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Hydrologic drought prediction under climate change: Uncertainty modeling with Dempster–Shafer and Bayesian approaches

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ABSTRACT

Representation and quantification of uncertainty in climate change impact studies are a difficult task. Several sources of uncertainty arise in studies of hydrologic impacts of climate change, such as those due to choice of general circulation models (GCMs), scenarios and downscaling methods. Recently, much work has focused on uncertainty quantification and modeling in regional climate change impacts. In this paper, an uncertainty modeling framework is evaluated, which uses a generalized uncertainty measure to combine GCM, scenario and downscaling uncertainties. The Dempster–Shafer (D–S) evidence theory is used for representing and combining uncertainty from various sources. A significant advantage of the D–S framework over the traditional probabilistic approach is that it allows for the allocation of a probability mass to sets or intervals, and can hence handle both aleatory or stochastic uncertainty, and epistemic or subjective uncertainty. This paper shows how the D–S theory can be used to represent beliefs in some hypotheses such as hydrologic drought or wet conditions, describe uncertainty and ignorance in the system, and give a quantitative measurement of belief and plausibility in results. The D–S approach has been used in this work for information synthesis using various evidence combination rules having different conflict modeling approaches. A case study is presented for hydrologic drought prediction using downscaled streamflow in the Mahanadi River at Hirakud in Orissa, India. Projections of n most likely monsoon streamflow sequences are obtained from a conditional random field (CRF) downscaling model, using an ensemble of three GCMs for three scenarios, which are converted to monsoon standardized streamflow index (SSFI-4) series. This range is used to specify the basic probability assignment (bpa) for a Dempster–Shafer structure, which represents uncertainty associated with each of the SSFI-4 classifications. These uncertainties are then combined across GCMs and scenarios using various evidence combination rules given by the D–S theory. A Bayesian approach is also presented for this case study, which models the uncertainty in projected frequencies of SSFI-4 classifications by deriving a posterior distribution for the frequency of each classification, using an ensemble of GCMs and scenarios. Results from the D–S and Bayesian approaches are compared, and relative merits of each approach are discussed. Both approaches show an increasing probability of extreme, severe and moderate droughts and decreasing probability of normal and wet conditions in Orissa as a result of climate change.

1. Introduction

Uncertainty in projected climate change arises from a number of sources [5]: (1) the formulation and accuracy of the General Circulation Model (GCM); (2) the magnitude of anthropogenic emissions; and (3) the temporal and spatial impacts of natural variations internal to the climate system. The first source of uncertainty, referred to as GCM uncertainty, can be attributed to the structural set-up (e.g. the choice of grid resolution and climate processes included), and variability in the internal parameterizations of a GCM. The second source of uncertainty, referred to as scenario uncertainty, arises due to uncertainty in evolution of socio-economic scenarios and human action. To account for the GCM and scenario uncertainties, the use of GCM and scenario ensembles is recommended for a realistic assessment of climate change impacts. Unlike the other sources of uncertainty, the third type of uncertainty resulting from the chaotic nature of the climate system is an inherent property of the real climate system. Some studies use ensembles of GCMs with different initial conditions for representing the impacts of this type of uncertainty. This uncertainty will always be present and cannot be reduced by human actions. The other sources of uncertainty are human caused, either by inadequate modeling or by uncertain understanding of how political and social processes turn out. Assessing regional hydrologic impacts of climate change through downscaling adds another source of uncertainty, through the choice

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of downscaling method. These uncertainties, arising from 'incomplete' and 'unknowable' information [26], propagate through the climate change impact assessment in an inter-dependent, but not necessarily additive or multiplicative manner. Thus, cascading uncertainties up to the regional or local level leads to large uncertainty ranges at such scales [33,43]. It is necessary to apply rigorous methods for representing and quantifying uncertainty in order to assist a risk-based approach to decision-making.

Recent studies to quantify uncertainty in large-scale climate change prediction have typically used a comparison or spread of results from various GCMs, scenarios and downscaling methods, perturbation analysis of simplified climate models or expert opinion to quantify uncertainty in climate variables [16]. Uncertainty in predictions resulting from the GCMs is estimated by developing probability distributions of key parameters (such as climate sensitivity or strength of the terrestrial carbon sink), which are then propagated through the GCMs using a Monte Carlo method. Model structural uncertainty is usually assessed by generating and comparing results from multiple model formulations. Such uncertainty analysis results in a probability distribution for global or regional temperature increase corresponding to each emissions scenario. However, subjective judgments are often used for the choice of probability distributions for model parameters (e.g., [24]). Recently, Bayesian Monte Carlo updating approaches have been used to represent uncertainty in key model parameters [10,26,38,39]. Greene et al. [13] generated probabilistic regional temperature projections by using a multi-model ensemble of atmosphere–ocean GCMs, using a Bayesian linear model. A commonly used method of evaluating effects of climate change on flow regime is to use an ensemble of GCMs, scenarios and statistical downscaling/regional climate models to provide inputs to a hydrological model, and examine the range of effects on a statistic of the modeled hydrologic variables [1,3,24,29,44]. GCM and scenario uncertainties have been studied in terms of PDFs of a hydrologic drought indicator such as standardized precipitation index (SPI) [11], using an imprecise probability approach [12] and through a possibilistic approach for streamflow downscaling [25]. Prudhomme and Davies [28] examined uncertainties in climate change impact analyses on river flow regimes in the UK, using either a statistical or dynamical downscaling model for downscaling precipitation from an ensemble of GCMs and scenarios, propagated to river flow through a lumped hydrological model. They showed that uncertainties from downscaling techniques and emission scenarios are of similar magnitude, and generally smaller than GCM uncertainty. Kay et al. [17] compared sources of uncertainty with respect to impact on flood frequency in England. They considered six different sources of uncertainty: future greenhouse gas emissions; Global Climate Model (GCM) structure; downscaling from GCMs (including Regional Climate Model structure); hydrological model structure; hydrological model parameters and the internal variability of the climate system (sampled by applying different GCM initial conditions). Minville et al. [23] studied the impact of climate change on the hydrology of the Chute-du-Diable watershed in Canada by comparing the statistics on current and projected future discharge. They used ten equally weighted climate projections from a combination of five general circulation models (GCMs) and two greenhouse gas emission scenarios (GHGES) to define an uncertainty envelope of future hydrologic variables.

