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Against a 'wait and see' approach in adapting to climate change

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Simulations of future climate change impacts are highly uncertain, particularly for catchment hydrology, where output from models of complex dynamic systems (global climate) are used as inputs to models of complex dynamic systems (hydrology models). This is problematic where decision-making for adaptation is underpinned by future climate predictions, and where policy-makers have opted to delay adaptation until either uncertainties are reduced, or climate change signals emerge from observations. This paper, using the Boyne catchment in the east of Ireland as a case study, discusses the uncertainties involved in climate change impact assessment for catchment hydrology and highlights why uncertainties are unlikely to be constrained or reduced in the time-scale required for adaptation. In addition, by calculating the time required for climate change signals to emerge from the observational record and the magnitude of change required for detection, it is highlighted that waiting for climate signals to be statistically detectable is not an option for effective adaptation. The paper concludes by considering how a paradigm shift in how we use the output from climate impact assessments can progress the adaptation agenda given the limits to prediction identified.

Keywords: uncertainty; limits of prediction; detectability; adaptation; exploratory modelling

Introduction

There is growing evidence that human-induced increases in atmospheric greenhouse gases have driven observed changes in the global hydrological cycle over the past fifty years (Gedney *et al*. 2006, Huntington 2006). This includes increases in runoff and extreme events (flooding and drought) at continental scales (Groisman *et al*. 2005, Milly *et al*. 2008, Dai *et al*. 2004). At more regional levels, results from hydrological models that use downscaled output from Global Climate Models (GCMs) often suggest that river flows will change in a greenhouse gas-induced warmer future climate. In Ireland, previous research has indicated that, by the 2020s, increases in winter flows, in addition to significant reductions in summer flows, are likely, with changes becoming progressively larger as the century progresses (Charlton *et al.* 2006, Murphy and Charlton 2008, Steele-Dunne *et al*. 2008).

It is clear that such changes would have widespread implications for water resource management and effective defence from extreme events while posing risks to the delivery of targets as part of international commitments (e.g. good ecological status as part of the European Water Framework Directive). Recent extreme events

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such as the November 2009 floods in Ireland have resulted in calls for investment in flood protection, while key reports from the Irish Academy of Engineers (IAE 2009) have highlighted the risk posed by climate change to critical infrastructure that is fundamental to societal well-being. Associated with these calls have been requests for improved climate scenarios, reduced uncertainties and a move towards probabilities for future impacts, particularly for extreme events. These are understandable requests given the importance of statistical analysis of past, observed, climate used in the design of critical infrastructure such as flood defences or water supply infrastructure. Additionally, given the long design life of hydrological infrastructure and the lead time required for planning and operationalisation, it is crucial that adaptation be considered as soon as possible. However, these types of demands may be placing unrealistic expectations on the information that can be reliably derived from highly uncertain climate change impact assessments. In this context a paradigm shift is required in how we use future climate projections for adaptation. As a result of uncertainties, attention is focused on observations and their analysis to identify climate change signals and the postponement of crucial decision-making until climate change signals are statistically detected. This paper argues that it is unacceptable to delay decision making until climate change signals emerge due to the confounding factors involved in eliciting climate change signals from observations.

Detection of climate change signals at the scale relevant for decision-making is hampered due to the relatively weak signal to noise ratio of climate change compared with the large inter-annual variability of rainfall and river flows. Additionally there are subjective choices in the identification of indices for analysis, assumptions of statistical tests and significance testing that need to be met and complicating factors like urbanisation, arterial drainage, and changes in monitoring practices that can confound trend detection and association (Kundzewicz and Robson 2004, Radziejewski and Kundzewicz 2004, Svensson *et al.* 2005, Wilby *et al.* 2008, Fowler and Wilby 2010). Therefore, despite the identification of change points due to natural climate variability in hydrological records (Kiely 1999), robust attribution of changes in hydrology at the basin scale is not feasible at present. However, progress is being made in determining the time horizons within which the formal detection of trends will be possible. Work in the US and UK suggests that climate-driven trends in seasonal runoff are unlikely to be found until at least the second half of the twenty-first century (Zeigler *et al.* 2005, Wilby 2006). Wilby (2006) has also used detection-time relationships to estimate the strength of trend required for detection by specified time horizons in the UK. Results suggest that changes of $\sim$25% in runoff would be needed for detection by the 2020s in the most sensitive basins and significantly longer for basins with high levels of natural variation (Wilby 2006).

