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UNCERTAINTY SOURCES IN CLIMATE CHANGE IMPACT MODELLING OF WATER RESOURCE SYSTEMS

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Modelling climate change impacts on water resources have been widely acknowledged to have various complexities. These complexities are due to the complex, dynamic and non-linear characteristics of the changes in atmospheric, climatological and hydrological processes. These changes are majorly as a result of human activities. Assessment of the potential impacts of these changes with the goal of planning adaptation strategies has given birth to numerous methodologies and approaches. However, uncertainty still occurs at almost every phase of the modelling process; from the development and downscaling of emission scenarios to the use of hydrological models. This paper reviews some of the current methods employed in hydrological modelling of climate change impacts and identifies the key sources of uncertainty inherent at each stage of the hydrological modelling process. Strategies that would incorporate of all sources of uncertainty while ensuring complementary modelling are suggested. These strategies would help in achieving meaningful progress with respect to the development of adaptive water resource systems, and also positively influence decision-making by relevant stakeholders.

Keywords: Bias correction, downscaling techniques, emission scenarios, global climate models, uncertainty

Introduction

The knowledge of weather and climate has always been of high importance to the global community, as it is upon them that the activities and life of humans on earth depend. It has been widely accepted over the past decades that human activities are changing the composition of the atmosphere and consequently, climate at both global and regional levels are affected. The dominant cause of current climate change is our past and current emissions of greenhouse gases (GHGs), in particular carbondioxide (IPCC 2007). Among the effects of these emissions are changes to energy concentrations received by the planet from the sun, as this energy is trapped for a longer period, making the planet go warmer.

The phenomenon of climate change is of great concern for hydrology as this change is expected to affect water availability and its use significantly, with wide range implications even beyond the water sector. Increasing temperatures are having profound effect on evaporation, thereby affecting water storage in the atmosphere. This in turn affects the frequency and intensity of rainfall events, its seasonal and geographic distribution, as well as its variability from year to year (Knoesen et al. 2009). In reality, many of the most serious impacts of climate change on non-water areas are mediated via water (Zhu and Ringler 2010). The impacts of climate change on other processes associated with water include changes in soil moisture, irrigation water demands, heat wave episodes and meteorological and hydrological droughts. These have multiplier effect on the aforementioned processes.

Studies have further found changes in climate. Chiew (2006) stated that temperature and precipitation can have direct consequences on the quantity of evaporation and also on both quantity and quality of run-off component. These changes will however affect the quantity and quality of water supply for domestic and industrial use. In addition, aquatic life in wetlands and ecological reserves will be affected as air and water temperatures rise and change. This change may either lead to migration of certain species in order to survive or extinction of some.

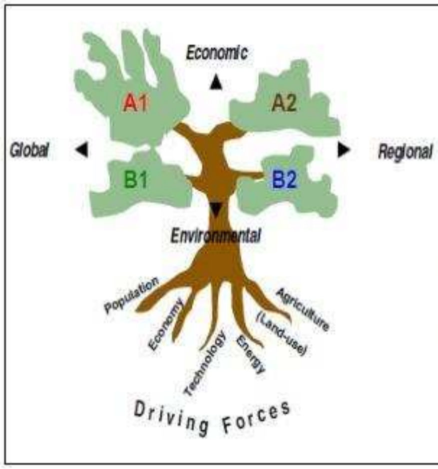
Due to the impacts of changing climate on both natural and social environment, the need for adequate planning into the future and putting in place adaptive measures is of crucial importance. Numerous studies have been carried out to understand the current and future impacts of climate change. Different approaches have been employed by researchers in understanding these impacts and making projections into the future. The impact modelling process of climate change involves many phases which include (i) the development of GHG emission scenarios, (ii) the use of Global Climate Models (GCMs) to project possible future climates, (iii) downscaling techniques and (iv) the use of hydrological models to simulate hydrological impacts of climate change.

However, there exist some uncertainty in each phase of the modelling processes (Xu et al. 2005), and these are due to the complex nature of the processes. Such uncertainty generate grey areas in the interpretation of future hydroclimatological projections. The main purpose of this paper is to review the current methods employed in hydrological modelling and the sources of uncertainty inherent in each phase of the hydrological modelling processes.

