Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

Evaluating impacts of climate change on future water scarcity in an intensively managed semi-arid region using a coupled model of biophysical processes and water rights

Bangshuai Han[1*], Shawn G. Benner[2,3], and Alejandro N. Flores[2,3*]

[1]*Natural Resources and Environmental Management, Ball State University, Muncie, IN, 47304*

[2]*Geosciences, Boise State University, Boise, ID, 83725, USA*

[3]*Human-Environment Systems, Boise State University, Boise ID, 83725, USA*

**Corresponding authors: B. Han, bhan@bsu.edu; A.N. Flores, lejoflores@boisestate.edu*

Key Points:

- A new efficient method that captures the plausible range of variability of future climate change along with central tendencies
- A model that explicitly captures the spatiotemporally varying irrigation activities as constrained by local water rights
- An application to a semi-arid watershed to project water scarcity patterns under future climate change scenarios

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

Abstract

In semiarid and arid regions with intensively managed water supplies, water scarcity is a product of interactions between complex biophysical processes and human activities. Evaluating water scarcity under climate change necessitates modeling how these coupled processes interact and redistribute waters in the system under alternative climate conditions. A particular challenge on the climate input lies in adequately capturing the plausible range of variability of future climate change along with central tendencies. This study generates a large ensemble of daily climate realizations by combining a stochastic weather generator, historical climate observations, and statistically downscaled General Circulation Model projections. Three climate change scenario groups, reflecting the historical, RCP4.5, and RCP8.5 conditions, are developed. A modeling framework is built using the Envision alternative futures modeling platform to 1) explicitly capture the spatiotemporally varying irrigation activities as constrained by local water rights; and 2) project water scarcity patterns under climate change. The study area is the Treasure Valley, an irrigation-intensive semi-arid human-environment system. Climate projections for the region show future increases in both precipitation and temperature. The projected increase in temperature has a significant influence on the increase of the allocated and unsatisfied irrigation amount. Projected changes in precipitation produce more modest responses. The scenarios identify spatially distinct areas more sensitive to water scarcity, highlight the importance of climate change as a driver of scarcity, and identify potential shortcomings of the current water management. The approach of creating climate ensembles overcomes deficiencies of using a few or mean values of individual GCM realizations.

Key words:

Climate change, weather generator, general circulation models, water security, water rights, integration

1. Introduction

Simulations of the global climate system, often called General Circulation Models (GCMs), provide valuable insight into future climate change [Stocker et al., 2014]. There is a growing need to extend these climate model scenarios to regional and local water resources to understand potential impacts at a scale relevant to policy decision making (Giorgi et al., 2009). Climate change is anticipated to impact water resources in a variety of ways including increased vapor pressure deficits associated with higher temperatures [Will et al., 2013], increased frequency of extreme flooding and drought [Cai et al., 2014], shifts in precipitation phase from snow to rain, and changes in the timing and rate of melt of mountain snowpacks [Klos et al., 2014; Vano et al., 2015]. In arid and semi-arid systems where water availability is limited, e.g., the Western US, areas of the Iberian Peninsula, etc., climate change may stress the capacity of physical, cyber, and/or social infrastructure that has been developed to supply sufficient water to meet demands [Bosher et al., 2007; Marston and Cai, 2016].

Despite the importance of climate change on water resources, incorporating the effects of climate change into regional hydrologic model is challenging, as both climate and hydrologic systems are complex with numerous underlying uncertainties [Fowler et al., 2007]. Large-scale GCMs are most appropriately used for predicting climate change at

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

global scales, and large ensemble experiments with GCMs have shown significant regional, decadal-scale variability despite strong agreement at the global scale [Dominguez et al., 2012; Fildes and Kourentzes, 2011]. Statistical and dynamical downscaling methods have been developed to take outputs from GCMs and create forcings for models in an effort to assess climate change impacts at regional and local scales. However, and despite the increasingly sophisticated process representations within GCMs and improved spatial resolution, GCMs are not designed for the application of hydrological responses to climate change, and little confidence can be placed in application at daily time scales [Ashfaq et. al., 2010; Wilby and Wigley, 1997].

