that is at the forefront of the fight against ongoing illegal ASM activities. Ghana has an estimated 9.17 Mha of forest cover accounting for about 40% of its total land area (FAO, 2021). In recent years, Ghana's forest resources have experi-

enced a significant rate of deforestation and forest degradation, with estimated forest loss at 3% annually (approximately 135,000 ha/year) (Ankomah et al., 2020; Kyere-Boateng and Marek, 2021). The country's high rate of deforestation is of great concern to the nation as these forests provide many ecosystem services and functions that support the national agricultural economy (Ankomah et al., 2020). Deforestation in Ghana is largely driven by human activities such as illegal and unsustainable logging and mining, agricultural and urban expansion (Ankomah et al., 2020; Boadi et al., 2016). Mining has been found to contribute to high deforestation rates in Ghana, with an average conversion rate from forest to mining of about 2,600 hectares annually (Barenblitt et al., 2021).

To ensure the reproducibility of the CPD method, two study areas in the High Forest Zone (HFZ) (i.e. contains forest species that are in high demand for timber and the major gold belts of Ghana), located in the tropical forests of the Western and Ashanti regions with two distinct tropical forest ecosystems, were incorporated (see Figure 5.1). Existing mining sites were initially identified by visually inspecting historical high-resolution images from Google Earth and then confirmed using Sentinel-2 images, to form the basis of the assessment in this study. Ten points of interest (POI) were selected from the existing mining sites at approximately 100 m intervals, depending on the availability of cloud-free images in both study sites (Figure 5.1). The Western and Ashanti regions were chosen because of their increasing deforestation rates and have been reported as regions in Ghana where illegal ASM activities are most prevalent (Gallwey et al., 2020; Owusu-Nimo et al., 2018).

Test Site 1: The Ashanti test site is located in the Atwima Mponua District in the Ashanti Region of Ghana. The study area lies between longitude $2^{\circ}1'50''\text{W} - 2^{\circ}2'20''\text{W}$ and latitude $6^{\circ}30'\text{N} - 6^{\circ}30'10''\text{N}$ (Figure 5.1a). The area is located in the wet semi-equatorial forest zone in Ghana that is made up of mainly semi-deciduous forest cover with valuable tree species such as Wawa, Sapele, Esa, and Asafena (Derkyi et al., 2013; Atwima Mponua District Assembly, 2018). The area experiences two main rainfall seasons. The first and major rainfall period occurs from March to July, peaking in May every year. The second and minor rainy season starts in August and ends in November. Generally, the average annual rainfall for the major rainy season ranges between 1700 and 1850 mm (Atwima Mponua District Assembly, 2018). Although the study area experiences heavy rainfall throughout the year, December to February tends to be hot and dry. In general, the annual average temperature is about 27°C , while monthly mean temperatures range between 22°C and 30°C throughout the year (Atwima Mponua District Assembly, 2018). The soils in the area are generally suitable for agriculture and can be classified into two categories based on their major characteristics, including moderately suitable and marginally suitable soils. Beneath these soils lie Birimian and Tarkwaian rocks, which are rich in minerals such as gold and bauxite, which further enhances the area's economic potential. In 2021, the area's population was 155,254, with the majority of people engaged in

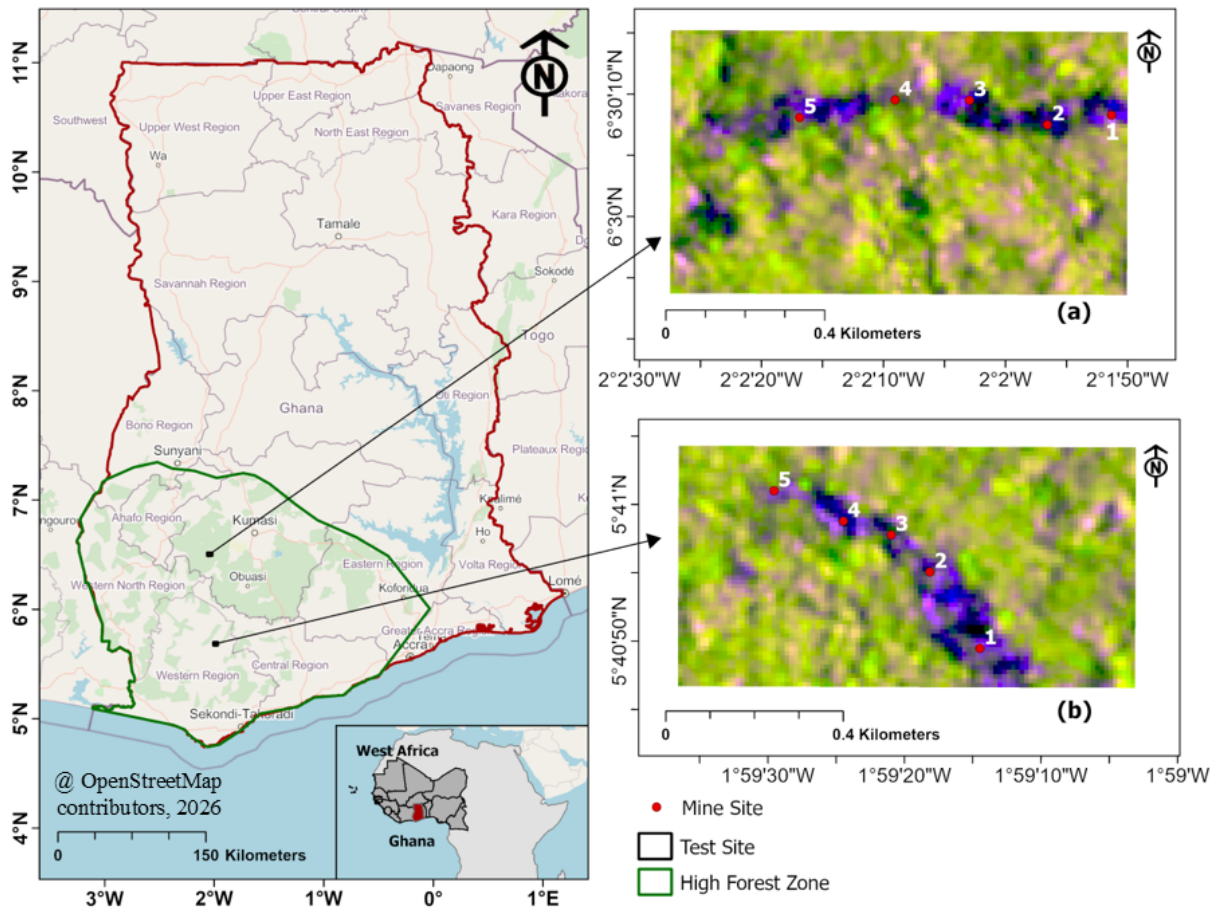


Figure 5.1: Study area containing test sites located in the high forest zones in southern Ghana. A post-event Sentinel-1 SAR false colour composite image comprised of the red channel (VV), green channel (VH), and blue channel (VV/VH) of each test site showing the ten mining sites spaced at least 100 m apart. (a) Ashanti test site (b) Western test site.

agriculture, followed by commerce, manufacturing, and services. Manufacturing activities in the region are generally practiced on a small scale, primarily including palm oil processing, wood-based industries, metal works, and mining ([Atwima Mponua District Assembly, 2018](#); [Service, 2021](#)).

Test Site 2: The Western test site is located in the Wassa Amenfi East District in the Western Region of Ghana. It lies within the longitude $1^{\circ}59'30''\text{W} - 1^{\circ}59'10''\text{W}$ and latitude $5^{\circ}40'50''\text{N} - 5^{\circ}41'\text{N}$ ([Figure 5.1b](#)). The site is covered by semi-deciduous, tropical forest with transitional zones in between, but the primary vegetation is tropical rainforest where rainfall is heaviest, with dominant tree species such as Sapele, Odum, Mahogany, Wawa ([Wassa Amenfi East Municipal Assembly, 2018](#)). The study area falls within the rainfall belt of the country and experiences two main rainfall regimes. The primary rainy season occurs between March and July, and the second starts in September and ends in early December. The average annual rainfall ranges between 1400 mm and 1730 mm ([Wassa Amenfi East Municipal Assembly, 2018](#)). Despite heavy rainfall during the year, average annual temperatures are generally

high, ranging between 24°C to 29°C. The test site is considered a hotspot for ASM activities (Mantey et al., 2017; Owusu-Nimo et al., 2018). The area features three primary geological soil formations: upper Birimian, lower Birimian, and granite. The granite deposits enhance the region's mineral wealth, especially in gold. Moreover, the area's active rainfall, coupled with its varied soil types, leads to a dense vegetation cover throughout the region (Wassa Amenfi East Municipal Assembly, 2018). As of 2021, the region had a population of 179,696, with most people primarily engaged in farming. The key agricultural products include cocoa, oil palm, rubber, plantain, and cassava. However, poor farming practices and mining activities, particularly small-scale and illegal mining, continue to degrade the natural environment in the area (Service, 2021; Wassa Amenfi East Municipal Assembly, 2018).

5.4.2 Datasets

5.4.2.1 Sentinel-1 SAR Images

Dual-polarized (VV and VH) S1 SAR Ground Range Detected (GRD) products acquired in the respective study sites from January 2019 to March 2020 were selected in the Google Earth Engine (GEE) platform (Gorelick et al., 2017). The GRD images were acquired in interferometric wide-swath (IW) mode with a 5 x 20 m resolution and a swath width of 250 km. The S1 imagery used in this study includes all of the GRD Sentinel 1A and 1B imagery products acquired in both ascending and descending orbits, available in the study area, and resampled to a pixel spacing of 10 m with a revisit time of 12 days. The S1 GRD scenes provided in GEE were first processed for thermal noise removal to generate calibrated, ortho-corrected products before being ingested into GEE. For the ten mining test sites in both the Ashanti and Western study areas, the time series was formed from a total of 120 images for each test site acquired between January 1, 2019, and March 31, 2020. The S1 data time period was selected based on the availability of cloud-free optical data for validation.

5.4.2.2 Reference data: multispectral satellite imagery

The main goal of this study was to detect ASM activity quickly after the removal of trees or thinning (see Figure 5.2). To evaluate the accuracy of detecting the exact timing of early stage ASM activity using the S1-based CPD approach, a series of known change dates was created by visual interpretation of time series Normalised Difference Vegetation Index (NDVI) profiles over the mine sites during a cloud-free period. The NDVI calculated from multispectral data was used to confirm the occurrence of ASM activity and also to verify the date of the start of ASM. For validation purposes, ASMs that occurred outside the rainy season were selected to reduce the persistent cloud cover problem in the study area. The cloud-free images from Sentinel-2 collections between January 1, 2019, and March 31, 2020, for both test sites were collated in GEE. The Sentinel-2 images include all Sentinel-2A and Sentinel-2B imagery prod-

ucts acquired with 13 spectral bands and a combined revisit time of five days. From the GEE platform, Sentinel-2 surface reflectance (Level 2A) was selected, and cloud-free images were created by removing all pixels identified as cloud, snow, or shadow. The NDVI time series was formed from a total of approximately 20 images for each mining site point of interest acquired between January 1, 2019, and March 31, 2020.

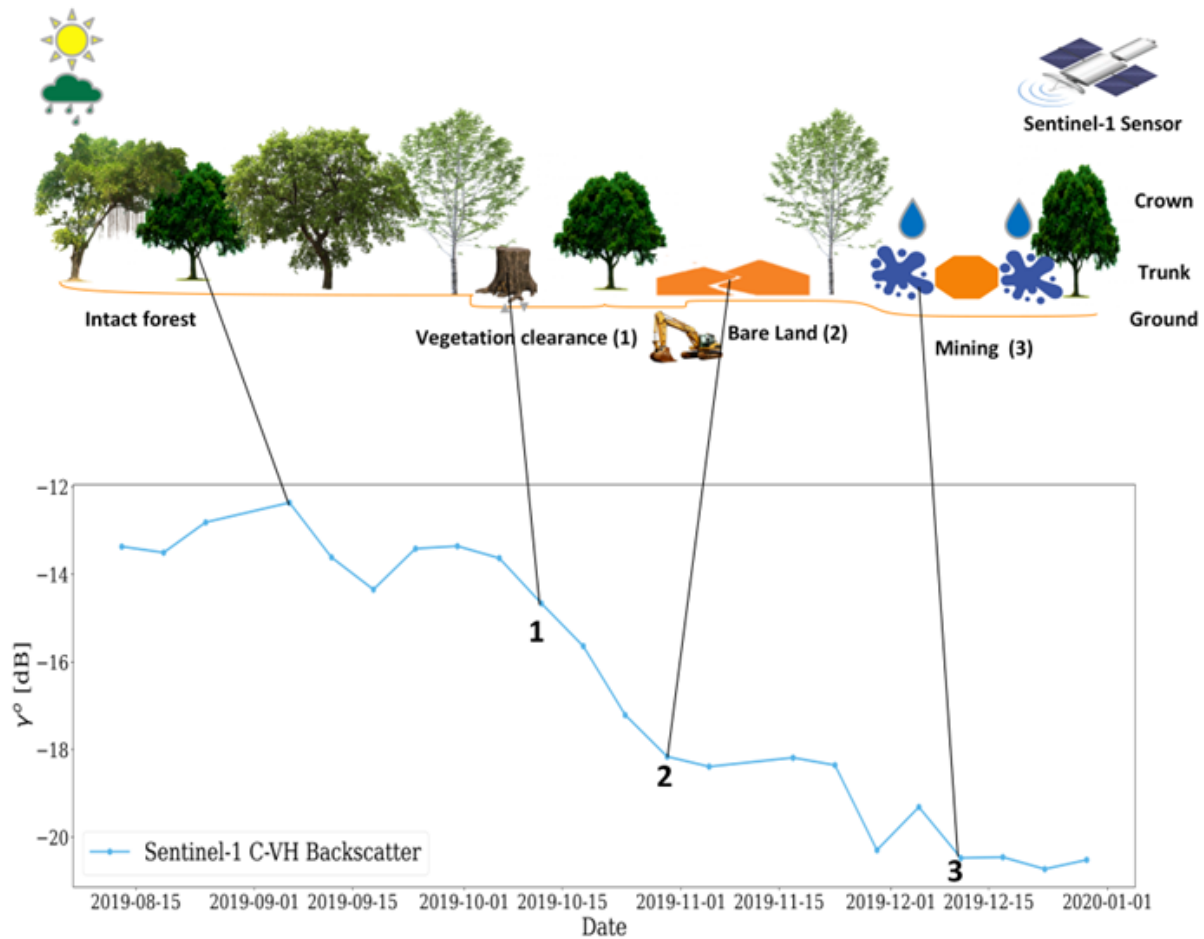


Figure 5.2: Schematic diagram showing the interaction of Sentinel-1 C-band (5.5 cm) VH signals with forest canopy and considerations for detecting the different ASM stages (1) vegetation removal/thinning, usually removing small lines of trees or thinning (2) bare land after vegetation removal, (3) mining commences and formation of pools of water interspersed with bare soil or vegetation, as water is added or channelled in during the mining stage for mining. The goal of this study is to identify early ASM activity as soon as possible after stage 1 begins.

The Sentinel-2 time series NDVI profile over mining site 5 in the Ashanti test site that was used for visual interpretation to observe the date of the start of ASM activity is illustrated in [Figure 5.3](#). ASM typically undergoes different stages starting from vegetation removal or thinning, then bare land after vegetation removal, and finally a mining stage associated with the introduction or pumping of water. From [Figure 5.3](#), we see this confirmed for our test case using optical imagery, where an intact tropical dense rainforest begins with high NDVI values (i.e. 0.6 and above). The early stage of the ASM activity causes a change in the forest cover, which is seen as a drop in NDVI values (i.e. about 0.25) that occurred on the 7th of January

2020. Then there is a further drop in NDVI values (i.e. to around 0.1) when more trees are cleared to leave the ground bare after vegetation clearance on the 12th of January 2020. Finally, the mining stage also causes another drop in NDVI values (i.e. below 0.1), usually resulting from the formation of pools of water as it is pumped or channelled in for the extraction of minerals during mining.

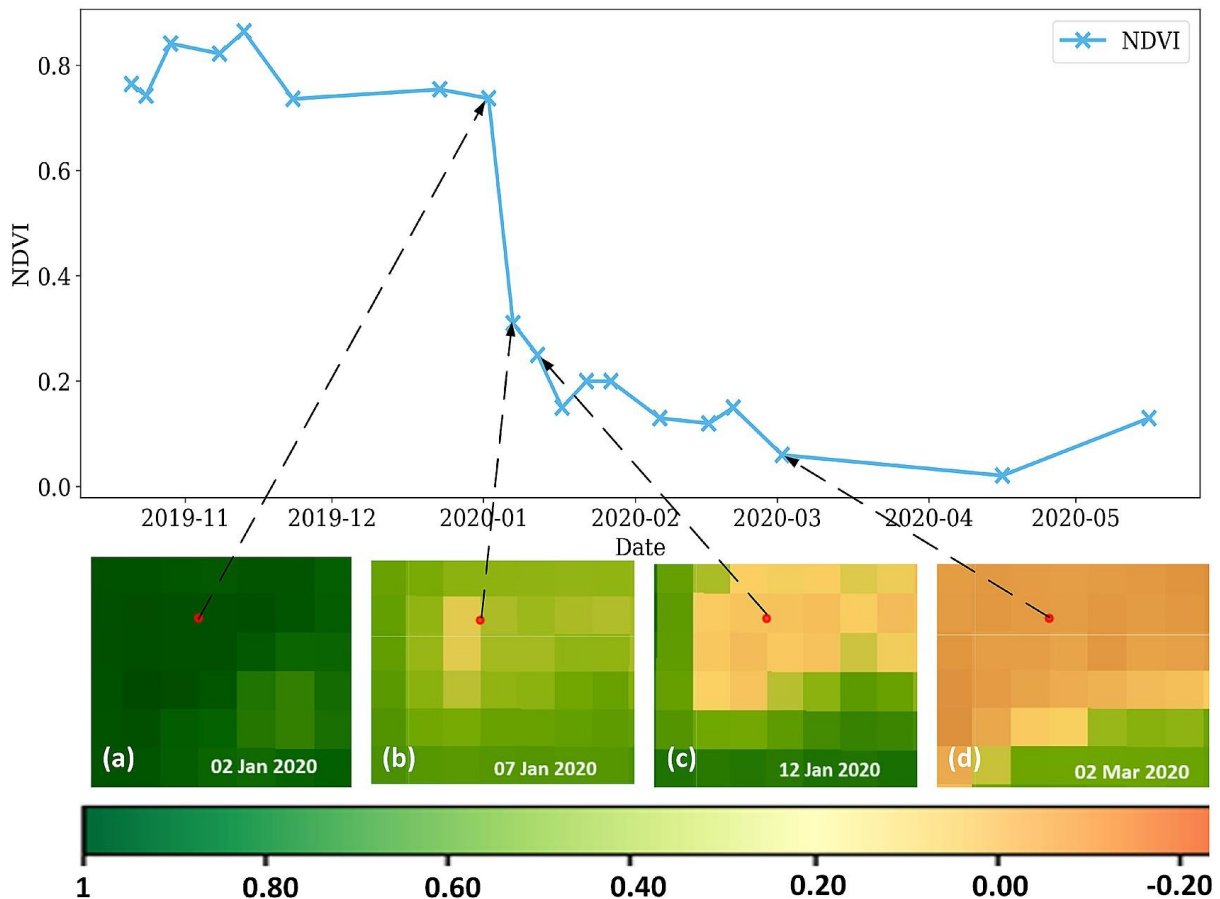


Figure 5.3: Sentinel-2 time series NDVI profile visual interpretation for the early detection of ASM activity in the Ashanti mine site 5 for validation. (a) no disturbance – intact forest, ASM mining activities display a decrease in NDVI values (b) thinning/vegetation removal at the early stage of ASM activity occurred on 7th of January 2020, (c) the next stage bare land after vegetation removal on 12th of January 2020, (d) the later mining stage associated with water as water is used for mining before forest regrowth from May 2020.

5.5 Methods

We selected three CPD algorithms belonging to structurally different approaches in identifying change points in univariate time series data to develop a robust method for the timely detection of ASM activity in the wet tropical rainforest in southern Ghana using smoothed time-series S1 SAR data. We tested: (1) cumulative sum (CuSuM), a likelihood threshold approach that analyses the temporal signature for each pixel through the deviation of a pixel from its mean; (2) linearly penalised segmentation (PELT), a temporal segmentation method that minimizes

the computational cost while retaining the ability to find optimal segmentations; and (3) binary segmentation (BinSeg), temporal segmentation approach that sequentially splits time series data into distinct homogeneous segments, and a likelihood ratio test is used to determine the significance of differences among the resulting segments. The flowchart summarizing the methodology employed in this study for robust early stage ASM automatic detection is shown in Figure 5.4.

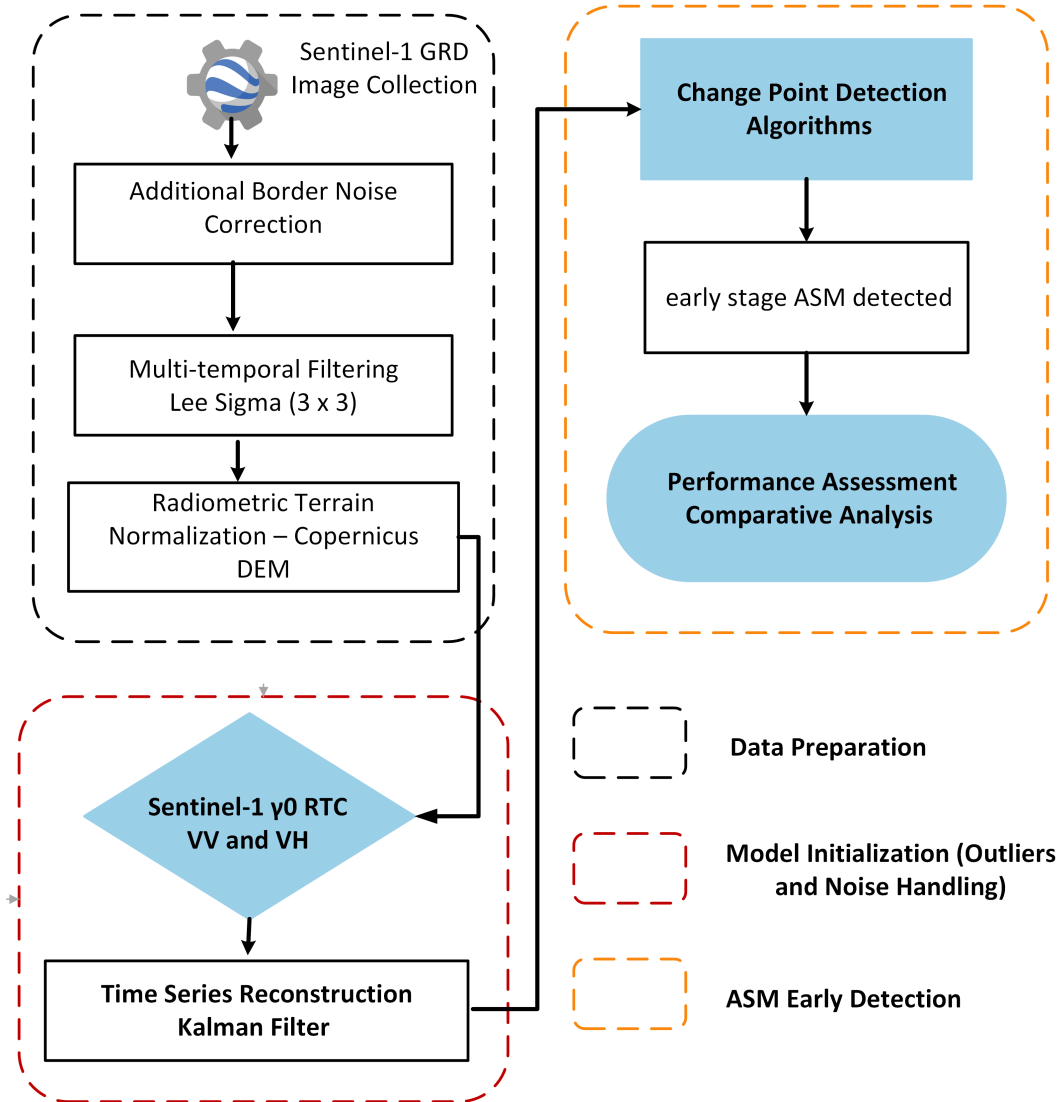


Figure 5.4: Workflow for the robust early detection of ASM activity, including the Sentinel-1 SAR image collection Analysis Ready Data (ARD) preparation, model initialization to reconstruct the ARD data, and the CPD ASM early stage detection steps in complex wet tropical rainforest.

5.5.1 Generation of Sentinel-1 SAR backscatter analysis ready data (ARD)

In an initial study, we began by exploring the suitability of the S1 backscatter data for detecting ASM-induced deforestation in our study area (Mensah et al., 2024b), as described in Section 4.6.1. This study of the initial processing stages of our approach recommended radiometric

terrain corrected (RTC) γ^0 over σ^0 backscatter data for large-scale continuous mapping of ASM activities, particularly in areas of steep topography. Therefore, this study utilises the S1 γ^0 RTC backscatter designed to mitigate the effect of topographic variations in southern Ghana. The S1 ARD data were created by replicating the workflow explained in [Mullissa et al. \(2021\)](#). Border noise correction was first applied to remove any remaining border artifacts in S1 images during the creation of the ARD data. This was followed by a multi-temporal speckle filtering that was reported as an effective filtering technique for mapping ASM ([Janse van Rensburg and Kemp, 2022](#)), using the framework proposed by [Quegan and Yu \(2001\)](#). The multi-temporal filtering was applied using the improved Lee Sigma filter ([Lee et al., 2009](#)) of kernel size 3 x 3 pixels and a restricted number of 10 images involved in the filtering for optimal filtered products. Radiometric terrain normalization was applied to mitigate the effect of topography on the SAR backscatter using the 30 m Copernicus (COP30) DEM. In southern Ghana, the COP30 DEM was found to be least affected by geometric distortions and performed better on steep slopes in mitigating the effects of topography when detecting deforestation stages caused by ASM ([Mensah et al., 2024a](#)), as explained in Section 4.6.2. Thus, COP30 DEM has been proposed as suitable to create S1 γ^0 RTC backscatter data to detect ASM-induced deforestation for extensive continuous monitoring applications. Finally, a volume scattering model was adopted for the radiometric terrain normalisation as described in [Hoekman and Reiche \(2015\)](#) and [Vollrath et al. \(2020\)](#).

5.5.2 Reconstruction of time series Sentinel-1 data

In forested areas, S1 is impacted by artifacts occurring due to atmospheric effects, particularly in scenes acquired during rainy or wet seasons in wet tropical environments ([Forkuor et al., 2020](#)). The Kalman filter (KF) has long been considered more efficient for many data prediction tasks, as it always achieves the minimum mean square error possible ([Faragher, 2012](#); [Kalman, 1960](#)). It can predict measurements recursively, allowing new measurements to be processed immediately as they arrive, providing great potential for satellite-based early detection systems. The KF has shown promising results for reducing outliers in satellite-based time series observations for near real-time monitoring of defoliation ([Olsson et al., 2016](#)) and near real-time monitoring of forest disturbances ([Ye et al., 2021](#)) using MODIS and Landsat images, respectively. Our study applies the KF to S1 SAR images to reduce the influence of high-intensity rainfall events and seasonality by smoothing the data and to better approximate the true value of γ^0 backscatter for periods with low-quality backscatter observations for early detection of ASM activities in wet tropical environments.

The KF applied in this study was based on the following state space representation ([Faragher, 2012](#)) (Equation 5.1 and Equation 5.2):

$$\text{State equation: } \gamma_t^0 = A \cdot \gamma_{t-1}^0 + B \cdot u_{t-1} + w_t \quad \text{Equation 5.1}$$

$$\text{Observation equation: } Y_t = C \cdot \gamma_t^0 + z_t \quad \text{Equation 5.2}$$

where γ_t^0 is the true value of the γ^0 backscatter (i.e., the state of the system) at time t ; u_{t-1} is the input to the system or KF; Y_t represents the observations of the γ^0 backscatter from the S1 SAR data at time t ; w_t is the process noise of the model; and z_t is the measurement noise. The matrices A , B , and C are the coefficient matrices that depend on the quality of the γ^0 backscatter retrieved from the S1 SAR data.

