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# Stochastic watershed models for hydrologic risk management

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ABSTRACT

Over half a century ago, the Harvard Water Program introduced the field of operational or synthetic hydrology providing stochastic streamflow models (SSMs), which could generate ensembles of synthetic streamflow traces useful for hydrologic risk management. The application of SSMs, based on streamflow observations alone, revolutionized water resources planning activities, yet has fallen out of favor due, in part, to their inability to account for the now nearly ubiquitous anthropogenic influences on streamflow. This commentary advances the modern equivalent of SSMs, termed 'stochastic watershed models' (SWMs) useful as input to nearly all modern risk based water resource decision making approaches. SWMs are deterministic watershed models implemented using stochastic meteorological series, model parameters and model errors, to generate ensembles of streamflow traces that represent the variability in possible future streamflows. SWMs combine deterministic watershed models, which are ideally suited to accounting for anthropogenic influences, with recent developments in uncertainty analysis and principles of stochastic simulation.



## 1. Introduction

For pedagogic purposes, when introducing a new conceptual approach to planning for the future, it is instructive to consider how we routinely plan our personal finances. Consider the personal problem of planning for retirement to ensure an adequate source of income until death, say 30 years from now. On the one hand, one could plan for retirement assuming that future financial and investment markets will mimic, exactly, the historical market over the past 30 years. Using only historical financial markets would result in an adequate income over the next 30 years with a reliability of just 50%. This result is predicated on stationarity of the past and future market in which case the future 30-year market would generally have an equal probability of delivering higher or lower returns on investment than the historical market. The Monte-Carlo method was introduced to address this issue (see [21]) and is now a pervasive approach to personal retirement planning with proprietary software for personal web-based implementation; it is currently offered by nearly every major financial institution. The Monte-Carlo approach to retirement planning is based on a stochastic representation of the market, enabling evaluation of ones retirement nest egg over hundreds of possible future 30-year markets to ensure that with some reliability (typically in the range of 90–95%) the nest egg will deliver adequate income over that entire planning horizon. Such an approach to managing personal financial risk is more generally defined by the concept of Value-at-Risk [22].

Risk management approaches are now pervasive in the world of finance, and the concept of Value-at-Risk has emerged as the industry standard. By analogy, hydrologic risk management approaches based on Monte-Carlo simulation experiments were introduced in the middle of the twentieth century along with the necessary digital computational resources to enable their application. The creation of the field of 'operational hydrology', or 'stochastic streamflow modeling', introduced by Maass et al. [47], Yevjevich [103], Fiering [19], Matalas [51], Valencia and Schaake [88] and others, revolutionized water resources planning, design and management because it enabled hydrologists to generate what

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they believed (under stationarity assumption) to be representative ensembles of streamflow series over future planning horizons, thus enabling the exploration of consequences of future hydrologic conditions not experienced historically, along with the application of modern risk management approaches [46]. Stochastic Streamflow Models (SSMs) were designed to mimic our historical hydrologic experience, while simultaneously enabling us to recognize the range of statistically possible future hydrologic conditions and the risk of failure associated with water infrastructure. For example, with only a single experience of the 'flood of record' or the 'drought of record', SSMs can provide thousands of possible future hydrologic scenarios, each with its own flood and/or drought of record; such exercises provide a much richer set of hydrologic possibilities with which to evaluate water resource system security. SSMs also enabled hydrologists to generate streamflow traces over planning periods which are either longer or shorter than the arbitrary length of the available historical records upon which they are based. Researchers have also incorporated model parameter uncertainty into generated series to represent the limited precision with which model parameters can be estimated in a stationary world [91,76,77].

Until the arrival of SSMs, reliability based planning for water supply was challenging because hydrologists based their plans on the single n-year drought of record, which under the assumption of stationarity, has a probability of only 50% of being exceeded (or not), in future n-year planning horizons (see [92], for a detailed discussion of this issue). This was analogous to the use of the historical market for planning financial risk prior to the now pervasive use of Monte-Carlo financial risk software described above.