Due to internal climate variability, single realizations from climate models are often insufficient for model comparison to the observational record, model intercomparison, and future projections [Kay et al., 2015]. For example, research has found that even models sharing similar parameterization schemes may produce considerably different daily precipitation statistics [Frei et al., 2003]. Slight changes of the initialization of a GCM have been shown to produce completely different regional climate realizations after decades due to the internal randomness and chaos, even though the models still produce consensus estimates at the global scales [Kay et al., 2015]. This climate internal variability/uncertainty can be transferred and enlarged in the daily hydrological models when simulating hydrological runoff responses [Chen et al., 2012].

To overcome this, previous studies have been using multiple downscaled GCMs to incorporate a range of climate change projections [Abatzoglou and Brown, 2012], or using the averaged values from multiple GCMs to reduce the uncertainties from

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Discussions

individual GCMs [Fordham and W., 2011]. Currently available dynamically and statistically downscaled datasets used for climate change impacts studies at regional scales do not adequately capture uncertainties both within and between climate models in a way that can support robust quantification of the probability distribution function of outcomes of interest, like insufficiencies in water supply.

What is needed are large ensembles of realizations of forcings to drive regional models that capture uncertainties within individual GCMs, as well as variability across GCMs. Developing forcing ensembles using either statistical and/or dynamical downscaling [Abatzoglou and Brown, 2012; Dosio and Paruolo, 2011] can be prohibitively expensive because of requirements of storage, computational time, or both. Nevertheless, projections of future climate derived from GCMs reflect our best current knowledge of future climatic conditions and judicious and thoughtful use in regional climate impacts and adaptation studies remains a promising path forward. It is important to recognize, in particular, that no single climate model reliably represents future climate at the spatiotemporal scales required to support regional and local climate change impacts assessments.

Stochastic weather generators represent a potentially useful tool to help overcome some of the challenges of downscaling of GCMs. Stochastic weather generators [Chen, et al., 2010; Richardson, 1981; Richardson and Wright, 1984; Semenov and Barrow,1997; Wilks, 2010] were developed to create plausible realizations of weather variables (particularly temperature, precipitation, and other environmental variables) at locations and temporal resolutions when only climatic statistics are available. Typically,

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

stochastic weather generators take as input climatic parameters like the average duration of time between storms, average storm duration and depth, monthly average daytime high temperature and produce realizations of variables like precipitation intensity, air temperature, and wind speed at temporal resolutions of days or hours. In generating realizations of weather variables, they often rely on a number of simplifying assumptions (e.g., exponential distribution of between-storm duration, etc.). They have the advantage of being far more computationally efficient than, for example, using a numerical weather model to generate weather conditions at a location. As a result, stochastic weather generators are useful for generating large ensembles of weather conditions required as input to models.

At the same time, stochastic weather generators are associated with important limitations with the assumptions underlying the form of the weather generator itself and, perhaps more importantly, the stationarity of the climate processes summarized by the statistics required as input. Specifically, stochastic weather generators cannot predict future climate change because they assume stationarity in the underlying statistics provided as input. Moreover, care is required when using stochastic weather generators to create environmental model forcings to evaluate sensitivities to future climate change because the climate statistics input to stochastic weather generators are likely correlated and cannot be perturbed independently of each other. Additionally, due to the intrinsic uncertainties associated with the output of stochastic weather generators (i.e., the output of a weather generator is a single realization of a stochastic process) it is not possible to identify a single realization as being the most representative or useful. To robustly characterize the probabilistic behavior environmental systems in response to

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

uncertain forcings it is necessary to: (1) generate an ensemble of realizations of weather, (2) use this ensemble to create a corresponding ensemble of environmental outcomes by supplying each weather realization as input to an environmental model, and (3) examine the central tendency and variability across all outcomes.