Uncertainty Linked To GHG Emission Scenarios

The Intergovernmental Panel on Climate Change (IPCC) developed long-term scenarios which have been widely used in the analysis of possible climate change, its impacts and options to mitigate climate change (IPCC 2007). These future levels of GHG emissions were developed using “storylines” (Nakicenovic et al. 2000), and are products of a very complex, ill-understood dynamic system, driven by forces such as demographic change, socio-economic development and rate and direction of technological change. These scenarios are used as a basis for the assessment of climatic change and in GCM initialization by modelers.

The special report on emission scenarios (SRES) (IPCC 2013) comprise of four narrative storylines designated A1, A2, B1 and B2. These emission scenarios are usually based on an internally consistent and reproducible set of assumptions which centers on the fundamental relationships and driving forces of change (Figure 1). The understanding of these relationships and driving forces of change are derived from both historical and present situations. However, the complex nature involved in deriving and understanding these driving forces make accurate predictions of these emission scenarios virtually impossible (IPCC 2013). This generates difficulty in translating and understanding the linkages between driving forces and quantitative inputs for scenario analysis. As a result, uncertainty arise in the interpretation of the scenario storylines as translated by individual modelers carrying out climate change impact assessment studies. Other factors that contribute to emission scenario uncertainty include the choice of storylines for the purpose of climate change simulation and the occurrence of events considered to be “rare future” events, which might produce outcomes that are fundamentally different from those produced by SRES model runs (Nakicenovic et al. 2000).



A1: A world of rapid economic growth and rapid introductions of new and more efficient technologies

A2: A very heterogeneous world with an emphasis on family values and local traditions

B1: A world of dematerialization and introduction of clean technologies

B2 A world of emphasis on local solutions to economic and environmental sustainability

Figure 1. SRES scenario storylines considered by IPCC (Schulze et al. 2011).

Recently, efforts have been directed towards reducing these emission scenario uncertainty as numerous researchers have developed interest in assessing the degree of uncertainty and its impacts on hydrological processes. The norm is to employ multiple storylines and multi-model approaches in future scenario analyses. A foundation for the use of scenario modelling as a tool for integrated water resource management was laid in Angola (Andersson et al. 2006). To account for the uncertainty in future GHG emissions, data from GCMs forced with two contrasting GHG emission scenarios (A2 and B2) were used. As such, the range of future GHG concentration in the atmosphere between these two scenarios may encompass much of the uncertainty in the future global cycles of carbon and other GHGs. Results showed that simulations from both emission scenarios were close to the baseline conditions for the simulations of hydroclimatological variables in all the GCMs employed. Though simulations showed clear tendency for all the models to simulate reduced precipitation and flow, the magnitude of change for both scenarios differ across selected future time-slices. It was concluded that irrespective of the fact that the model system provided a good representation of historical monitored hydrological conditions, uncertainty as a result of differences in magnitudes of change between the scenarios were high, which further opens up the need for further work at reducing emission scenario-related uncertainty. Results obtained from Olsson et al. (2011) were also in firm agreement with that of Andersson et al. (2006), as two sets of projections among the twelve used in their study differed across the four IPCC emission scenarios employed. The initial monthly projections differed substantially, although latter projections showed close agreement. The authors submitted that the IPCC emission scenarios employed contributed to the differences in hydrological impacts in the uncertainty assessment study.

In summary, the accurate prediction of emission scenarios is relatively impossible and is therefore a source of uncertainty (Galavi and Shui 2012), as results from the use of IPCC emission scenarios may indicate widespread projections depending on the specific scenarios used. Consequently, it is not only important to employ different scenarios, but also to identify the most influential ones (Olsson et al. 2011). The need for a comprehensive understanding of the relationships between GHGs and its driving forces is also of high importance, so is the provision of updates as regards improvement in the development of GHG emission scenarios. Following the conceptualization of the fifth phase of the Coupled Model Inter-comparison Project (CMIP5)

(Taylor et al. 2012), which entails a new set of coordinated model experiments, it is expected that the implementation of CMIP5 would help facilitate the reduction of uncertainty inherent in future climate change simulations and impact assessment studies.