Over time, SSMs have enabled a much richer understanding of the reliability, vulnerability and resilience of future water resource systems [28]. Such computational tools and principles also enabled a more complete integration of uncertainty into water resource decision making and have been in common use by the U.S. Army Corps of Engineers [87] and the U.S. Bureau of Reclamation [43,66,82], and other agencies, worldwide, for over 50 years. SSMs were the prerequisite to modern Risk Based Decision Making (RBDM) approaches. RBDM is a well-established methodology that can enable determination of an appropriate level of investment based on the expected benefits and damages avoided versus the cost of the infrastructure required [58] and is now standard practice by U.S. Federal agencies (see [8]; and [73]; for references). Lempert et al. [45] and others have introduced a robust decision making (RDM) framework for making decisions based on a large number of imperfect forecasts of the future.

Instead of relying on a single probabilistic forecast of the future, RBDM and RDM seek robust strategies that are likely to lead to better outcomes (at least on average) than would result from planning with a single scenario for the future. Both approaches employ computational tools that represent the diversity of reasonable futures. Stakhiv [73] argues that the application of RBDM and RDM approaches depends critically upon a "new family of hydrologic techniques for risk, reliability and uncertainty analysis that could be used for emerging aspects of climate (and other forms of) uncertainty." (Also see [64].) Similarly, in an interagency initiative on water resources management, Brekke et al. [8] argue that "stochastic modeling can be useful for developing climate scenarios that include a wide range of potential hydroclimatic conditions. The expanded variability may allow more robust evaluation of planning alternatives".

Clearly a fundamental requirement for nearly every RBDM simulation study addressing water security, are methods for generating ensembles of streamflow traces which can characterize future hydrologic conditions. Unfortunately, as is described below, most SSMs originally designed for RBDM are no longer adequate because they do not capture changing hydrologic conditions due to anthropogenic influences. Milly et al. [53] argue that "we need to find ways to identify nonstationary probabilistic models of relevant environmental variables and to use those models to optimize water systems. The challenge is daunting."

The following section documents the fragmented state of the art associated with stochastic modeling of nonstationary hydrologic processes which serves as justification for a new approach to the development of nonstationary SSMs advanced here, termed Stochastic Watershed Models (SWMs). SWMs combine advances in deterministic watershed models (DWMs), uncertainty analysis for DWMs and stochastic streamflow modeling, together, to provide a comprehensive set of tools for hydrologic risk management under nonstationary conditions. SWMs are simply deterministic watershed models implemented in a stochastic mode (see [18]) using (possibly nonstationary) stochastic meteorological series for the purpose of generating ensembles of representative streamflow traces that represent the trend and variability in possible future flows as is illustrated in Fig. 1. Interestingly, using DWMs in this manner can also lead to novel insights into existing problems. For example, when ones goal is to calibrate a DWM for the purpose of generating representative streamflow traces, ones view of the role of model error, parameter error and input data errors evolve [39], enabling development of new approaches to model calibration, model hypothesis testing and most importantly improving our ability to ensure future water security.

## 2. What happened to the field of stochastic streamflow modeling?

Two arguments exist for the apparent demise of SSMs (1) an unrealistic reliance, focus and diversion of attention to purely deterministic approaches in planning frameworks and (2) the inability of traditional SSMs to account for the nonstationary hydrologic behavior now of interest. Koutsoyiannis et al. [38] argue that "Engineering hydrologists understood early that the design of engineering projects based on deterministic approaches would largely be a hopeless task and appreciated the usefulness of probabilistic approaches. Yet, during the last two decades, hydrology, following other geophysical disciplines, changed perspective and invested its hopes in deterministic descriptions and models."

A second argument for the demise of SSMs relates to the inability of nearly all traditional models to capture changes in streamflow regimes resulting from a variety of anthropogenic and climatic influences. This is in spite of our now pervasive understanding that human activity and influence is an integral component of the hydrologic system [52,53,95].

One emerging approach to handle hydrologic change is to adapt stationary SSMs to accommodate hydrologic change. Another approach is to adapt existing DWMs for use as SSMs, which is the central focus of this commentary. A new generation of SSMs termed Stochastic Watershed Models (SWMs) are advanced in this commentary for considering the integrated impacts of changes in climate, land use, water withdrawals, and other factors, within the context of water resource planning for ensuring water security. This section sets the stage for an introduction to a new generation of SSMs for handling nonstationary hydrologic processes, termed Stochastic Watershed Models, by summarizing past efforts to develop SSMs under nonstationary conditions.