The true value of the backscatter γ_t^0 cannot be observed directly by the satellite sensors due to uncertainties present at the time of measurement. Therefore, the KF uses Y_t , which represents the observations of the γ^0 backscatter from the S1 SAR data. The KF algorithm recursively computes γ_t^0 by integrating historical information, predictions from the system models, and noisy measurements. The KF algorithm works in two main steps: (1) the true value of γ_t^0 is first estimated using the state equation (Equation 5.1), and (2) Equation 5.2 once a new observation Y_t becomes available, γ_t^0 is updated to predict its optimal γ^0 backscatter value. The algorithm was applied using the *FilterPy* module (Labbe, 2015) in Python 3.7.

The KF predictions were improved through fine-tuning by visually comparing the predicted γ^0 backscatter with the time series of raw γ^0 backscatter for different coefficient parameters A , B , and C , and by varying the noise terms w_t and z_t . These are user-defined parameters that are crucial for achieving accurate and reliable KF predictions, depending on the quality of the raw measurements or observations. For the VH polarisation, a process noise parameter $w_t = 0.05$ and a measurement noise parameter $z_t = 0.09$ were used. Additionally, a process noise parameter $w_t = 0.10$ and a measurement noise parameter $z_t = 1.0$ were utilized for the VV polarization. Since the true backscatter value γ_t^0 was unknown, the optimization was performed by considering temporary spikes or decreases in the raw γ^0 backscatter time series to be likely outliers, while two consecutive low backscatter values were assumed to likely be forest disturbance, which was considered to occur due to mining activities.

Figure 5.5 shows the KF fitted model that follows the raw γ^0 time series backscatter trajectory to reduce outliers to obtain the filtered data for both VV and VH polarizations in the Ashanti site. As shown in Figure 5.5, outliers seen as temporal spikes (red) due to atmospheric effects from high-intensity rainfall events using S1 imagery values are predicted using the KF algorithm. These outliers correspond with the wet seasons of the region, which are reported to fall between March and October (Forkuor et al., 2020).

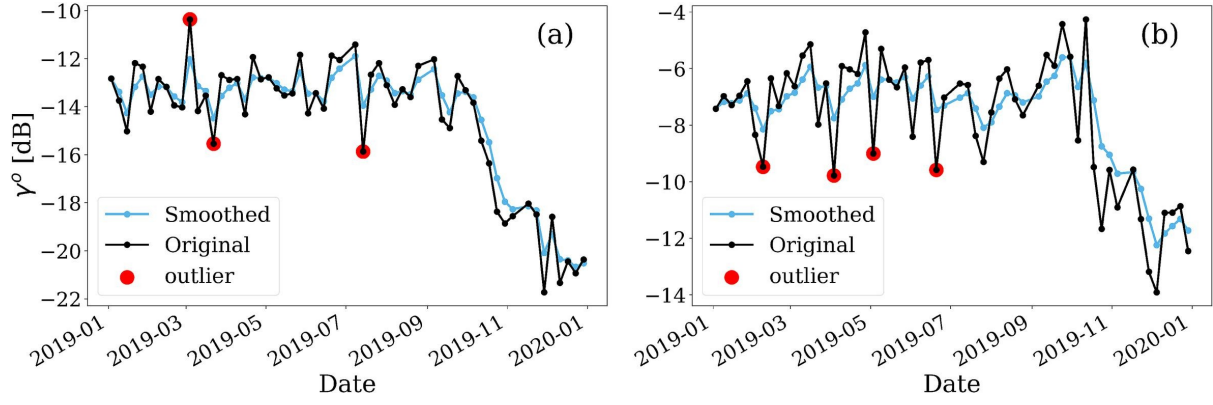


Figure 5.5: Comparison of KF-smoothed and original Sentinel-1 backscatter time-series data, mitigating outliers or artifacts occurring due to atmospheric effects from high-intensity rainfall events in the Ashanti mine site. (a) VH polarization (b) VV polarisation.

5.5.3 Change point detection algorithms

5.5.3.1 Early detection of Artisanal and Small-Scale Mining (ASM): CuSuM

The CuSuM algorithm was applied to the entire smoothed data stacks and to analyse the temporal signature of each pixel to identify the point of change, which was assumed to occur due to mining activities. The data stacks included all observations extending at least one year before the start of the mine to reduce seasonal effects and false positive detections. Here, for the time series data γ_t^0 , the CuSuM monitors the deviation between each pixel at time t and the mean $\overline{\gamma_i^0}$ (i.e. the residuals) (Taylor, 2008). The cumulative sum of these residuals, $R_{\text{sum}t}$, was computed, and the magnitude of change, $R_{\text{sum_diff}}$, was calculated as the difference between the maximum value $R_{\text{sum_max}}$ and the minimum value $R_{\text{sum_min}}$ of the cumulative sum of residuals, as shown in Equation 5.3 and Equation 5.4:

$$R_{\text{sum}t} = \sum_{t=1}^n (\gamma_{t,i}^0 - \overline{\gamma_i^0}) \quad \text{Equation 5.3}$$

$$R_{\text{sum_diff}} = R_{\text{sum_max}} - R_{\text{sum_min}} \quad \text{Equation 5.4}$$

The change point T_{CP} before the start of ASM activity was identified as the time when the cumulative sum of the residuals $R_{\text{sum}t}$ curve reached its maximum peak, as shown in Equation 5.5. The date of acquisition of the next observation after T_{CP} is defined as the time of early stage ASM activity, $T_{\text{early_stage}}$.

$$T_{\text{CP}} = t (R_{\text{sum}i} = R_{\text{sum_max}}) \quad \text{Equation 5.5}$$

Bootstrap analysis was then performed based on the magnitude of change ($R_{\text{sum_diff}}$) to accept or reject the detected change. Bootstrapping involves randomly reordering the original time series data and then comparing the resulting cumulative sum curves (Ygorra et al., 2021). Here, 1500 randomisations were used for the bootstrap analysis, which produced a sufficient number of bootstraps to determine the confidence level (CL) of the detected change event or point. Using the magnitude of change ($R_{\text{random_diff}}$) obtained from the bootstrap analysis, the CL was computed as shown in Equation 5.6.

$$CL = \left(\frac{n_{\text{greater}}}{n_{\text{bootstraps}}} \right) \times 100\% \quad \text{Equation 5.6}$$

where n_{greater} is the number of bootstraps for which $R_{\text{random_diff}}$ is greater than $R_{\text{sum_diff}}$ estimated from the original time series, and $n_{\text{bootstraps}}$ is the total number of bootstraps. Studies have shown that 90% or 95% confidence is usually required to identify a significant change in the original time series data (Manogaran and Lopez, 2018). This study, therefore, used a change point threshold greater than 95% to confirm the change as an early stage ASM activity (Equation 5.7).

$$T_{\text{CP}} : CL > 95\% \quad \text{Equation 5.7}$$

5.5.3.2 Early detection of ASM: Pruned Exact Linear Time (PELT) algorithm

The Pruned Exact Linear Time (PELT) was selected as the second CPD algorithm that allows more computationally efficient detection of multiple changes in a time series (Killick et al., 2012) and was implemented using the Python ruptures library (Truong et al., 2020). The PELT method was used to extract the change point m (i.e. the last observation before the start of ASM activity) of the forest dynamics based on time series data stacks. For the time series data stacks $y_{1:n}$, of size n , and m number of breakpoints at dates $(\tau_{1:m})$, change points can be detected by minimising the optimisation problem defined in Equation 5.8 (Wambui et al., 2015):

$$\sum_{i=1}^{m+1} [C(y_{\tau_{i-1}+1}, \dots, y_{\tau_i}) + \beta] \quad \text{Equation 5.8}$$

where C is the cost function for the i^{th} segment and β is the added penalty to guard against overfitting. The PELT algorithm works by combining Equation 5.8 with pruning to obtain exact and computationally efficient segmentation, ensuring that the total cost is lower than a change point cost plus an additional segment cost (Wang and Fan, 2021). The optimal segmentation is given by $F(n)$, as shown in Equation 5.9.

$$F(n) = \min_{\tau_m} \{F(\tau_m) + C(y_{\tau_m+1}, \dots, y_n)\} \quad \text{Equation 5.9}$$

This study used the radial basis function as the model input. The minimum interval between change points was set at 10, with a jump parameter of 5 and a penalty of 5 to ensure robust detection.

5.5.3.3 Early detection of ASM: Binary segmentation (BinSeg) algorithm

Binary Segmentation (Binseg) was chosen as the third CPD method, which is characterized by its low computational complexity and sequential process (Fryzlewicz, 2014). The algorithm was applied using the *ruptures* module in Python (Truong et al., 2020) and uses a sequential approach to analyse the variance in multiple homogeneous groups to find the breakpoint (m) before the start of the ASM activity. For the time series data stacks (γ_t^0), the Binseg algorithm works by first searching for a breakpoint (m), then the series is split into two around this breakpoint. Subsequently, the operation is repeated on the resulting segments until the stopping criterion is met. To identify the breakpoint m , a likelihood ratio test is proposed in the BinSeg algorithm that optimally minimises the sum of costs (Fryzlewicz, 2014; Truong et al., 2020). Here, a radial basis function was used as the model input with a jump parameter of 1 and a minimum segmentation length of 10. It is worth noting that the number of change points was predefined as 1 to handle the seasonality effects.

5.5.4 Accuracy assessment

An accuracy assessment for early detection monitoring systems should be made based on detection speed rather than penalizing a monitoring system for missing parts of a change event, as long as disturbance events are clearly flagged by the system (Tang et al., 2019). Here, because existing mining sites were used, the detection accuracy of each CPD algorithm was assessed by evaluating the timeliness of the detection of early stage ASM activity using both VV and VH polarizations. Thus, in the current study, we are not concerned with evaluating the magnitude of forest cover loss or the spatial extent of the change events caused by ASM activities.

The lag time, defined as the time (i.e. number of days) between the SAR-based detection using the CPD methods and the start of ASM activity observed from optical NDVI, was used as a metric to evaluate the accuracy of the models developed in this study. The lag time for early detection of ASM activity using VV and VH polarisations and each CPD algorithm across the ten mining sites in both Western and Ashanti test sites was computed. The lag time is defined as (Equation 5.10):

$$LT = \text{observed date} - \text{predicted date} \quad \text{Equation 5.10}$$

where LT is the lag time for detecting the early stage ASM activity. The detection dates were identified using the Sentinel-2 NDVI values and were considered the *observed date*. The SAR-based ASM early detection dates were used as the *predicted date*.

5.6 Results

5.6.1 Performance of smoothed and original Sentinel-1 data for early detection of ASM

Figure 5.6 and Figure 5.7 present the ASM early detection results before and after the filtering of the different CPD algorithms investigated in this study in both the Ashanti and Western test sites, respectively. The KF-smoothed (gold) and original (gray) S1 backscatter time series for intact forest (left) and ASM-induced deforested (right), with their corresponding early stage ASM detection by the three CPD algorithms (vertical lines) in the Ashanti and Western test sites, respectively. The change (early stage) using smoothed data (dotted black line) and original data (dotted purple line) is shown in the next observation in the time series. The date from optical NDVI (dotted red line) was used as validation.

The algorithms demonstrate strong performance when comparing smoothed and original S1 backscatter time series data for VV polarization, with significant improvements in accurately detecting the start time of ASM activity using the smoothed data in both test sites (see Figure 5.6 and Figure 5.7). Previous unsupervised near real-time studies that ignore pre-disturbance conditions often resulted in low detection sensitivity and high commission errors, especially with limited satellite observations preceding the early disturbance stage, leading to delays in creating reliable disturbance maps (Bullock et al., 2022; Ye et al., 2024). Compared to the original S1 VV backscatter, the smoothed data showed high detection sensitivity, especially when early disturbance observations were significantly affected by atmospheric conditions in the Ashanti site (see Figure 5.6b, Figure 5.6d, and Figure 5.6f). This led to reduced sensitivity lag and faster response to reliably detect the start date of ASM activity compared to the original data for all CPD algorithms. PELT exhibited the longest delay or lowest detection sensitivity compared to CuSuM and BinSeg when using the original S1 VV backscatter data at the Ashanti site. While CuSuM and PELT showed similar results before and after the filtering at the Western site for VV polarisation, BinSeg produced a false alert when using the original S1 VV backscatter data (see Figure 5.7f).

On the other hand, the smoothed S1 VH data showed improved early ASM detection

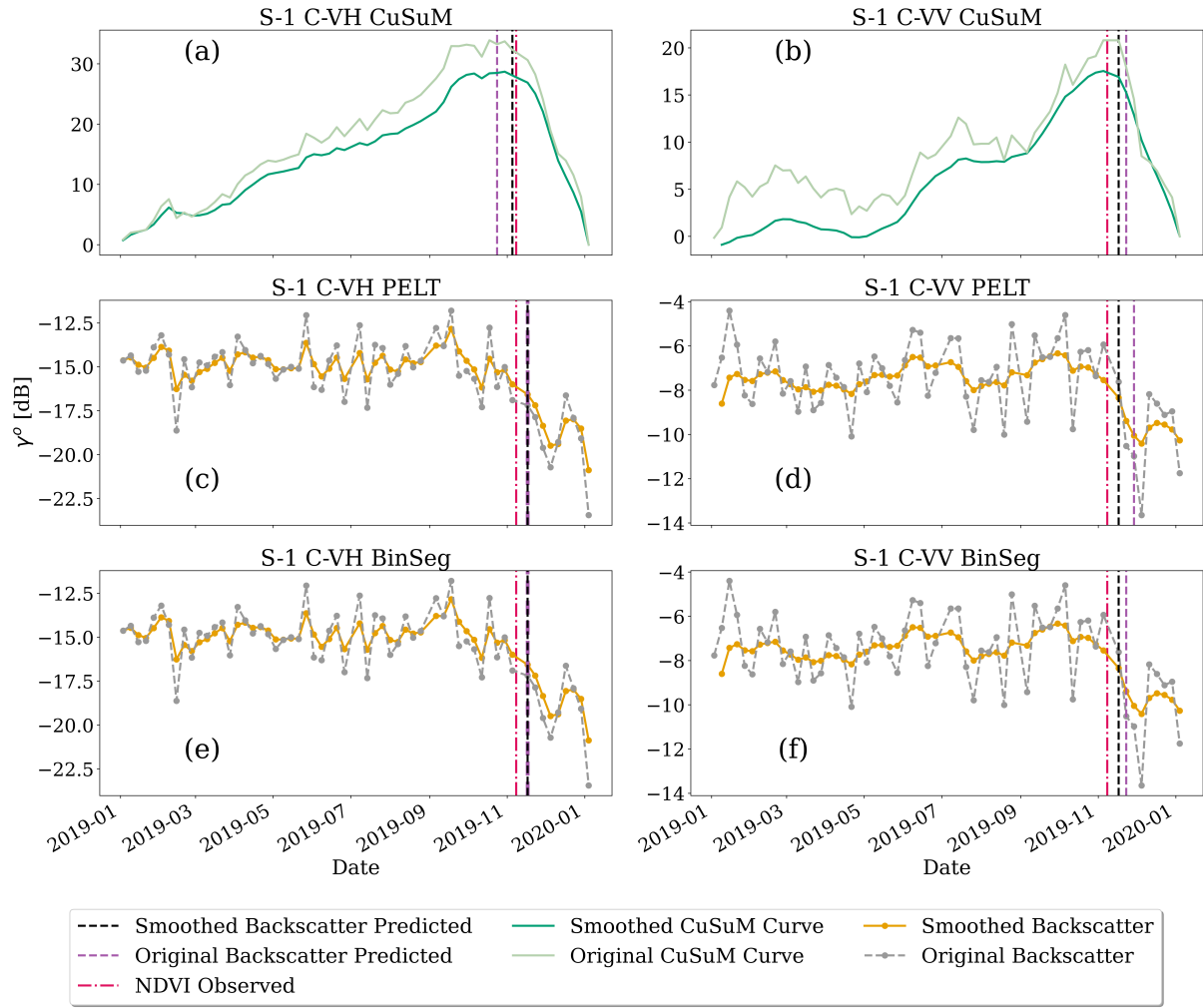


Figure 5.6: Comparison of KF-smoothed and original Sentinel-1 backscatter time-series data for early detection of ASM activity using the three CPD algorithms. Intact forest (left) and ASM-induced deforested (right) smoothed (gold) and original (gray) S1 backscatter time series over a mine site in the Ashanti test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms for both smoothed and original S1 backscatter are presented (vertical lines). The change (early stage) using smoothed data (dotted black line) and original data (dotted purple line) is shown in the next observation in the time series. The date from optical NDVI (dotted red line) was used as validation.

results compared to the original data in both test sites (see Figure 5.6 and Figure 5.7). To identify change points, CPD methods based on S1 data are influenced by variations in backscatter caused by fluctuating soil moisture levels, leading to false positives, especially during wet seasons (Sabir et al., 2024). The smoothed S1 backscatter effectively reduces ambiguity in identifying the exact change point caused by ASM activities. CuSuM gave the most improved performances in both test sites after filtering, followed by PELT and then BinSeg algorithms (Figure 5.6a and Figure 5.7a). This improvement helps reduce false alerts or delays due to atmospheric and forest canopy seasonality effects when utilizing the KF-smoothed data during severe atmospheric conditions with the CuSuM and PELT CPD algorithms (see Figure 5.6a

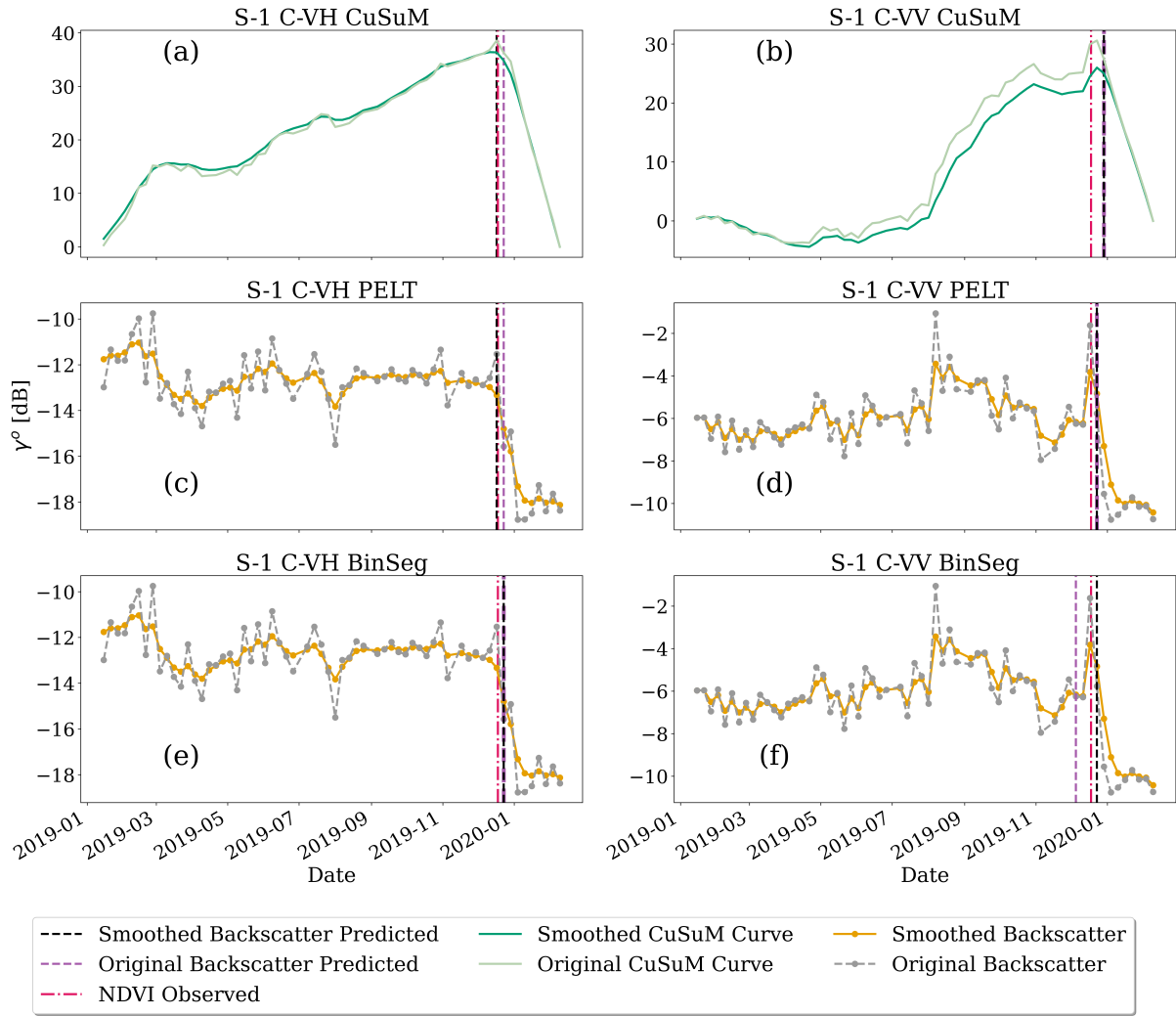


Figure 5.7: Comparison of KF-smoothed and original Sentinel-1 backscatter time-series data for early detection of ASM activity using the three CPD algorithms. Intact forest (left) and ASM-induced deforested (right) smoothed (gold) and original (gray) S1 backscatter time series over a mine site in the Western test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms for both smoothed and original S1 backscatter are presented (vertical lines). The change (early stage) using smoothed data (dotted black line) and original data (dotted purple line) is shown in the next observation in the time series. The date from optical NDVI (dotted red line) was used as validation.

and Figure 5.7b). Although this study used ASM with start dates outside of the rainy seasons for validation purposes, we observed that the CPD algorithms performed significantly better after filtering the S1 data at both sites. This improvement is demonstrated by the relatively fast response and high detection sensitivity of ASM activity tracking when utilizing smoothed S1 backscatter data, making it a viable option for near real-time monitoring. Therefore, the subsequent analysis in this study will be based on the KF-smoothed S1 backscatter data.

5.6.2 Change point detection algorithms for early detection of ASM

Figure 5.8 and Figure 5.9 show the smoothed S1 backscatter time series for intact forest (left) and ASM-induced deforested (right) with their corresponding early stage ASM detection by the three CPD algorithms (vertical lines) for mine 2 and mine 4 in the Ashanti and Western test sites, respectively. The CPD algorithms were evaluated assuming that time series data were normally distributed. The two mining sites were chosen because they showed significant signal variations due to adverse weather conditions and seasonal variability of vegetation. Figure A1 – Figure A8 in Appendix A provide further details of the timely ASM detection results for both polarisations across the remaining mining sites using all the CPD algorithms at the two case study areas.

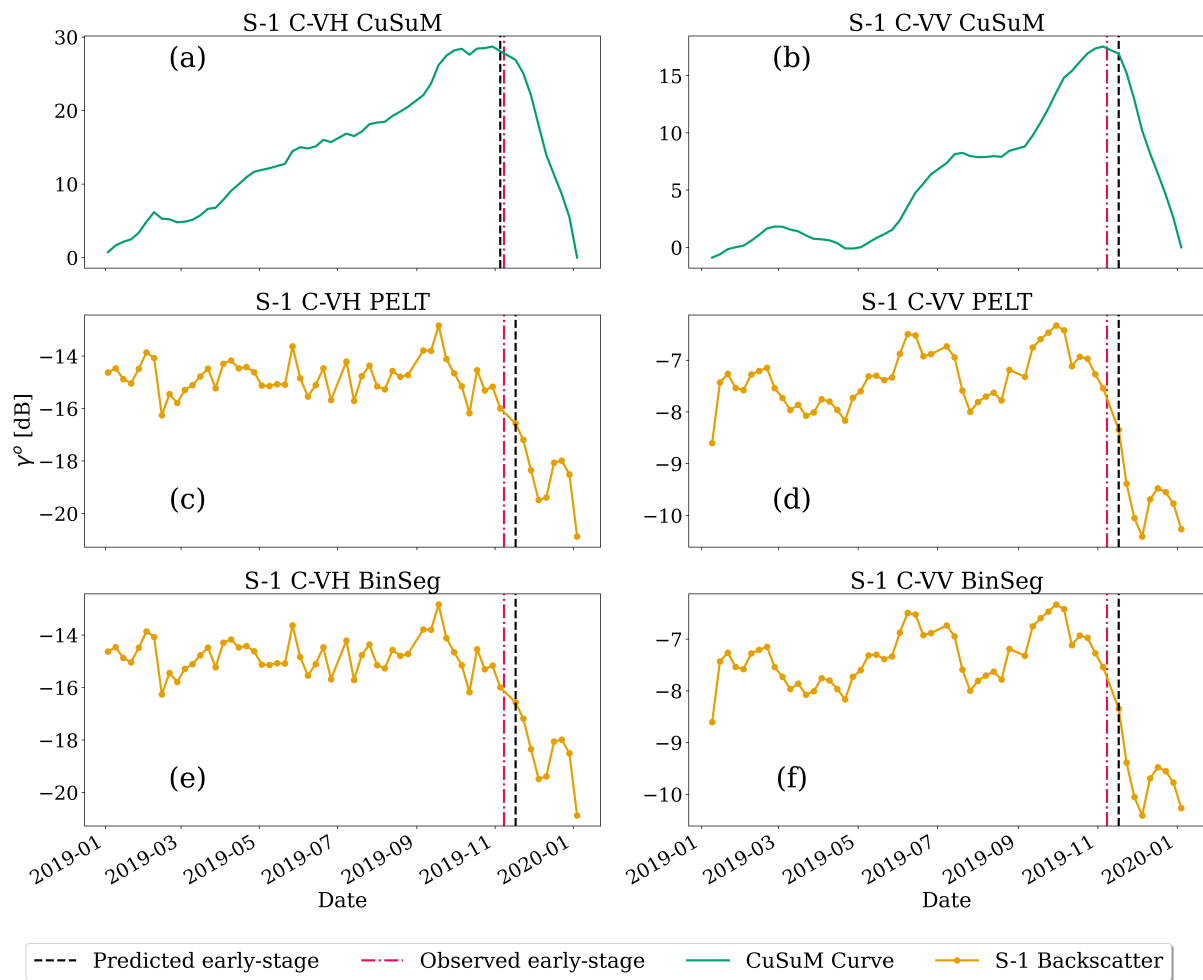


Figure 5.8: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 2 in the Ashanti test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

The results suggest that the VH polarization is more robust to adverse atmospheric effects

and more effective for early detection of ASM than the VV polarisation in both mining sites (see Figure 5.8 and Figure 5.9). Using VH polarisation, the algorithms demonstrated robust performance in detecting early stage ASM activity while effectively addressing backscatter variations due to seasonal effects from vegetation structure and adverse atmospheric conditions caused by heavy rainfall events in wet tropical rainforests. However, the CuSuM approach was consistently more accurate at detecting early stages of ASM that were less sensitive to backscatter variations compared to PELT and BinSeg algorithms using VH polarisation (see Figure 5.8a and Figure 5.9a).