Uncertainty Linked To Global Climate Models (GCMs)

Global Climate Models (GCMs) are used to simulate the present climate in order to estimate future climatic change at global scales. GCMs use equations which are the basis of complex computer programs to simulate the complex interactions between the atmosphere, oceans and biosphere (Graham et al. 2011). The interactions are dependent on natural and anthropogenic emissions which are estimated through emission scenarios. GCMs use emission scenarios as a founding measure in their generation of future climatological parameters that are in turn used to force the hydrological impact models. However, certain discrepancies may occur in the generation of climatological parameters in GCMs. These discrepancies are majorly due to imperfect representations in the topography and climate processes in GCMs, as well as computation limitations, which arise from the coarse resolution (approximately 200-300km grid squares) of GCMs. The coarse resolution limits the direct use of their outputs in impact models which are generally employed regionally at scales of 10-50km (Knoesen et al. 2009).

Nowadays, downscaling techniques are employed to reduce the conflicts generated by the performance of GCMs at the regional partial scales. However, studies have found that a large percentage of the uncertainty in regional climate change simulations are connected to the GCM used for deriving the information (Hawkins and Sutton 2009). This is because results from GCMs are influenced by various factors which contribute to uncertainty. One major factor is that large-scale features of the originating GCMs are preserved and can still be traced in subsequent phases of the impact modelling process. As a result, GCMs are now being considered as a major contributor to climate change signal at finer temporal and spatial scales (Déqué et al. 2007).

A major source of GCM uncertainty that has been widely accepted in climate change studies is the choice of GCM employed. Each GCM has its unique and specific features with respect to process descriptions and parameterizations (internal structure), initialization, as well as spatial and temporal resolutions. Jiang et al. (2012) assessed the temporal variability of flood frequency to flood drivers across multiple time-scale using 16 GCMs. It was found that most of the GCMs employed lacked the ability to produce observed monthly precipitations patterns, while few simulated low-frequency variability. They concluded that current GCMs do not adequately capture multi-scale temporal variability of precipitation, even though they showcased some degree of potentiality in capturing long-term monthly mean. Booij (2005) simulated the impacts of climate change on river discharge in the Nile Basin using 3 GCMs with different spatial resolutions. All the GCMs supplied climatological datasets for the same period based on two emission scenarios. Results showed no much agreement between the different GCM-SRES combinations and future trends. The differences between the observed and simulated spatio-temporal representations of climatological forcing point to the fact that irrespective of the downscaling and bias correction procedures applied to the GCM outputs, large-scale features of the GCMs used remain evident in the projections made. These are clear indications of uncertainty as a result of choice of GCMs. Therefore, the choice of GCM should be considered a major factor when carrying out impact assessment studies, in order to reduce overall uncertainty in climate change impact asessments.

Another source of uncertainty linked to GCMs is related to their process of initialization, which have been found to affect estimated near-future changes in climate (Olsson et al. 2011).

Kay et al. (2009) investigated the degree of uncertainty related to climate change impacts on flood frequency in two catchments in England. Six different sources of uncertainty were analyzed. Results found that GCM initial conditions accounted for a more significant portion of the uncertainty, if the results of extreme GCM simulations are excluded. Il-Won et al. (2012) in their flood frequency analysis established that uncertainty due to GCM initialization have great influence on near-future changes or projections. The GCM structure was attributed to uncertainty in shorter flood frequency change (e.g., 2 and 5-year flood). This further unveils GCM initialization uncertainty especially as it relates to the estimation of near-future changes in climate.

It can be concluded that the application of GCMs is a major source of uncertainty in climate change impact modelling; as uncertainty develop from the choice of GCM employed to the processes involved such as its spatial and temporal resolution, initialization and structural construct. Therefore, adequate knowledge of the merits, excesses and drawbacks of the GCM would facilitate uncertainty reduction in GCM use. In addition, further studies directed towards the use of multiple GCMs would help identify the inherent characteristics of various GCMs.

Uncertainty Linked To Downscaling Techniques

As ealier discussed, the difference in model resolution between GCMs and hydrological impact models generate some discrepancies if GCM outputs are employed at regional scales. Hence, there is need to convert GCM outputs into local meteorological variables required to achieve reliable modelling of hydroclimatological processes. The process of converting GCM outputs for use at regional and local scales is termed "downscaling". The primary objective of downscaling is to address the scale mismatch between coarse resolution GCM output and regional or local catchment scales required for climate change impact assessment and hydrological modelling (Fowler and Wilby 2007). Dynamical and empirical downscaling techniques are two primary methods used for downscaling GCM outputs, and uncertainty linked to them are discussed in the following sections.