### 2.1. A very brief review of the field of stochastic streamflow modeling

The field of stochastic hydrology began around the same time as digital computational resources became available in the 1960's and may be attributed to numerous hydrologists including, but not limited to Hurst, Fiering, Thomas, Yevjevich, and Beard, who intro-

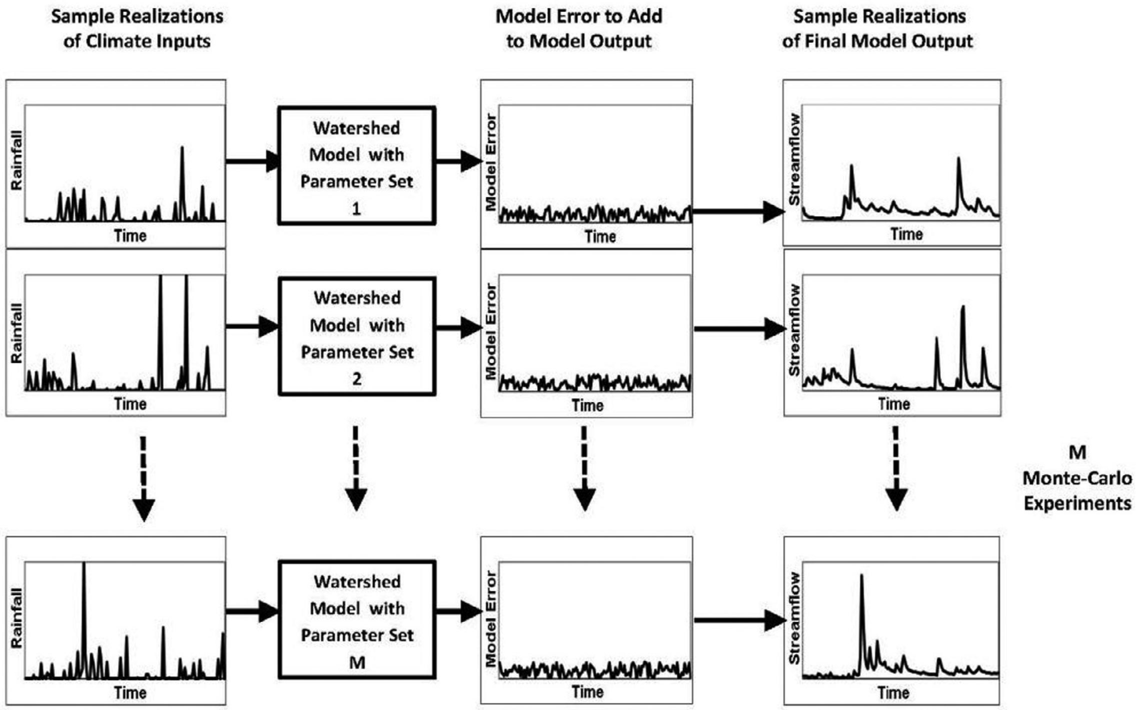


**Fig. 1.** Illustration of the implementation of M Monte-Carlo experiments using a stochastic watershed model to generate M sets of streamflow traces from M sample realizations of: climate inputs, watershed model parameters and watershed model error.

duced many of the early versions of SSMs along with associated applications. A broad overview of stationary SSMs are nicely summarized in a variety of textbooks: Salas et al. [65], Loucks et al. [46], Bras and Rodriguez-Iturbe [7], and Hipel and McCleod [30] and recent review articles by Hao and Singh [27] and Sveinsson and Salas [83]. The following discussion briefly reviews the original purpose of and software developed for implementing SSMs and then reviews the relatively few recent efforts to develop SSMs for nonstationary hydrologic processes.

### 2.1.1. Purpose of stochastic streamflow models and stochastic watershed models

The purpose of an SSM (and thus an SWM) is to generate many representative synthetic streamflow sequences that are possible realizations of what could occur in the future [19,51,75]). The multiple synthetic streamflow series derived from SSMs (and SWMs) can be used in a very wide range of water resource planning, design and management activities including: reservoir operations, irrigation scheduling, hydropower operations, drought analysis, flood control, and environmental flows; as well as studies of the behavior of estimators of drought frequency and severity and other hydrologic statistics.