In such situations, adaptation must take place in advance of change being detected. Similarly the prospect of reducing uncertainty in any significant way in the timescales required for adaptation are remote, and in fact the opposite is likely to be the case. In exploring these issues, this paper, using the Boyne catchment in the east of Ireland as an exemplar, will illustrate the challenges and opportunities that present themselves. The paper is structured as follows; section 2 places the challenge of uncertainty in context, while section 3 discusses the range of future impacts typical for the flow regime of the Boyne catchment. Given the wide ranges of future impacts derived, section 4 will counter the argument of waiting for a climate change signal to be observed by indicating the time required for climate change to emerge and providing an indicative magnitude of change required for statistical detection over the coming decades. The paper concludes with a discussion on how we might proceed with implementing anticipatory adaptation.

The challenge of uncertainty

Walker *et al.* (2003 p.8) define uncertainty as '. . . any departure from the unachievable ideal of complete determinism', a departure that is omnipresent in modelling dynamic, chaotic, non-linear natural systems. This is particularly the case for climate change impact assessments on hydrological response where output from models of complex dynamic systems (global climate models) are used as input to models of complex dynamic systems (catchment hydrological models). In addition to random processes, uncertainty in the prediction of climate change impacts is also introduced as a result of non-random factors, which are in many cases unquantifiable. Non random or epistemic uncertainties are particularly evident in the definition of model structures, the estimation of boundary conditions, uncertainties about the future (e.g. political, social, economic change) and indeed human behaviour in response to risk, that cannot be assessed in a probabilistic way.

Foley (2010) highlights the additional uncertainties introduced by the current epistemological limitations of science in effectively modelling the climate system. Despite our ability to recognise the complexities, thresholds and feedbacks in natural systems, our inability to represent in mathematical form the complexity that is perceived in natural dynamic systems results in subjective simplifications of reality. Similar problems are evident in the simulation of catchment hydrology. Our inability to mathematically describe these complex systems in quantitative terms requires simplifying assumptions to be made in representing key processes through parameterisations, or approximations. In cases of complexity coupled with still limited computing power, the omission of processes that are deemed to have a negligible effect on the system, despite our incomplete understanding of their role under conditions different to that in the observational record, is commonplace. As a result, different models (both global climate models and hydrological models) will have different model structures, while different routines used to parameterise complex processes will result in different model simulations, thereby introducing uncertainty into model outcomes.

Calibration as a process also induces uncertainty. Measurements themselves can be subject to error and may be recorded at different scales to that required in the models; a particular problem for the representation of sub-grid processes in coarse GCMs and a common problem in hydrology, e.g. the modelling of hydraulic conductivity (Beven 2009). Calibration, a process heavily dependent on the information content of observations also requires assumptions, where, in a system undergoing change, past observations are unlikely to be a robust estimator of future behaviour. The issue of non-stationarity brought about by climate change is well covered by Milly *et al.* (2008) in the context of water management.

An associated problem is related to the increased number of processes included in models brought about by increasing computing power. The limited information content of observations, along with added complexity has increased the risk of over-parameterisation, where models may perform well for observations after optimisation, but may not be robust estimators of performance outside of the constraints of calibration data. How do we calibrate hydrological models to represent extreme events that are likely to increase in magnitude and frequency from observations that contain little information on such events, and have confidence in their output? Further, there is no guarantee that the optimally-identified parameters are the only ones that will give a good fit to the observations; rather there may be many such model formulations, a concept known as equifinality. While equifinality is becoming accepted as common place in hydrological modelling, long computing times and the movement towards physical realism in GCMs has meant that the assessment of such has been entirely neglected to date. Even more fundamentally, we are currently forced to assume that parameters are optimal for all time steps, modes of response, and will remain representative over time-scales of a century or longer, which is particularly problematic when extremes are of interest and the values of parameters estimated through optimisation are expected to represent floods, droughts and average conditions. This assumption of time invariant parameters is currently being tackled at NUI Maynooth and we hope we can provide some directions forward on this important issue.

Uncertainty due to random processes, epistemic sources and subjectivity in the decision-making process of the application of models is manifest in the entire methodology for producing climate change impacts on hydrological response. This uncertainty can be traced back to problems of representing our understanding in model formulations, problems of scale and space, and problems of representing uncertainty; in that not all uncertainties are quantifiable, errors may be difficult to extract and the use of different methods of representing uncertainty for decision-makers results in different estimates of uncertainty. Therefore it is incumbent upon modellers to quantify uncertainties using the available methods so as the best possible data, with the highest information content achievable, within limiting conditions, are provided for policy-makers.