In this work, we develop a framework for combining the outputs of statistically downscaled output from multiple GCMs with stochastic weather generators to evaluate the probabilistic potential impacts of climate change on a coupled socio-hydrologic system. Using the combination of GCM output and stochastic weather generators has previously been used to examine hydrological and ecological impacts of climate change [Mikhail, 1997; Xu, 1999]. These previous studies, however, relied on output from only one GCM projection, thereby missing potential impacts of climate change across uncertainties associated with the spectrum of GCMs currently used for global climate change analysis as part of the Intergovernmental Panel on Climate Change (IPCC) quadrennial review. In this study, we extend previous efforts by developing techniques to use information from multiple GCMs along with an existing stochastic weather generator to produce a suite of daily weather variables useful for a broad range of environmental models. The developed method first uses statistically downscaled output from multiple GCMs to derive an empirical probability distribution function of key statistics required as input to the stochastic weather generator. Then the method uses a statistic weather generator (WXGN) to create an ensemble of realizations of weather and applies it to a hydrologic model.

We use this approach to examine the potential ramifications of climate change in a coupled socio-hydrological system through an integrated hydrologic model in an irrigation-intensive, semi-arid watershed. In particular, the coupled socio-hydrological model simulates both biophysical hydrological processes, as well as redistribution of water in accordance with the spatiotemporal regime of water rights operating in the region. By creating an ensemble of climate impacts, this approach allows us to project both future water use and scarcity under three climate change scenarios. An outcome of particular value is insight into the spatial and temporal distribution of disruptions to water supply predicted by the simulations. This information may be at a spatiotemporal scale that is of direct value to stakeholders to help manage their limited water resources. What follows is a description of the methodological approach and experimental setup, a summary of relevant results, and a discussion of potential implications, limitations, and extensions of this work.

2. Methods

2.1 Using downscaled GCMs to drive stochastic weather generator

2.1.1 The WXGN weather generator

A stochastic weather generator produces synthetic time series of weather data of specified length for a location based on statistical characteristics of observed weather at that location [Bouzaher et al., 1994]. Due to its consistency and simplicity, various stochastic weather generators have been designed, built, tested and applied [Chen et al., 2010; Flecher et al., 2010; Forsythe et al., 2014; Hayhoe and Stewart, 1996; Ivanov, 2007; Kilsby et al., 2007; Qian et al., 2004; Racsko, 1991; Richardson, 1981; Richardson and Wright, 1984; Semenov and Barrow,1997; Wilks, 2010]. WXGN (varyingly also abbreviated as WGEN or WXGEN in the literature) is a frequently used weather generator for daily weather variables that are used in various hydrologic, agricultural, or environmental models, specifically being developed to support the Environmental Policy Integrated Climate (EPIC) Model, Agricultural Policy/Environmental eXtender (APEX) Model, and Soil & Water Assessment Tool (SWAT). WXGN is based on the daily weather data generator developed by Richardson [1981] and Richardson & Wright [1984]. While many stochastic weather generators only focus on "major" weather variables such as rainfall and/or temperature, WXGN generates a comprehensive package of daily weather parameters for any number of years for a location. Generated variables include precipitation, maximum and minimum temperature, relative humidity, solar radiation, wind speed, and wind direction. It is designed to preserve the dependence in time, internal correlation, and the seasonal characteristics that exist in actual weather and climate data [Richardson and Wright, 1984]. In WXGN, precipitation and wind are generated independent of other variables. Precipitation is simulated using a first-order Markovian technique that produces time series of daily occurrence of precipitation (i.e., wet or dry days). On wet days, precipitation amount is generated using a skewed normal distribution. Maximum temperature, minimum temperature, and solar radiation are generated based on a continuous multivariate stochastic process, and constrained by whether the day is wet or dry [Richardson, 1981]. Relative humidity is obtained from a triangular distribution that takes into account the occurrence of rainfall on a particular day. Wind speed is

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

generated using a two-parameter gamma distribution that with location and shape parameters related to the velocity and frequency of the velocity. Wind direction is simulated using an empirical frequency distribution of wind direction specific for each location which is essentially the cumulative probability distribution from the monthly percentages of wind from each of the 16 directions given by the “Climate Atlas of the United States”. To estimate wind direction for any day, WXGN draws a uniformly distributed random number and locates its position on the appropriate monthly cumulative probability distribution of the wind direction.

2.1.2 Climate change scenarios design

Three broad climate categories are developed using the stochastic weather generator to facilitate the assessment of climate change effects on water resources. These categories include:

1) Historical: This scenario group evaluates a 30-year historical period as a baseline, against which the two other categories of climate change impacts are compared.