Uncertainty Linked To Dynamical Downscaling Technique

Dynamical downscaling involves the use of regional climate models (RCMs) which are of higher resolution when compared to GCMs. RCMs simulate climate features dynamically at resolutions of about 50km or less using GCM data as boundary condition (Fung et al. 2011). RCMs gives better representation of the physical processes or small scale features of the atmosphere such as extreme climate events and regional scale climate anomalies or non-linear effects, when compared to what is obtainable in GCMs. One major process of employing RCMs in climate modelling is to nest them with GCMs. Many researchers have conducted impact modelling studies by setting up a number of GCMs and RCMs in a matrix (Graham et al. 2011; Olsson et al. 2011; Kienzle et al. 2012). However, some limitations have been identified in the use of RCMs. They include the propagation of the uncertainty that originates from the driving GCM, which create some biases that are mostly pronounced in the RCM numerical representations of major climatic variables such as precipitation and temperature. This shows that misrepresentations of regional and local parameters still occur despite the use of RCMs; as the choice of RCM or its parameterization scheme goes a long way to determining the degree of uncertainty (Kjellström et al. 2011). Therefore, there is need to mitigate this uncertainty by fine-tuning the GCM/RCM outputs through a process called bias correction. Bias correction is needed to remove bias between model and observations over the region of study (Minville et al. 2008). Two methods commonly used in the correction of biases include (i) the delta approach and (ii) the scaling approach.

The Delta Approach

The delta approach often referred to as “delta change” or “change factor” involves the modification of observed historical time-series by adding the difference between future and actual climate simulated by the climate model. The delta change method has been widely used to improve the usability of climate model projections in various hydrological climate change impact studies. Kienzle et al. (2012) estimated the impacts of climate change on water yield, streamflow extremes and regimes in a Canadian watershed. The delta change method was employed to downscale the GCM outputs. Projected monthly changes in air-temperature and precipitation were used to perturb a 30-year historical climate record. Results showed that not only did the precipitation estimates significantly affect simulation response, they also produced diverse future precipitation projections in terms of magnitude and directions. It was concluded that certain uncertainty still exist with respect to having better spatially distributed climate data, as the delta method assumed that spatial pattern of the present climate remain unchanged in the future. Likewise, Arnell (2003) applied the delta change method to correct GCM outputs in his assessment study carried out in Britain. Percentage changes in hydroclimatological variables such as precipitation, temperature and potential evapotranspiration were used to perturb the baseline time-series. Results showed that although it was easier to use the delta method to alter the baseline climate time-series, it was rather more difficult to alter the relative variability of the time-series. Limbrick et al. (2000) and Graham et al. (2007) also reported similar results with respect to the delta approach.

Results from past studies provides evidence of limitations in the delta approach, especially as it concerns better representation of spatially distributed climate data or variability across future climates. However, the degree of uncertainty inherent in the use of delta approach is considered to be small enough to be dealt with by the hydrological model (Chen et al. 2011). Furthermore, various researchers (Diaz-Nieto and Wilby 2005; Akhtar et al. 2008; Senatore et al. 2011) have employed the delta change method and have found it to be very efficient, as resultant scenarios from its adoption incorporates details of the station records as well as the areal average climate change of the climate model grid-boxes.

The Scaling Approach

The second approach employed for the purpose of bias correction is the scaling approach. This method involves the use of scaling factors to adjust the outputs of climate models so as to make them statistically comparable to observations, in terms of mean and standard deviation. Graham et al. (2011) applied the distributed-based scaling (DBS) approach developed by Yang et al. (2010) to adjust all RCM projections for the purpose of bias correction. Using the DBS approach, correction factors were derived by comparing the RCM output with observed climate variables in the control period and then applied to the RCM outputs for the future period. Results of the RCM projections which were downscaled using the scaling method were compared to that of statistically downscaled (SD) projections. Results showed that the scaling method produced relatively smaller deviations in present climate compared to SD projections. The SD projections were expected to fall relatively close to observed values without the need for additional bias correction techniques due to the dependence of the SD technique on observations of the present climate. It was concluded that the DBS bias correction technique was effective at ensuring that RCM projections fall relatively close to observations statistically. Results from Chen et al. (2011) was in line with the submission of Graham et al. (2011) as simulations carried out using a local intensity scaling method developed by Schmidli et al. (2006) were highly correlated to the observed climatological time-series. The positive influence of the scaling approach in modelling of hydrological processes have also been reported in various climate change impact studies (Olsson et al. 2011; Il-Won et al. 2012).