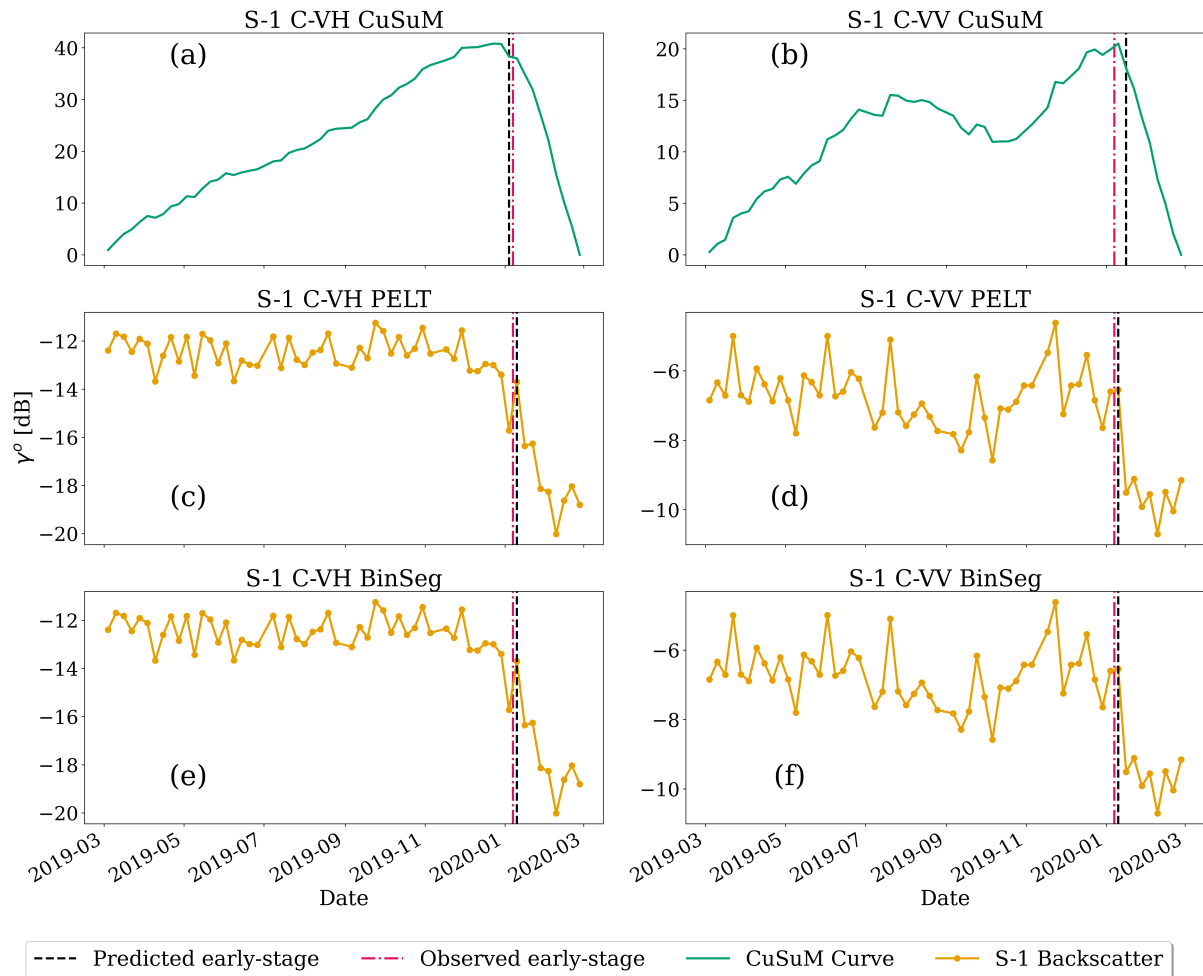


Figure 5.9: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 4 in the Western test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

On the other hand, the S1 VV polarisation was more affected by atmospheric effects due to high-intensity rainfall events in detecting early stage ASM. This leads to significant variations in backscatter, evident in the CuSuM curve as a trough (see Figure 5.8b and Figure 5.9b). These variations differ greatly across test sites depending on the forest structure and soil mois-

ture content, impacting the accuracy of identifying change points caused by ASM activity. CuSuM showed more sensitivity to variations in backscatter than PELT and BinSeg algorithms using VV polarisation during the active rainy season (see Figure 5.8b and Figure 5.9b). The backscatter variations seem to be aligned with rainfall patterns in the test sites, which is reported to peak between September and October in the Western site (Osei-Yeboah et al., 2020) (see Figure 5.9b) and in May (Atwima Mponua District Assembly, 2018) in the Ashanti site (see Figure 5.8b).

5.6.3 Latency between reference NDVI and SAR-based change detection

The temporal lag between reference NDVI dates and SAR-based change detection dates for both VV and VH polarizations is shown in Figure 5.10 and Figure 5.11. The horizontal black line highlights the best possible expected lag time (our benchmark) for early stage ASM activity occurrence, confirmed using the Sentinel 2 NDVI time series profile. The negative lag values indicate where S1 detection with CPD lagged behind that of the optical sensors and vice versa. Table A1 and Table A2 in Appendix A give further details of the temporal lag for detecting the early stage of ASM activity for both polarisations across the two test sites using all the CPD algorithms investigated in this study, comparing the S1 change occurrence dates to the optical detection dates. Generally, our results demonstrate that the VH polarisation signal showed the shortest delay for identifying the early stages of ASM activity when compared to the VV polarisation signal for both test sites (see Figure 5.10a and Figure 5.11a).

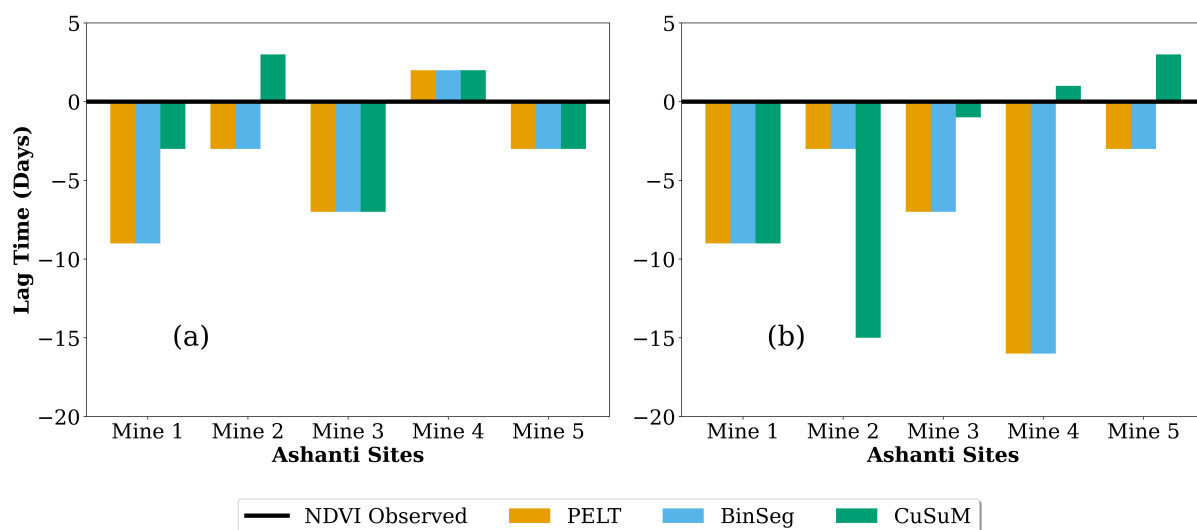


Figure 5.10: Temporal Lag between reference optical NDVI ASM detection and SAR-based CPD algorithms in the Ashanti mining sites. (a) VH polarisation (b) VV polarisation, negative lag time indicates optical first detections, whilst positive lag time represents SAR first detections using Sentinel-1 SAR.

All CPD models performed similarly across the ten existing mining sites investigated, but the CuSuM was the quickest to detect early stage ASM activity, followed by PELT and then

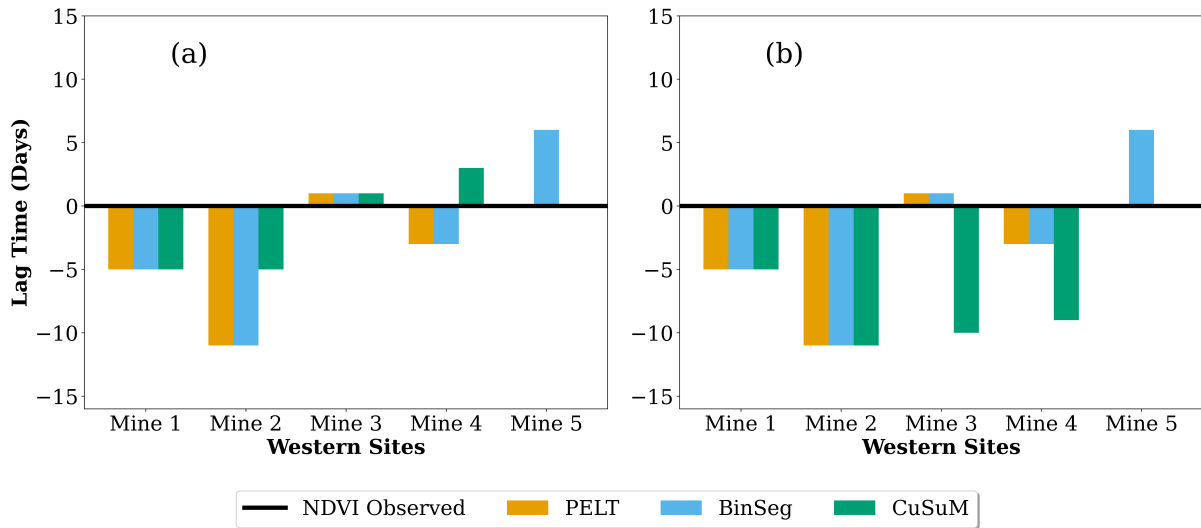


Figure 5.11: Temporal Lag between reference optical NDVI ASM detection and SAR-based CPD algorithms in the Western mining sites. (a) VH polarisation (b) VV polarisation, negative lag time indicates optical first detections, whilst positive lag time represents SAR first detections using Sentinel-1 SAR.

BinSeg using VH polarization (see [Figure 5.10a](#) and [Figure 5.11a](#)). In detecting early stage ASM activity using VH polarisation, the CuSuM method shows a clear advantage, having the shortest lag time across four mining sites compared to other tested algorithms (see [Figure 5.10a](#) and [Figure 5.11a](#)). This highlights its effectiveness for timely ASM detection. The PELT algorithm achieved similar performances as the BinSeg for all mining sites using the cross-polarised (VH) backscatter except for mine 4 in the Western test site ([Figure 5.11a](#)). Overall, CuSuM demonstrated the shortest lag time, with delays of up to 9 days, followed by the PELT and BinSeg methods with delays up to 11 days using the VH polarisation.

In contrast, the VV polarization showed more significant delays in timely detecting early stage ASM activity using all the algorithms across the mining sites (see [Figure 5.10b](#) and [Figure 5.11b](#)). PELT and BinSeg were found to be superior to the CuSuM method, having the shortest lag time, particularly in the Western test site (see [Figure 5.11a](#)). While both PELT and BinSeg demonstrated improved performance in timely detecting early stage ASM compared to the CuSuM method, their cost optimizations resulted in notable delays of up to 16 days in the Ashanti site compared to CuSuM of up to 15 days ([Figure 5.10b](#)). Our results generally suggest that the SAR-based methods significantly lag behind the optical detections across the majority of the mining sites (i.e. 7 out of 10 sites) using all algorithms.

5.7 Discussion

5.7.1 Performance of SAR-based change detection algorithms

In this study, we developed and compared the sensitivity of three CPD algorithms to variations in backscatter caused by atmospheric effects and seasonal vegetation structure. Our goal was to achieve early detection of ASM activity during the active rainy season using smoothed S1 imagery in wet tropical rainforests. Forkuor et al. (2020) found that S1 SAR is affected by atmospheric effects due to heavy rainfall, which prevents early detection of ASM, especially during the rainy season in wet tropical regions. However, our results in Figure 5.6 and Figure 5.7 showed that the smoothed time series data, compared to the original data, can significantly enhance the early detection of ASM, allowing relatively quick detection of early stage ASM activity. This improvement is achieved by reducing noise in the time series and eliminating outliers caused by atmospheric effects during heavy rainfall events. In recent years, time series smoothing techniques have shown their effectiveness in SAR applications, such as monitoring deforestation (Kellndorfer, 2019) and mapping sugarcane (Li et al., 2024), and we believe these techniques will be an essential preprocessing step for continuous ASM monitoring using time series SAR in wet tropical regions in the future.

Furthermore, the robust SAR-based timely ASM detection approach proposed in this study improves upon previous studies (Forkuor et al., 2020; Gallwey et al., 2020; Snapir et al., 2017) by addressing major challenges that have previously hindered continuous ASM monitoring throughout the year, even during the rainy season in wet tropical regions using S1 data. The models provided strong generalised predictions across the regions studied (see Figure 5.10 and Figure 5.11). Thus, this method can be adapted for various wet tropical areas in West Africa while exploring the best time series filtering for S1 data in ASM detection.

The CuSuM method has been found to be less influenced by seasonal vegetation changes when using S1 data, making it more effective in detecting changes in the vegetation structure caused by forest cuts (Ruiz-Ramos et al., 2020; Ygorra et al., 2021). However, our findings indicate that this applies exclusively to the cross-polarized channel, while the co-polarized channel can be affected, especially during the rainy season in wet tropical regions (Figure 5.10b). Studies have shown that as the water depth increases, the forest cover of tall, dense vegetation in forest wetlands shows a backscatter increase due to double-bounce scattering (Pope et al., 1997; Zhang et al., 2022). In contrast, short, sparse vegetation shows a backscatter decrease due to specular reflection. This is more sensitive to the co-polarised backscatter because of less or no depolarisation (Brisco, 2015). The significant deviations from the target value in the co-polarized backscatter during the rainfall seasons result in large variations in the backscatter due to the fluctuating soil moisture levels, leading to difficulties in identifying the exact point of change caused by ASM activity (see Figure 5.10b and Figure 5.11b). Nevertheless, the CuSuM

approach was observed to be consistently more accurate at detecting early stages of ASM using VH polarisation that is robust to atmospheric effects from active rainfall events compared to PELT and BinSeg algorithms (see [Figure 5.10a](#) and [Figure 5.11a](#)).

On the other hand, temporal segmentation algorithms (i.e. PELT and BinSeg) showed greater robustness against atmospheric effects caused by heavy rainfall for both VH and VV polarisations when compared to the CuSuM method. PELT uses a linear penalised method to minimize cost functions, which eliminates the need for prior information on seasonal vegetation trends ([Fuentes et al., 2024](#); [Wambui et al., 2015](#)). Likewise, BinSeg employs an optimal segmentation approach that is not sensitive to the distributional characteristics of the time series data ([Montefiore et al., 2022](#)). Both PELT and BinSeg algorithms are recognised for their computational efficiency and flexibility ([Fryzlewicz, 2014](#); [Killick et al., 2012](#)). PELT, in particular, has proven to be faster at detecting changes in urban areas, achieving a time accuracy of 86% using SAR data ([Li et al., 2023](#)). However, the cost optimizations associated with these methods led to delays in detecting the early stage of ASM activity compared to the CuSuM approach in this study. The CuSuM algorithm is susceptible to subtle shifts in the process mean, making it a powerful tool for the early detection of changes ([Taylor, 2008](#)). Importantly, the CuSuM model for VH polarisation can detect the early stages of ASM activity a little earlier or at the same time as optical sensors, depending on the forest structure and soil moisture content dynamics (see [Figure 5.8a](#) and [Figure 5.9a](#)). In the case of CuSuM, the longest lag time was observed to be 9 days behind the optical data benchmark, whereas PELT and BinSeg each took up to 11 days to detect the early stage of ASM activity using the VH polarisation (see [Figure 5.10a](#) and [Figure 5.11a](#)). This highlights its potential for near-real ASM applications on a large scale.

Our results also suggest that detection of early stage ASM activity using S1 SAR data can be at a disadvantage against optical in terms of speed, provided there is less persistent cloud cover, particularly when using co-polarised (VV) at both test sites, which can lag as long as 15 days with CuSuM and 16 days with both PELT and BinSeg behind optical data (see [Figure 5.8b](#) and [Figure 5.9b](#)). The delay might be due to NDVI responding immediately to forest losses of vegetation phenology (greenness) after vegetation clearance, whereas SAR sensors respond to changes in forest structure or surface roughness ([Tang et al., 2023](#)). We believe that the existence of the rainy seasons warrants the S1 approach, but there is potential for further improvement using data fusion. Nevertheless, since ASM activities often take place in remote areas, the actual detection could not be estimated with certainty due to a lack of ground truth or field data on the start date of the ASM activities, although NDVI data from Sentinel-2 were used to confirm the findings in this study. Thus, it would be useful to explore the detection accuracy of this approach further using high-resolution data or field data and to scale the analysis to the regional level to demonstrate its extensive applicability in complex wet

tropical environments.

5.8 Conclusion

This study compares the effectiveness and timeliness of the CuSuM, PELT, and BinSeg CPD algorithms for early detection of ASM activity using S1 data in the Western and Ashanti wet regions in southern Ghana during the rainy season. The findings contribute to enhancing the understanding and methodologies for monitoring structural changes caused by ASM in wet tropical rainforests. In contrast to earlier studies, the KF smoothing technique was exploited to reduce SAR noise in the temporal domain and mitigate atmospheric effects due to heavy rainfall events, especially during the rainy season. The findings indicate that the utilisation of S1 smoothed data significantly enhances the timeliness and effectiveness of CPD algorithms for the early detection of ASM activity during the rainy season, in comparison to the original backscatter data. This significantly reduces uncertainties caused by heavy rainfall in identifying change points due to ASM activity at both test sites for both VV and VH polarisations. The use of PELT and BinSeg for temporal segmentation offers a reliable method for detecting changes associated with early stage ASM using both S1 VV and VH polarisations. Nevertheless, these methods show notable delays in identifying ASM activities compared to CuSuM. CuSuM generally shows robust performances and ensures a faster response for early ASM detection. We found that the VH polarisation signal is more effective at detecting the early stages of ASM activity than the VV polarisation, providing a faster detection response during the rainy season. Although all algorithms showed similar performance across the mining sites, CuSuM had the minimum delays of up to 9 days, followed by the PELT and BinSeg methods, which had delays of up to 11 days when using the VH polarisation. The quick response demonstrated using this approach for detecting ASM highlights its promise for large-scale, near real-time ASM applications.

This study considers only a small study area, but robust performances across various geographical regions demonstrate the potential scalability of this approach for large-scale continuous ASM monitoring in wet tropical environments. Therefore, the potential of using the approach discussed in this Chapter for the timely detection of ASM activities on a large scale is tested in Chapter 6 of this thesis.

Chapter 6

Deep learning-based approach for timely Artisanal and Small-scale Mining (ASM) mapping using Sentinel-1 time series data in the tropics

6.1 Context

While the ASM-induced binary change detection alert method presented in Chapter 5 offers a robust and reliable approach to detect ASM-related canopy degradation in mining landscapes rapidly, it often provides limited insight into the specific nature of those disturbances. This chapter corresponds to the final stage of the SAR-based ASM monitoring methodological approach proposed in this thesis, extending the binary ASM-induced forest disturbance alert method into a multi-class change detection paradigm. It aims to address the research objective *“design a novel, scalable SAR-based DL model for near real-time (NRT) ASM monitoring capable of reliably and accurately distinguishing ASM-related disturbances from other forest land use changes in complex tropical environments”*. This chapter is the first to apply deep learning (DL) to S1 C-band SAR data for the timely and reliable mapping of ASM, distinguishing ASM-related disturbances from other forest land use changes in complex tropical environments across various geographical areas and seasons. The performance of the deep learning approach is benchmarked against existing pixel-based machine learning (ML) methods.

In addition, the performance of the CuSuM binary ASM-induced forest disturbances alert system introduced in Chapter 5 is further assessed in this chapter for the timely detection of ASM across diverse geographical landscapes and seasons on a large scale in the wet tropics.

This study has been submitted to the *International Journal of Applied Earth Observation and Geoinformation* and is currently under review.

6.2 Introduction

Artisanal and Small-scale Mining (ASM) is an important economic activity for over 49.5 million people across 86 countries globally ([ASM Inventory, 2025](#)). Approximately 20% to 25% of the world's annual production of cobalt, tin, gold, diamonds, and tantalum comes from ASM operations, with roughly two-thirds sourced from countries in the Global South ([Schwartz et al., 2021](#)). Although ASM provides essential economic benefits for countries and local communities, it significantly contributes to global land and environmental degradation, and remains a global concern with the ever-growing demand for precious minerals ([Hirlekar et al., 2025](#)). Despite these problems, there is a lack of effective mapping methods to accurately locate these mines in a timely manner, limiting our insights into ASM's spatial distribution and impacts to support their sustainable development.

Remote sensing is especially useful for mapping remote areas and enabling the timely mapping of ASM activities for timely reporting and targeted intervention on the impacts of disturbances, though the use of optical imagery is hindered by persistent cloud cover, a common problem faced by countries in the tropics, such as Ghana ([Coulter et al., 2016](#); [Dogbey et al., 2022](#)). Synthetic Aperture Radar (SAR) offers a solution for continuous mapping and monitoring in cloud-prone areas due to its capability to penetrate clouds ([Pulella et al., 2020](#)). Researchers have investigated the use of freely available S1 C-band SAR imagery for mapping ASM activities in tropical regions ([Forkuor et al., 2020](#); [Kimijima et al., 2022a](#); [Janse van Rensburg and Kemp, 2022](#); [Kimijima et al., 2022b](#)). These approaches produced promising results but were significantly affected by adverse atmospheric effects from active rainfall and SAR speckle noise, resulting in increased false alerts and reduced classification accuracy, especially during the rainy season.

A recent study proposed a cumulative sum (CuSuM) change point detection (CPD) technique for timely and reliable monitoring of ASM activity in the tropics ([Mensah et al., 2025a](#)). Applied to smoothed S1 data, CuSuM effectively reduces speckle-related noise and mitigates atmospheric effects from active rainfall, thereby enabling the rapid detection of ASM activity even during the rainy season. Since SAR backscatter is highly sensitive to local biophysical and environmental conditions, the effectiveness of the CuSuM method depends on its adaptation to region-specific conditions to create reliable disturbance maps on a large scale ([Sabir et al., 2024](#)). Although the CuSuM binary alert system offers a robust and reliable approach to rapidly detect ASM-related canopy degradation in mining landscapes, it is often limited to timely reporting and targeted intervention on the impacts of these disturbances. [Fuentes et al.](#)

(2024) emphasizes the necessity of incorporating a secondary classification stage to attribute the causes of vegetation change more accurately, particularly in heterogeneous tropical ecosystems where multiple disturbance drivers coexist. These advancements for ASM alert systems could be essential for prioritisation and strengthening rapid response strategies, as well as supporting reclamation efforts. For instance, understanding the specific nature of a detected disturbance, whether it is related to ASM or agriculture, is crucial in assessing the legality of a change event and the appropriate government bodies that may play a role in the rapid interventions (Slagter et al., 2023).

Change detection methods, such as continuous change detection and classification (CCDC), have been widely utilised to monitor various land cover changes through identifying consecutive change observations (Zhu and Woodcock, 2014). While effective for long-term monitoring, it often exhibits delays in precisely determining the timing of change events, which can limit its effectiveness for timely mapping applications (Fuentes et al., 2024; Verbesselt et al., 2011). Furthermore, the performance can vary considerably depending on forest type and the complexity of disturbance regimes, often resulting in high omission and commission errors (Cohen et al., 2017). For ASM monitoring and mapping, traditional machine learning (ML) approaches have struggled to achieve consistent accuracy, particularly in distinguishing ASM disturbances from other forest changes in the complex wet tropical regions (Janse van Rensburg and Kemp, 2022; Snapir et al., 2017). Recent advances in deep learning (DL) present opportunities to overcome these limitations, with demonstrated improvements in mapping ASM activities in the wet tropics using optical imagery (Couttenier et al., 2022; Gallwey et al., 2020). While these studies have been successful, they do not exploit temporal domain information, which is crucial for ASM studies (Fonseca et al., 2024; Mensah et al., 2025a). Currently, there have been no remote sensing studies that have applied DL techniques to S1 SAR images for ASM detection, especially in differentiating ASM disturbances from other forest changes in complex wet tropical regions.

This study proposes a novel approach that integrates temporal-domain information with a DL technique to timely map ASM activities in persistently cloudy regions in the wet tropics using S1 imagery. Specifically, the method employs spectral-temporal information derived from the CuSuM algorithm (Mensah et al., 2025a) and spatial information from a DL model to classify CuSuM-identified forest land-use ‘breaks’ and differentiate ASM from other forest disturbances. In this study, we address key areas regarding the timely detection of ASM and spatially explicit differentiation of ASM disturbances from other forest changes using S1 imagery in the tropics. Our specific objectives are as follows:

- (i) to assess the performance and constraints of using the CuSuM algorithm for timely detection of ASM activities across diverse geographical landscapes and seasons in the wet tropics on a large scale,

- (ii) to demonstrate the use of DL applied to S1 imagery incorporating temporal-domain information to classify CuSuM-identified forest land-use ‘breaks’ into ASM and other forest disturbance drivers across various tropical forest conditions and seasons,
- (iii) to benchmark the model’s performance against other traditional ML classification methods, and
- (iv) to assess the trade-off between the timeliness of classification and the level of confidence in detecting changes in mining areas within the context of practical use scenarios during both rainy and dry seasons.

This study is organised as follows: Section 6.3 presents a brief description of the study area and an overview of the datasets used to develop and validate the model developed in this study. The DL methodology proposed in this study to classify CuSuM-identified forest land-use ‘breaks’ into ASM and other forest disturbance drivers from S1 imagery is presented and explained in Section 6.4. It also details how the labelled datasets for model training, validation, and testing were collected. Additionally, the performance metrics used to evaluate the S1-based change and predicted maps are discussed in this section. The results of the performance of the developed models for the timely mapping of ASM are detailed in Section 6.5, and the discussion is presented in Section 6.6. Finally, Section 6.7 concludes by summarising the relevance of the findings.

6.3 Study area and datasets

6.3.1 Study sites

Two sites in the wet tropical rainforests of southern Ghana were selected: the Ashanti site (a) and the Western site (b), as they have been recognised as hotspots for ASM operations (Owusu-Nimo et al., 2018; Gallwey et al., 2020), as shown in Figure 6.1. The Ashanti site is located in the Atwima Mponua District of the Ashanti Region of Ghana, situated between longitudes 1°58’W and 2°4’W and latitudes 6°31’N and 6°36’N (Figure 6.1a). The Western site is located in the Wassa Amenfi East District in the Western Region of Ghana, within longitudes 1°56’W and 2°2’W and latitudes 5°38’N and 5°46’N (Figure 6.1b). The study sites have a tropical climate with two main rainfall periods and distinct wet and dry seasons. The primary rainfall period is from March to July, with a minor season from August to early November. Annual rainfall ranges from 1700 to 1850 mm at the Ashanti site and 1400 to 1730 mm at the Western site (Atwima Mponua District Assembly, 2018; Wassa Amenfi East Municipal Assembly, 2018). Despite the significant rainfall throughout the year at both sites, average annual temperatures remain notably high, reaching up to 27°C at the Ashanti site and 29°C at the Western site (Atwima Mponua District Assembly, 2018; Wassa Amenfi East Municipal

Assembly, 2018).

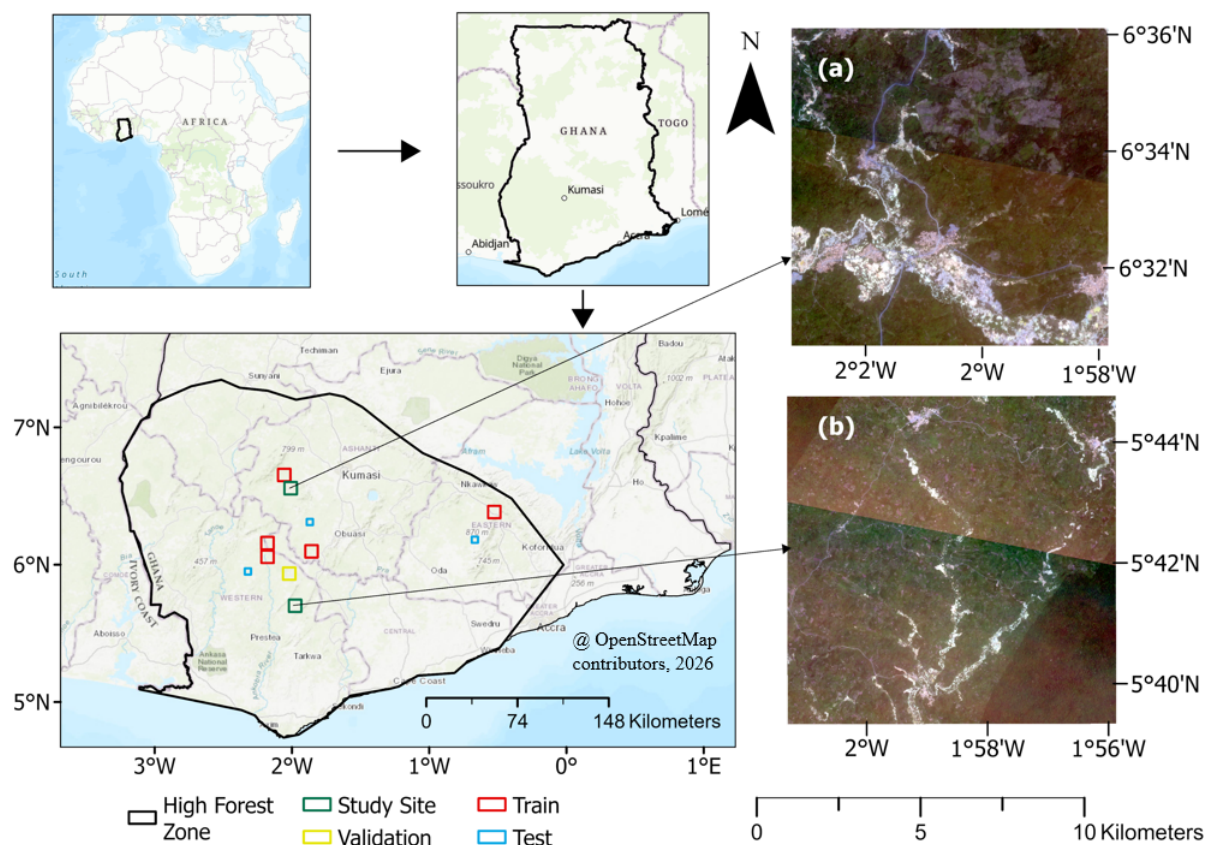


Figure 6.1: The study area in Ghana's wet tropical rainforest includes study sites (green), training sites (red), a 10 km validation tile (yellow), and testing tiles (light blue). A post-mining PlanetScope true colour image of each study site for reference: (a) Ashanti site image from December 2021 in the dry season, and (b) Western site image from April 2021 in the rainy season.