2) RCP4.5: This scenario group adopts the GCM projections from IPCC Representative Concentration Pathways (RCPs) RCP4.5, reflecting the stabilization scenario in which total radiative forcing is assumed to be stabilized before 2100 by employing a range of technologies and strategies for reducing greenhouse gas emissions. It assumes that net anthropogenic radiative forcing values in the year 2100 will be 4.5 W/m^2 above preindustrial values.

3) RCP8.5: This scenario group adopts the GCM projections from IPCC RCP8.5, reflecting increasing greenhouse gas emissions over time. This scenario group represents the most extreme warming outlook captured by the IPCC assessment and is meant to represent a "business as usual" response to global warming. It represents a net anthropogenic radiative forcing of 8.5 W/m^2 relative to preindustrial values in the year 2100.

For each scenario group, we generate an ensemble of realizations of daily weather variables required as input to a model of a coupled socio-hydrological system, using the WXGN stochastic weather generator. We explicitly represent uncertainty in future projections of climate change by sampling the climate parameters required as input to WXGN from an empirical distribution function representing multiple GCMs. We then use these daily weather ensembles to force an existing model of a coupled socio-hydrological system based on the Envision framework [Bolte et al., 2006]. We compare simulations of future climate against the benchmark historical simulations, allowing us to compare both the central tendencies of future changes to the system along with potential ranges of variability about those central tendencies. Details are provided below.

Figure 1 The flow chart of climate data generation

Daily climate data were extracted from weather stations (historical) and downscaled GCMs (projections of RCP4.5 and RCP8.5). The data were then summarized to get monthly climate variables which were then statistically analyzed to get the representative ranges (25% to 75%). Future projections of the monthly climate variables

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

were generated using a Latin Hypercube Sampling. Then Ensembles of daily variables were generated using statistical weather generator (WXGN). These data (210 sets of 30-yr daily climate data) were then employed as input for Envision runs to drive the integrated hydrologic model.

2.2 Climate data collection and processing

The flowchart of climate data collection and processing is shown in Figure 1. The historical climate data corresponds to observations collected at the Boise Air Terminal weather station from 1980 – 2014. Future regional climate projections were adopted from MACAv2-METDATA dataset, which used the Multivariate Adaptive Constructed Analogs (MACA) statistical downscaling method to downscale GCMs from the Coupled Model Inter-Comparison Project 5 (CMIP5) [Abatzoglou and Brown, 2012]. The dataset has been bias corrected and was trained using the gridded, high resolution (4 km), daily surface meteorological dataset METDATA [Abatzoglou, 2013], which was bias corrected and validated against an extensive network of weather stations including RAWS, AgriMet, AgWeatherNet, and USHCN-2. A total of 20 GCMs were downscaled, and 11 downscaled GCMs were selected due to the data availability at the time of downloading, and data completeness (Table 1). The data are then processed following the steps below.

Table 1 CMIP5 models used in this study for downscaled climate data and the model development centers

Step #1: Analyzing representative ranges

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

13 climate variables (V_i) that are needed by WXGN for the generation of daily weather files are calculated and summarized for the historical observations and downscaled GCMs of RCP4.5 and RCP8.5 (Table 2). This step creates one set of climate variable statistics for the historical climate, and 11 sets of climate variable statistics for the 11 sets of GCMs. Each set of climate variable statistics include average monthly climate variables as shown in Table 2. The historical scenario group only has one set of climate variable statistics. However, for the RCP4.5 and RCP8.5 scenario groups, multiple GCMs incorporate extreme values that are "outliers" of general future climate projections in the variable statistics (Figure 2). As such, we used the 25th and 75th percentiles of each monthly variable statistics as the representative ranges of possible climate projections. For RCP4.5 and RCP8.5 scenario groups, we sorted the values of each variable statistics, and calculated the percentiles as $100\times(0.5/n)th, 100\times(1.5/n)th, ..., 100\times([n-0.5]/n)th$ ($n=11$ in this case). Then the 25th percentile $V_{i_{25th}}$ and the 75th percentile $V_{i_{75th}}$ are linearly interpolated based on the closest percentile values, and we use the range between $V_{i_{25th}}$ and $V_{i_{75th}}$ to denote the representative values of the sample. This design removes the extreme variations of each variable statistics, and can better reflect the climate change paths that are more likely to occur by the projection of GCMs.