Generally, it is clear that despite the improvements in RCMs, their outputs are still too coarse to adoption in some applications such as in small catchments which may require local and site-specific climate scenarios (Chen et al. 2011). Bias correction methods will help reduce shortcomings inherent in the downscaling technique, thereby enhancing the reliability on future hydroclimatological projections. Notwithstanding, the overall uncertainty in this phase can be further reduced by carrying out comparative studies between different bias correction methods so as to ascertain their effects on future projections.

Uncertainty Linked To Statistical Downscaling Technique

The use of statistical downscaling (SD) technique involves the development of quantitative relationships between the large scale features of GCM (predictors) and regional scale variables (predictands). This is making the regional scale variables a function of the large-scale variables from GCMs. Correlation consistencies in frequency distribution, annual and inter-annual variability and persistence of the main climate characteristics are usually considered in statistical downscaling. SD has earned wide recognition due to its less computational demand and ability to provide information on specific sites (which is critical to climate change studies). It has been employed for the purpose of downscaling GCM outputs by many researchers. However, the major limitation of statistical downscaling which brings about some degree of uncertainty is that their basic assumption is not verifiable; as the statistical relationships developed for the present day climate may also hold under the different forcing conditions of possible future climate (Wilby et al. 2004). Statistical downscaling techniques have generally been classified into three main categories, based on the techniques used, namely: (i) Transfer function approach (ii) weather typing and (iii) stochastic weather generators.

Transfer Function Approach

Transfer function approach involves the direct quantification of the relationship between a predictand and a set of predictor variables (Giorgi et al. 2001). These relationships can either be statistically linear or non-linear. The transfer function approach is majorly a regression based downscaling method. Methods such as linear and non-linear regression, canonical correlation analysis, artificial neural networks (ANN), and support vector machines (SVM), etc. have been employed to derive predictor-predictand relationships. The major advantage of transfer function approach is their relative simplicity in application, as ensembles of high resolution climate scenarios may be produced, thereby increasing its versatility. Application of transfer function method in climate change impact studiesmay be found in Cannon and Whitfield (2002); Tripathi et al. (2006); Bürger (2009); Vasiliades et al. (2009); and Chen et al. (2011).

A major drawback to the transfer function method is the possibility of an unstable relationship between the predictors and predictands which may result to under-prediction of the observed variance (Fung et al. 2011). Therefore, there is a need for the model be constrained in order to preserve local co-variance and also the artificial inflation of the variance of the downscaled predictand. Although, this may translate into the production of additional white noise for better match observations, it could however lead to degradation of other aspects of the time-series such as its autocorrelation structure.

Weather Typing

Weather typing involves the classification of regional climate into a number of discrete weather types and circulation patterns, and relating it to different classes of atmospheric circulation. The weather classes may be defined subjectively as obtainable in the lamb weather types (LWT) in the UK and European Grosswetterlagen (GWL) (Kyselý and Huth 2006). It may also be defined objectively by using computer-assisted techniques such as fuzzy clustering (Bárdossy et al. 2002) and principal component analysis (PCA) (Sheridan 2002). In addition, a combination of both the subjective and objective weather classes can be implemented to form a hybrid version as applied in the study conducted by Ghosh and Mujumdar (2008).

The advantages of the weather typing approach include its ability to downscale a wide range of hydroclimatological variables and interpret trends in extreme events such as floods and droughts. It also produces high positive correlation between regional scale variables and large scale variables, even for non-linear scenarios. The fundamental assumption in weather typing is that the relationships between weather type and regional climate variables will continue to be valid under future forcing. However, the major drawback is that the assumption may not hold, as the occurrence of inconsistencies in the relationship between weather type and regional climate is inevitable.