The Ashanti site features semi-deciduous forest, while the Western site has semi-deciduous and tropical rainforest, especially in areas with heavy rainfall. Human activities have significantly disturbed these regions, resulting in the loss of valuable tree species and important forest commodities (Ankomah et al., 2020). Vegetation loss in these areas is mainly due to human activities like illegal logging, mining (i.e. illegal ASM), poor farming practices, and urban expansion, which continue to degrade the natural environment (Ankomah et al., 2020; Atwima Mponua District Assembly, 2018; Wassa Amenfi East Municipal Assembly, 2018). ASM operations along riverbanks heavily impact these areas, with some activities occurring in protected forests. Ecological issues include deforestation, mercury contamination, reduced water quality, land degradation, and pollution of air and water (Bansah et al., 2018).

6.3.2 Datasets

6.3.2.1 Sentinel-1 SAR imagery

We used calibrated, ortho-corrected Sentinel-1A and 1B dual-polarised (VH and VV) Ground Range Detected (GRD) products acquired in ascending orbits available in the Google Earth Engine (GEE) platform for the study period ([Gorelick et al., 2017](#)). The GRD images were acquired in interferometric wide-swath (IW) mode at 5 x 20 m resolution with a 250 km swath width, resampled to 10 m pixel spacing, and with a combined 6-day revisit time. For the Western study site, the time series consisted of 198 images from January 1, 2018, to April 30, 2021. The Ashanti site included 274 images from January 1, 2017, to December 31, 2021. The different periods accounted for the evaluation of the effectiveness of the proposed approach for the timely mapping of ASM during the rainy and dry seasons.

6.3.2.2 Reference data: Optical images and ASM mining footprints

The accuracy and timeliness of the S1 detections were evaluated using Sentinel-2 and high-resolution PlanetScope optical imagery from the period when ASM activity was detected. The optical images acquired within +/- 8 days of the S1 detection dates were utilised to verify the occurrence and timing of change events and to distinguish mining activities from other forest disturbances. The Sentinel-2 surface reflectance (Level 2A) includes all cloud-free imagery products from Sentinel-2A and 2B, acquired with 13 bands and a 5-day revisit time. We used the PlanetScope surface reflectance product, which is orthorectified and scaled, with a pixel resolution of approximately 3 m and four spectral bands (i.e. red, blue, green, and near infrared). To evaluate our methodology during the dry season, the Ashanti site image was acquired on 22 December 2021 ([Figure 6.1a](#)), while the Western site image was acquired on 18 April 2021 to assess ASM detection in the rainy season ([Figure 6.1b](#)). As part of the validation framework, we incorporated annual datasets of ASM footprints for southern Ghana, covering the period 2015–2024. These datasets were collected through SERVIR West Africa in collaboration with the Centre for Remote Sensing and Geographic Information Services (CERGIS) at the University of Ghana ([Abramowitz et al., 2023](#)). The ASM footprint data provide an independent reference, enabling robust temporal validation of the model outputs against observed forest land-use changes. Additionally, the ASM footprint data were used to guide the labelled data collections.

6.4 Methods

The general workflow for the proposed novel SAR-based DL methodology for timely mapping of ASM activities is summarised in [Figure 6.2](#). It involves four major steps: (1) S1 SAR image preprocessing, (2) CuSuM algorithm to generate forest land-use breaks, (3) Creation

of labelled datasets for DL model (U-Net) training on S1 backscatter, cross-polarisation ratio (vegetation index), textural features, topographic variables, and change magnitude (temporal domain information) derived from CuSuM-detected forest land-use breaks, and (4) Secondary classification on the last image in the time series where a change event is evident, distinguishing mining from other change drivers. For comparative assessment, various classical pixel-based machine learning classifiers were used to benchmark the performance of the DL method against existing practices.

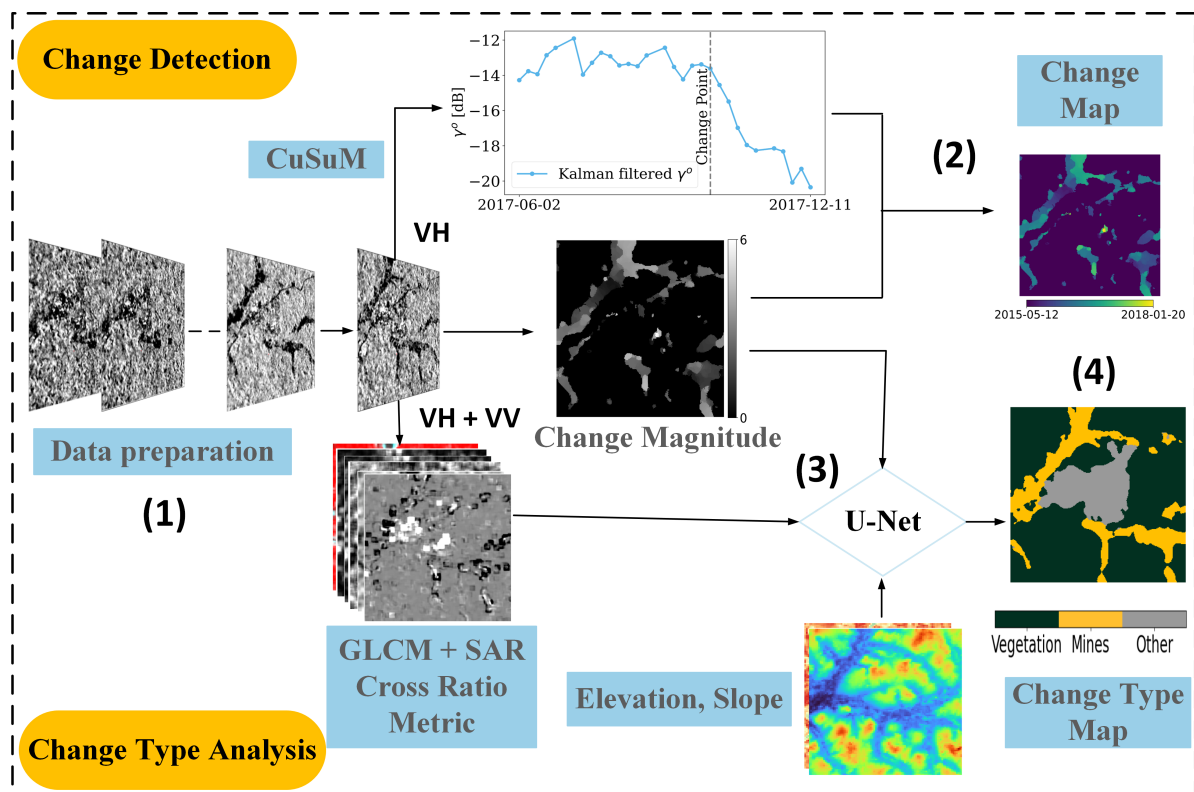


Figure 6.2: Schema representing the workflow for the SAR-based deep learning methodology for the timely mapping of ASM activities from Sentinel-1 imagery in the wet tropics. The historical period is utilised to create forest land-use ‘breaks’, then a U-Net is used to perform secondary classification on the last image in the time series where a change event is evident, distinguishing mining from other forest canopy change drivers.

6.4.1 Sentinel-1 images pre-processing

We first created an ARD stack for the S1 GRD images in each VV and VH polarisations separately, following the optimal S1 backscatter ARD methodology proposed in Chapter 4. Pre-processing in GEE involved removing border noise and artifacts, followed by a multi-temporal adaptive speckle filtering to reduce speckle using the workflow recommended in Mullissa et al. (2021). We then performed radiometric terrain normalisation using the angular-based method suggested in Vollrath et al. (2020) to create γ^0 S1 data. While SAR imagery is generally less affected by cloud cover, its performance during the rainy season, especially shorter-wavelength

SAR, can be hindered by atmospheric effects from intense rainfall in wet tropical regions (Forkuor et al., 2020). To this effect, we applied the Kalman filter (KF) (Kalman, 1960), as demonstrated in Section 4.6.3 (Mensah et al., 2025a), to remove extreme outliers caused by high-intensity rainfall events before applying the CuSuM algorithm. Additionally, the cross-polarisation ratio (vegetation index) was derived from the S1 GRD data. This index enhances the accuracy of classification by improving the vegetation structure and condition (Nicolau et al., 2021), thereby contributing to the robustness of the model. The details of the S1 bands and the derived index used in this study are summarised in Table 6.1.

Table 6.1: Sentinel-1 GRD SAR polarisations and the corresponding vegetation index, including their respective acronyms and associated frequency or equations.

S1 GRD Metric	Acronym	Equation / Frequency	Reference
Co-polarization	γ_{VV}^0	5.405 GHz	Kellndorfer (2019)
Cross-polarization	γ_{VH}^0	5.405 GHz	Forkuor et al. (2020)
Cross ratio	CROSSPOL	VV/VH	Nicolau et al. (2021)

6.4.2 Change point detection: CuSuM algorithm

We employed the CuSuM algorithm proposed in Chapter 5 of this thesis to generate forest land-use breaks for subsequent spatially explicit differentiation of ASM from other forest land use changes using the U-Net model, utilising VH polarisation, which has been proven to be more effective than VV for ASM mapping (Forkuor et al., 2020; Mensah et al., 2025a). The CuSuM method is less affected by seasonal vegetation variation using S1 data, making it more effective at detecting both subtle and abrupt changes in forest cover (Aquino et al., 2022; Ruiz-Ramos et al., 2020; Ygorra et al., 2021). The CuSuM method analyses the temporal signatures of the entire S1 VH smoothed data stacks (γ_t^0), identifying change points when backscatter variation exceeds a predefined threshold. The method tracks deviations between each pixel's values and the mean ($\overline{\gamma_i^0}$) (i.e. residuals) over time (t), and computes the CuSuM of residuals using Equation 6.1 and determines the magnitude of change using Equation 6.2 (Taylor, 2008).

$$R_{\text{sum},t} = \sum_{i=1}^n \left(\gamma_{t,i}^0 - \overline{\gamma_i^0} \right) \quad \text{Equation 6.1}$$

$$R_{\text{sum_diff}} = R_{\text{sum_max}} - R_{\text{sum_min}} \quad \text{Equation 6.2}$$

where $R_{\text{sum},t}$ is the cumulative sum of residuals, $R_{\text{sum_diff}}$ is the change magnitude, $R_{\text{sum_max}}$ represents the maximum CuSuM value, and $R_{\text{sum_min}}$ denotes the minimum CuSuM value. We masked the residuals using the 10th percentile of the difference $R_{\text{sum_diff}}$ as a threshold and then recalculated the CuSuM of the residuals.

Specifically, we confirm a spectral breakpoint when the product of the detection confidence level (CL) and the change point significance ($CP_{\text{significance}}$) is less than a predefined change point threshold ($CP_{\text{threshold}}$), as defined in Equation 6.3. The CL and $CP_{\text{significance}}$ values were initially computed using Equation 6.4 and Equation 6.5, respectively, employing the change magnitude $R_{\text{random_diff}}$ obtained through a bootstrap analysis (Ygorra et al., 2021). Bootstrapping entails the random reordering of the original smoothed data stacks and subsequent comparison of the resulting CuSuM curves.

$$\text{Change: } CL \times CP_{\text{significance}} < CP_{\text{threshold}} \quad \text{Equation 6.3}$$

$$CL = \frac{n_{\text{greater}}}{n_{\text{bootstraps}}} \quad \text{Equation 6.4}$$

$$CP_{\text{significance}} = 1 - \frac{R_{\text{random_diff_sum}}}{n_{\text{bootstraps}} \times R_{\text{sum_diff}}} \quad \text{Equation 6.5}$$

where n_{greater} represents the number of bootstrap iterations in which $R_{\text{random_diff}}$ exceeds the $R_{\text{sum_diff}}$ estimated from the original time series, and $n_{\text{bootstraps}}$ denotes the total number of bootstrap iterations.

We used 50 randomisations ($n_{\text{bootstraps}} = 50$), which has been recommended as optimal for detecting changes in forest cover across diverse forest types (Sabir et al., 2024; Mensah et al., 2025a), while the $CP_{\text{threshold}}$ was set to 0.5. To minimise false detections and compensate for random noise in the change indices, we applied a 9×9 median filter, along with a sieve filter from the Geospatial Data Abstraction Library (GDAL) to remove polygons smaller than eight pixels using ten-connectedness, as suggested by Sabir et al. (2024). The CuSuM algorithm provided both the change magnitudes and acquisition dates. The change magnitudes were subsequently used as a predictor variable in the secondary classification step.

6.4.3 Disentangling ASM from other forest disturbance drivers

A supervised classification approach, discussed in Chapter 2 Section 2.5.1, benefiting from its ability to improve accuracy with labelled datasets (Gallwey et al., 2020), was employed in the secondary classification step to distinguish ASM from other forest disturbance drivers using a U-Net model. However, since S1 backscatter alone may not be effective in distinguishing small-scale ASM from other anthropogenic disturbances (Janse van Rensburg and Kemp, 2022), we extracted textural features using the Gray-Level Co-Occurrence Matrix (GLCM) and topographic data, which were included as predictor variables to improve classifi-

cation accuracy.

6.4.3.1 Textural and topographic datasets to improve classification accuracy

A recent study has shown that SAR-based textural features calculated using a kernel size of 5 provided optimal results across various forest disturbance types, reducing omission errors and improving the timeliness of detection (Balling et al., 2023). We computed the textural metrics following previously established methodologies (Conners et al., 1984; Haralick et al., 1973). Following an initial exploration to assess the effectiveness of differentiating ASM from other forest land use changes using textural metrics from S1 data in our study area (see Figure 6.3), seven GLCM features were used in this study, as summarised in Table 6.2. The GLCM features were computed from the grayscale values of the last image in the time series where a change event is evident for both the S1 VV and VH bands, using a kernel size of 5×5 pixels in GEE.

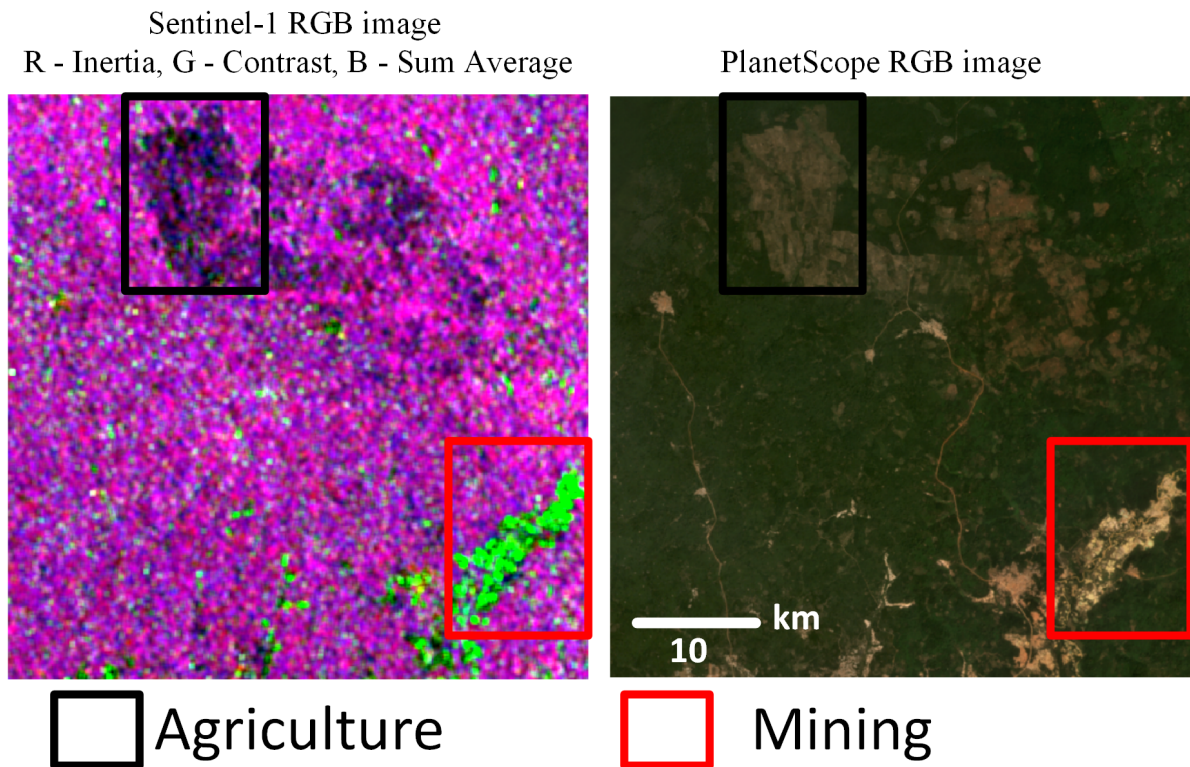


Figure 6.3: Textural metrics from S1 data used to effectively differentiate ASM from other forest disturbance drivers (agricultural lands) in southern Ghana.

Additionally, essential terrain metrics, such as slope and elevation, were derived from the Copernicus 30 m DEM (Mensah et al., 2024a) and used in this study. These metrics enabled the model to effectively capture variations in canopy cover driven by terrain-induced changes (Schlickmann et al., 2025; Mensah et al., 2024a). The Copernicus 30 m DEM was downloaded from the Open Topography portal available at <https://opentopography.org/>. By incorporating the S1 backscatter (i.e. VH and VV bands), vegetation index, topographic information (i.e. slope and elevation), change magnitude derived from the CuSuM forest land use breaks,

and textural data (i.e. 14 GLCM features for both VH and VV bands), our dataset expanded to include a total of 20 predictor variables.

Table 6.2: The seven GLCM features applied in this study, along with their corresponding acronyms and mathematical equations. The $p(i, j)$ represents the probability of the (i, j) -th entry in the GLCM matrix, μ_x and μ_y are the means of p_x and p_y , and N_g represents the total number of unique gray levels present in the quantized image, obtained by reducing the original image’s gray value range to a fixed number of levels for analysis (Conners et al., 1984; Haralick et al., 1973; Balling et al., 2023; Schlickmann et al., 2025).

GLCM Metric	Acronym	Description	Equation
Contrast	CONT	Local variations present in an image within a GLCM	$\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i - j)^2 P(i, j)$
Sum Average	SVG	Average of pixel pairs within a GLCM	$\sum_{k=2}^{2N_g} k P_{x+y}(k)$
Difference Variance	DVAR	Variance of difference of pixel pairs within a GLCM	$\sum_{k=0}^{N_g-1} (k - \mu_{x-y})^2 P_{x-y}(k)$
Difference Entropy	DENT	Difference in the randomness of the grey-level distribution within a GLCM	$\sum_{k=0}^{N_g-1} P_{x-y}(k) \log P_{x-y}(k)$
Dissimilarity	DISS	Variations between pixel pairs within a GLCM	$\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} i - j P(i, j)$
Inertia	INERTIA	Intensity between a pixel and its neighbourhood within a GLCM	$\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i - j)^2 P(i, j)$
Shade	SHADE	Cluster shade of grey-level distribution within a GLCM	$\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i + j - \mu_x - \mu_y)^3 P(i, j)$

6.4.4 Creation of labelled datasets

As discussed in Section 2.5.1, data labelling or data annotation is a crucial task in DL that involves assigning a human-annotation label to different classes to train a supervised learning model (Ponnusamy et al., 2017). Supervised learning models learn from annotated labels, providing context for algorithms to recognize complex patterns, categorize information, and make accurate predictions. High-quality labelled training datasets are essential for robust DL model performance and accurate predictions on unseen datasets.

We aimed to develop a robust model that generalises well in the high forest zones across southern Ghana, where ASM operations are most prevalent, as described in Chapter 3. We used PlanetScope global monthly mosaics basemap (<https://www.planet.com/basemaps/>) to initially identify potential regions of interest (ROIs) of forest change from 2017 to 2024 for training, validation, and testing (Figure 6.1). These regions of interest were carefully chosen to

ensure a balanced representation of land cover, climate, and the distribution of ASM operations across southern Ghana to account for potential temporal and spatial variations. This strategic choice enhances image quality and diversity, ensuring a robust final model that performs well throughout the year, even during periods of heavy rainfall.

To create labelled training data for the model, each 10 km x 10 km training region of interest (ROI) was manually digitised, incorporating images from different times between 2017 and 2024 (see [Figure 6.1](#)). Using the yearly ASM footprints as a guide, we manually digitised the S1 false colour composite image, which includes the red (VV), green (VH), and blue (VV/VH) channels for each ROI. In this study, three main land cover classes are considered, including vegetation, mines, and others ([Table 6.3](#)). The S1 false colour composite image provided adequate visibility of mines, built-up areas, and agricultural fields for human digitising. In cases of confusion, the high-resolution PlanetScope monthly mosaic images were used, taking into account the temporal differences between the datasets. One operator digitised the training area labels, and another verified them to ensure accuracy and reliability. To reduce the impact of atmospheric effects from heavy rainfall on the final model developed, we ensured that the training datasets included images or data from both dry and rainy seasons at different times between 2017 and 2024 in each ROI.

Table 6.3: Description of the dominant forest land cover classes in the study area used in this study.

Class	Description
Vegetation	Combined stable pixels and vegetation (background) over the period.
Mines	Small- and large-scale ASM sites that exist as single, clusters, or corridors.
Other	Built-up areas, smallholder agriculture, large-scale agriculture, and shifting cultivation.

For validation datasets, a region of interest of size 10 km by 10 km (see [Figure 6.1](#)) was digitised using the same methodology described previously. These unseen validation datasets were used for fine-tuning during model training, allowing for performance evaluation under various climatic conditions across different geographical regions and seasons. For testing, we digitised three 256 x 256 pixel image tiles using the same workflow in three different geographical regions in southern Ghana (i.e. Western, Ashanti (Obuasi), and Eastern) ([Figure 6.1](#)). The unseen test datasets (i.e. not used during model training) were selected to evaluate the model's segmentation ability to differentiate mining from other forest land use changes in both agricultural and settlement areas. The image tiles included in the test datasets were acquired from different years and seasons.

6.4.4.1 Training and validation image patches extraction

To manage high computational demands during model training, it is essential to slice the full-digitised 10 x 10 km training images into smaller and more manageable image patches or tiles

for efficient DL training. Patch-based splitting is a necessary strategy that allows for more efficient data handling because only a subset of the image tiles is loaded at a given time, thus reducing the high memory demands and improving the training process. However, the choice of image patch size is an important consideration that must balance computational efficiency while providing adequate spatial context for the model to learn meaningful complex patterns in SAR images. Generally, the minimum image patch size is influenced by the spatial resolution of the imagery (i.e. higher-resolution imagery usually requires larger patches to preserve contextual features relevant to the target classes sufficiently) (Quintana et al., 2023).

In this study, a random patch extraction strategy proposed by Wang et al. (2019) was implemented to divide the full training and validation images and their corresponding ground truth labels into many overlapping patches of size 256×256 pixels, as described in Figure 6.4. Overall, 256 image tiles (256×256 pixels) were randomly selected from each predictor variable (i.e the 20) from the training ROIs to create the training datasets.

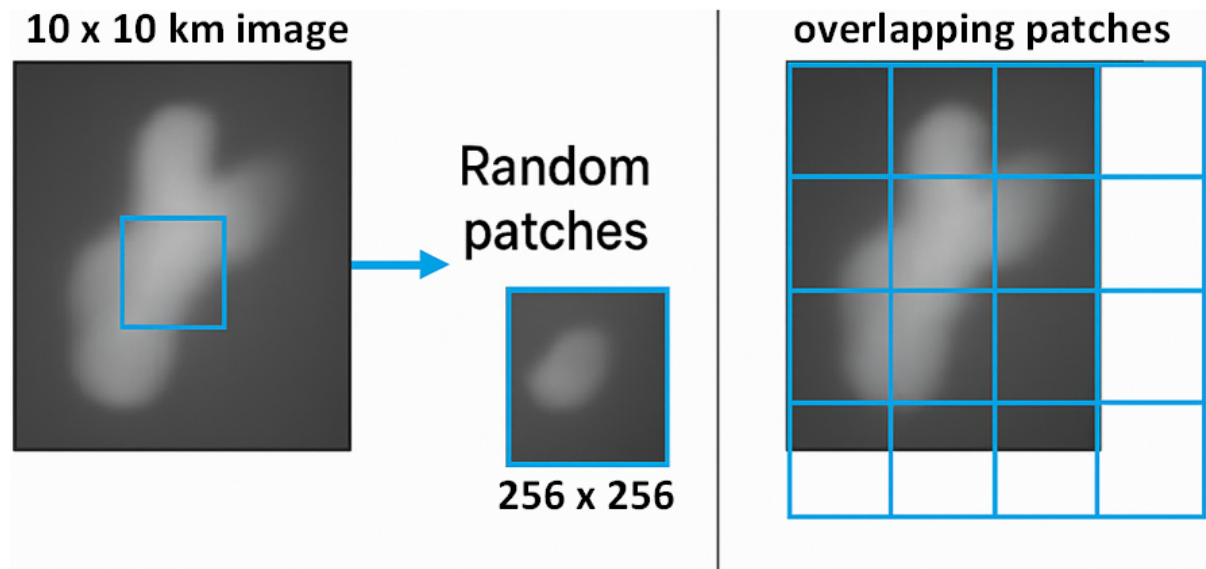


Figure 6.4: Patch-based strategy adopted in this study to split full-digitized 10×10 km images and their corresponding ground truth labels into smaller images and randomly selected training and validation image and label tiles (256×256 pixels) from ROIs for model training and validation.

6.4.4.2 Data augmentation

Data augmentation is an important technique in deep learning to artificially increase the size and diversity of training samples by creating modified versions of original or existing data (Wangiyana et al., 2022). This technique is crucial for creating a robust model that reduces overfitting and improves the model's ability to accurately predict new or unseen datasets (i.e. generalisation capabilities of the model). Common data augmentation methods in DL include noise injection, geometric transformations (cropping, rotation, and flipping), colour space adjustments, and advanced pixel transformations (Wangiyana et al., 2022).

As a common practice in DL, we augmented the training sample images by randomly applying horizontal and vertical flips, as well as random rotations through 90° , 180° , and 270° . In total, 1536 image patches (256×256 pixels) were created from each predictor variable for training.

6.4.4.3 Data normalisation

Data normalisation is a critical step in DL, as it helps the model to train more efficiently by transforming the data into a uniform scale, which facilitates the learning of complex patterns in the datasets (Wang et al., 2019). In this study, various predictor input variables, including topographic data (i.e. elevation and slope), textural features, S1 backscatter, vegetation index, and change magnitudes (temporal domain information) derived from the CuSuM algorithm, were used for model training. Consequently, data normalisation was performed on these input images to have a zero mean and unit variance to facilitate faster convergence during training.

6.4.5 U-Net model development

We employed a U-Net type model to classify ASM from other forest disturbance drivers in this study, an effective encoder-decoder fully convolutional neural network (CNN) initially designed for biomedical image segmentation (Ronneberger et al., 2015). The U-Net architecture is a DL model for image classification, consisting of a symmetrical encoder (downsampling, left-hand side) and decoder (upsampling, right-hand side) path, connected by skip connections that transfer fine-grained features from the encoder directly to the decoder (Ronneberger et al., 2015), allowing a more precise pixel-level segmentation, essential in satellite image analysis. It has been demonstrated to be a computationally efficient CNN-based architecture with less effort for model training and inference, especially for problems with limited training samples, while mitigating overfitting (Ronneberger et al., 2015; Torres et al., 2020). U-Net has been extensively employed in numerous remote sensing applications to detect spatial patterns in remotely sensed data, for example, mapping forest types and tree cover (Brandt et al., 2020; Wagner et al., 2019), deforestation mapping (Wagner et al., 2023), and detecting forest degradation (Dalagnol et al., 2023) with promising results.

The U-Net model implemented in this study is adapted from the original model by Ronneberger et al. (2015), as shown in Figure 6.5. We modified the original U-Net for S1 SAR data by adjusting the number of filters within the convolutions (i.e. 32 filters in the first layer), and by using 256×256 pixel image tiles as input. We built and trained our model with TensorFlow v2.1 (Abadi et al., 2016) in Python v3.7 on a desktop computer with an Intel Core i7 CPU and 128 GB of RAM. Due to the limited training data used in this study, various regularisation strategies were used during model training to reduce overfitting. In addition to the data augmentation techniques described in Section 6.4.4.2, we added 25% dropout layers in the encoder

path and at the model's midpoint (bottleneck). The dropout layers randomly reset a portion of the output features to zero during model training to prevent the model from overfitting and improve its generalisation capabilities (Srivastava et al., 2014).