Table 2: 13 climate variables summarized from GCMs for WXGN use to generate ensemble of daily climate realizations.

Figure 2: Boxplot of monthly climate variables over 11 GCMs, using only precipitation as an example. Boxplot of the other 12 variables is included in the

appendix A. The circles indicate the historical monthly precipitation. The large variance indicates that an ensemble of climate realizations is necessary to capture the variations of future climate change.

Step #2: Random sampling

Latin Hypercube Sampling (LHS) was used to sample 10 sets of monthly climate statistics within the representative range ($V_{i_{25th}} \sim V_{i_{75th}}$) of each variable statistics for RCP4.5 and RCP8.5 scenario groups. For a function of a certain number of variables, the LHS approach equally divides the range of each variable into M (here, M = 10) probable intervals. Within each interval, the variable is randomly sampled once. This method ensures that each variable is evenly sampled, and the M (here, M = 10) random sampled values for each variable will include values that have a relatively low probability of occurrence. As such, the approach allows a stable output with a much smaller number of samples than a simple Monte Carlo sampling. Since distributed daily hydrologic models are usually computationally expensive, this sampling method makes simulation more practical with limited number of samples. This step generates 10 sets of randomly sampled monthly statistics for RCP4.5 and RCP8.5 scenario groups, respectively.

Step #3: Daily weather generation

We used WXGN to create 10 sets of daily weather data based on each randomly sampled RCP4.5 and RCP8.5 variable statistics, and the historical monthly statistics. This step creates 100 sets of 30-year (3000 years) future daily weather data for the

RCP4.5 scenario group, 100 sets of 30-yr (3000 years) of future daily weather data for the RCP8.5 scenario group, and 10 sets of 30-yr (300 years) of future daily weather data for the historical scenario group. The daily data reflects the statistics of the 10 sets of samples from RCP4.5, 10 sets of samples from RCP8.5, and the 1 set of statistics from historical observations. These daily weather datasets, reflecting future climate scenarios, were then served as inputs for the daily time step hydrologic model in Envision.

2.3 Coupled socio-hydrology systems model

An integrated socio-hydrologic model that simulates spatially explicit water use based on local water rights is used to evaluate spatiotemporal patterns of water scarcity in the context of potential future climate. A detailed overview of the biophysical and water rights components of the model, the datasets used to parameterize boundary conditions, calibration to and verification against historical data, and limitations of the model in the context of those calibration/verification exercises was previously described by Han et al. [2017]. Here we provide a brief overview of the key model components pertinent to this study.

The socio-hydrologic model is developed within the Envision modeling framework, a spatially explicit multi-agent simulation platform for evaluating potential landscape changes arising from interactions between and among complex biophysical and social processes [Bolte et al., 2006]. The model used here employs a slightly revised semi-conceptual Hydrologiska Byråns Vattenbalansavdelning (HBV) model to simulate hydrologic processes. The HBV model is implemented here as a semi-lumped model, operating on spatial elements of Hydrologic Response Units (HRUs) with relatively similar elevation and land cover. At each HRU, the instantaneous temporal change in five water reservoirs (snow, soil moisture, an upper groundwater reservoir, a lower groundwater reservoir, and lake storage) is balanced by incoming precipitation, outgoing evapotranspiration, and outgoing runoff fluxes. Precipitation phase (snow vs. rain) is determined based on whether the daily average air temperature exceeds a constant threshold. Evapotranspiration is modeled using the FAO56 Penman–Monteith method as specified by the UN Food and Agriculture Organization (FAO) in paper number 56 (Allen et al., 1998) and in Allen and Robison (2007). In this approach, potential evapotranspiration at each HRU is the product of a land use dependent crop coefficient and a calculated reference potential evapotranspiration corresponding to full-cover alfalfa, given the meteorological forcings of that day. Runoff is parameterized through a series of three outflow equations wherein runoff is linearly proportional to water in excess of a threshold value in the upper groundwater reservoir, storage in the upper groundwater reservoir, and storage lower groundwater reservoir. The constants of proportionality for these outflow equations are treated as calibrated parameters. Runoff generated at each HRU is routed via two quasi-linear equations to the stream network (represented by hydrography data), wherein channel routing is treated as a linear reservoir process.