### 2.1.2. Stochastic streamflow modeling software packages

Due to the need to use SSMs in water resource planning and design for a wide array of activities (see [65]) several software packages were developed by U.S. federal agencies and others. A recent summary of the wide range of SSMs used in practice can be found in Sveinsson and Salas [83]. Examples of four SSM software packages include HEC-4 [87], SPIGOT developed by Grygier and Stedinger [23], Grygier and Stedinger [24], SAMS (Stochastic Analysis Modeling and Simulation) developed by the United States Bureau of Reclamation and Colorado State University [43,66,82], and CASTALIA developed by Efstratiadis et al. [15]. HEC-4, SPIGOT, SAMS and CASTALIA only consider lagged values of streamflow as explanatory variables, without considering the other multivariate watershed, biophysical and climatic factors which impact streamflow as is the central goal here.

### 2.1.3. Nonstationary stochastic streamflow models

A review of the literature reveals a relatively immature literature on the use and development of SSMs within a nonstationary context. This section summarizes existing approaches to handling nonstationarity within the context of stochastic streamflow modeling including: (1) application of either a stationary long-memory or shifting mean SSM which can capture some of the features of nonstationary hydrologic processes, (2) the use of a stationary SSM using a conditional Monte Carlo simulation approach referred to as 'position analysis' (PA) or 'ensemble streamflow prediction' (ESP), (3) introduction of SSM model parameters and/or moments which vary as a function of covariates, (4) nonparametric and quasi-nonparametric resampling algorithms, and (5) the use of DWMs in a stochastic mode, which we term stochastic watershed models, the approach recommended here.

*2.1.3.1. Application of a stationary SSM in a nonstationary context.* Sveinsson and Salas [83] and Salas et al. [67] have suggested applying a stationary SSM within a nonstationary context, by removal of the historical anthropogenic influences from the streamflow observations to make the streamflow series stationary prior to fitting an appropriate stationary SSM. This approach is similar to the common approach of detrending or removal of periodicities prior to fitting of a stationary SSM. Another approach is to employ a stationary SSM which can exhibit properties of nonstationary processes. For example, SSMs which exhibit long-term persistence are capable of generating streamflows which exhibit abrupt shifts, long-term periodicity and even trends similar to those that have been observed in some historical records (see for example [60,36]. Even some short-memory models such as the shifting mean model (see Sveinsson et al. [81]) can exhibit abrupt shifts and trends. An example of the application of a stationary SSM which exhibits long-term persistence within a nonstationary context is the ARMA(2,1)-lognormal model utilized by Stedinger and Crainiceanu [74].

*2.1.3.2. Position analysis and ensemble streamflow prediction.* Another promising approach to the use of stationary SSMs in a nonstationary context is the use of very short term planning horizons and ensemble streamflow forecasts using either 'position analysis' (PA) [31] or Ensemble Streamflow Predictions (ESP) [14]. Both PA and ESP produce conditional ensemble streamflow forecasts yet differ critically in how the forecasts are used. PA uses the forecasts to model the influence of human activities such as reservoir storage, environmental releases, water shortages, and hydropower. Both ESP and PA are conditioned on initial conditions which generally exhibit seasonal or other nonstationary behavior, enabling the use of a stationary SSM within a nonstationary context. Hirsch [32], Tasker and Dunne [86] and Henley et al. [29] illustrate how PA may be applied within a drought context. Henley et al. [29] illustrate how PA can be conditioned upon drivers of climate and climate change. ESP employs short-term streamflow forecasts, each a possible realization of streamflow, conditioned upon a particular system and/or state variables and has found widespread use by the National Weather Service in improving flood management activities (see for example [102,17].

*2.1.3.3. SSM parameters and/or moments which vary as a function of covariates.* There are now many examples of studies which have combined expressions which describe the time-varying nature of model parameters and/or streamflow moments with stationary hydrologic models to enable a nonstationary representation of streamflow (see review by [34]). Although most such studies have been within the context of nonstationary flood frequency analysis, Sveinsson and Salas [83] have suggested this approach be applied to convert a stationary SSM into a nonstationary SSM.