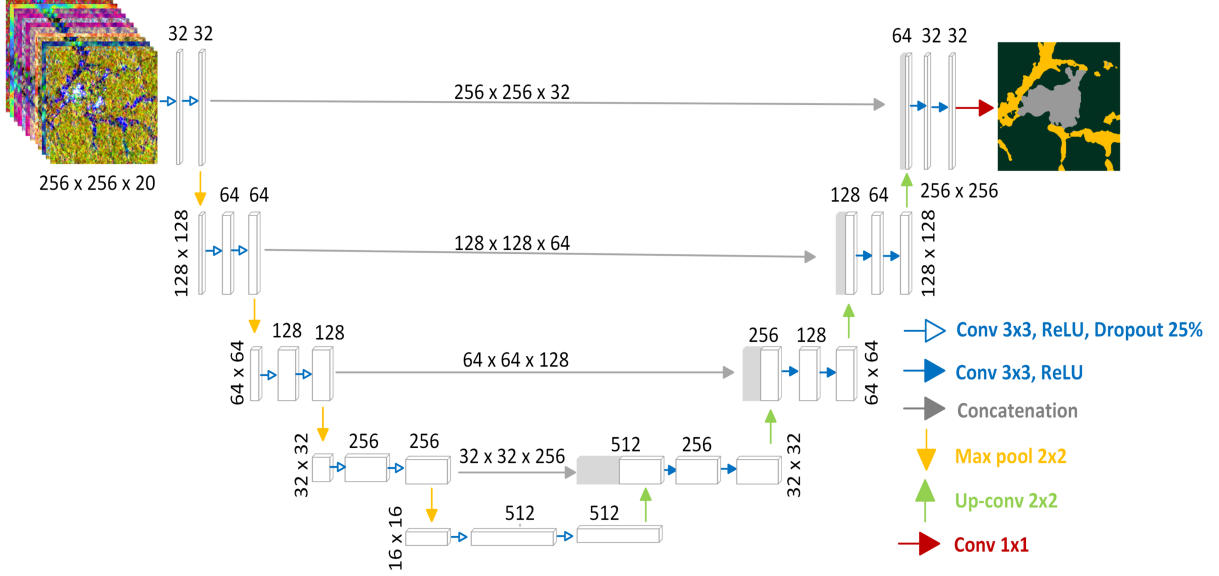


Figure 6.5: The modified U-Net architecture used to distinguish ASM from other forest disturbance drivers from S1 SAR imagery. The model takes Sentinel-1 VV and VH bands, the vegetation index (i.e. VV/VH ratio), temporal domain information from CuSuM (change magnitude), GLCM features, and topographic data as input in 256×256 pixel image tiles, which are then processed through multiple convolutional layers. The final output is a 1-channel prediction mask that identifies different change or forest land cover types.

We used the Adam optimisation algorithm due to its adaptive learning capabilities (Kingma and Ba, 2017), with an initial learning rate of 1×10^{-3} and reduced by 10% when validation loss stopped decreasing for 5 epochs. To effectively manage memory constraints while enhancing training efficiency, the model was trained using a batch size of 16. In this study, the early stopping technique was not employed during model training. Nevertheless, we continuously monitored validation loss during model training, and a clear divergence between training and validation accuracy occurred after approximately 30 epochs. Consequently, the number of epochs for model training was set at 30. To address the class imbalance in the labeled datasets, the focal loss function was implemented together with a dice loss function to improve the multi-class segmentation accuracy, along with applying a weighting factor of 0.5 to the majority class (vegetation). The dice loss function enhanced segmentation performance for minority classes by emphasizing the overlap between predicted and actual masks, whereas focal loss improved the accuracy of segmentation across multiple classes.

6.4.6 Traditional pixel-based ML benchmark algorithms

We benchmark the performance of our U-Net model against several pixel-based conventional ML algorithms. We selected Random Forest (RF) and Support Vector Machine (SVM) classi-

fiers, which have been used to map ASM using S1 data in the tropics (Janse van Rensburg and Kemp, 2022). Additionally, the extreme Gradient Boosting (XGBoost) classifier, which has been shown to produce better classification results than RF and SVM in various forest types in the tropics (Xie et al., 2025). We selected 100 image patches (256×256 pixels) for each predictor variable from the training datasets described in Section 6.4.4.1 for ML model training. These images were flattened and normalised to have zero mean and unit variance to facilitate faster convergence prior to training. We undersampled the majority class (vegetation) to match the minority class (mining) to address class imbalance in the datasets.

The RF and SVM models were developed using the Scikit-learn library (Pedregosa et al., 2011), while the XGBoost model was created with the xgboost library (Chen et al., 2025) in Python. We utilised 300 estimators for the RF model and a maximum depth of 15. For the XGBoost model, we used 100 estimators with a maximum depth of 10 and a learning rate of 0.1. For the SVM model, we used the RBF kernel with a gamma value of 0.1 and a regularisation parameter C of 1. After training the ML models, we used the test datasets described in Section 6.4.4 to make predictions. The prediction masks were then reshaped to match the original image dimensions for accuracy evaluation against the human-annotated ground-truth masks.

6.4.7 Change detection and classification for timely and reliable ASM monitoring

To evaluate our model's generalisation capabilities and performance during both wet and dry seasons on a large scale, we selected 2021 as our ASM target monitoring year, utilising available Sentinel-1A and 1B data. The trained model was applied to predict two unseen areas, each encompassing over 10,000 hectares in both study sites in Ghana (see Figure 6.1a and Figure 6.1b). First, the CuSuM algorithm is used to create a forest land-use alert change map over the study period, detailing the timing and location of change events. Next, the U-Net model is used to classify the forest land-use 'breaks' using the last observation in the time series, where a change event is evident, to analyse ASM patterns and different change types over the period.

For the Ashanti site, the change map was created using S1 images from January 1, 2017, to December 30, 2021, with classification based on the dry season image from December 30, 2021. In the Western site, the change map utilised S1 images from January 1, 2018, to April 22, 2021, with secondary classification based on the image from April 22, 2021, during the rainy season.

6.4.8 Model detection accuracy and evaluation of timeliness

In this study, we conducted two assessments to evaluate our model using evaluation metrics from both the remote sensing and computer vision communities. The first assessment evaluated

the U-Net model's performance against the ML models, comparing the model's prediction masks to manually digitised ground-truth masks for each test site described in Section 6.4.4. We computed the recall (R), precision (P), Intersection over Union (IoU), and F1-score, which are commonly used in computer vision applications. Precision, also termed as user accuracy (UA), refers to the proportion of true positives (TP) to total positives (TP+FP) predicted by the U-Net model, as defined in Equation 6.6. Recall, also termed as producer accuracy (PA), denotes the proportion of true positives (TP) from reference data to all actual true positives (TP+FN), computed using Equation 6.7. The IoU was used to evaluate the spatial overlap between predicted and ground-truth class regions, calculated using Equation 6.8. We assessed the overall model's prediction performance with the F1-score using Equation 6.9.

$$Precision = \frac{TP}{TP + FP} \quad \text{Equation 6.6}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{Equation 6.7}$$

$$IoU = \frac{TP}{TP + FP + FN} \quad \text{Equation 6.8}$$

$$F1\text{-score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad \text{Equation 6.9}$$

Stratified samples were employed in the second assessment to evaluate the model's performance for timely ASM mapping on a large scale, as the computer vision evaluation metrics do not provide a direct comparison with the point-based stratified random sampling accuracy assessments explained in Olofsson et al. (2014) and used in existing remote sensing ASM mapping studies, such as in Gallwey et al. (2020) and Janse van Rensburg and Kemp (2022). By employing a stratified random sampling method suggested by Olofsson et al. (2014), we used 300 stratified points to assess each of the forest cover change and the classified maps with a 1% desired standard error. The change maps were first converted to a binary mask of changed and stable pixels using point class allocation of 150 points for each class. For the classified maps, point class allocations were determined based on class proportions in these maps. For the Ashanti site, points were allocated as follows: 40% for the majority class (vegetation) and 30% for each of the minority classes, resulting in totals of 120, 90, and 90. In the Western site, the allocation was 50% for vegetation, 30% for mining, and 20% for the other class, resulting in total points of 150, 90, and 60, respectively. All 300 sampling points were compared against relevant reference PlanetScope RGB images, basemaps, and mining footprints for each study site. The evaluation metrics used included the F1-score, omission, and commission errors.

We also assessed the rate of SAR-based ASM detection and the disentangling of mining from other change types in a near real-time (NRT) scenario. Due to the persistent cloud cover problems, ASMs that occurred outside the rainy seasons were used for this assessment. The reference date for ASM activity was determined using Sentinel-2 or PlanetScope RGB images, and the temporal lag of ASM detection was estimated from the SAR detection date against the reference date to evaluate change detection and classification rates.

6.5 Results

6.5.1 Results comparison with benchmark algorithms

The effectiveness of the proposed U-Net model is evaluated by benchmarking its performance against the conventional ML algorithms using the test tiles, as illustrated in [Figure 6.6](#). The Sentinel-2 RGB image for each test site is used as a reference. In addition, the quantitative results and comparison of the proposed U-Net model with the traditional ML methods in the timely mapping of ASM activities from S1 SAR imagery are presented in [Table 6.4](#). [Table 6.5](#) presents the results of the class-wise IoU analysis and comparison, while the class-wise F1-score analysis and comparison are shown in [Table 6.6](#).

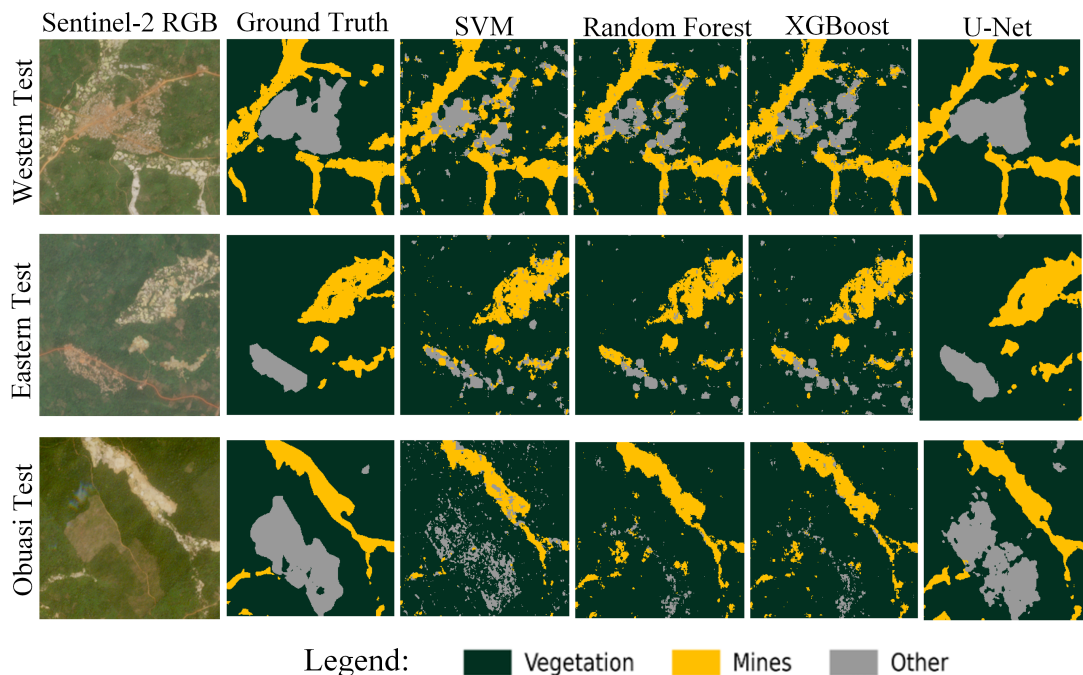


Figure 6.6: Qualitative view of the sample patches (256 x 256 image tiles) results from the test sites assessment of pixel-based ML algorithms and the proposed U-Net model for distinguishing mining-induced disturbances from other forest disturbance drivers in the tropics in Ghana from Sentinel-1 SAR imagery. Reference information for all test tiles is displayed along with the corresponding prediction masks across various ML methods. The Sentinel-2 RGB image is used as a reference image.

Overall, we observed that the U-Net model achieves robust performance in SAR-based ASM mapping when discriminating mining from other forest change types, demonstrating significant improvements over the traditional ML algorithms across several key evaluation metrics (Table 6.4). It outperforms the RF, SVM, and XGBoost algorithms, achieving an exceptional average of the overall accuracy (0.94), precision (0.90), recall (0.92), F1-score (0.89), and mean IoU (0.82) across the various test sites evaluated in this study. As shown in Figure 6.6, the U-Net provides the best results in discriminating mining from other forest land use types in both agricultural areas (Obuasi Test) and built-up areas (Western and Eastern Test), significantly reducing class ambiguities. For instance, the U-Net model does not suffer from the pixel-level noise associated with the other traditional ML methods in SAR-based ASM detection in complex wet environments (see Figure 6.6).

Table 6.4: Quantitative analysis and comparison of traditional machine learning algorithms with the proposed U-Net model for timely mapping of ASM activities using Sentinel-1 SAR imagery. Bold text indicates the classifier’s performance metric scores averaged across all three test sites.

		Accuracy	Precision	Recall	F1-Score	MeanIoU
SVM						
Western	20/01/2018	0.83	0.75	0.72	0.72	0.59
Eastern	27/11/2024	0.90	0.71	0.70	0.71	0.59
Obuasi	24/03/2022	0.83	0.79	0.67	0.72	0.59
Average		0.85	0.75	0.70	0.72	0.59
Random Forest						
Western	20/01/2018	0.86	0.82	0.75	0.77	0.65
Eastern	27/11/2024	0.90	0.71	0.64	0.67	0.56
Obuasi	24/03/2022	0.81	0.81	0.63	0.61	0.51
Average		0.86	0.78	0.67	0.68	0.57
XGBoost						
Western	20/01/2018	0.86	0.82	0.76	0.78	0.66
Eastern	27/11/2024	0.89	0.69	0.66	0.67	0.56
Obuasi	24/03/2022	0.80	0.78	0.59	0.60	0.49
Average		0.85	0.76	0.67	0.68	0.57
U-Net						
Western	20/01/2018	0.93	0.90	0.93	0.88	0.80
Eastern	27/11/2024	0.96	0.92	0.92	0.91	0.84
Obuasi	24/03/2022	0.92	0.88	0.91	0.89	0.81
Average		0.94	0.90	0.92	0.89	0.82

For a more detailed comparison, the class-wise IoU comparison shown in Table 6.5 and the class-wise F1-score comparison in Table 6.6 further emphasize the advantages of the U-Net model in SAR-based ASM detection. This model demonstrates strong generalization ability and outperforms others in segmenting the mining class across all test sites, with an average

IoU of 0.78 compared to XGBoost (0.63), RF (0.63), and SVM (0.62). Notably, the traditional ML algorithms struggle to segment the other class from mining, with an IoU as low as 0.08 for RF and XGBoost, SVM (0.30), whereas U-Net achieves the highest (0.73) in the Obuasi Test site (Table 6.5). Additionally, the class-wise F1-score comparison (Table 6.6) emphasizes the predictive performance of the U-Net model, providing a good balance between precision and recall. As presented in Table 6.6, the U-Net demonstrates robust performances, achieving high F1-scores across various classes—vegetation (0.95), mines (0.88), and other (0.86). The U-Net model outperforms other algorithms, achieving an overall F1-score of 0.89, followed by SVM of 0.72, and 0.68 for both RF and XGBoost algorithms.

Table 6.5: Class-wise IoU comparison of pixel-based ML algorithms and U-Net model for ASM detection using Sentinel-1 SAR imagery.

		Vegetation	Mine	Other	MeanIoU
SVM					
Western	20/01/2018	0.82	0.59	0.35	0.59
Eastern	27/11/2024	0.90	0.63	0.25	0.59
Obuasi	24/03/2022	0.82	0.65	0.30	0.59
Average		0.85	0.62	0.30	0.59
Random Forest					
Western	20/01/2018	0.84	0.67	0.43	0.65
Eastern	27/11/2024	0.90	0.56	0.21	0.56
Obuasi	24/03/2022	0.80	0.66	0.08	0.51
Average		0.85	0.63	0.24	0.57
XGBoost					
Western	20/01/2018	0.84	0.69	0.45	0.66
Eastern	27/11/2024	0.89	0.57	0.21	0.56
Obuasi	24/03/2022	0.79	0.60	0.08	0.49
Average		0.84	0.62	0.25	0.57
U-Net					
Western	20/01/2018	0.89	0.74	0.75	0.80
Eastern	27/11/2024	0.95	0.80	0.78	0.84
Obuasi	24/03/2022	0.90	0.80	0.73	0.81
Average		0.91	0.78	0.75	0.82

Table 6.6: Class-wise F1-score comparison of pixel-based ML algorithms and the proposed U-Net model for ASM detection using Sentinel-1 SAR imagery.

		Vegetation	Mine	Other	MeanF1-Score
SVM					
Western	20/01/2018	0.90	0.74	0.52	0.72
Eastern	27/11/2024	0.95	0.77	0.39	0.71
Obuasi	24/03/2022	0.90	0.78	0.46	0.72
Average		0.92	0.76	0.46	0.72
Random Forest					
Western	20/01/2018	0.92	0.80	0.60	0.77
Eastern	27/11/2024	0.95	0.72	0.35	0.67
Obuasi	24/03/2022	0.89	0.79	0.15	0.61
Average		0.92	0.77	0.37	0.68
XGBoost					
Western	20/01/2018	0.92	0.81	0.62	0.78
Eastern	27/11/2024	0.94	0.73	0.35	0.67
Obuasi	24/03/2022	0.88	0.75	0.15	0.60
Average		0.91	0.76	0.37	0.68
U-Net					
Western	20/01/2018	0.94	0.85	0.86	0.88
Eastern	27/11/2024	0.97	0.89	0.87	0.91
Obuasi	24/03/2022	0.95	0.89	0.84	0.89
Average		0.95	0.88	0.86	0.89

6.5.2 Performance of change detection and classification models for regular ASM monitoring

The novel SAR-based approach proposed in this study effectively generates forest cover change and classification maps, allowing regular monitoring of ASM activities as new S1 images become available. This approach facilitates the rapid identification of the timing and location of each change, as well as the category of change (i.e. the driver of forest disturbance). To demonstrate the effectiveness of our SAR-based methodological approach for comprehensive ASM detection, we selected two areas, each of over 10,000 hectares across various geographical regions in southern Ghana, to show the detection results during both the dry and rainy seasons.

Figure 6.7 and Figure 6.8 present the timely ASM mapping results at the Ashanti site within Atwima Mponua during the dry season and at the Western site within Wassa Amenfi East during the rainy season, respectively. The pre-event high-resolution Planet basemaps from each test site are displayed in Panel A (Figure 6.7A and Figure 6.8A). The forest cover change

maps (i.e. forest land use alerts) over the change period from each site are shown in Panel B, detailing the precise location and timing of each change over the period (Figure 6.7B and Figure 6.8B). Panel D presents the classification maps of the last image in the time series where a change event is evident, providing an understanding of each change type corresponding to the forest land use change alerts (Figure 6.7D and Figure 6.8D). The post-event high-resolution Planet basemaps from each test site are displayed in Panel C as reference (Figure 6.7C and Figure 6.8C).

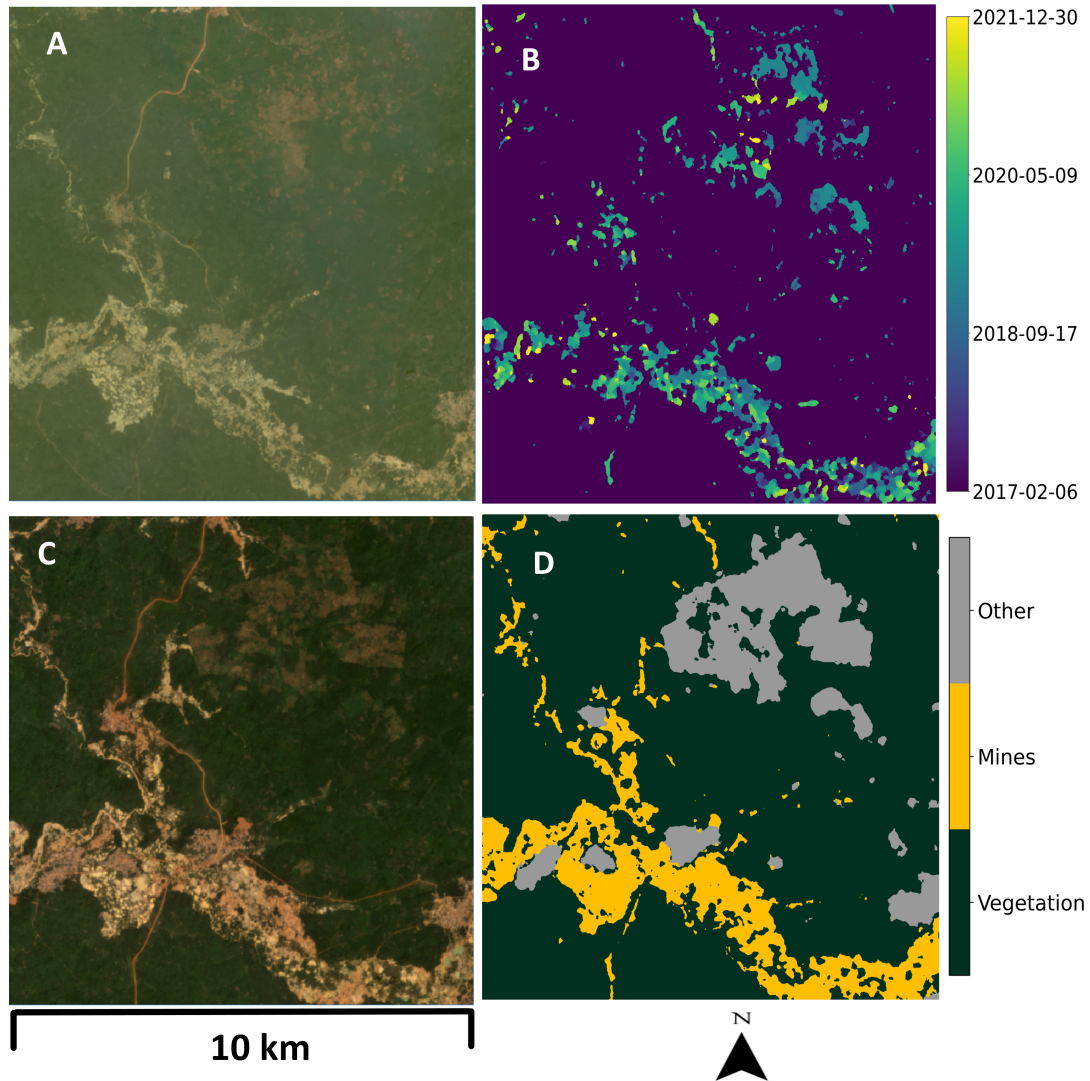


Figure 6.7: The timely detection of ASM using the proposed method at the Ashanti test site within the Atwima Mponua District during the dry season. (A) The pre-event high-resolution Planet basemap from January 2017. (B) The CuSuM change map over the change period, showing the timing and precise location of forest land use change alerts. (C) The post-event high-resolution Planet basemap from December 2021. (D) The classified map of the last image in the time series, where a change event is evident, shows the various forest change types corresponding to the forest land use change alerts.

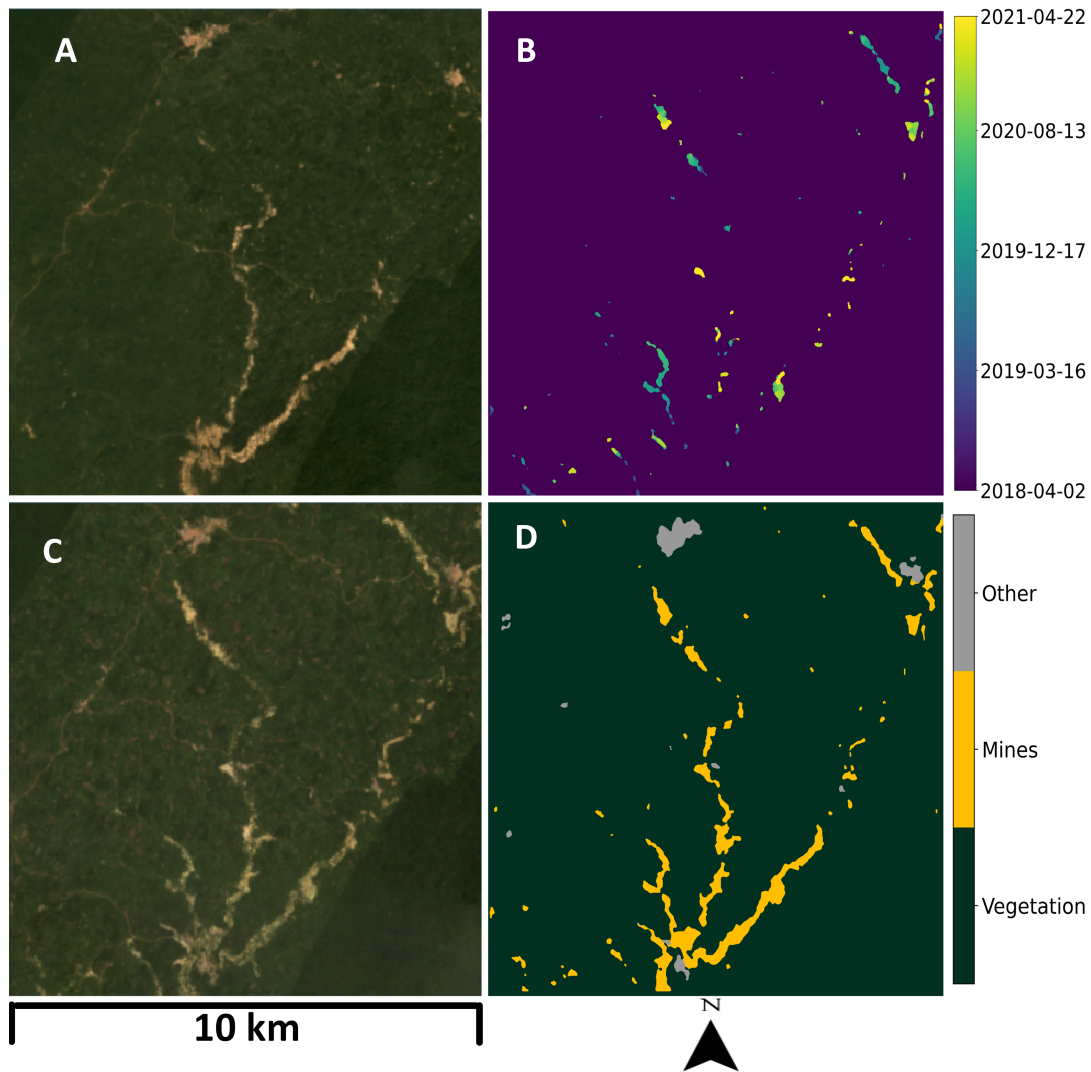


Figure 6.8: The timely mapping of ASM using the proposed method at the Western test site within the Wassa Amenfi East District during the rainy season. **(A)** The pre-event high-resolution Planet basemap from January 2018. **(B)** The CuSuM change map over the change period, showing the timing and precise location of forest land use change alerts. **(C)** The post-event high-resolution Planet basemap from April 2021. **(D)** The classified map of the last image in the time series, where a change event is evident, shows the various forest change types corresponding to the forest land use change alerts.

[Table 6.7](#) and [Table 6.8](#) illustrate the results of the classification accuracy assessments for classified maps at the Ashanti site during the dry season and at the Western site during the rainy season, respectively. The classification accuracy results ([Table 6.7](#) and [Table 6.8](#)) show that the U-Net model consistently accurately distinguishes ASM from other types of changes with very high accuracy from the S1 imagery, achieving an overall F1-score of 0.97 at both sites. The results indicate relatively low commission and omission errors for the mining and vegetation classes, each below 7% at both sites ([Table 6.7](#) and [Table 6.8](#)). A previous optical study to map ASM activities in Ghana ([Gallwey et al., 2020](#)) found higher class accuracies than pixelwise assessments, attributed to probability voting during ensembling and a lower chance of random

samples coinciding with confusion regions along class boundaries, which aligns with what is observed here. The high commission error of 10% for the other class during the rainy season at the Western site is mainly due to: 1) shifting cultivation leading to secondary vegetation regrowth in agricultural fields during heavy rainfall events; and 2) confusion in differentiating the mining class from the other class during the early stages of a change event.

Table 6.7: Confusion matrix and performance metrics for the stratified sampling assessment in the Ashanti site for ASM detection during the dry season. Metrics include class F1-score, omission error, and commission error.