Irrigation activities are simulated based on water rights data provided by the Idaho Department of Water Resources; these water rights are based on the Doctrine of Prior Appropriation (Tarlock, 2000). Each record in the water rights dataset is associated with: 1) a priority date on which a water user is entitled to withdrawals from the surface water distribution system, 2) the geographic point of diversion, 3) the maximum diversion rate from the point, and 4) the geographic place of use. Within each time step and for each HRU, the model examines the available water in the stream, the biophysical water demand of the agricultural land within the HRU, and the water rights associated with a place of use coincident with the HRU. Water allocated for irrigation is the minimum of these three quantities. The unsatisfied water is the difference between the amount of water demanded and allocated for each place of use in the model. The model was calibrated and validated by varying the parameters using a Monte-Carlo approach and comparing the simulated hydrographs with observations under historical conditions corresponding to water years 2006-2013. Detailed descriptions of the calibration and validation processes, and the underlying algorithms are described by Han et al., [2017].

As previously stated, the upstream surface water hydrology boundary condition in the Lower Boise River Basin corresponds to hydrologic output of a system of large reservoirs within the Upper Boise River Basin, a snow-dominated, mountain, largely forest covered, watershed. Although climate change, particularly in the form of shifts in precipitation phase from snow to rain, is expected to significantly alter hydrologic regimes in the Upper Boise River Basin, we do not consider these potential changes in order to reduce the complexity of our analysis. As such, the upstream inflow boundary to our simulation domain (the discharge from the Lucky Peak Reservoir) is set to be the same as a normal year, taking 2012 as an example. While future changes in water rights depend on future real estate transactions, growth in the extent of urban areas, and potential changes in water rights laws, we assume that the attributes of the water rights data remain the same over time. Further, we do not take into account technological changes that may significantly increase water use efficiency in the agricultural sector and lead to a lower irrigation water demand and actual water use in the future. Given these assumptions, the impacts of climate change on water availability at the watershed were quantified based on the allocated irrigation amount and the unsatisfied irrigation amount for the years from 2071 to 2100. Since the weather generator replicates overall statistics instead of "predicting" inter-annual differences, the comparison between any specific two years within a scenario group are meaningless. As such, we treat the data of each year as an independent realization of the potential outcomes within the large ensemble of data over the thirty years of simulation. Ensemble characteristics and statistics are then compared between the three scenario groups.

2.4 Datasets used in the model

Environmental forcing data used in this study corresponds to statistically downscaled output from a suite of GCMs that are summarized in Table 1. Each forcing dataset includes daily precipitation, maximum temperature, minimum temperature, specific humidity, solar radiation, and wind speed. These variables, required as input drivers to the socio-hydrologic model, were extracted for the grid point that coincides with the Boise Air Terminal (43.5644° N, 116.2228° W) for the years 2071-2100 to represent the local future climate. Historical data of the same forcing variables at Boise Air Terminal were obtained from the National Climatic Data Center and National Solar Radiation Database for the period 1981-2014. Water rights data was obtained from the Idaho

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

Department of Water Resources, which provides the point of diversion, priority date, maximum allowable allocation, and place of use records required as input to the socio-hydrologic model, updated as of 2010. We selected only those records associated with an irrigation water use. Input to the Boise River at the upstream boundary of the domain corresponds to daily historical discharge from Lucky Peak reservoir for calendar year 2012, and is assumed consistent between years and were obtained from the US Bureau of Reclamation Pacific Northwest Hydromet database. Land use data corresponds to the National Landcover Dataset (NLCD 2011) and is used to both to construct the computational domains and HRUs and in calculation of evapotranspiration. Stream and watershed boundaries were obtained from the NHDPlus Version 2 dataset, which provides geospatial data used in flow routing. These datasets are summarized in Table 3.