*2.1.3.4. Nonparametric and quasi-nonparametric resampling algorithms.* The nonparametric bootstrap has been adapted to enable stochastic simulation of nonstationary hydrologic processes driven by atmospheric [54] and oceanic indices [44]. Bootstrap resampling algorithms for generating stochastic streamflow traces from precipitation, temperature and other climatic records have also been combined with decomposition of hydroclimatic time series in the frequency domain using spectral based methods (see [41,42,59,44,16]). Such approaches can handle processes which give rise to a nonstationary power spectrum offering significant opportunities for improving upon traditional stationary SSMs.

## 3. Stochastic watershed models to the rescue

The brief literature review revealed that in spite of the long history associated with the field of stochastic hydrology, nearly all traditional SSMs assume stationary hydrologic conditions and are based solely on streamflow observations, thus are unable to capture complex anthropogenic and/or climatic impacts on streamflow. That review also revealed a cursory literature on nonstationary SSMs concentrating mostly on statistical models with little attention given to the tremendous advances in DWMs which have occurred over the past few decades. The following sections provide a conceptual basis for SWMs and describe the challenges and opportunities in adapting DWMs to generate representative sets of stochastic streamflow traces, under conditions of hydrologic change for use in hydrologic risk management.

### 3.1. A concepual basis for stochastic watershed models

Bras and Rodriguez-Iturbe ([7], Section 1.3 titled "Simulation of Hydrologic Processes") provide a rigorous conceptual basis for the use of repeated Monte-Carlo experiments for converting sets of stochastic realizations of various inputs to a DWM to generate corresponding sets of stochastic realizations of model output. The general conceptual basis of Monte-Carlo experiments expressed by Bras and Rodriguez-Iturbe [7] provides a foundation for SWMs, but with a change in the input variables, decision variables and output variables, which tend to be more complicated and varied for an SWM than for their illustration (see Fig. 1). More recently, Montanari and Koutsoyiannis [56] introduce a generalized mathematical framework for converting a DWM into a SWM. In principle, when the joint probability distribution of all of the model inputs, parameters and errors are known, the Monte-Carlo method can be employed to obtain an approximation to the probability distribution of any hydrologic variable which is generated as output from a DWM. This is a formidable task, because all climatic, water demand and other model inputs, model parameter estimates and model errors are interrelated random variables, with future properties that are extremely challenging to predict. How to accomplish this task in practice, remains a continuing challenge for our field. Still the state of the art is promising as evidenced by recent advances in uncertainty analysis of DWMs by Pappenberger and Beven [61], Kuczera et al. [39], Brown [10], Schoups and Vrugt [69], Renard et al. [62], Beven and Binley [5], Montanari and Koutsoyiannis [56], Sikorska et al. [70] and others.

Arguably, a conceptual basis for the application of SWMs now exists within the context of the now hundreds of studies which have employed advanced methods of uncertainty analysis in combination with DWMs in order to develop uncertainty bounds, or prediction intervals associated with either streamflow predictions (i.e. see previously cited studies) and/or other water resource system variables [1,6,57]. The methods employed for constructing uncertainty intervals for watershed model predictions can easily be adapted for use in generating and evaluating representative streamflow traces, and that is one of the central points of this commentary.

### 3.2. Some examples of stochastic watershed models (SWMs) in practice

The conversion of DWMs for use as SWMs is not new. Clark et al. [11], Schaake et al. [68], and others in the flood forecasting community have used DWMs to generate representative sequences of streamflow using a sensible joint resampling of both historical climatic model inputs and model calibration residuals now known as the "Schaake Shuffle". The application of a DWM in a 'stochastic mode' holds great promise for generating nonstationary stochastic streamflow traces. In fact, Farmer and Vogel [18] document that unless DWMs are used in a stochastic mode by adding model error to simulation output, systematic bias will arise in simulated extreme events because their variance and other upper moments will be generally, too small.