Dry season – 30 Dec 2021		Predicted			Class F1-score	Omission error	Commission error
		Vegetation	Mines	Other			
True	Vegetation	118	2	2	0.97	3%	2%
	Mines	2	85	0	0.96	2%	6%
	Other	0	3	88	0.97	3%	2%
Overall F1-score							0.97

Table 6.8: Confusion matrix and performance metrics for the stratified sampling assessment in the Western site for ASM detection during the rainy season. Metrics include class F1-score, overall F1-score, omission error, and commission error.

Rainy season – 22 Apr 2021		Predicted			Class F1-score	Omission error	Commission error
		Vegetation	Mines	Other			
True	Vegetation	149	3	3	0.98	4%	1%
	Mines	0	96	2	0.97	2%	4%
	Other	1	1	45	0.93	4%	10%
Overall F1-score							0.97

Additionally, we evaluated the performance of the CuSuM algorithm in creating reliable forest land use change alerts at both sites during dry and wet seasons using smoothed S1 data in the spatial domain. [Table 6.9](#) and [Table 6.10](#) present the results of the accuracy of change detection in the spatial domain to create forest cover change maps at the Ashanti site during the dry season and at the Western site during the rainy season, respectively. The CuSuM algorithm shows robust performance when comparing stable and changed pixels during the rainy and dry seasons, achieving an overall F1-score of 0.95 and 0.96 at the Western and Ashanti sites, respectively ([Table 6.9](#) and [Table 6.10](#)). The results of the accuracy assessment show relatively lower commission and omission errors in detected changes of less than 7% at both sites ([Table 6.9](#) and [Table 6.10](#)).

Table 6.9: Performance assessment of change detection in the spatial domain over the change period from 1 January 2017 to 30 December 2021 at the Ashanti site.

Ashanti Jan 2017 – Dec 2021	Stable pixels	Changed pixels	Total	Commission error
Stable pixels	143	5	148	4%
Changed pixels	7	145	152	3%
Total	150	150		
Omission error	3%	5%	Overall F1-score	0.96

Table 6.10: Performance assessment of change detection in the spatial domain over the change period from 1 January 2018 to 22 April 2021 at the Western site.

Western Jan 2018 – Apr 2021	Stable pixels	Changed pixels	Total	Commission error
Stable pixels	145	9	154	3%
Changed pixels	5	141	146	6%
Total	150	150		
Omission error	6%	3%	Overall F1-score	0.95

6.6 Discussion

6.6.1 ASM mapping and monitoring timeliness analysis

This study examined the minimum number of images required for the proposed SAR-based methodological approach to generate alerts for confirmed pixel changes. The temporal lag between the reference date of the ASM activity and S1 change detection dates, as well as dates to reliably differentiate mining activities from other change categories over mining sites A and B, is illustrated in [Figure 6.9](#). The S1 VH backscatter time series profiles over the mining sites are displayed, accompanied by the dates of detected changes (right-hand side). The minimum images required before a change event (i.e. the historic period), optical ASM confirmed date (gray), and S1 detected dates (red) are displayed. Additionally, pre- and post-change Planet and Sentinel-2 imagery is provided.

We observed a delay of 6 days at mine site A before an alert was generated, while a delay of 9 days was observed at mine site B from S1 imagery ([Figure 6.9c](#)). The results of this study generally show that the proposed approach can lag behind optical detections significantly across various ASM sites, which aligns with previous studies ([Tang et al., 2023](#); [Mensah et al., 2025a](#)). This delay occurs because optical sensors respond immediately to forest losses related to vegetation phenology following vegetation clearance, while SAR sensors show responsiveness to variations in forest structural characteristics. The CuSuM method is sensitive to shifts in the mean, which are dependent on the timing of these changes, as it averages all backscatter values over the entire period ([Ygorra et al., 2024](#)). Consequently, changes that occur at the end of the observation period present greater challenges for detection. As a result, we found

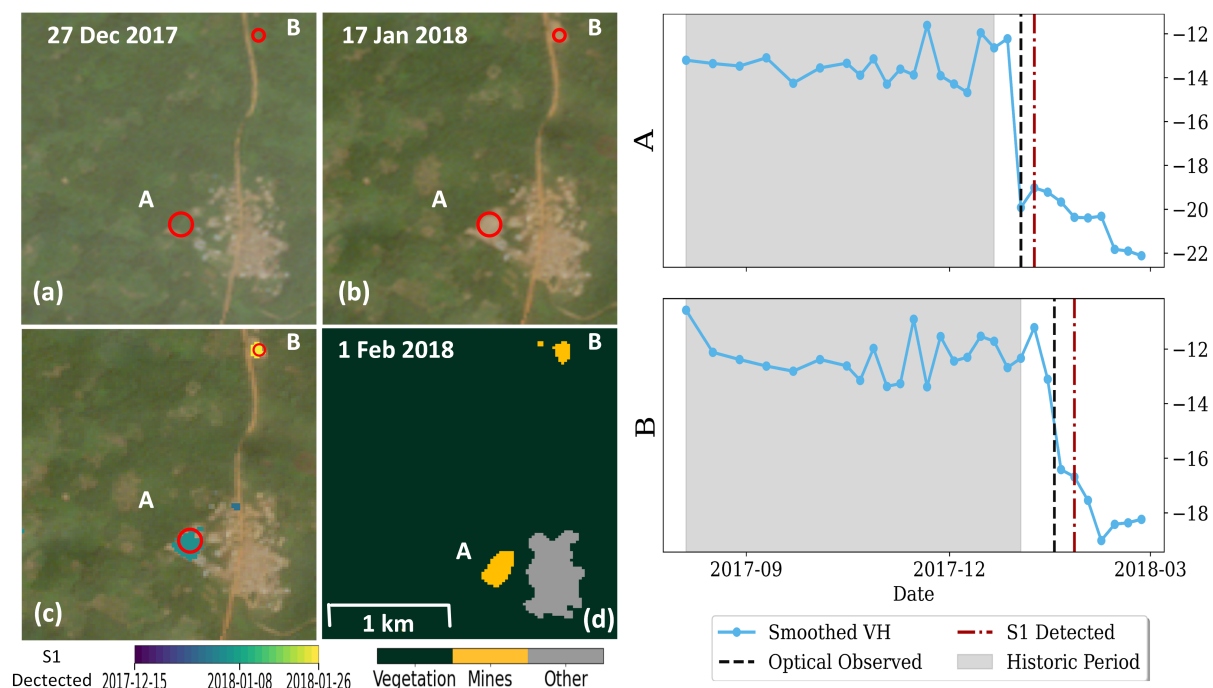


Figure 6.9: Timeliness analysis of the proposed method to reliably distinguish ASM from other change types for mine sites A and B in Ghana. (a) Planet image acquired on December 27, 2017, before the change event. (b) Sentinel-2 image acquired on March 17, 2018, showing the change events at both mine sites. (c) CuSuM change alerts map showing changes fully detected at mine A on January 8, 2018, with a possible 6 days compared to the optical detection dates (January 2, 2018), as well as for mine site B on January 26, 2018, with a possible 9 days compared to the optical detection dates (January 17, 2018). (d) Change type predicted map for Sentinel-1 image acquired on February 1, 2018 (i.e. mining can be distinguished from other forest disturbances within the 18-day delay inherent in our approach). The S1 VH backscatter time series profiles over the mining sites are displayed, accompanied by the dates of detected changes (right-hand side). The minimum images required before a change event (19 images, i.e. the historic period), optical ASM confirmed date (gray), and S1 detected dates (red) are displayed. Additionally, pre- and post-change Planet and Sentinel-2 imagery is provided.

that three consecutive images (i.e. 18 days) are needed after a change event and 19 images before the change event to reliably generate an alert. Using more S1 images before the change event (i.e. more than 19 images) often affects the detection of subtle changes and introduces delays in creating alerts, whereas using a few images results in unstable time series that are highly sensitive to false alerts. Therefore, the optical delay using our SAR-based approach to produce a change alert can be up to 18 days. Our findings indicate that a temporal lag of up to 18 days was sufficient to enable the U-Net model to reliably distinguish ASM activities from other forest disturbances in the study area with high certainty. In future research, incorporating the Bayesian updating method following initial detection could be advantageous. This approach would use each new observation to refine the probability of forest loss by utilising prior information, thereby improving the NRT detection capabilities of the proposed approach.

6.6.2 Performance of CuSuM for timely ASM monitoring on a large scale

Our findings highlight that CuSuM applied to S1 smoothed data provides a robust approach for timely ASM monitoring in wet tropical environments on a large scale across different geographical areas throughout the year (Figure 6.7B and Figure 6.8B). By mitigating false positives caused by atmospheric effects from active rainfall, this approach significantly enhances the accuracy and reliability of SAR-based detection. This confirms the effectiveness of smoothing S1 data for forest applications, as demonstrated by previous studies. These studies have highlighted the benefits of smoothing S1 data for detecting ASM activity on a small scale (Mensah et al., 2025a), mapping sugarcane (Li et al., 2024), monitoring vegetation phenology (Schlund and Erasmi, 2020; Soudani et al., 2021), and assessing deforestation (Kellndorfer, 2019). Moreover, the accuracy of change maps created using CuSuM and S1 imagery during the wet seasons is significantly affected by variations in soil and vegetation moisture content. These fluctuations lead to uncertainty in identifying the precise point of change, resulting in a high false positive rate (Sabir et al., 2024). However, our results in Figure 6.7B and Figure 6.8B suggest that the smoothed S1 data significantly suppresses the impact of soil and vegetation moisture, allowing the generation of a more accurate change maps during both the wet and dry seasons, with overall F1-scores of 95% and 96% in the spatial domain, respectively. The results obtained in Table 6.9 and Table 6.10 demonstrate that CuSuM is reliably able to generate forest disturbance alerts caused by ASM, with relatively low commission and omission errors of less than 7% when comparing stable and changed pixels during both the rainy and dry seasons.

6.6.3 Performance of the U-Net model for disentangling ASM from other change types

Previous studies employing S1 SAR and traditional ML methods to identify ASM and its associated deforestation in the wet tropics encounter challenges due to speckle or signal noise, leading to increased false positives and compromised classification accuracy (Janse van Rensburg and Kemp, 2022). The performance of the U-Net model demonstrates its superiority over traditional ML methods to address core challenges in mapping ASM activities in the tropics using S1 SAR data. The findings in this study suggest that the U-Net model is significantly more accurate than the baseline ML classifiers in terms of both false negatives and false positives (Table 6.7 and Table 6.8) and is not impacted by the pixel-level noise due to speckle or signal noise problems associated with the other traditional methods (see Figure 6.6). U-Net outperforms other methods, achieving an average F1-score of 89% compared to XGBoost (68%), Random Forest (68%), and SVM (72%) across the various test sites (Table 6.6). These findings are consistent with those earlier reported by Gallwey et al. (2020) in detecting ASM activity from Sentinel-2 data using DL in southern Ghana. Additionally, the model showed strong generalisation abilities across the various test sites with a mean IoU (0.80 to 0.84) com-

pared to XGBoost (0.49 to 0.66), Random Forest (0.51 to 0.65), and SVM (0.59), as illustrated in [Table 6.5](#). This suggests that the model can be effectively utilised across various countries in the Sub-Saharan African region, provided relevant local training samples are added.

Furthermore, the stratified random sampling assessment ([Table 6.7](#) and [Table 6.8](#)) demonstrates the high accuracy of the predicted maps, with omission and commission errors consistently below 7%, except for the other class, which had a 10% commission error during the wet season. These findings demonstrate improvements compared to previous SAR-based methods reported in the literature for mapping ASM activities in wet tropical regions with typical commission/omission errors ranging from 10% to 30% ([Janse van Rensburg and Kemp, 2022](#)). The observed commission error of 10% for the other class during the wet season is attributed to shifting cultivation, which allows secondary vegetation to reemerge, as well as challenges in accurately distinguishing the mining class from other classes during the early stages of a change event.

Despite the strong performances achieved by the U-Net model, we observed through visual inspection of the classified maps that polluted rivers with high sediment loads are often classified as mines due to the limited land cover classes used in the model. Future studies could benefit from broadening the model's classification schemes to encompass different forest land cover classes, such as polluted water, logging, and natural causes of forest disturbances like drought and forest fires. This expansion could help create a more robust model for analysing change types more accurately and comprehensively. Studies have shown that the U-Net may struggle with the contextual understanding of complex patterns in SAR images ([Hasimoto-Beltran et al., 2023](#); [Prajapati et al., 2025](#)), which are crucial for distinguishing ASM from other changes in forest cover. Our developed method significantly improved the accuracy of ASM detection in the wet tropics through the integrated use of backscatter, topographic data, change magnitudes, and GLCM textural features. However, future research could benefit from exploring the significance of each input predictor in timely ASM mapping.

6.7 Conclusion

This study proposed a novel SAR-based approach that integrates temporal-domain information with a U-Net DL model to timely detect and characterise ASM activities from other forest land use changes in persistently cloudy regions in the wet tropics using S1 imagery. The accuracy assessment results indicate that CuSuM applied to KF-smoothed S1 imagery showed robust performances in the timely and reliable detection of ASM activities in mining landscapes in the tropics on a large scale. CuSuM achieved a commission and omission error of less than 7% when comparing stable and changed pixels in the spatial domain across the rainy and dry seasons. While the CuSuM effectively tracks ASM-induced forest disturbances, it is sensitive

to the number of images analysed before a change event. The use of more images prior to a change event often affects the detection of subtle changes in forest cover caused by ASM and introduces delays in creating alerts, whereas using a few images results in unstable time series that are highly sensitive to false alerts. In this study, 19 images before a change event were found to be optimal for the timely detection of ASM activities in the study area. Additionally, our findings demonstrate that integrating GLCM textural features, topographic information, and temporal domain information derived from CuSUM detected forest land use breaks significantly enhanced the performance of the DL model, mitigating limitations often encountered when applying the U-Net to SAR imagery. We observed that the proposed approach enables timely tracking and characterisation of ASM from other forest land use changes, with possible delays of up to 18 days, highlighting its operational potential for NRT monitoring of ASM activities. These results underscore the capability of this approach to continuously detect new or ongoing ASM sites, thereby addressing limitations identified in previous studies on the use of S1 SAR imagery for ASM detection in southern Ghana ([Forkuor et al., 2020](#); [Janse van Rensburg and Kemp, 2022](#)). The U-Net model outperformed classical pixel-based ML classifiers, achieving an average overall F1-score of 89% compared to XGBoost (68%), Random Forest (68%), and SVM (72%). Furthermore, the stratified random sampling-based classification accuracy assessment indicates that the predicted or classified maps achieve high levels of reliability, with omission and commission errors of up to 10% during the wet season and below 7% in the dry season. The model's strong generalisation demonstrates significant potential for scalable monitoring of ASM-related land-use changes in the wet tropics globally.

Chapter 7

Synthesis

7.1 Introduction

In this chapter, an overview of the key findings regarding the SAR-based integrated methodological approach for timely and reliable ASM monitoring in persistently cloudy regions, leveraging change detection, cloud computing, and DL are presented. This overview is then followed by a discussion of the limitations of the data, models, and methods used in this study. The implications of the results for stakeholders and local communities, as well as a consideration of how the methods evaluated in this thesis could be operationalised for NRT monitoring of ASM in the tropics, are discussed.

7.2 Research overview and summary of key research findings

This study was motivated by the urgent need to develop a methodology to quickly detect ASM activities, something that has been repeatedly identified as essential to reduce the social and environmental impacts of ASM. Specifically, this research focused on developing a new SAR-based methodology for regular ASM monitoring in cloudy regions, particularly during rainy seasons. Therefore, this study is the first to develop a cost-effective, integrated methodological approach for NRT monitoring of ASM activities in tropical rainforest regions by leveraging S1 time-series data and state-of-the-art statistical CPD and DL-based classification approaches. Despite growing interest in these advanced remote sensing mapping technologies, their application for SAR-based ASM monitoring has remained unexplored.

The findings of this study demonstrate the potential of this novel approach based on S1 imagery to quickly identify and characterise ASM activities, thus significantly reducing the

delay from several months using traditional approaches to within 18 days to generate NRT maps that delineate the spatial distribution, extent, and dynamics of ASM activities in the tropics. A summary of the key findings is presented in Figure 7.1, with further details provided in the following subsections. These key findings are based on the core objectives outlined in the introductory chapter and are further grouped under each methodological chapter of this thesis, assessing how well they were addressed using the integrated methodological approach employed in this thesis.

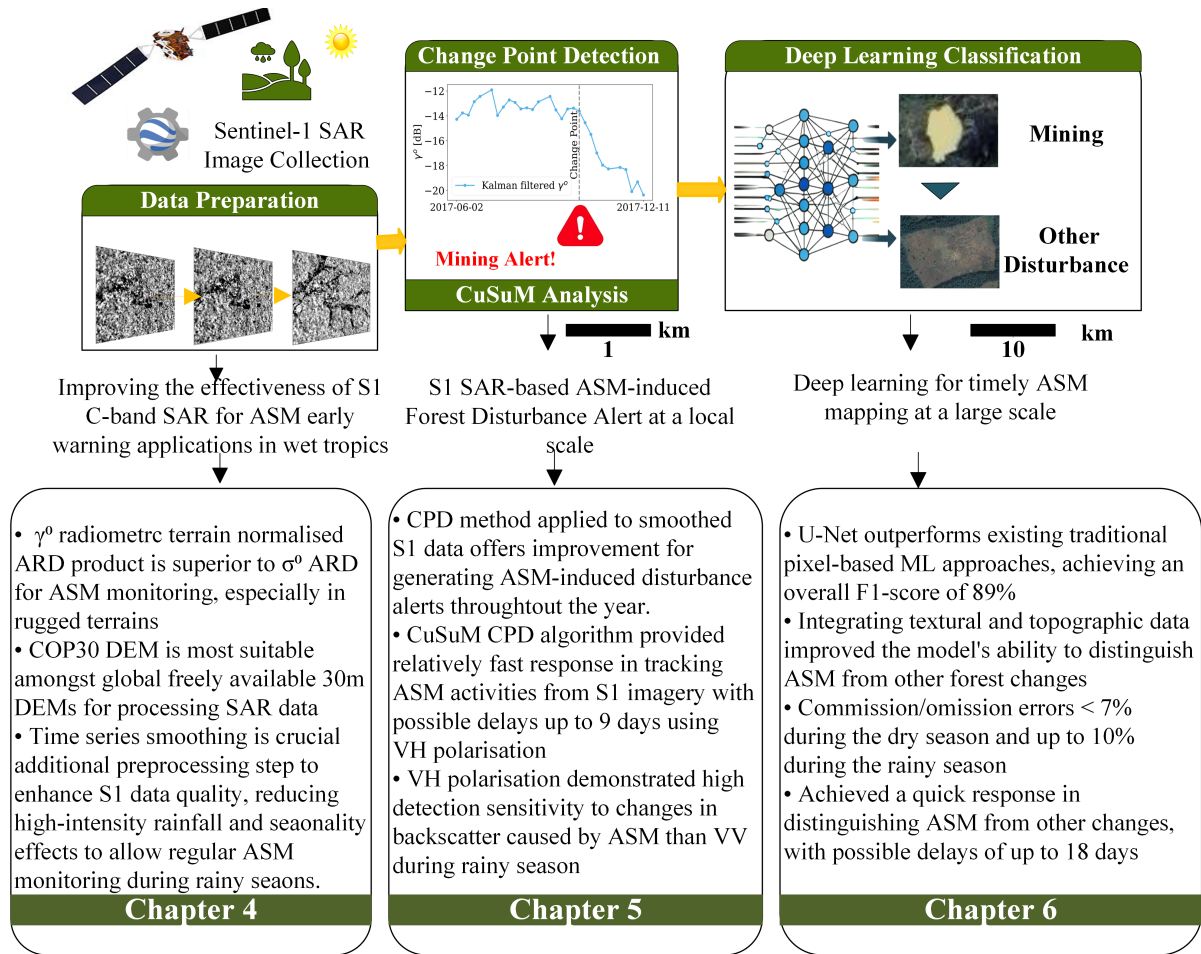


Figure 7.1: Overview of the novel S1 SAR-based integrated methodological approach for timely monitoring and mapping of ASM activities in the tropical rainforest, along with the summary of key findings of this study.

7.2.1 A novel methodology to improve S1 data quality and analytical readiness for ASM early warning applications in the wet tropics

To address the challenges of using S1 C-band SAR data for regular ASM monitoring, as highlighted in Chapter 2 of this thesis, such as high-intensity rainfall effects, forest canopy seasonality, topographic variations, etc, the proposed approach first leverages the continuous availability of S1 data within the GEE environment to create high-quality data updates, allowing for timely

and reliable ASM monitoring in the wet tropics. For example, the use of S1 C-band SAR data can be affected by various factors, such as topography, speckle noise, and atmospheric effects resulting from heavy rainfall, leading to high false alert rates, reduced accuracy, and increased measurement uncertainties (Forkuor et al., 2020; Janse van Rensburg and Kemp, 2022; Kimijima et al., 2022b; Chike and Balz, 2024).

- **Objective 1: Establish evidence-based guidelines for optimising the choice of backscatter normalisation approaches (σ^0 vs. γ^0) for generating S1 ARD products within the GEE environment.**

In Chapter 4, the suitability of using conventional S1 σ^0 and γ^0 radiometric terrain-normalised ARD products was first assessed within the GEE environment for ASM monitoring in the tropical rainforest (Mensah et al., 2024b). An important finding of this study was that the S1 GRD processed imagery, available by default in GEE, if incorporated in any processing workflows without additional preprocessing, is not suitable for timely and reliable ASM monitoring applications in the wet tropics. Some essential SAR preprocessing steps, such as speckle filtering and radiometric terrain normalisation, are not performed on the ingested S1 imagery available by default in GEE (Mullissa et al., 2021). Consequently, using the S1 imagery available by default in GEE may compromise the accuracy and effectiveness of any future SAR ASM detection methods, making further preprocessing essential for achieving reliable results. The findings from this study suggest that to achieve optimal performance using S1 data for timely ASM monitoring in the tropics, any time series images must be radiometrically terrain-corrected (i.e. adjusting the image pixel values to remove the impact of topography on backscatter). Incorporation of this additional preprocessing step is crucial to ensure consistent measurements are achieved between images acquired at different times, thereby allowing for the accurate retrieval of surface changes caused by ASM activity. For example, the conventional orthorectified S1 σ^0 ARD products without radiometric terrain normalisation were found to display higher measurement errors when used in areas with steeper landscapes, resulting in a significant variance of over 130%, compared with about 50% for the γ^0 radiometric terrain-normalised ARD product. These findings demonstrate the importance of using S1 γ^0 radiometric terrain-normalised ARD products to address potential topographic distortions for timely and reliable ASM monitoring on a large scale in the tropics.

- **Objective 2: Investigate the analysis readiness of open-source global DEMs for generating S1 radiometric terrain normalisation γ^0 products for timely and reliable ASM monitoring in the tropics across different forest types and varied topography, including mountainous areas.**

This thesis demonstrated that the choice of DEM when creating γ^0 radiometric terrain-corrected backscatter products should receive greater consideration when attempting to mitigate

terrain-induced effects on SAR backscatter. Chapter 4 of this thesis was the first to evaluate the analysis readiness of four open-source 30m global DEM options (i.e. SRTM, NASADEM, COP30, and AW3D30) for processing S1 SAR data (Mensah et al., 2024a). The details of the DEMs employed here were discussed in Chapter 3 of this thesis. The findings provide valuable insights into the choice of open-source 30m global DEM options to improve the performance of terrain normalisation for γ^0 ARD products. The results demonstrated that the COP30 DEM was the most suitable for creating S1 radiometrically terrain-normalised γ^0 backscatter ARD products among the global open-source 30m DEMs evaluated in this study, particularly in undulating and steep landscapes. This improvement was demonstrated by effectively mitigating terrain-induced effects and achieving the lowest backscatter dispersion response to seasonal rainfall effects and forest canopy seasonality. These findings show the benefits of using the COP30 DEM for processing SAR for extensive ASM monitoring applications.

- **Objective 3: Develop a novel methodology to model backscatter variations caused by (i) seasonality and (ii) outliers from adverse atmospheric conditions to improve the accuracy of ASM detection using S1 SAR data in the wet tropics, particularly during the rainy season.**

Despite the advantages of SAR for regular monitoring in cloudy regions, images acquired in the rainy seasons can be significantly impacted by adverse atmospheric conditions from high-intensity rainfall events. These adverse effects, coupled with backscatter variations due to seasonal variations in forest structure and biomass, have significantly limited the effectiveness of S1 imagery for timely and reliable ASM monitoring in the wet tropics in prior studies. Chapter 4 makes a significant contribution to addressing this limitation by proposing KF as an effective smoothing method to reconstruct time series S1 SAR data and reduce SAR outliers in the temporal domain, aiming to improve the early detection of ASM activity in wet tropical rainforests (Mensah et al., 2025b). Significantly, these findings also suggest that KF provides the most robust description of the seasonal dynamics and is effective for smoothing S1 time-series data with prominent outliers from active rainfall during rainy seasons. These findings establish time-series smoothing as an essential additional SAR preprocessing step and the KF method as a robust and practical approach for effectively smoothing S1 data with outliers during the rainy season.

These findings highlight the importance of using the smoothed S1 radiometrically terrain-normalised γ^0 ARD product, which is processed using the COP30 DEM, for timely and reliable ASM monitoring in tropical regions throughout the year. This ensures that challenges such as topographic distortions, atmospheric effects from active rainfalls, and forest canopy seasonality that significantly influence SAR backscatter are effectively addressed to improve the accuracy and timeliness of ASM detections in the wet tropics. These findings can be used as a guide for future processing of SAR data for timely and reliable ASM mapping applications in the tropics.

7.2.2 CPD for creating S1 SAR-based ASM-induced forest disturbance alert in the tropical rainforest

The challenges associated with the use of S1 C-band data for ASM monitoring in wet tropical regions, as described in the previous section, coupled with persistent cloud cover problems that limit the effectiveness of optical imagery (Gallwey et al., 2020; Snapir et al., 2017), result in a lack of research to date that has explored the timely detection of ASM to facilitate rapid response.

- **Objective 4: Develop a robust approach to automatically detect the early stage of ASM activity using S1 time series data across different geographical areas in the tropics.**

Chapter 5 introduced the first S1 SAR-based ASM-sensitive forest disturbance alert, assessing the potential of using the KF-smoothed S1 radiometric terrain normalisation γ^0 ARD product for timely ASM detection in the tropics (Mensah et al., 2025a). Three statistical CPD algorithms, including CuSuM, PELT, and BinSeg, were tested across ten existing mining sites in different geographical areas in Ghana, comparing the performance of using S1 smoothed γ^0 ARD and original γ^0 ARD (i.e. without smoothing) for the timely detection of ASM.

Identifying the exact change point in SAR time series caused by the start of ASM activity during the rainy season was crucial for the timely detection of ASM activities in the tropics. For example, backscatter variations caused by fluctuations in vegetation and soil moisture content and seasonality introduce uncertainties in generating ASM-induced forest disturbance alerts. CPD methods applied to smoothed S1 imagery showed high detection sensitivity (i.e. ability to detect subtle loss in canopy caused by ASM activities) in the timely detection of ASM. This was achieved by reducing the inherent SAR noise and artifacts caused by heavy rainfall and forest canopy seasonality in the original time series during the wet seasons. As a result, the CPD algorithms enable a significant decrease in uncertainties that cause false alerts or delays in tracking ASM activities using S1 imagery in the wet tropics.

Chapter 5 also assessed the effectiveness of the different S1 C-band SAR polarisations (i.e. VH and VV) for the timely detection of ASM activities in the wet tropics. This study revealed that, for specific forest types and conditions, the VV polarisation exhibited significant variations during the rainy seasons, leading to high uncertainties and significant delays in accurately and timely generating forest disturbance alerts caused by ASM activity. In contrast, the VH polarisation was found to be most sensitive to backscatter changes caused by ASM activities and less affected by seasonal variations in forest structure and biomass, making it the preferred and viable option for the timely tracking of ASM activities in the wet tropics during the rainy season.

In terms of ASM detection timeliness using the CPD algorithms, the results indicate that CuSuM provided the fastest response in tracking ASM activities in both test sites. VH polarisation exhibits a possible delay of up to 9 days in generating the ASM-induced forest disturbance alerts in the best-case outcome. The findings also suggest that the CPD model generalises well across the different geographical regions, offering great potential for NRT monitoring of ASM activities in the tropics throughout the year. The results suggest that CPD techniques can be used as a new alternative approach to analyse S1 time series data and quickly identify early stages of ASM activity continuously throughout the year, delivering timely alerts for swift intervention to prevent its associated destruction of the local environment.