Stochastic Weather Generators

Stochastic weather generators are regarded as complex random number generators designed to reproduce statistical features of a local variable. Weather generators have the ability to produce weather time series in regions of data sparsity, by interpolating observed data, while also adjusting its parameters according to future changes in mean climate and variability. The assumption is that statistical correlations between climatic variables derived from observed data are valid under a change climate.

Markov chain models have been widely used in weather generators to simulate precipitation occurrence for wet-day/dry-day transitions (Fung et al. 2011). These models may be first-order, second-order or third-order models (Fowler et al. 2007). Mason (2004) and Dubrovský et al. (2004) both employed the higher-order Markov chain models to enhance wet-and-dry spell persistence, as parameters were conditioned on specific climate events, rather than weather patterns which reduces the ability of the generator to accurately describe persistent and rare events. Wilby et al. (2002) developed the statistical downscaling model (SDSM), which is a combination of both stochastic weather generator and regression methods and have been found useful for downscaling purposes. A new approach developed by Kilsby et al. (2007) involves applying change factors to observed weather series and subsequently calibrating the model using the perturbed record rather than observations. This method has been seen as an improvement upon the Markov chain method as it produced better representation of variability and extremes within the climatic time series (Kilsby et al. 2007).

In general, weather generators are now being employed for statistical downscaling purposes especially in developing countries where they are used for generating artificial climatic series in data sparse environments. However, despite their high degree of accuracy, they tend to underestimate inter-annual variability (Mason 2004), and may create an ambiguous effect on the temporal characteristics of simulated weather (Dubrovský et al. 2004). Moreover, since weather generators are conditioned using local climate relationships, they may not be automatically applicable in other climates (Fowler et al. 2007).

Numerous studies have been conducted in which different downscaling and bias correction methods have been compared and their inherent uncertainty assessed. An in-depth analysis of such uncertainty assessment studies are available from literature (Fowler et al. 2007; Seguí et al. 2010; Chen et al. 2011; Teutschbein and Seibert 2012). Generally, some degree of uncertainty in hydrological modelling of climate change impacts are connected to the choice of downscaling technique, especially as it relates to variability and extremes. Various studies have been carried out to assess the uncertainty that downscaling techniques pose to hydrological modelling, and the importance of making the right choice as regards downscaling technique have been stressed (Wood et al. 2004; Im et al. 2010). Considering that each technique has its unique advantages and drawbacks, it is therefore necessary to evaluate these techniques on a case by case basis depending of the objectives of the study so as to reduce uncertainty levels in climate change impact assessments (Chen et al. 2011).

Uncertainty Linked To Hydrological Impact Models

Hydrological models are tools developed to provide a simplified and detailed interpretation of complex, dynamic and non-linear processes relating to water resources, thereby providing solution to various related problems under different climatic conditions irrespective of location. All hydrological models take meteorological parameters as their inputs and transform them to create hydrological outputs. Fung et al. (2011) classified hydrological models in terms of their theoretical complexities, spatial resolutions, and temporal resolutions.

In terms of their theoretical complexities, hydrological models can be classified into:

(i) Empirical models: These models are often based on mathematical equations and statistical relationships, and are the simplest in terms of application as they only describe the behavior of hydroclimatological parameters without taking into account the underlying processes. They can be very effective for the specific circumstance for which they were developed, as their performance cannot be predicted outside this range (Fung et al. 2011). Therefore, they have found limited application for implementation of appropriate model components in studies related to climate change impacts on water resources.

(ii) Physically-based models: These models incorporate laws based on the physics of water movement in catchments, and considering that the governing equations are physically-based, model parameterization can be achieved by direct measurement of catchment characteristics. However, difficulty in model parameterization, complexities in formulation, huge data demand and high computational requirement serve as drawbacks to the use of physically-based models (Beven 2002; Oyebode et al. 2014a; Oyebode et al. 2014b)

(iii) Conceptual models: These models are able to capture dominant hydrological processes for different parameter set at the appropriate scale with accompanying formulations (Booij

2005). They are deliberately configured to portray the behavioral characteristics of the catchment, making them effective for assessing the impact of climate change on water availability. However, they need to be calibrated as it is impossible to derive the model parameters directly from field measurements.