In spite of the large number of studies which have applied uncertainty analysis to DWMs for the purpose of computing streamflow prediction or uncertainty intervals, it is challenging to find studies which have used DWMs within the context of hydrologic risk management, based on either robust decision making and/or risk based decision making analyses. Some studies have sought to adapt a DWM for use as a SWM to generate and evaluate multiple representative streamflow series [100,26,79,80]. Steinschneider et al. [79] combined a stochastic model of climatic inputs with two different DWMs, followed by the stochastic simulation of multiple synthetic streamflow series while accounting for both model parameter uncertainty and a probabilistic treatment of model errors. *Perhaps the best example of the approach suggested in this commentary*, to date, is provided by Steinschneider et al. [80] who apply an SWM for the purpose of generating multiple streamflow traces which are in turn used to evaluate robust reservoir operating decisions under climate change. Steinschneider et al. [80] illustrate the central goal of this commentary which is the application of a SWM for use in hydrologic risk management.

### 3.3. Stochastic streamflow traces are needed; not uncertainty intervals

There are now many studies which have employed methods of uncertainty analysis in combination with DWMs to develop uncertainty intervals associated with either streamflow predictions [4,5,69,62] or other water resource system variables [1,6,57]. However, there are very few examples of studies which have adapted those very same methods of uncertainty analysis for generating representative traces of streamflow and evaluated the degree to which those traces reproduce the expected behavior of streamflow series [39] and applied them to hydrologic risk management [79,80]. While uncertainty intervals are interesting and useful, the resulting intervals are of little value in the type of RBDM and RDM approaches which are now in common use worldwide and sorely needed to solve future water security challenges. However, if the streamflow ensembles used to produce uncertainty intervals are representative of actual streamflow series, then those ensembles could be extremely useful for hydrologic risk management, another central point of this commentary. It is difficult to assess the human implications of future streamflows based on uncertainty intervals, alone, yet simulation modeling of the human response to future streamflow patterns, using streamflow ensembles derived from uncertainty analysis, can be useful for estimating the human implications of streamflow change.

### 3.4. Stochastic watershed models: verification and validation

A central goal of developing a SWM is to enable the generation of multiple sequences of meteorological inputs and streamflows that as a set (ensemble), represent the distribution of possible future hydrometeorological sequences that would effect the operation of water resource systems. Prior to the application of an SWM for evaluating the impact of hydrologic change, one must ensure that the model is credible. Such an evaluation of a SWM would follow the basic guidelines associated with the construction, verification and validation of any stochastic simulation model summarized by Stedinger and Taylor [75] and Salas et al. [65] and now common practice in the much larger field of simulation modeling. Stedinger and Taylor [75] suggest that "Verification of a" SWM "would be a demonstration that the generated flows have the means, variances, correlations, and other statistics [such as jumps and/or trends] that flows with the selected multivariate distribution and the estimated parameters should have. Validation of a SWM would be a demonstration that the model reproduces characteristics of historical streamflows not explicitly reproduced as a result of the parameter estimation process." Klemes [35] describes a set of hierarchical operational procedures suited to the development and testing of SWMs under conditions of hydrologic change whether that change is occurring over space and/or time. Model validation exercises should also evaluate if the SWM can generate streamflow traces which can reproduce important hydrologic and water resource system properties which are related to the actual RBDM and RDM activities which the model is intended to address (see [75]; and Chapter 3 of [65]; for examples). For example, if ones interest is in water supply planning, reproduction of various drought, storage and water deficit statistics would be a priority (see [84,85]).

Importantly, model validation exercises would also evaluate the overall behavior of model residuals to ensure that they are approximately independent and identically distributed (iid). The idea of iid residuals is only a goal, and if it is not possible or realistic, then the goal would be to develop a SWM which could properly represent the stochastic behavior of the non-iid behavior of the residuals. When model residuals exhibit non-iid behavior, they contain deterministic information which ideally, would be represented by the model, not its residuals. Surely there will be a tradeoff between model goodness-of-fit and the degree to which residuals exhibit iid behavior. Cosby and Hornberger [12] and Cosby et al. [13] found that even for a much simpler deterministic photosynthesis-light model, the goal of iid residuals was unrealistic.