Unfortunately, the cascading and additive nature of uncertainties in climate change impact assessment means that it is highly unlikely that we can reduce uncertainties to the extent required to attribute robust likelihoods to specific impacts for implementing adaptation options. This conclusion is supported by Dessai *et al.* (2009) who draw attention to the fact that, following more than 20 years at the top of international research agendas, the uncertainty ranges for climate sensitivity (temperature response of the global climate to a doubling of carbon dioxide levels in the atmosphere) have not been significantly reduced, while no approaches have emerged for successfully constraining uncertainties. In reality the further exploration of epistemic uncertainty is likely to uncover further processes and feedbacks that were previously unknown, thereby increasing uncertainty. This is exemplified by the increased uncertainty associated with sea level rise due to the discovery of new processes involved in the melting of large land-based ice sheets.

The most promising approach for reducing uncertainty in modelling is increased investment in monitoring, but much work is required here if we consider that even for heavily monitored catchments it is impossible to measure all of the variables in which we are interested (Blöschl and Zehe 2005). Therefore future decisions on climate change at the catchment scale will require the development of methodologies for decision-making under conditions of deep uncertainty.

Such large ranges of uncertainty have not been welcomed by policy-makers. Hall (2007) draws attention to the heavy criticisms proffered to the ranges of future changes presented in the Intergovernmental Panel on Climate Change's (IPCCs) Fourth Assessment Report, for not providing sufficient information on which to base decisions about the future and the conception that uncertainty ranges are so large as to be useless. In essence these criticisms have called for likelihoods to be associated with future impacts projections. However, given the uncertainties outlined above, probabilistic approaches are subject to the same difficulties as the scenario approaches presented, particularly epistemic uncertainty, and can only represent a fraction of the uncertainty space. Hall (2007) highlights that probabilistic outputs are highly conditional on the assumptions made in their construction, the models used and even the statistical methods adopted.

For example, Bayesian Model Averaging (BMA) and the Generalised Likelihood Uncertainty Estimation (GLUE) methods are widely used for the propagation of uncertainty in impact studies. Bastola *et al.* (2011) derived quite different ranges of model outputs for average river flow conditions for selected catchments in Ireland, depending on the technique used. Therefore there is uncertainty about uncertainty analysis and it is difficult to prioritise one approach over the other in terms of performance (Beven 2006). There is also no guarantee that the adopted techniques provide statistically valid prediction limits for future impacts, where subjective choices such as the selection of an informal likelihood measure in GLUE, is based on the modeller's perception of uncertainty.

Given all this, Hall (2007) highlights that the traditional use of probabilities in engineering for optimum design is potentially dangerous in the context of climate change, if the major caveats and assumptions involved are not communicated in a transparent manner. Indeed, he also stresses that calls to reduce all of the uncertainty in climate change impacts modelling to a single probability distribution function is to misrepresent and place unrealistic demands on current scientific knowledge. Existing statistical theory is not adequate in the context of such epistemic uncertainties and non-stationarities (Beven 2008).

In advancing the science of climate change prediction, Beven (2006) highlights that we need to deal with uncertainty in an open and transparent manner and identify ways of constraining it. This is unlikely to happen in the near- or medium-term future given the complexity of the problem. The current movement in the science is also toward increasing the physical realness of models, as evident by the current focus in many climate modelling centres on increasing the complexity, resolution and sub-grid parameterisations of models, rather than exploring the ranges of possible outcomes. With end-users and policy makers this approach can run the risk of confusing precision and accuracy. This confusion is often evident in the selection of dynamically downscaled regional climate model output over the same information statistically downscaled directly from GCMs because of the spatial resolution of the former.