2.5 Study area

The study site corresponds to the Lower Boise River Basin, also known as the Treasure Valley, in southwest Idaho, USA (Figure 3). The region is the most populous and rapidly growing area within the state and serves as a natural laboratory for studying ongoing challenges associated with population growth, urbanization, agricultural production, and climate and hydrologic change. Climate in the Treasure Valley is generally consistent with a semi-arid Mediterranean with hot, dry summers and cold, wet winters. In the absence of agricultural and developed land uses, vegetation cover in the region is consistent with the Sagebrush-steppe ecosystem of the larger Great Basin ecoregion. Historical average precipitation is 296 mm/y at the Boise Air Terminal weather station.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

Importantly, the Treasure Valley is home to Idaho's three largest cities (Boise, Meridian, and Nampa). Population of the Boise City-Nampa Metropolitan Statistical Area (MSA) was estimated to be 690,423 as of 2016, up from 616,561 in the 2010 Census, an average annual increase of 1.9%. Thus, the Treasure Valley region is being subjected to significant land use conversion, resulting in changes to biophysical and social systems, and interactions between the two.

Climate exerts a significant control on the use of water resources within the region. More than half of the total precipitation that falls within the Treasure Valley, which is not sufficient to support many high-value crops, occurs during the non-irrigation season. As such, local agriculture relies heavily on irrigation water from the Upper Boise River Basin, particularly during the hot, dry portion of the growing season. Climate change driven increase in temperatures in the Treasure Valley not only increases atmospheric water demand during the growing season, but impacts of climate change shifts the timing, amount, and phase of precipitation that will lead to earlier runoff and increased variability from the Upper Boise River Basin.

Irrigation is facilitated by a series of reservoirs upstream of the Treasure Valley that store and regulate water from the Upper Boise River Basin. Lucky Peak Reservoir, which is operated jointly by the US Army Corps of Engineers and the Bureau of Reclamation for purposes of flood control and irrigation water supply, is the lower-most of these reservoirs. Water released from Lucky Peak Reservoir flows along the Boise River for about 103 km (64 miles) northwestward through the Treasure Valley to its confluence with the Snake River. A number of canals and diversion dams have been built along the Boise River to divert water to water rights holders, the vast majority of which are farmers using the water for irrigation. Irrigation has dramatically altered the originally desert landscape into a patchwork of seasonally irrigated agricultural lands of varying crops. Urban growth, shifts in crops grown in the Treasure Valley associated with global marked demands, and changes in irrigation practices (e.g., shifts from flooding to sprinkler and drip irrigation) drive changes in the spatial patterns of land and water use. Despite the importance of water resources and potential threats of water scarcity, there have been limited studies regarding future water availability and scarcity in this region [Petrich, 2004; Urban and Petrich, 1996]. This research aims to examine the agricultural irrigation water demand and water scarcity under future climate change scenarios, using the generated ensemble of climate change realizations. The work is built upon an integrated hydrologic model that incorporates hydrological processes and the irrigation activities which follow the local water rights. Three important outcomes of this study are 1) a methodology that facilitates the creation of an ensemble of climate change scenarios that is suitable for daily hydrologic model input; 2) A modeling framework for the integration of hydrological processes, human irrigation activities, and climate change; 3) References to help local stakeholders with decision making to adapt to future climate change.

Figure 3: Study area: the Treasure Valley.

3. Results

3.1 Climate change analysis

To illustrate the degree to which the use of the stochastic weather generator captures variation in key climate parameters across GCMs, we show the probability density

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

functions (PDFs) of the output of the stochastic weather generator for annual precipitation amount, maximum temperature and minimum temperature (Figure 4). Overall, the most likely precipitation amount in the RCP8.5 scenario group is larger than that in the RCP4.5 group and Historical group, as shown in the probability density function figure (Figure 4). The average annual precipitation increases by 11% from Historical to RCP4.5 conditions, and by 29% to RCP8.5 conditions. However, a significant overlap between precipitation probability density functions exist in the three scenario groups. For example, it is likely that precipitation in RCP8.5 is smaller than that in RCP4.5 or even Historical group in some sets of climate realizations.