Stedinger and Taylor [75] document that verification of the SWM is not a simple matter of comparing the historical streamflow statistics to the statistics of the modeled flows, which has been incorrectly implemented in nearly every previous study, because sample estimators of the various statistics such as variance, skewness and autocorrelation can exhibit considerable bias. Thus Stedinger and Taylor [75] introduce unbiased estimators of those statistics in their Eqs. (12)–(14) which are uniquely suited to the verification of SWMs. Those equations, or analogous equations developed for other statistics such as jumps and trends, must be used to verify that the model can reproduce the statistics upon which the model is based.

### 3.5. Stochastic weather generation for stochastic watershed models

As our awareness evolves concerning the impact of climate change on water resource systems, there is a corresponding evolution in approaches for modeling our future climate at a scale commensurate with hydrologic and water resource impact assessment models. Unfortunately, the spatial and temporal scales of general circulation models (GCMs) and hydrological models are different [101], in part because climate models were not developed to provide the level of accuracy required for adaptation-type analysis which the water resources community needs [40]. Koutsoyiannis et al. [37] and Anagnostopoulos et al. [2] have compared the output of various climate models to temperature and precipitation observations at various locations around the world and found that both point scale and spatially integrated climate model projections gave poor agreement with historical data. Of course the goal should be for climate model projections to give a good representation of the future and not the past. One strategy for determining if they may be able to do so is to use them in hindcast mode (for example using the past century of increasing greenhouse forcing) and evaluating the trends that may be observed in the hydrologic traces they generate and compare those to the actual hydrologic records that have been observed. To move forward on stochastic nonstationary weather generation for hydrologic modeling we need to perform such experiments to evaluate if the models produce results that are plausible representations of the future. There will continue to be considerable uncertainties propagated through the morass of computations from emissions scenarios, GCMs, regional climate models, and bias corrections, to hydrologic and water resource systems models, referred to by Foley [20] as the "uncertainty cascade".

An alternative to the use of GCMs are stochastic weather models, which can be used to generate random weather sequences that are statistically consistent with historical weather observations, analogous to the way in which SSMs are used to generate streamflow sequences which are statistically consistent with historical streamflow observations. A burgeoning literature exists on stochastic weather generation (see an early review by [99]; and the more recent literature review in [90]). Stochastic weather generators are attractive because they can be designed to reproduce historical climate, and may also be used in combination with GCMs

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to generate forecasts [98], though such forecasts suffer from all the shortcomings mentioned above.

What is sorely needed is a strategy for testing methods for generating representative ensembles of future atmospheric inputs to a SWM that provide confidence that they can reasonably represent the variability and trends (or lack of trends) that we see represented in the historical climate of the last several decades. Using hindcasts driven by the actual history of greenhouse forcing must be a part of this process. Wilby [97] offers a set of five principles for comparing models and improving the current suite of climate models to serve better the needs of the hydrologic modeling community.

## 4. Stochastic watershed models: challenges and opportunities

This commentary has outlined the long and rich history of the application of stochastic streamflow models (SSMs) in risk based decision making (RBDM) and highlights that most existing models were designed and constructed to generate stationary streamflow sequences. Since most existing SSMs are based solely on streamflow observations, it is not possible to explore the impact of changes in land use, water use and climate on streamflow. This limitation is becoming increasingly important and constraining as we continue to acknowledge nonstationary behavior of hydrologic systems due to anthropogenic influences [53,93,94,95,89,63,33]; and many others). Due to the now widespread acceptance that hydrologic systems often have and will undergo significant change, it is no longer reasonable to plan our future water resource systems by assuming that future conditions will replicate past hydrologic experience. Anthropogenic influences on streamflow regimes are now pervasive, creating a need for a new generation of nonstationary SSMs termed stochastic watershed models (SWMs), for addressing all the same water resource planning, design and management activities for which stationary SSMs were originally designed to address, and in addition, to respond to the numerous challenges which SSMs are unable to address. For example, in addition to their ability to account for nonstationary anthropogenic and other complex influences on watershed behavior, SWMs can be used to evaluate new land, water and energy management policies. The following challenges and opportunities associated with SWMs are envisioned:

### 4.1. Opportunities for an immature field

The brief review of nonstationary SSMs revealed an immature and fragmented literature with little guidance for a cohesive approach to address the myriad of issues relating to nonstationary hydrologic processes. Most nonstationary SSMs developed to date appear to require a high level of statistical competence including: Bayesian statistics, wavelets, and spectral analysis in addition to a background in simulation modeling and stochastic processes needed for the development, implementation and validation of any SSM. This commentary has highlighted a tremendous need for the development, verification and validation of SWMs for use in risk based planning activities under nonstationary conditions, a need which appears to be rapidly increasing [8,9,49,25].