Estimating the range of future impacts

In order to portray the range of impacts associated with future climate change, the range of simulations produced for the Boyne monthly flow regime is presented here. The approach presented accounts for the uncertainty derived from GCM, emission scenario and impact models. While this is by no means an exhaustive representation of associated uncertainty it does represent the fullest account taken for Irish conditions to date. For illustrative purposes the work uses the GLUE method to propagate uncertainty into future simulations. Four conceptual rainfall-runoff models are calibrated to represent the hydrological response of the Boyne catchment. The models are; HyMOD (see Wagener *et al.* 2001), NAM (see Madsen 2000), TANK (Sugawara 1995) and TOPMODEL (Beven *et al.* 1995). Each of these models varies in the way they conceptualise key hydrological processes and in their complexity, primarily related to the number of parameters requiring calibration. Among the four selected models, NAM and TANK describe the behaviour of each component of the hydrological cycle at the catchment level by using a group of conceptual elements. Conversely, TOPMODEL and HyMOD are both variable contributing area models. In TOPMODEL the spatial variability is taken into account through indices derived from topography, whereas in HyMOD the model spatial variability within the basin is modelled using a probability distribution function. All four models employ a single linear reservoir to model groundwater.

The GLUE method is based on the premise that for a physically-based hydrological model, no single optimum parameter set exists; rather a range of different sets of model parameter values may represent the process equally well. Different model structures, as well as different parameter sets in a particular model structure, can be easily combined within this framework. The technique is based on Monte Carlo simulation where a model is run a large number of times with different parameter sets. In GLUE, it is assumed that the error associated with a particular model and/or parameter set will be similar in prediction to those found in calibration. Full details on the calibration of models and the application of the GLUE technique can be found in Bastola *et al.* (2011).

The calibration (1971–1990) and validation (1991–2000) results for the Boyne catchment are shown in Table 1 where results from each conceptual rainfall runoff model are shown independently in the form of the Nash Sutcliffe goodness of fit measure (NSE) calculated for the median of simulations, the Count Efficiency (CE), which represented the proportion of observations contained within the GLUE prediction bounds and the Prediction Interval (PI) representing the range of the uncertainty bounds for each model. Best performance values in terms of NSE are obtained for HyMOD and NAM, while similar performance levels for both calibration and validation highlight the robustness of each of the models in capturing the hydrology of the catchment. The combined prediction interval of simulations is shown in Figure 1 for selected years in the calibration and validation periods.

Table 1. Calibration and validation performance for each rainfall runoff model.

		NSE (Median)		CE		PI (m3/s)	
Period (Calib/Valid)	Basin (Model)	Calib	Valid	Calib	Valid	Calib	Valid
1971–1990/1991–2000	Boyne (HyMOD)	0.79	0.76	0.80	0.83	28.2	29.4
	Boyne(NAM)	0.76	0.74	0.77	0.78	23.8	25.1
	Boyne (TANK)	0.70	0.73	0.67	0.75	25.6	27.1
	Boyne (TOP)	0.69	0.68	0.52	0.57	23.3	24.7

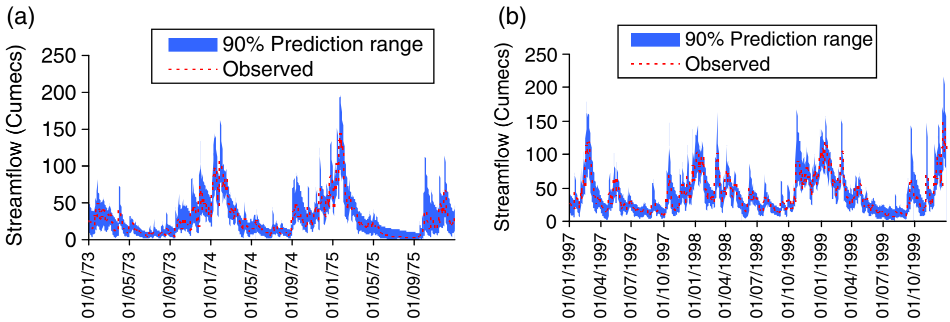

Figure 1. Prediction interval for Boyne basin including observed flow produced from multimodal ensemble of four selected models using Generalised Uncertainty Estimation (GLUE) method for the selected period a) from 1973 to 1975 (calibration) and b) from 1997 to 1999 (validation).

Six sets of statistically downscaled climate scenarios derived from three GCMs and two SRES emission scenarios, namely A2 and B2, downscaled for Ireland by Fealy and Sweeney (2007) were used to characterise future climate evolutions. The GCMs considered included: HADCM3 from the Hadley Centre for Climate Prediction and Research (Met Office, UK); CCGCM2, from the Canadian Centre for Climate Modelling and Analysis (CCCMA, Canada) and CSIRO-Mk2 from the Commonwealth Science and Industrial Research Organisation (CSIRO, Australia). The A2 and B2 scenarios represent future emissions levels that could be considered 'medium-high' (A2 emission) and 'medium-low' (B2 emission).