In terms of their spatial resolutions hydrological models may be (i) distributed model, which breaks the hydrological system down into smaller geographical units and produces results for many variables for each of the units; (ii) lumped model, which represents the entire hydrological system as a single entity; and (iii) semi-distributed models, which falls in between the lumped and distributed models. Their configuration is obtained by breaking the catchment under study into a number of discrete units with similar characteristics (Fung et al. 2011).

Hydrological models can also be classified according to their temporal resolution, as the modelling of time-series of hydrological response to climatic variables is of high importance. Therefore, the appropriate temporal resolution of a hydrological model must be selected in a manner that will give a good representation of the system being modeled. The choice of time steps could be daily, weekly, monthly or yearly. The choice of hydrological model for any specific hydrological problem depends on availability of base hydrological data, availability of future climate data and the complexity of the physical hydrological system being modeled.

Considering the aforementioned categories of hydrological models, the major source of uncertainty remains as to what renders a hydrological model appropriate for selection, in terms of process representations and the manner by which the major state variables and outputs are relevant to simulating responses to projected future climates are computed (Schulze 2005).

Generally, the choice of hydrological model for the purpose of climate change impact modelling is of high importance so as to ensure the development and adoption of models with structure that would be sufficiently detailed enough to capture principal hydrological processes and their natural variability (Booij 2005). Furthermore, the ability of hydrological models to obtain appropriate spatial scale and carry out simulations at different time-steps is crucial. The choice of hydrological models for climate change impact assessment is also influenced by the positive experience recorded in terms of previous applications under different climatological and geographical regions (Bergstrom et al. 2001). Finally, the need to obtain a good compromise between simplicity on one hand, and firm physical basis on the other hand remain key in order to reduce uncertainty in climate change impact studies (Booij 2005).

Uncertainty associated with the use of hydrological models can be classified into two (2) categories; uncertainty due to model structure and uncertainty due to model parameterization.

Uncertainty Due To Model Structure

This uncertainty relates to system identification which involves the selection of appropriate structures for the representation of a real system. It allows for definition of sets of proper mapping via equations that represent the relationships between the model inputs, parameters, states and outputs. Uncertainty in model structure may arise during model development as a result of the initialization of quantitative diagnostic measures, which may also be attributed to expert knowledge and subjectivity (Liu and Gupta 2007). Model structure uncertainty includes a wide range of choices and assumptions made by the modeler either explicitly or implicitly during model development or implementation.

Butts et al. (2004) examined the impact of model structure error and complexity on model performance and model uncertainty using models with different structures in the Blue River catchment, United States. Results found large variations in model performance amongst the selected model structures, with model performance showcasing some degree of sensitivity to model structure. It was found that models with distributed routing and distributed rainfall values produced higher simulation accuracies and predictive capabilities, while those with spatially distributed catchment parameters performed better than others during calibration although outperformed by other models during validation. More recently, Montanari and Di Baldassarre (2013) conducted an investigative study on how appropriate choice of model complexity could impact on observation uncertainty. The impact of data error on hydrological model projections was examined. Results were in close agreement with the submission of Butts et al. (2004), as it was found that model structural uncertainty induces a feedback on the impact of data errors. These feedbacks were found to be more significant in models with simpler structures. Jiang et al. (2007) employed six monthly water balance models to evaluate hydrologic model structural uncertainty. Large differences in projected results were observed across hydrological models of different structural makeup.

Therefore, the model structure should be considered as an important factor in making appropriate selection of hydrological model in climate change impact assessment studies. An understanding of the processes captured therein would be of strategic importance towards upgrading their structures. In addition, the adoption of multiple models with different structural characteristics may help improve the overall accuracy of hydrological simulations, thereby reducing uncertainty.

Uncertainty Due To Model Parameterization

The impacts of climate change have been found to be highly sensitive to model parameterization in some regions (Jiang et al. 2007; Booij et al. 2011; Poulin et al. 2011; Il-Won et al. 2012). Uncertainty occurs in the method employed and in the ability of the model to estimate hydrological parameters of real systems. Errors in the estimates of parameter values can translate into huge errors in the model outputs (Liu and Gupta 2007). These errors can occur at any of the stages of parameter estimation.