7.2.3 DL-based timely mapping of ASM activities in the tropics using S1 imagery, distinguishing ASM from other forest disturbances

In the context of large-scale monitoring of ASM activities, a binary ASM-induced forest disturbance alert system is often inadequate for timely reporting and targeted intervention on the impacts of disturbances, particularly in heterogeneous tropical ecosystems where multiple disturbance drivers coexist. Subsequently, the CuSuM-identified forest land use ‘breaks’ were refined through a DL model that accurately distinguished ASM activities from other forest disturbances, thereby reducing false positives and enhancing the operational capabilities of the proposed approach.

- **Objective 5: Design a novel, scalable SAR-based DL model for NRT ASM monitoring capable of reliably and accurately distinguishing ASM-related disturbances from other forest land use changes in complex tropical environments.**

Chapter 6 proposed an innovative approach to apply DL to SAR data to classify the CuSuM-identified breaks for timely mapping of ASM activities, distinguishing ASM from other forest disturbances in the wet tropics during both the dry and rainy seasons. The U-Net model was employed for supervised classification, leveraging GLCM textural metrics and topographic data from the Copernicus 30 m DEM to mitigate speckle noise effects and improve classification accuracy. The performance of the U-Net model was validated against existing traditional pixel-based classifiers (i.e. RF, SVM, and XGBoost) used in previous studies and through individual visual assessments.

To improve the robustness of the final DL model, images acquired at different times during both the dry and rainy seasons were included in training. This best-practice DL approach enhances image quality and diversity, ensuring a robust final model that performs well throughout the year, even during periods of heavy rainfall. The results of this study demonstrated that a U-Net model outperforms existing traditional pixel-based ML approaches in accurately distinguishing ASM-induced disturbances from other forest disturbances from S1 SAR imagery,

with a *mean IoU* of 0.82 and an overall *F1-score* of 89%. The model showed robust performance for accurate ASM detection and characterisation during the dry seasons compared to the wet or rainy seasons, with omission and commission errors of up to 10% during the wet season and below 7% during the dry season.

The findings from this thesis indicate that increasing the quantity of training samples through data augmentation techniques significantly improved the generalisation ability of the final model. The final model was tested on a completely new set of S1 images acquired at different times of the year during both dry and wet seasons from three regions in southern Ghana (i.e. Western, Eastern, and Ashanti). Although these images showed significant backscatter intensity variability due to changes in surface characteristics and moisture content, a higher accuracy was achieved at all sites to accurately distinguish mining from other forest disturbances (*meanIoU* ≥ 0.80 and *overallF1 – score* $\geq 88\%$). The results demonstrate the strong generalisation ability of the final model developed in this study, capable of addressing the spatial and temporal variations in the test datasets.

Furthermore, the study highlighted the benefits of incorporating topographic data (i.e. slope and elevation) in the modelling and reinforces the importance of the earlier chapters on DEM testing. Its integration improves classification accuracy, allowing for accurate identification of ASM hotspot areas or subtle and abrupt elevation shifts caused by early ASM activities. For example, in Ghana, ASM operations are characterised by the use of heavy earth-moving equipment such as excavators during the initial vegetation clearance stage. The results suggest that topographic information is useful in identifying the ASM spatial distribution patterns, playing a crucial role in mapping ASM activities.

This study also investigated the potential impact of the use of textural and temporal domain information as predictors when classifying ASM using SAR imagery. The results from this study indicate that by incorporating spectral-temporal information derived from the CuSuM-identified alerts and GLCM textural features, the capability of the U-Net model to understand complex patterns in SAR significantly improved for accurately differentiating ASM from other forest disturbances. This was particularly crucial in addressing the ‘speckled’ effects problem in the final classified maps related to existing traditional pixel-based approaches. The GLCM textural metrics identified in this study as useful for improving classification accuracy in ASM mapping applications using SAR imagery include the contrast, sum average, difference variance, difference entropy, dissimilarity, inertia, and shade.

The S1-based proposed methodological approach tested for the timely detection and mapping of ASM activities on a large scale demonstrated robust performances and quick response in timely tracking and characterising ASM activities in the tropics. While timely ASM-induced forest disturbance alerts can be generated within 6 days after the change occurred, there are de-

lays to reliably discriminate identified alerts into changes caused by ASM activities from other forest land use changes that can be up to 18 days. The optimal number of S1 images required before a change event to accurately generate an alert using the methodology proposed in this study was found to be 19. Using more S1 images before the change event (i.e. more than 19 images) often affects the detection of subtle changes and introduces delays in creating alerts, whereas using a few images results in unstable time series that are highly sensitive to false alerts.

In summary, it can be concluded that the research outlined in this thesis achieved the overarching research aim of this study, established in Section 1.4. The proposed SAR-based methodologies demonstrated high accuracies for the timely and reliable detection of ASM activities when tested for ASM monitoring at a relatively small area (Chapter 5) and on a larger area (Chapter 6) across different geographical areas during both the dry and rainy seasons in southern Ghana. The results showed that the proposed approach has the potential for operational NRT monitoring of ASM activities in cloud-prone regions with demonstrated capabilities for broader applications within sub-Saharan Africa and globally.

7.3 Challenges of using the SAR-based integrated methodological approach for NRT monitoring of ASM activities

This section discusses the challenges associated with the development and application of the novel SAR-based methodologies for the timely detection and mapping of ASM activities in tropical regions. While the approach proposed in this thesis provides timely monitoring tools for creating maps that show the spatial distribution patterns, extent, and operational dynamics of ASM activities throughout the year with minimal delay, further development is crucial to addressing these challenges and enhancing its operational value.

7.3.1 Sourcing sufficient ground truth data

ASM operations often occur in remote and dangerous areas, making field data collection challenging and often impossible. As a result, exact ASM detection dates could not be established with confidence due to the lack of ground truth data specifying the start date of the ASM activities. However, this study relied on high-resolution optical imagery (i.e. Sentinel-2 at approximately 10m resolution and PlanetScope at ~ 3 m spatial resolution) to validate the timeliness of the models developed in this study. In addition, due to persistent cloud cover in southern Ghana, especially during the rainy season, ASMs occurring outside the rainy season were generally used for validation (Chapter 5). However, the effectiveness of the approach for timely ASM monitoring during the rainy season was tested using images acquired during the rainy season for validation (Chapter 6).

At the early stages of this PhD study, extensive efforts were made to collaborate with a Government of Ghana Taskforce (Galamstop) set up in 2019 to combat illegal ASM activities in Ghana to acquire ground truth. Unfortunately, the data obtained was not sufficient (i.e. relatively few drone images acquired over a small area) for a robust and comprehensive validation of the models developed in the thesis, necessitating the reliance on high-resolution optical imagery.

7.3.2 Limited labelled data and land cover classes

One of the most important factors influencing the predictive performance of machine learning models is the amount of available labelled training data. Generally, larger training sample sizes lead to significantly better performance and a more generalised model (Ramezan et al., 2021). A robust and generalised model can be characterised by its ability to accurately distinguish ASM from other forest land cover classes in SAR images acquired at different times and its transferability across various geographic landscapes. However, in remote sensing applications, acquiring sufficient labelled training data to train a DL model can be limited and costly, and links back to the restrictions on ground truth data mentioned in Section 7.3.1. In this study, data augmentation techniques were explored to increase the training data sample size and diversity to enhance the accuracy of classification, a common practice in DL (Chapter 6). Nonetheless, the need to increase the amount of labelled data and allow the model to learn the complex patterns in SAR images more accurately is crucial to further improve the models developed in this study. Additionally, the use of limited forest land cover classes (i.e. forest disturbance drivers) in this study introduced challenges in accurately classifying image pixels associated with mining. For example, turbid water pixels were often misclassified as mining due to the high volume of water used in the mining process. Hence, expanding the labelled classes to include other forest land cover/use classes, such as polluted water, logging, and forest fires, is crucial for further improvement in classification accuracy.

7.3.3 Sentinel-1 SAR image resolution challenges

Although SAR time-series data were used in this study, the moderate spatial resolution of S1 (i.e. an azimuth resolution of approximately 20m and a ground range resolution of roughly 5m, resampled to a pixel spacing of 10×10 m used in this study) can pose a challenge in detecting small-scale ASM sites, which are typically around 20 m in diameter and therefore challenge the spatial resolution limits of S1. This often results in mixed pixels, making the effective detection of these sites particularly difficult.

7.3.4 High computational resource requirements

Generally, training a DL model can be a highly demanding task in terms of computational resources. This is largely due to the need to process large amounts of labelled datasets across complex neural networks with millions of parameters that need to be trained. For example, the training of the 1536 image patches (256×256 pixels) in Chapter 6 was carried out using a Desktop computer with an Intel Core i7 CPU and 128 GB of RAM, which lasted approximately 8 hours. It is therefore expected that higher computational resources will be required to retrain the model with more labelled datasets to upscale for regional or country-level NRT monitoring of ASM activities.

7.4 Implications for policy, stakeholders, and the socioeconomic impact

In light of the alarming rise in ASM activities worldwide, the novel SAR-based approach outlined in this research offers timely monitoring tools to enable NRT monitoring of ASM activities throughout the year in persistently cloudy regions. This swift intervention is crucial for preventing environmental destruction associated with ASM, especially during the rainy seasons in wet tropical regions, where existing SAR-based methods for detecting and mapping ASM activities have been problematic (Forkuor et al., 2020; Janse van Rensburg and Kemp, 2022; Kimijima et al., 2022b). The effective management of ASM has been hindered by several factors, including the informal and undocumented nature of the sector, inadequate government resources, and limited monitoring of ASM activities due to the remote locations of mines (Adu-Baffour et al., 2021; Corbett et al., 2017). By harnessing the early detection capabilities introduced in this research, this approach unlocks exciting new possibilities for robust ASM early warning systems (Chapter 5). This ASM early warning system can play a crucial role in promoting sustainable forest management, supporting action against illegal ASM activities, and enforcing legislation aimed at combating climate change. Furthermore, this initiative would help governments in the Global South in achieving several important targets, such as ending poverty (SDG1 and SDG2), ensuring good health and well-being for miners (SDG3 and SDG12), promoting decent work and economic growth (SDG5 & SDG8), and improving life on land (SDG6, SDG13, and SDG15). Its advantages are directly linked to 9 of the 17 United Nations Sustainable Development Goals (SDGs) (Hilson and Maconachie, 2020).

While ASM offers socioeconomic benefits, illegal ASM undermines economic growth by reducing investor confidence, limiting government revenue, and creating long-term challenges for sustainable economic development (Yeboah, 2023). For instance, the government of Ghana lost about \$2.3 billion in tax revenue between 2010 and 2017 due to illegal mining activities (Yeboah, 2023). This significantly affects the government's ability to fund development

projects and provide essential services. Our findings present critical insights into effectively managing and monitoring ASM activities. The insights drawn from this study are invaluable as they equip policymakers and environmental managers to not only strengthen regulatory frameworks but also take decisive action against illegal mining and promote responsible mining practices that benefit both the environment and the welfare of local communities. The findings will contribute to reducing delays in the production of real-time maps that depict the spatial distribution patterns, extent, and dynamics of ASM activities, thereby facilitating quick responses and supporting restoration actions. Moreover, these findings offer cost-effective, timely monitoring tools that could be valuable for sustainable forest management and assessing progress towards sustainable development objectives, such as the Reducing Emissions from Deforestation and Degradation (REDD+) target.

Within the context of ASM monitoring in Ghana, these findings align closely with national enforcement priorities, particularly the mandate of Operation Vanguard, the government task force established in 2017 to combat illegal mining activities (Botchwey et al., 2019). By delivering an ASM alert system, this research enables sustainable monitoring of ASM hotspots, thereby strengthening evidence-based decision-making and operational response capacities across the country. Typically, the SAR-based ASM alert system, as described in Chapter 5, is more suitable for local-level monitoring, such as in forest reserves, where ASM activities are most prevalent. For extensive NRT monitoring of ASM activities at the regional or country level, the method described in Chapter 6 is more appropriate.

In transitioning from research to implementation, it is expected that the methodology outlined here could be incorporated into a web-based dashboard for stakeholders and the public. This operational dashboard would provide weekly updates as new images become available, using cloud-based platforms such as GEE. Additionally, it can also be recoded to create a user interface software package that is accessible to GIS technicians or local assistants with extensive knowledge of the local terrain and ASM activities in the region. The collection of labelled datasets for model training and validation is straightforward, as described in Chapter 6, and can be done by trained local assistants or a GIS technician. The optimal backscatter ARD preparation methodology in Chapter 4 to enhance S1 data quality and analysis readiness can be automated when new images become available. More importantly, the training of the deep learning model described in Chapter 6 initially requires high computational resources and a significant time investment. However, after the model is successfully trained, it can be used to automatically make generalised predictions without the need for any subsequent retraining. The workflow of our model is designed for computational efficiency, allowing local GIS technicians to execute it easily and ensuring user-friendliness and scalability. While this study primarily focused on Ghana, the presented methodology demonstrates potential for broader applications in mapping ASM across various environmental conditions worldwide.

Overall, the methodologies developed in Chapters 4–6 are robust and scalable, achieving the overarching research aim as outlined in the introductory section: “*to develop a scalable, SAR-based methodology that leverages cloud computing, change detection, and DL methods for timely and reliable ASM monitoring in persistently cloudy regions*”. These novel methodologies are developed leveraging a cloud-based GEE geospatial image processing platform and open-source Python libraries, allowing the methods to be replicated by other users with a strong foundational knowledge and skills in machine learning, Python programming, GEE platform, and basic remote sensing, and to integrate these methodologies into existing ASM monitoring workflows. As a result, the methodologies developed in this research can be broadly applied for NRT monitoring of ASM activities globally.

7.5 Overall summary, conclusions, and future works

This section provides a summary of how this research has advanced the body of knowledge for the use of remote sensing technologies for ASM mapping and monitoring in the tropics. It also provides suggestions for future avenues to pursue research on how the methodologies developed in this study can be further improved for the timely and reliable monitoring of ASM activities.

7.5.1 Thesis summary

ASM is an important economic activity for more than 49.5 million people worldwide ([ASM Inventory, 2025](#)), but is often associated with major environmental and social problems in developing countries ([Bansah et al., 2018](#); [Fritz et al., 2018](#)). Despite these problems, there is a lack of effective mapping methods to locate these mines in a timely manner to support their sustainable development. Remote sensing approaches have been widely used to detect and map ASM, although the use of optical images has faced challenges, such as spatial resolution and persistent cloud cover, which limit its capabilities for regular ASM monitoring ([Gallwey et al., 2020](#); [Snapir et al., 2017](#)). In recent years, the availability of open-source S1 C-band radar data from the Copernicus programme offers new possibilities to overcome these limitations and allow timely ASM monitoring in cloudy regions, such as southern Ghana. However, the use of S1 imagery has faced challenges that have limited its effectiveness for the development of effective early warning systems for timely and reliable ASM monitoring in the tropics ([Forkuor et al., 2020](#); [Janse van Rensburg and Kemp, 2022](#); [Kimijima et al., 2022b](#)). For example, it has been shown that S1 SAR images have been influenced by several factors such as speckle noise, atmospheric effects from active rainfall events, and topography, leading to a greater or lesser degree of high false alerts and measurement uncertainties. The advance of remote sensing theory and applications, including statistical CPD methods, DL techniques, cloud-based image processing platforms, and advanced time-series modelling, has been recognised as a valuable

complementary tool for extensive SAR-based forest monitoring applications ([Gong et al., 2017](#); [Gorelick et al., 2017](#); [Kellndorfer, 2019](#); [Wang et al., 2022](#)). However, the potential of these technologies has not been explored to develop new scalable methodologies suitable for timely and reliable ASM monitoring using S1 SAR images in the tropics. The research presented in this thesis aimed to investigate new methodologies to improve the quality and effectiveness of S1 C-band imagery to facilitate timely monitoring of ASM, leveraging the GEE cloud-based processing platform, DL, and CPD techniques in persistent cloudy regions.

7.5.2 Future work

A number of areas were identified during the development of the methodologies outlined in this thesis for future work to improve the methods for timely and reliable mapping and monitoring of ASM activities.

7.5.2.1 Improving the timeliness and reliability of ASM detection

One of the key areas recommended for potential improvement is the timeliness of ASM detection and the reliability of the models developed in this research. The inherent delay in confidently classifying forest disturbance as ASM using the models developed in this study was 18 days. Upcoming L-band satellite missions, for example, the newly launched NASA-ISRO SAR (NISAR) satellite mission will provide freely available S-band (with a wavelength of approximately 10 cm) and L-band (with a wavelength of roughly 24 cm) SAR data at a global satellite revisit time of 12 days and spatial resolution ranging from 3 to 10 m ([NASA, 2025](#)). Future studies could benefit from the fusion of S1 C-band SAR and L-band NISAR for a potential improvement in the timeliness of ASM detection. The increased spatial resolution (i.e. ranging from 3 to 10 m) can possibly overcome the high commission/omission error of up to 10% observed with S1 detections during rainy seasons due to the lower sensitivity of L-band to atmospheric effects from active rainfall events, as described in Chapter 2. There is also the potential to detect small ASMs through the fusion of S1 C-band SAR and L-band NISAR to overcome the limitations of using S1 of approximately 20 m resolution.

Additionally, future research is recommended to explore incorporating the Bayesian updating method following the initial CuSuM-identified alerts. This approach would use each new observation to refine the probability of forest loss being caused by ASM activity by utilising prior information, thereby improving the reliability of accurately classifying forest disturbances as ASM using the proposed approach.

7.5.2.2 Improving the robustness and performance of the deep learning model

Despite the strong performance of the deep learning model, visual inspection of predicted maps revealed that rivers with high sediment loads were often misclassified as mines due to the

limited land cover classes used in this study. Future studies could benefit from broadening the model's classification schemes to encompass different forest land covers, such as polluted water, logging, and natural causes of deforestation like drought and forest fires.

Furthermore, integrating topographic and textural data improved the classification accuracy of the deep learning model. However, the contribution of each of these auxiliary data to the accuracy of classifying a disturbance as ASM was not evaluated in this study. Further research is, however, needed to explore the significance of each input predictor used in this study in ASM detection.

7.5.3 Main contributions

The main contributions of this research can be summarised as follows:

- The S1 GRD processed imagery available in GEE, without any further processing, is influenced by several factors such as speckle noise, atmospheric effects from active rainfall events, seasonality, and topography. These effects make it unsuitable for timely and reliable ASM detection in the wet tropics (Chapter 4).
- It is recommended to use radiometrically γ^0 and geometrically terrain-corrected products for timely and reliable ASM monitoring applications in the tropics using SAR imagery. This effectively addressed distortions caused by topography and was essential for achieving reliable results for both time-series change detection, classification tasks, and single-scene image classification applications in identifying ASM activities (Chapter 4).
- Using the appropriate DEM for processing SAR data is crucial to address the influence of topography on SAR backscatter for effective continuous mapping of ASM activities on a large scale, particularly in undulating and steep landscapes. The Copernicus 30 m DEM was identified as the most suitable among the freely available global DEMs for reducing terrain-induced effects on SAR backscatter (Chapter 4). This represents a significant advancement over the SRTM that has been the best DEM for processing SAR for forestry applications.
- Applying methods to address SAR signal variability caused by heavy rainfall and forest canopy seasonality is vital for creating timely and accurate maps that show spatial distribution patterns, extent, and operational dynamics of ASM activities throughout the year with minimal delay. This was achieved through time-series modelling and smoothing to enhance S1 data quality by predicting periods of low-quality data due to these signal variation effects (Chapter 4).
- CPD is a powerful statistical technique for analysing SAR time-series data to locate ASM

activities promptly, facilitating swift interventions to protect lives and the natural environment, and promote responsible mining. When applied to smoothed S1 SAR radiometric terrain-normalised γ^0 products, CuSuM CPD offered a faster response for tracking ASM activities compared to PELT and BinSeg, enabling timely and targeted intervention actions (Chapter 5).

- It is recommended to use the S1 VH polarisation rather than VV for timely ASM monitoring applications due to its high detection sensitivity to backscatter changes caused by ASM activities and reduced susceptibility to signal variability, leading to improved detection timeliness (Chapter 5). This aligns with established literature findings by [Forkuor et al. \(2020\)](#) using S1 imagery for mapping ASM in southern Ghana.
- DL is a powerful tool with the ability to learn complex patterns in SAR imagery for accurate ASM mapping and monitoring applications. This advanced technique has the potential to address inherent SAR speckle noise, providing an effective way to distinguish ASM-induced forest disturbances from other forest land use/cover disturbances in a timely manner (Chapter 6). A typical commission/omission error of less than 7% was achieved to accurately classify ASM during the dry seasons and up to 10% during the rainy season using the U-Net DL model (Chapter 6).
- The integration of topographic and textural data improved the discrimination capacity of the deep learning model, resulting in a general improvement in the accuracy of the classification (Chapter 6). This, however, incurs high computational costs, highlighting a critical trade-off that challenges its broader application for reliable monitoring of ASM activities on a large scale.
- Using imagery acquired during both rainy and dry seasons across different geographic areas and time periods, along with data augmentation techniques, enhanced the model's robustness to spatiotemporal variations in the test data. Although the research focused on two distinct case study areas in the Western and Ashanti regions of southern Ghana, the methods demonstrated strong generalisation ability and potential for global adaptation and reproducibility using appropriate labelled datasets (Chapter 6).
- While the methods developed in this study can generate ASM-induced forest disturbance alerts within days, it takes up to 18 days to confidently classify disturbance as ASM activity.

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Appendix A

Details of latency between reference NDVI and S1 SAR-based ASM timely detection

This supplementary material corresponds to the detailed analysis presented in Chapter 5 of this thesis and is available at the following <https://doi.org/10.1016/j.jag.2025.104525>. Figure A1 – Figure A8 show the results of the timely detection of ASM using the CPD algorithms that correspond to the details provided in Table A1 and Table A2 at the Ashanti and Western case study areas, respectively.

Table A1: Temporal Lag (days) to detect early stage of ASM activity using the CPD algorithms in the Ashanti test site for both C-VV and C-VH polarisations, comparing the Sentinel-1 predicted dates to the NDVI observed dates as validation.

Mine	CPD	Observed	Predicted VH	Predicted VV	Lag time (days) VH	Lag time (days) VV
Mine 1	PELT		18-Oct-2019	18-Oct-2019	-9	-9
	BinSeg	09-Oct-2019	18-Oct-2019	18-Oct-2019	-9	-9
	CuSuM		12-Oct-2019	18-Oct-2019	-3	-9
Mine 2	PELT		11-Nov-2019	11-Nov-2019	-3	-3
	BinSeg	08-Nov-2019	11-Nov-2019	11-Nov-2019	-3	-3
	CuSuM		05-Nov-2019	23-Nov-2019	3	-15
Mine 3	PELT		05-Dec-2019	05-Dec-2019	-7	-7
	BinSeg	28-Nov-2019	05-Dec-2019	05-Dec-2019	-7	-7
	CuSuM		05-Dec-2019	29-Nov-2019	-7	-1
Mine 4	PELT		11-Dec-2019	29-Dec-2019	2	-16
	BinSeg	13-Dec-2019	11-Dec-2019	29-Dec-2019	2	-16
	CuSuM		11-Dec-2019	12-Dec-2019	2	2
Mine 5	PELT		10-Jan-2020	10-Jan-2020	-3	-3
	BinSeg	07-Jan-2020	10-Jan-2020	10-Jan-2020	-3	-3
	CuSuM		10-Jan-2020	04-Jan-2020	-3	3

Table A2: Temporal Lag (days) to detect early stage of ASM activity using the CPD algorithms in the Western test site for both C-VV and C-VH polarisations, comparing the Sentinel-1 predicted dates to the NDVI observed dates as validation.

Mine	CPD	Observed	Predicted VH	Predicted VV	Lag time (days) VH	Lag time (days) VV
Mine 1	PELT		23-Nov-2019	23-Nov-2019	-5	-5
	BinSeg	18-Nov-2019	23-Nov-2019	23-Nov-2019	-5	-5
	CuSuM		23-Nov-2019	23-Nov-2019	-5	-5
Mine 2	PELT		29-Dec-2019	29-Dec-2019	-11	-11
	BinSeg	18-Dec-2019	29-Dec-2019	29-Dec-2019	-11	-11
	CuSuM		23-Dec-2019	29-Dec-2019	-5	-11
Mine 3	PELT		23-Dec-2019	23-Dec-2019	1	1
	BinSeg	24-Dec-2019	23-Dec-2019	23-Dec-2019	1	1
	CuSuM		23-Dec-2019	04-Jan-2020	1	-10
Mine 4	PELT		10-Jan-2020	10-Jan-2020	-3	-3
	BinSeg	07-Jan-2020	10-Jan-2020	10-Jan-2020	-3	-3
	CuSuM		04-Jan-2020	16-Jan-2020	3	-9
Mine 5	PELT		22-Jan-2020	22-Jan-2020	0	0
	BinSeg	22-Jan-2020	16-Jan-2020	16-Jan-2020	6	6
	CuSuM		22-Jan-2020	22-Jan-2020	0	0

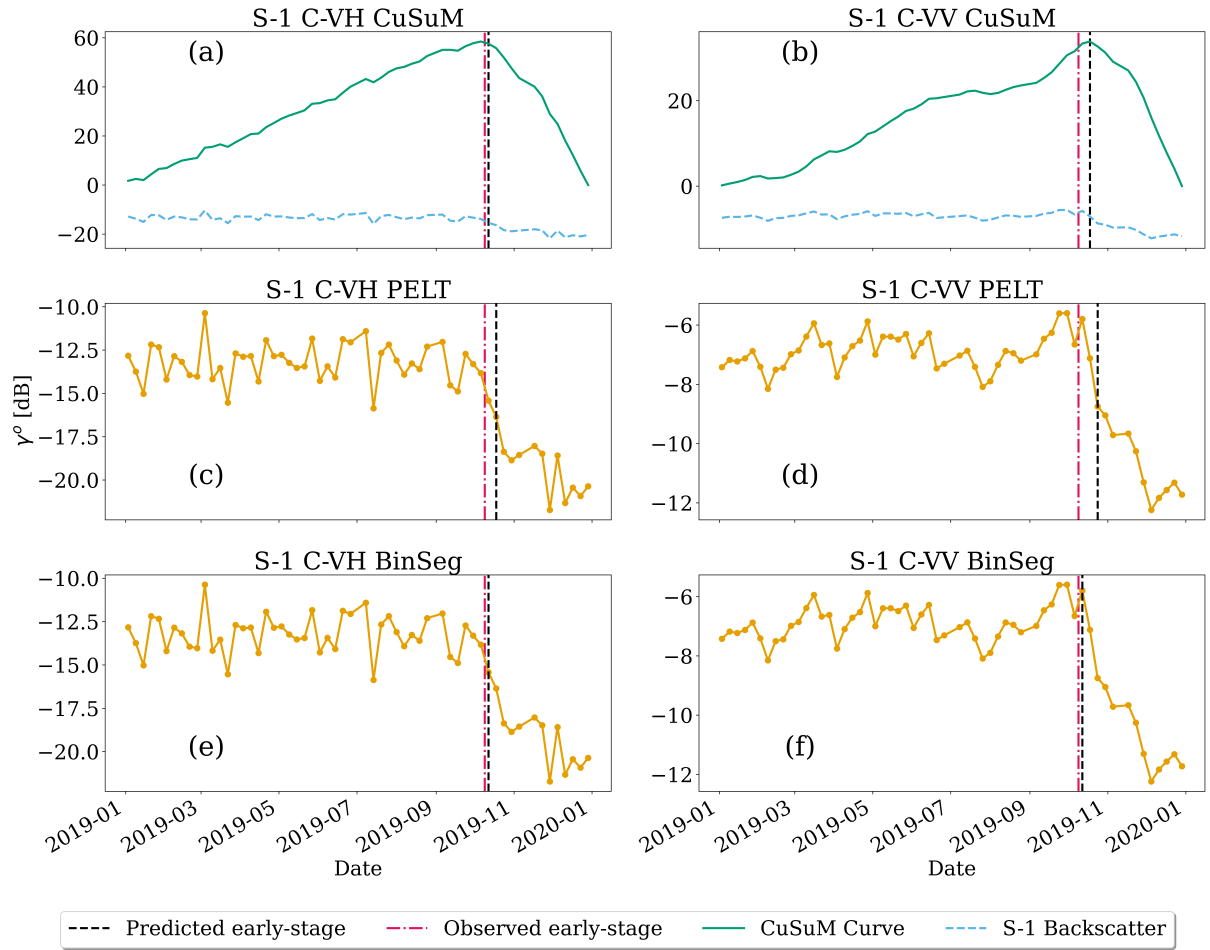


Figure A1: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 1 in the Ashanti test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