Simulations for three future time horizons representing early, mid- and late-century are shown in Figure 2. The prediction intervals and median simulations presented are the likelihood weighted output of the GLUE technique. These simulations account for uncertainties in greenhouse gas emissions scenarios, GCM sensitivity and uncertainty in rainfall runoff model structure and parameters. Even these do not comprise the full range of uncertainty, of notable absence is the uncertainty derived from regionalisation technique. Nonetheless, the range of uncertainty surrounding the future evolution of the monthly flow regime of the

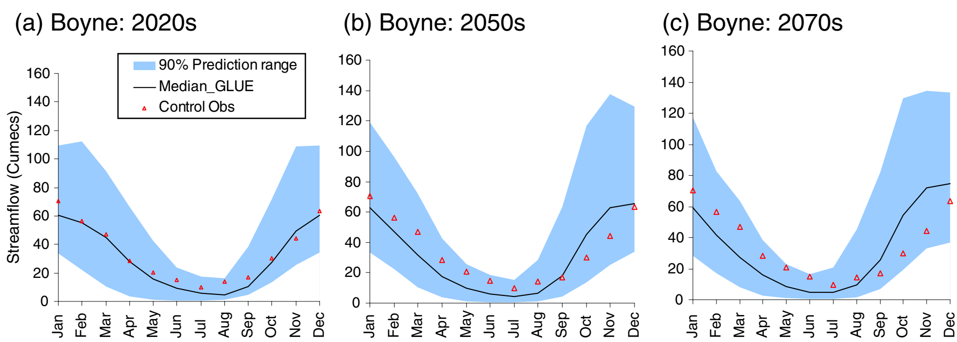

Figure 2. Total uncertainty envelopes derived from six climate scenarios and four hydrological models for Boyne basin and for three time periods using Generalised Likelihood Uncertainty Estimation method (GLUE).

Boyne catchment is abundantly clear. Simulations of extreme events rather than monthly means are likely to result in greater uncertainty. Of particular note from Figure 2 is that the direction of change relative to the control period (1971–1990) shows no clear direction of change for any month. Additionally, the 90% prediction intervals for mid-century and beyond show a significant increase, most notably for wetter months.

Obviously such uncertainty presents significant challenges for adaptation, particularly when adaptation in the water sector is likely to involve significant expenditure of exchequer finances on the maintenance, upgrade and development of existing and new infrastructure. This challenge is made all the more pressing given the current lack of capacity in water supply systems nationally, and the lack of knowledge of the protection provided by many of the state's flood defences in highly exposed areas and the inappropriate development on flood plains evident over the last decades. The scale of this challenge in terms of the social impact and monetary cost of failure is clearly illustrated by the hardships endured by flooding in November/December 2009 and the failure of water supply due to extreme weather conditions in December/January 2009/2010. In response, the government allocated €508 million for funding water services infrastructure in 2010, while the Office of Public Work's budget for flood alleviation and protection has been increased to €50 million in 2010 (an increase of 38%). Serious questions need to be raised in terms of how climate change and the associated uncertainties can best be factored into this significant investment, given the long design life of such critical infrastructure, upon which our modern society depends.

The uncertainty presented also gives rise to difficulties in terms of how engineers approach the design of such infrastructure. The traditional approach of optimising the design of, and investment in, long life infrastructure has, for a long time, been based on statistical assessments of meteorological and hydrological observations. Given that climate change introduces non-stationarity to statistical techniques which are fundamentally based on the assumption of stationarity, coupled with the uncertainty in future simulations, the realisation of optimum design for adapting to climate change impacts may not be possible. The idea of sub-optimal design, involving trade offs in ensuring performance across a range of conditions, is not a concept that sits comfortably with many. Therefore, the uncertainty confronted increases the risk of significant over- or under- design with associated significant excess expense and risk of failure.

Detection times for climate change and magnitudes of change required for detection

In the face of such high levels of uncertainty and risk, a common, and indeed understandable, response has been to 'wait and see' on climate change, until observational records reveal a climate signal that can serve to reduce uncertainty and focus resources. However, this approach is problematic. There is a general absence of robust, significant trends in Irish streamflow records that can be related to climate change. Indeed the identification of trends is complicated given the dynamic interaction between society and the natural system, with the lack of naturalised flows complicating the identification of trends. Of particular relevance to Ireland are the effects of arterial drainage which can have a profound impact on the statistical analysis of river flow records, while other confounding factors include land use change, urbanisation and channel engineering. In addition, where trends are identified, both the direction and strength of trends are highly dependent on the length of data investigated and by the presence of outliers at the beginning or end of particular series. In the context of climate change when these difficulties are considered along with those of extracting a climate change signal from large amounts of noise introduced by natural climate variability, the general absence of climate change-related trends in river flow records is not surprising. Nonetheless, the absence of trend is widely used as an argument against the implementation of adaptation planning.