### 4.2. The time is ripe for stochastic watershed models

SWMs are simply deterministic watershed models implemented in a stochastic mode (see [18]) using stochastic meteorological series to generate ensembles of streamflow traces that represent the possible variability in future flows (generally for some specific year). Many of the needed ingredients are now available for the implementation of SWMs. There are dozens of watershed models to choose from as evidenced by the variety of textbooks which summarize numerous software packages for their implementation (for example, see [3,96,72,71]) including a highly sophisticated National Water Model [48] which can provide near real-time, high spatial resolution streamflow forecasts for the entire U.S. Similarly, there are many methods of uncertainty analysis for creating uncertainty intervals for streamflow predictions from watershed models, as evidenced from the now over 1865 citations to the GLUE method introduced by Beven and Binley [4,5], (which comes with its own controversy; see [55,50]; and [78]). Existing methods of uncertainty analysis originally developed for the purpose of generating 'uncertainty intervals' or 'prediction intervals' (see previous citations) can be adapted for use in generating representative stochastic traces of streamflow series. Thus many of the necessary ingredients are in place for the development and testing of SWMs for use in risk-based decision making activities. Perhaps the most critical and vexing challenge remaining for the successful implementation of SWMs involves the generation of representative ensembles of future atmospheric inputs to a SWM described below.

### 4.3. Representative stochastic weather inputs – the missing link

A SWM is ideally suited to address challenges created by human actions on the landscape within a watershed, however, representative climate/weather models are needed as input to SWMs, to address challenges within the watershed, resulting from human activities occurring at regional and global scales which are transmitted through the atmosphere. Kundzewicz and Stakhiv [40] argue that while they are improving, climate models are still not ready for "prime time", at least for direct application to water management problems. They argue that much more research is needed and models need to be considerably improved before they can be used effectively for adaptation planning and design. What is sorely needed is a strategy for testing methods for generating representative ensembles of future atmospheric inputs to a SWM that provide confidence that they reasonably represent the variability and trends (or lack of trends) that we see represented in the historical observations from the last several decades.

### 4.4. Opportunities for new insights

While there are now many studies which have employed methods of uncertainty analysis in combination with DWMs in order to develop uncertainty intervals associated with either streamflow predictions [4,5,69,62] or other water resource system variables [1,6,57] there are very few examples of studies which have adapted those methods of uncertainty analysis for generating representative traces of streamflow [79,80] and evaluated the degree to which those traces reproduce the expected behavior of streamflow series [39]. It is anticipated that when existing DWMs are evaluated in a 'stochastic mode', that new insights, challenges and opportunities will arise. For example, it is now increasingly common to fit complex stochastic models to DWM residuals for the purpose of performing uncertainty analysis. An alternative approach would be to modify the objective function for the calibration of DWMs to ensure that model residuals are approximately independent and identically distributed (iid) while simultaneously ensuring a good fit to observed streamflows. When model residuals exhibit deterministic behavior such as persistence, seasonality and/or trend, those residuals are 'doing the work that the model should be doing'. The idea is for the watershed model to have most of the explanatory power, with little to no explanatory power left to the residuals. Furthermore, if a SWM can be fit in such a way as to ensure iid residuals, its application in a stochastic mode will be straightforward and would not require the high level of statistical sophistication currently needed for the application of commonly used methods of uncertainty analysis such as Markov Chain Monte Carlo and the Bayesian GLUE approach. There will clearly be a tradeoff between goodness-of-fit and the degree to which one can obtain iid residuals and it is that very tradeoff that may offer considerable new insights into our ability to calibrate, verify and validate SWMs as well for improving our scientific knowledge of hydrologic processes and performing RBDM. It is also expected that explorations of this tradeoff using some of the recent ideas on multi-objective calibration of DWMs [104] should also provide numerous benefits.

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