The present study evaluates the use of a generalized uncertainty measure using the Dempster–Shafer evidence theory, for quantifying uncertainty in regional climate change projections. An uncertainty modeling framework, which combines GCM, scenario and downscaling uncertainties is evaluated. The Dempster–Shafer (D–S) evidence theory, which can be considered a generalized Bayesian theory [6], is used for representing and combining uncertainty. The D–S theory has in recent years found wide applications in the fields of statistical inference, sensor fusion, expert systems, diagnostics, risk analysis, and decision analysis, due to its versatility in representing and combining different types of evidence obtained from multiple sources. In this work, the uncertainty combination methodology is applied to projections of hydrologic drought in terms of monsoon standardized streamflow index (SSFI-4) classifications, which are obtained from streamflow projections for the Mahanadi River at Hirakud in Orissa, India. Three GCMs (MIROC3.2, CGCM2 and GISS) with three scenarios each (A1B, A2 and B1) are used. A conditional random field (CRF) downscaling model [30] is used, whose output gives n-best predictions which are converted to SSFI-4 projections. These are then used to construct a Dempster–Shafer structure (DSS) through a basic probability assignment (bpa) on SSFI-4 classifications. Future projected DSSs of the hydrologic variable are combined using the Dempster–Shafer theory of evidence combination. Projections from GCMs are combined using Dempster's rule, Zhang's center combination rule and disjunctive consensus rule of combination to get the final projections for the hydrologic variable (SSFI-4 classifications) and the associated uncertainty. A Bayesian approach is also used to derive posterior distributions for frequencies of each SSFI-4 classification for the same case study from the ensemble projections of GCMs and scenarios. Caselton and Luo [4] presented a water resources example of an application of the Dempster–Shafer approach and compared results with those from a Bayesian scheme. Luo and Caselton [20] presented aspects of the D–S approach that contribute to its appeal when dealing with information sources on climate change through examples. Recently, Raje and Mujumdar [31] used the Dempster–Shafer theory for uncertainty modeling in development of a methodology to constrain uncertainty using a nonstationary downscaling relationship. The present study analyses the D–S approach in detail, and provides key insights into the applicability and advantages of the D–S theory in uncertainty representation and combination as compared to traditional uncertainty modeling approaches. A Bayesian approach is presented which combines GCM and scenario uncertainties to provide posterior distributions for each category of SSFI-4. Results from the D–S and Bayesian approaches are compared and contrasted in this paper, and the relative merits of each approach are discussed. It is seen that both approaches have several unique advantages, and could be used as complementary approaches in an uncertainty modeling framework for prediction of hydrologic impacts of climate change. The results from this work indicate an increasing probability of extreme, severe and moderate drought and decreasing probability of normal to wet conditions, as a result of decreasing monsoon streamflow in the Mahanadi River due to climate change.

The paper is organized as follows. Section 2 presents the uncertainty combination framework for hydrologic drought prediction using D–S theory. Section 3 presents the basis of the Bayesian approach used in this work. Section 4 presents a case study application of the methodologies to the Mahanadi River. Section 5 contains results and discussion. Section 6 presents concluding remarks and potential for future research.

2. Uncertainty modeling using Dempster–Shafer theory

2.1. Dempster–Shafer Theory

Risk analysts recognize two fundamentally distinct forms of uncertainty [14]: Type I uncertainty or aleatory uncertainty arising from environmental stochasticity, inhomogeneity of materials, fluctuations in time, variation in space or heterogeneity; and Type II or epistemic uncertainty which arises from scientific ignorance, measurement uncertainty, or other lack of knowledge. In the climate modeling and regional impact assessment problem, for example, Type I uncertainty typically arises from natural variability internal to the climate system, whereas GCM and scenario uncertainties can be classified as Type II uncertainty. Although probability theory is traditionally used to characterize both types of uncertainty, critics [35,41] claim that traditional probability theory using the frequentist approach may not be capable of capturing epistemic uncertainty. Bayesian probability applies traditional probabilistic methods to