Given the lack of robust climate change signals from observations, this section aims to perform two tasks; first, the strength of trend (% change) needed in order to become statistically detectable under widely used significance levels for the Boyne by early-century (2025) and mid-century (2055) was calculated. Second, the detection time, in years, for changes in streamflow due to climate change was estimated for annual, winter and summer flows. The methodology adopted is based on climate change detection work by Ziegler *et al.* (2005), Wilby (2006).

Trend detection in environmental series can be confounded in two ways. Firstly by Type I errors in which stochastic variations in the record are mistakenly accepted as trend, most notably for short records influenced by natural decadal variability. Secondly by Type II errors where a real trend is not identified because it is swamped by short-term stochastic variations. Errors of Type I are addressed by setting the probability of erroneous detection (α) at a predetermined level of confidence. The probability of making a Type II error ($1 - \beta$) depends on the power of the statistical test to detect a specified trend at the required confidence level α, and so varies with record length, trend magnitude and the distribution of the time series (Wilby 2006).

In line with Ziegler *et al.* (2005) and Wilby (2006)Wilby (2006a) conservative approach was taken towards committing Type I and II errors, with $\alpha = 0.05$ and $\beta = 0.10$ when estimating the strength of detectable trends or detection times. Sample variances of the observed time series were taken from reconstructed river flows derived by Harrigan (2010). To examine the sensitivity of detection times to the variance of observations, samples were taken from two sub-periods of the hindcast records; a long period (1951–1990) and a shorter period (1975–1990). The future climate change projection used is that of the median simulated flow described above for the Boyne, which provides a central estimate of the future evolution of river flows. Figure 3 shows the associated annual, summer and winter trends derived from this projection from 1990 to 2055, with the slope of the line used to derive future trend magnitudes.

Table 2 shows the magnitude of trend required for detection of the climate change signal by 2025 and 2055 based on the long and short period variances. Evident is the fact that large changes are required for statistical detection, particularly for summer flows where the variances are large. For instance, based on the variance of observations calculated from 1951–1990, a change of 96% in summer flows would be required in order to be detected using standard statistical approaches such as the Mann Kendall test for trend. The magnitudes of change required are smaller for annual and winter flows, but are still in excess of 40% by 2025 and 30% by 2055. Again there is consistency between the variances where river flow series with higher variances require larger magnitude changes for detection.