Booij (2005) highlighted the steps involved in parameter estimation in hydrological models. These steps include the determination of key parameters for calibration, sensitivity analysis with key parameters to obtain model optimal parameter set, and regionalization of the parameters to derive parameters for sub-basins. Furthermore, it involves the use of relationships between key parameters and river basin characteristics such as land use and soil type to access values for neighbouring sub-basins. Errors that occur in any of these stages can influence the results of the study, thereby generating uncertainty in future projections.

Poulin et al. (2011) carried out an assessment of hydrological model uncertainty by comparatively investigating the performance of a lumped conceptual model and a distributed physically-based model in a snow-dominated watershed. Parameter uncertainty was considered from the perspective of equifinality – a property of having several different parameter sets associating with the same optimal measure of tendency. Results showed that parameter uncertainty remained stable under future conditions, as the methodology employed in estimating the parameter sets enhanced the stability of future climate. Further investigations on snowless river basin were however suggested. Results from the study found that uncertainty due to model structure were more pronounced when compared to parameter uncertainty.

Il-Won et al. (2012)'s study focused on uncertainty modelling of two hydrologically distinct river basins; a snow-dominated and rainfall-dominated basin. The impacts of climate change on seasonal mean and extreme flow were examined in the two river basins using a precipitation runoff modelling system (PRSM). It was found that hydrological uncertainty varied significantly between the two basins given their climate regimes, as changes in run-off over different time-slices varied signficantly both in terms of season and basin. It was observed that change in winter runoff in the snow-dominated basin was more dependent on the hydrologic parameters. On the other hand, the influence of model parameterization on the rainfall-dominated basin were not significant. The results indicate that hydrological distinct river basins may have different ranges of model parameterization uncertainty. Bae et al. (2011) analyzed hydrological uncertainty under future climate by running of near optimal parameter sets for two hydrological models. Results indicated that major uncertainty sources may vary depending on the location of basins due to different hydroclimatological variablity. Hence, interpretation of climate change impact assessment results in extreme regions may require more understanding and carefulness in order for the results to be taken as reliable (Najafi et al. 2011).

Considering the results of uncertainty assessment studies conducted to determine the influence of hydrological models, a high degree of uncertainty can be attributed to the use of hydrological models in climate change impact studies. Therefore, making the right selection of hydrological models with particular reference to their structure and parameterization will not only increase the robustness of hydrological modelling tools, but also the veracity of their resultant projections. This would also positively influence interpretatbility of projections, thereby translating to meaningful progress for the field of water resource systems modelling.

Conclusion

An extensive review of climate change impact modelling techniques and their inherent sources of uncertainty has been presented in this paper. The major sources of uncertainty in identified and discussed include (i) uncertainty linked to GCMs which include future emissions of greenhouse gases and their interpretations, GCM process descriptions, spatial and temporal resolutions as well as GCM initialization; (ii) uncertainty in the representation of climatological variables at regional and local scales including the choice of downscaling and bias correction methods and (iii) uncertainty linked to the structure and parameterization of hydrological models used for climate change impact assessment.

Results from a wide range of uncertainty modelling studies have found uncertainty linked to GCMs to be the most significant and pronounced amongst other sources of uncertainty; with a substantial portion of GCM-based uncertainty attributed to their structural configuration. In addition, traces of large-scale features of GCMs remain evident throughout subsequent phases of the climate change modelling process. Downscaling and bias correction-related uncertainty must also be given more attention so as to achieve more accurate and reliable estimation of climate change impacts. Inasmuch as the choice of downscaling technique is climate specific, there is a need for evaluation of the techniques on a case by case basis depending on the objectives of the study in order to achieve better results. There is high possibility that the adoption of multi-downscaling techniques for uncertainty estimation in hydrologic studies would facilitate the accuracy of future projections. In like manner, efforts should be directed towards enhancing the structural and parameter identification features in hydrological models so as to allow for good representation of internal processes across wide range of river basins. It is however important to note that appropriate choice of hydrological models to suit a specific climate remains crucial to achieving accurate and reliable of hydrological projections.

Finally, there is a need for further research aimed at identifying, analyzing and reducing uncertainty associated with climate change impact modelling on water resource systems so as to improve the performance of developed models; by ensuring better predictive accuracy and reliability. This would assist water managers and other stakeholders in formulating policies and strategies which will translate into effective management of available water resources especially in this era of climate variability.

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