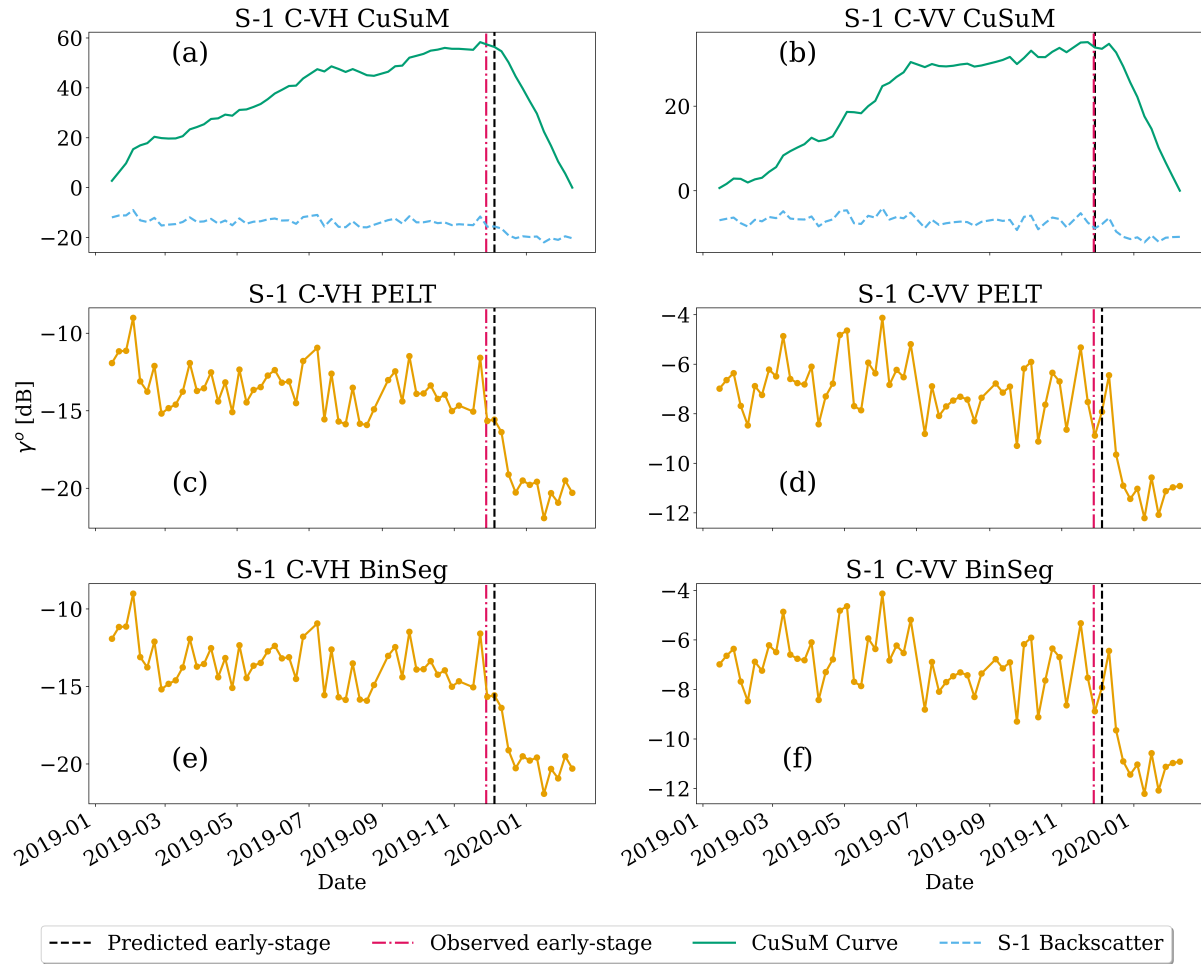


Figure A2: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 3 in the Ashanti test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

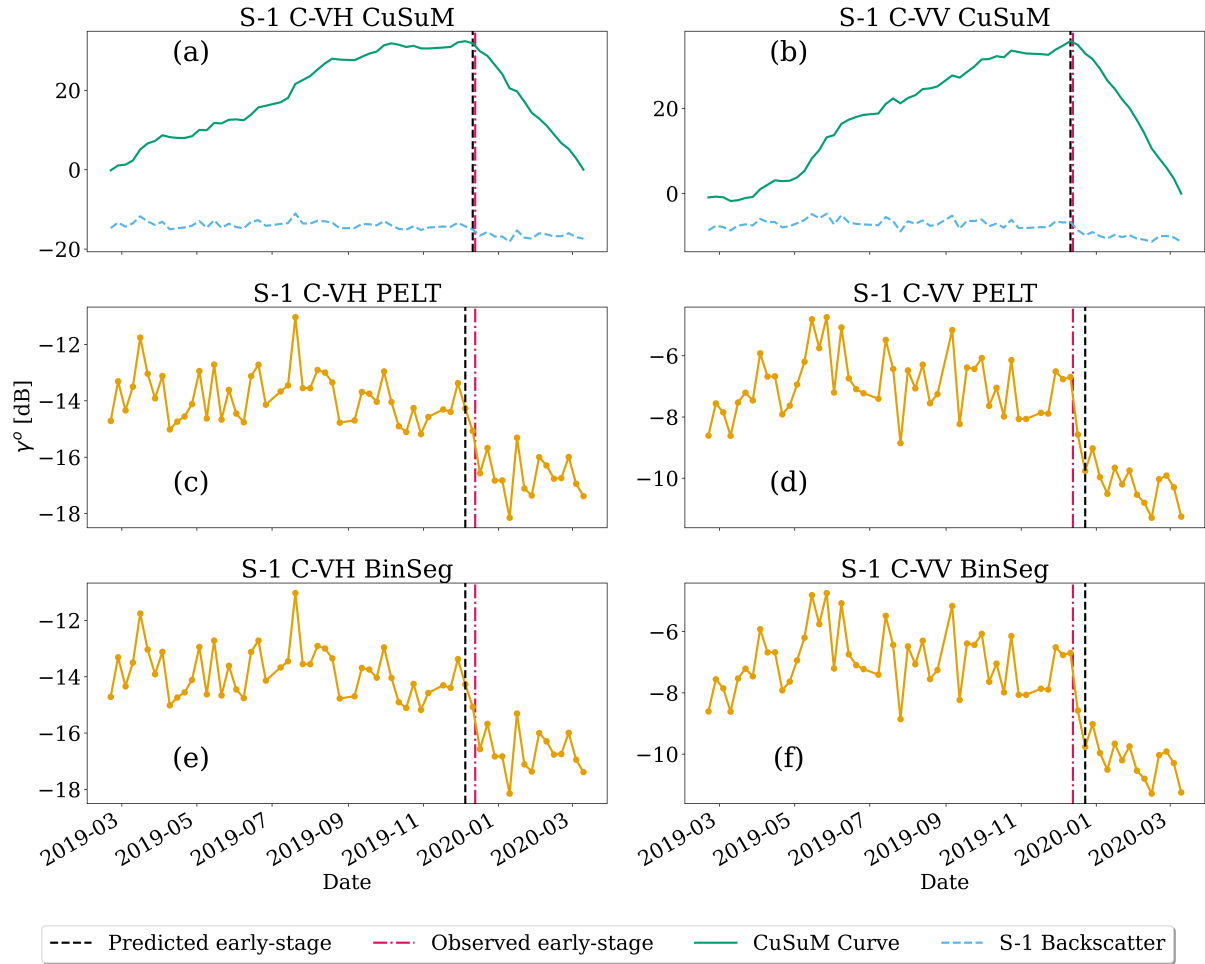


Figure A3: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 4 in the Ashanti test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

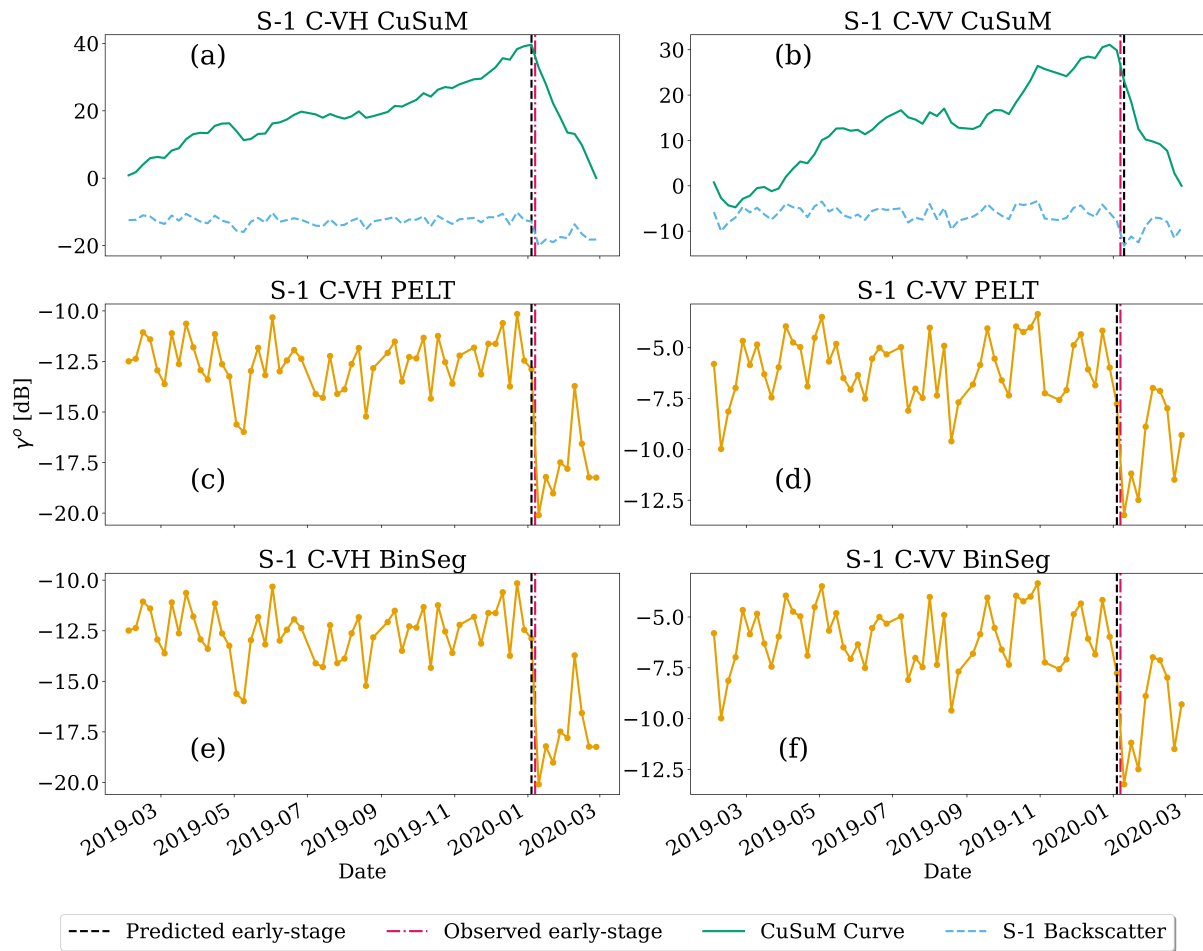


Figure A4: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 5 in the Ashanti test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

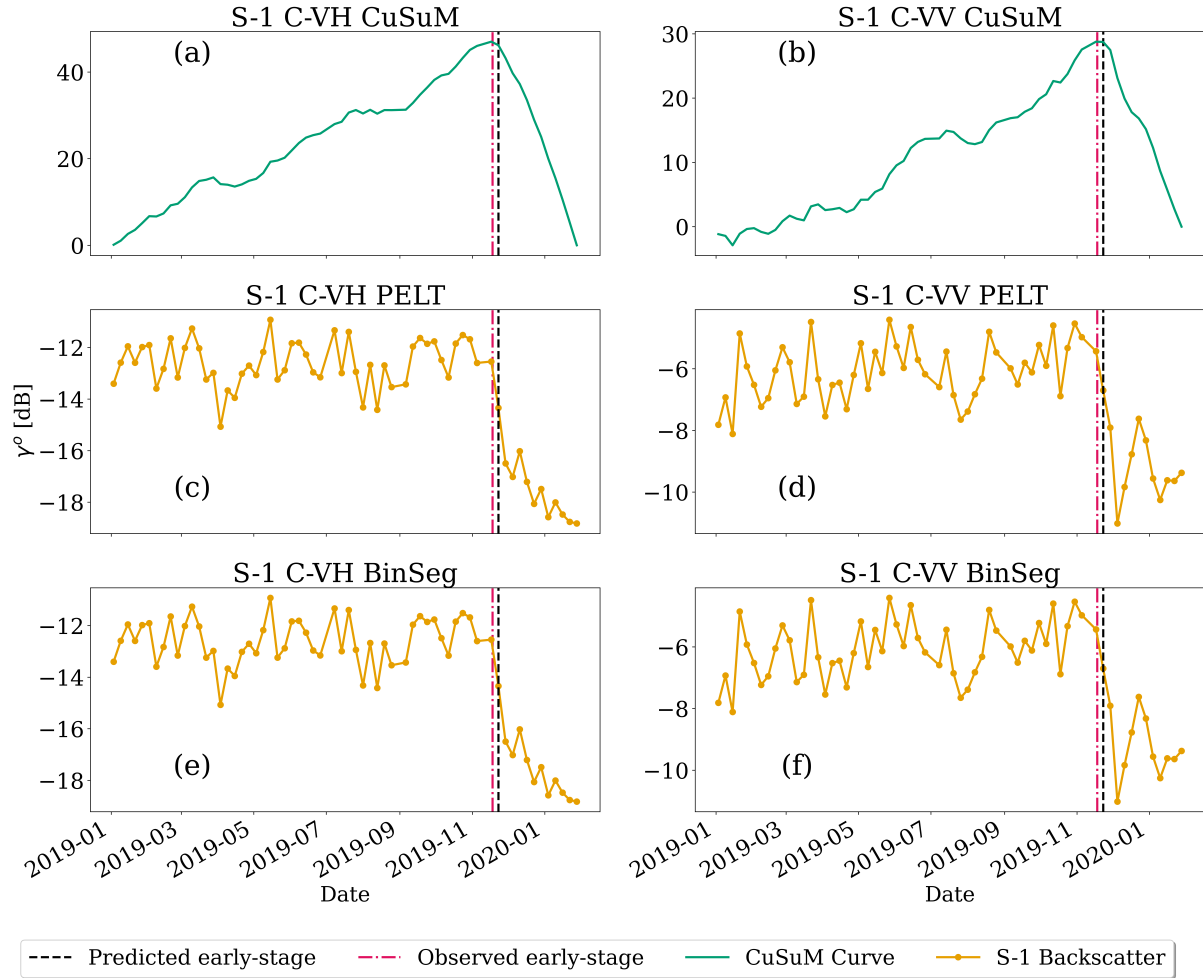


Figure A5: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 1 in the Western test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

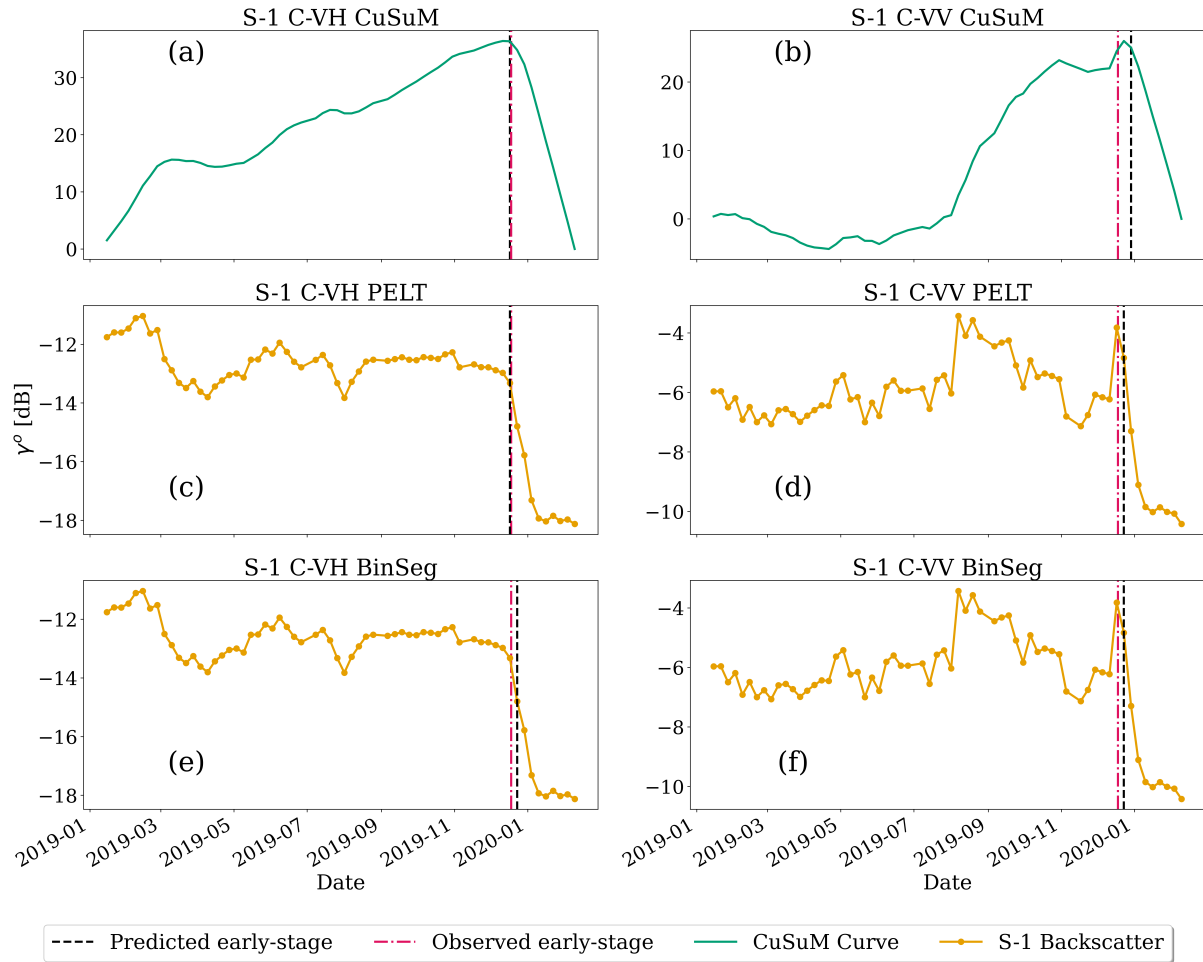


Figure A6: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 2 in the Western test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

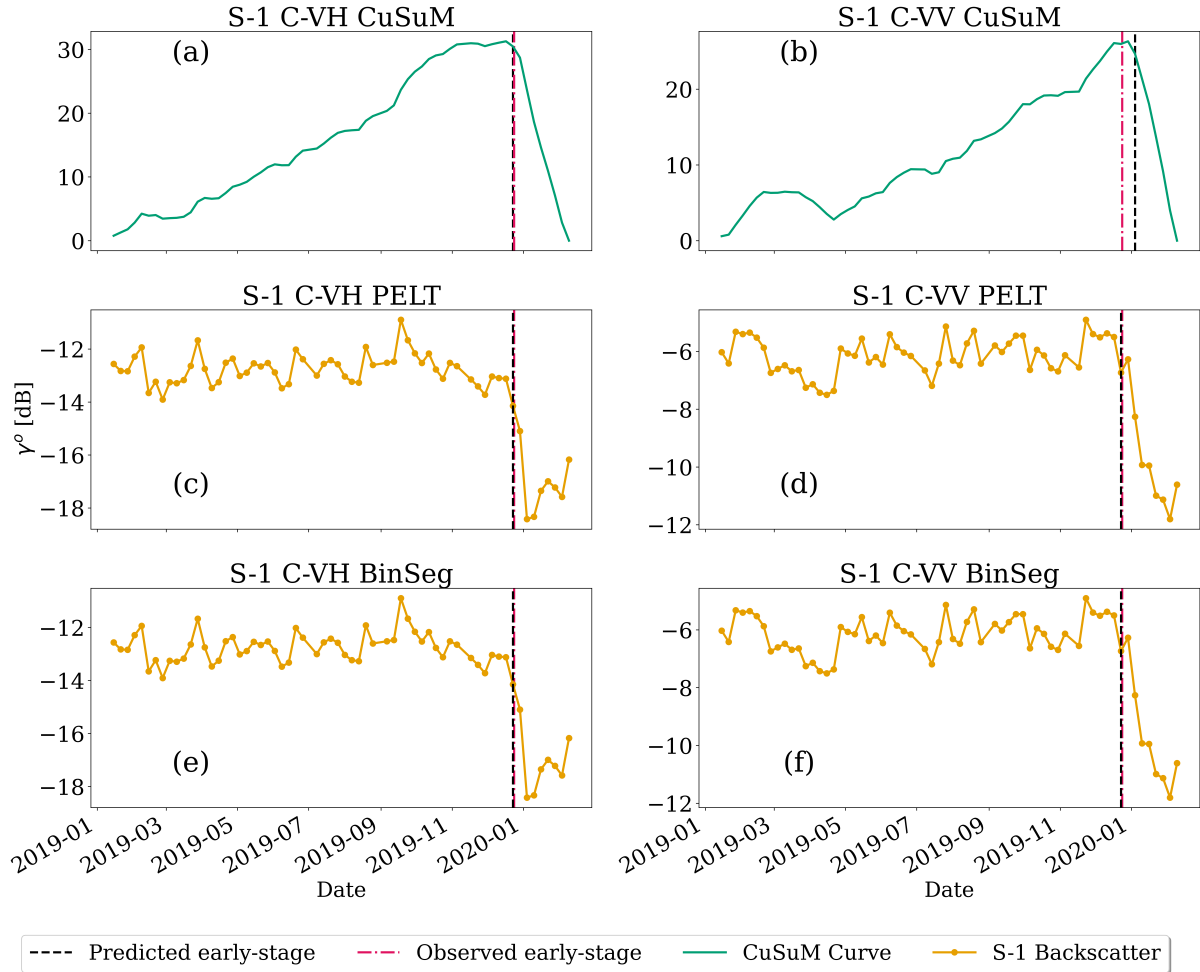


Figure A7: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 3 in the Western test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.



Figure A8: Intact forest (left) and ASM-induced deforested (right) smoothed S1 backscatter time series over mine site 5 in the Western test site for both C-VV and C-VH polarisations. Structural changes due to the start of ASM activity detected using CuSuM, PELT, and BinSeg algorithms are presented (vertical lines). The change (early stage) is shown in the next observation in the time series (dotted black line). The date from optical NDVI (dotted red line) was used as validation.

Appendix B

Declaration of Co-authorship

Paper 1 / Chapter 4 (partially)

This form is to accompany the submission of a PhD that contains research reported in published or unpublished work. **Please include one copy of this form for each co-authored work.** This form along with the published work should, under normal circumstances, appear in an Appendix.

Authorship Declaration Form

Publication Details:

Thesis Chapter/Pages	Chapter 4 (76 – 103)
Publication title	Evaluating the Influence of Global Digital Elevation Models (DEMs) for Sentinel-1 Radiometric Terrain Correction (RTC) for Tropical Forest Measurements in Google Earth Engine.
Publication status	Published
Type of publication	Conference paper
Publication citation	Mensah, I. O., Barrett, B., and Cahalane, C. (2024) <i>Evaluating the Influence of Global Digital Elevation Models (DEMs) for Sentinel-1 Radiometric Terrain Correction (RTC) for Tropical Forest Measurements in Google Earth Engine</i> . In: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Greece, July 2024. Athens: Institute of Electrical and Electronics Engineers (IEEE). doi:10.1109/igarss53475.2024.10641014 .

Nature/extent of my contribution to the work detailed above is as follows:

Nature/Extent of Contribution	Lead author
I led the main components of the investigation, including conceptualization, methodological developments, implementation of investigations, data curation, and formal analysis. In addition, I wrote the original manuscript and integrated all subsequent feedback.	☒ Yes ☐ No

The following co-authors contributed to the work (all contributing co-authors):

Name	Nature of contribution
Brian Barrett	Provided supervisory guidance, proofreading, and editing of the original manuscript for clarity and structure.
Conor Cahalane	Provided supervisory guidance, proofreading, and editing of the original manuscript for clarity and structure.

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-author's contribution to this work

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Co-author 1	Brian Barrett		18-02-2026
Co-author 2	Conor Cahalane		19-02-2026

Paper 2 / Chapter 4 (partially)

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Authorship Declaration Form

Publication Details:

Thesis Chapter/Pages	Chapter 4 (76 – 103)
Publication title	Towards Analysis Ready Data (ARD): Assessing Sentinel-1 Backscatter Data Suitability for Detecting Artisanal and Small-Scale Mining (ASM) Induced Deforestation Stages in the Tropics.
Publication status	Published
Type of publication	Conference paper
Publication citation	Mensah, I. O., Barrett, B., and Cahalane, C. (2024) <i>Towards Analysis Ready Data (ARD): Assessing Sentinel-1 Backscatter Data Suitability for Detecting Artisanal and Small-Scale Mining (ASM) Induced Deforestation Stages in the Tropics</i> . In: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Greece, July 2024. Athens: Institute of Electrical and Electronics Engineers (IEEE). doi:10.1109/igarss53475.2024.10640528 .

Nature/extent of my contribution to the work detailed above is as follows:

Nature/Extent of Contribution	Lead author
I led the main components of the investigation, including conceptualization, methodological developments, implementation of investigations, data curation, and formal analysis. In addition, I wrote the original manuscript and integrated all subsequent feedback.	☒ Yes ☐ No

The following co-authors contributed to the work (all contributing co-authors):

Name	Nature of contribution
Brian Barrett	Provided supervisory guidance, proofreading, and editing of the original manuscript for clarity and structure.
Conor Cahalane	Provided supervisory guidance, proofreading, and editing of the original manuscript for clarity and structure.

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-author's contribution to this work

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Paper 3 / Chapter 5

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Authorship Declaration Form

Publication Details:

Thesis Chapter/Pages	Chapter 5 (104 – 129)
Publication title	Assessing change point detection methods to enable robust detection of early stage Artisanal and Small-Scale mining (ASM) in the tropics using Sentinel-1 time series data
Publication status	Published
Type of publication	Research article
Publication citation	Mensah, I. O., Barrett, B., and Cahalane, C. (2025). Assessing change point detection methods to enable robust detection of early stage Artisanal and Small-Scale mining (ASM) in the tropics using Sentinel-1 time series data. <i>International Journal of Applied Earth Observation and Geoinformation</i> 139. doi.org/10.1016/j.jag.2025.104525 .

Nature/extent of my contribution to the work detailed above is as follows:

Nature/Extent of Contribution	Lead author
I led the conceptual design of the study, the development and implementation of the methodology, and the execution of all the investigative and analytical work. In addition, I wrote the original manuscript and coordinated all subsequent revisions.	☒ Yes ☐ No

The following co-authors contributed to the work (all contributing co-authors):

Name	Nature of contribution
Brian Barrett	provided supervisory guidance, proofreading, editing of the original manuscript for clarity and structure, and revision guidance that improved the quality of the final submission.
Conor Cahalane	provided supervisory guidance, proofreading, editing of the original manuscript for clarity and structure, and revision guidance that improved the quality of the final submission.

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-author's contribution to this work

	Name	Signature	Date
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Co-author 2	Conor Cahalane		19-02-2026

Paper 4 / Chapter 6

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Authorship Declaration Form

Publication Details:

Thesis Chapter/Pages	Chapter 6 (130 – 158)
Publication title	A deep learning-based approach for near real-time Artisanal and Small-scale Mining (ASM) detection in the wet tropics in Ghana using Sentinel-1 time series data.
Publication status	Unpublished (under review)
Type of publication	Research article
Publication citation	Mensah, I. O., Barrett, B., and Cahalane, C. (under review). A deep learning-based approach for near real-time Artisanal and Small-scale Mining (ASM) detection in the wet tropics in Ghana using Sentinel-1 time series data. <i>International Journal of Applied Earth Observation and Geoinformation</i> .

Nature/extent of my contribution to the work detailed above is as follows:

Nature/Extent of Contribution	Lead author
I led the conceptual design of the study, the development and implementation of the methodology, and the execution of all the investigative and analytical work. In addition, I wrote the original manuscript and coordinated all subsequent revisions.	☒ Yes ☐ No

The following co-authors contributed to the work (all contributing co-authors):

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Brian Barrett	provided supervisory guidance, proofreading, and editing of the original manuscript for clarity and structure.
Conor Cahalane	provided supervisory guidance, proofreading, and editing of the original manuscript for clarity and structure.

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-author's contribution to this work

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Student	Isaac Obour Mensah		13-02-2026
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Co-author 2	Conor Cahalane		19-02-2026