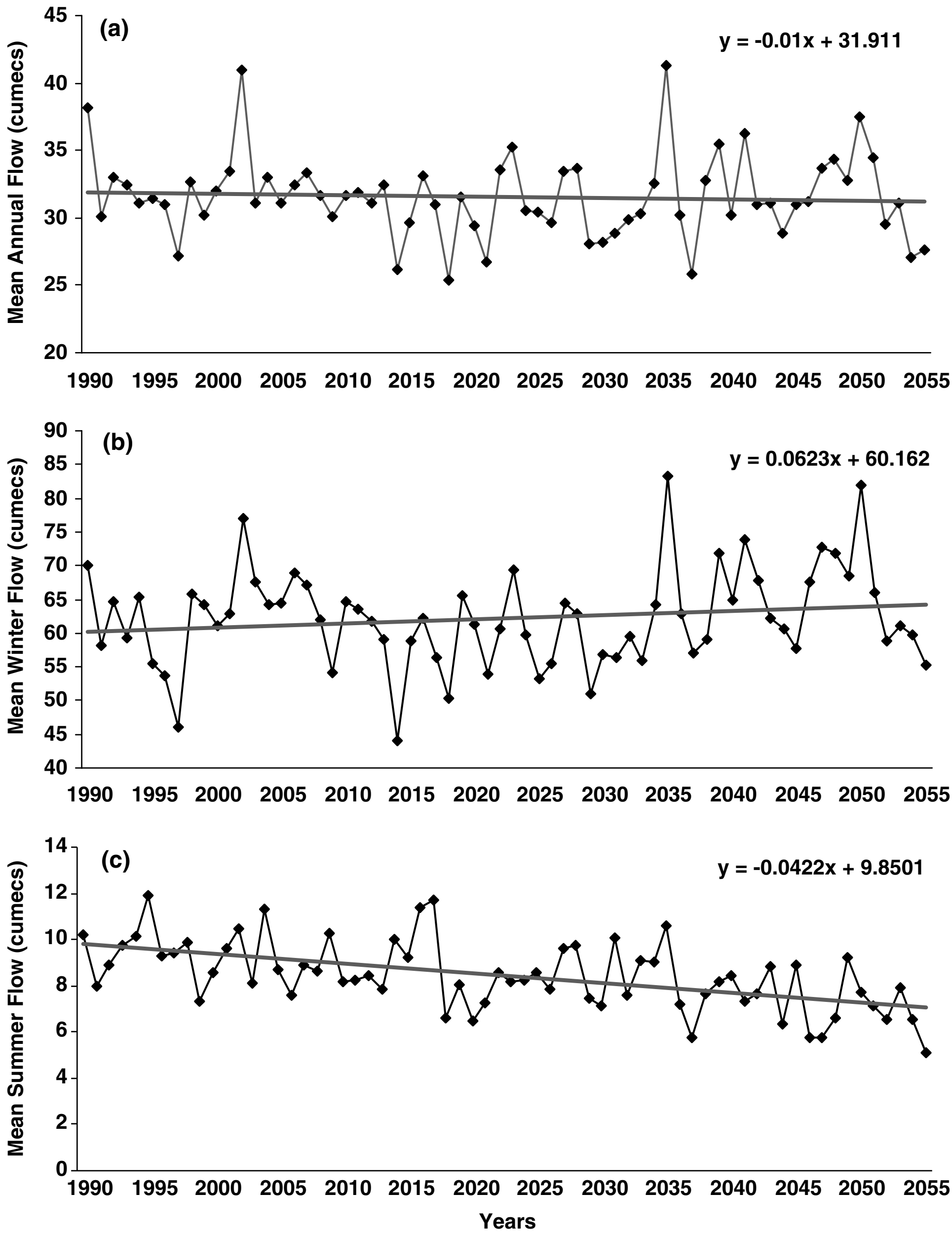

Figure 3. Trends in the evolution of climate scenario used for the estimation of detection times for a) annual, b) winter and c) summer for period 1990 to 2055.

These results have important implications for adaptation and policy formulation in the area of water management. In particular, the magnitude of changes required for detection by 2025 and even 2055 are larger than the changes projected by impact assessments to date. Therefore adaptation will have to take place before climate change signals are statistically detectable, moving the emphasis away from a ‘wait

Table 2. Magnitude of change (% change) required for statistical detection of climate change signal by 2025 and 2055 using long and short period variances.

	Year	Long	Short
Annual	2025	43	33
	2055	32	24
Summer	2025	96	108
	2055	71	79
Winter	2025	46	30
	2055	34	22

and see' philosophy towards the need for anticipatory adaptation, thereby increasing the pressure placed on decision making under highly uncertain model outputs.

Table 3 displays the number of years required to significantly detect the climate change signal for the Boyne using the Mann Kendall statistic. Again the results are closely tied to the variance of observations. In terms of the long period variance, the simulated changes in annual flow for 2025 would require 110 years for detection, assuming no change in the variance of flow with climate change. Once again the results from such an analysis highlight the importance of anticipating and adapting to the impacts of climate change, in many cases long before the signal has emerged from observations. The results presented here for both the magnitude of change and detection times are consistent with previous work of Ziegler *et al*. (2005) and Wilby (2006) for the US and UK respectively.

Adaptation under uncertainty

In responding to this challenge, a number of authors have highlighted the potential for strategies that are robust to uncertainty (Lempert and Schlesinger 2000, Hallegatte 2009, Wilby and Dessai 2010). Robust strategies have been qualified as those that: (1) are *low-regret,* in that they are functional and provide societal benefit under a wide range of climate futures; (2) are *reversible*, in that they keep at a minimum the cost of being wrong; (3) provide *safety margins* that allow for climate change in the design of current infrastructure or easy retrofitting; (4) use soft strategies that avoid the need for expensive engineering and institutionalise a long term perspective in planning; (5) reduce the decision time horizons of investments;

Table 3. Number of years from 1990 required to significantly detect climate signal derived from simulations for the Boyne. Results for both long and short period variances of observations are presented.

	Year	Long	Short
Annual	2025	110	91
	2055	413	343
Summer	2025	151	163
	2055	151	162
Winter	2025	115	86
	2055	181	176

and (6) are flexible and mindful of actions being taken by others to either mitigate or adapt to climate change (Hallegatte 2009, Wilby and Dessai 2010).

However, the movement to such an approach to adaptation necessitates a paradigm shift in how we deal with climate change data, requiring a movement away from predict and provide, top-down approaches, towards bottom-up approaches that allow climate scenarios to be used in exploratory modelling exercises that test the functionality of adaptation options to the uncertainties involved. Work in this respect is progressing and frameworks for robust adaptation and example applications in the water sector are beginning to emerge in the international literature (Dessai and Hulme 2007, Lopez *et al.* 2009, Hall and Murphy 2010). Key among these emerging examples is the usefulness of moving away from considering climate change impacts explicitly, but rather identifying where and when vulnerability to climate change may emerge and the application of frameworks for the identification and selection of robust adaptation options.

In Ireland, Hall and Murphy (2010) conducted a vulnerability analysis of future public water supply for catchments over the coming decades by accounting for current and future pressures within the water supply system. Where vulnerability was identified, potential adaptation options were screened for robustness using exploratory modelling to assess the effectiveness and robustness of the options portfolio. In the case of the Moy catchment, a realistic reduction of losses from leaking water infrastructure greatly reduced the vulnerability identified under all climate scenarios investigated up to mid-century, revealing a low regret strategy that is robust to uncertainty (Hall and Murphy 2010).

In a similar study of the Wimbleball water resource zone in southwest England, Lopez *et al.* (2009) used the ensemble of the ClimatePrediction.net experiment to test the performance of different adaptation options under climate change. By analysing the frequency of failures to meet peak water demand it was concluded that the previously-identified option of increasing reservoir capacity was not enough to tackle successive dry years and that demand reduction measures were also needed (Lopez *et al.* 2009).

Such studies suggest that adaptation must be approached as context specific; a successful set of adaptation options may work well in one region but may not be applicable in another. Adaptation has to be planned and implemented on international (for trans-boundary river basins), national and regional (basin) level. National planning and water management at the river basin scale can help us to understand current and future vulnerabilities and insufficiencies which need to be recognised and subsequently addressed (Stakhiv 1998). Detailed adaptation plans have to be implemented at individual river basin level. The fine-tuning of these plans ideally takes palace with a broad range of stakeholder involvement, to ensure that all possible options are considered. With stakeholder involvement, adaptation can allow water users to influence the adaptation process, enhancing the likelihood of success. Adaptation strategies have to be evaluated according to the best available knowledge on a regular basis, and reconsidered if necessary. This adaptation approach ensures flexibility and the ability to respond to changes as new scenarios emerge. This also reduces the risk of maladaptive action which will significantly constrain our future possibilities (Matthews and Le Quesne 2009). Matthews and Le Quesne (2009) therefore promote the application of a process-oriented 'vulnerability thinking' instead of 'impacts thinking' approach in adaptation planning. A 'vulnerability thinking' approach combines flexibility with planning over long time horizons and monitoring, as well as adaptive management, recognising the uncertainty in projected hydrological changes.

Conclusions

Modelling the future impacts of climate change is an inherently uncertain process. To date, the dominant approach to adaptation has been based on the 'predict and provide' approach to information provision for decision-makers. As highlighted by Wilby and Dessai (2010), the number of tangible adaptation practices that have emerged from this top-down approach are limited globally as a result of the wide ranges of associated impacts. As such, the demands placed on climate modellers to provide scenarios with reduced uncertainty they are unlikely to emerge in the time-scale necessary for adaptation, while climate change signals are unlikely to be detectable in river flow observations for some decades to come. Probabilistic approaches are subject to the same fundamental uncertainties as scenario-based approaches. In light of these constraints, it is incumbent upon researchers to develop alternative approaches to facilitating adaptation. The identification of vulnerability and the assessment of robust adaptation options through exploratory analysis using climate scenarios, that best quantify uncertainties in future outcomes, represents one potential, and promising, direction. However this approach, given its departure from traditions of optimal design, requires a paradigm shift towards sub-optimal solutions that are robust to the uncertainty in climate change modelling. A flexible and robust planning process is required where adaptation options can be re-evaluated and pathways adjusted as new emerging information becomes available.

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