The PDFs of maximum temperature and minimum annual temperature increase significantly in the future, and are much narrower in comparison to the precipitation pattern (Figure 5). The annual mean maximum/minimum temperature is highest in the RCP8.5 scenario group, lowest in the Hstorical scenario group. The maximum temperature in RCP8.5 group is consistently higher, on average by 4.1 °C than the temperature in the Historical group. The maximum temperature in the RCP4.5 group is consistently larger than that in the Historical group by an average of 1.7 °C. The minimum temperature in RCP8.5 is consistently larger than that in the Historical scenario by an average of 5.6 °C. The minimum temperature in RCP4.5 is consistently larger than that in the Historical group by an average of 3.2 °C. The average daily temperature increases by 4.9 °C in RCP8.5 scenario group, and by 2.5 °C in the RCP4.5 scenario group. Temperature increase in the Treasure Valley is at the higher end of the IPCC CIMP5 projected global trend which, in general, projects a temperature increase of 1.1°C to 2.6°C for RCP4.5, and an increase of 2.6°C to 4.8°C for RCP8.5 by the end of the 21st century [T F Stocker, 2014].

Figure 4: The annual precipitation used to drive the hydrologic model

Figure 5: The annual maximum (Tmax) and minimum (Tmin) temperatures used to drive the hydrologic model

3.3 Irrigation water analysis

The simulation results from a total of 210 runs of the integrated socio-hydrologic model indicate, unsurprisingly, that more irrigation water is needed to fulfill the crop water demand in the future. The average annual allocated irrigation water is highest in the RCP8.5 scenario group (Figure 6). The average annual allocated irrigation water in both RCP4.5 (8.2×10^5 acre-feet) and RCP8.5 (8.9×10^5 acre-feet) scenario groups is higher than the Historical scenario (6.7×10^5 acre-feet), an increase of 22% and 33%, respectively. However, the ensemble between the three scenarios overlap one another due to the extremes captured by realizations of the weather generator. This overlap indicates extreme water use scenarios that deviate significantly from the average future projections. As such, although examining the mean/median values from a large ensemble of analysis is useful for understanding the central tendencies of potential future agricultural water demands in the region, the entirety of the ensemble allows a more sophisticated interpretation of potential future outcomes, particularly those that could be low probability events but of significant consequences.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Figure 6: The annual amount of allocated irrigation water under 3 different scenarios

Similar to the allocated amount, the average annual unsatisfied irrigation water is also highest for RCP8.5 scenario group (Figure 7). The average annual unsatisfied irrigation water in both RCP4.5 and RCP8.5 scenario groups are higher than the Historical scenario group. Similar with allocated irrigation water, there is also overlap in unsatisfied irrigation between all scenarios. The mean value of the unsatisfied water increases from about 1.7 x 10^4 acre-feet in the Historical scenario group to about 2.7 x 10^4 acre-feet in the RCP4.5 scenario group and 4.2 x 10^4 acre-feet in the RCP8.5 scenario group, an increase of 59% and 147%, respectively. The results underscore the value of using ensembles of model simulations to assess potential future outcomes, as a few realizations were associated with extreme values of unsatisfied irrigation that are not reflected the central tendencies of the PDFs.

Figure 7: The annual amount of unsatisfied irrigation water under 3 different scenarios

The ensemble simulation also allows us to assess spatial locations within the domain most likely to be associated with unsatisfied water demand under future climates and, by comparing to geospatial data characterizing biophysical and social constraints on hydrology in the region, to draw inference about key characteristics of the landscape associated with water shortages (Figure 8, Figure 9). The model-simulated allocation rate indicates that the southwest part of the study domain receives the most allocated water, while the corridor immediately abutting the downstream portions of the Boise River receives relatively less allocated water. Conversely, the unsatisfied irrigation water is largest along the downstream Boise River.

However, there is also a significant amount of water scarcity in the southwest part of the domain (Wilder Irrigation District approximate to Lake Lowell). Throughout the domain, where there is water allocated to irrigation there is a significant increase in both water use and water scarcity relative to Historical conditions, in the RCP 4.5 and RCP 8.5 conditions. Looking more specifically at the southwest part (Wilder Irrigation District), the mean allocated irrigation rate increases from 737 mm/y to 909 mm/yr to 996 mm/yr from the Historical to the RCP4.5, and then to the RCP8.5 scenario groups, an increase of 23% and 35% respectively. Although the area is senior in water rights (water rights in the region were claimed between 1864 to 1927), the mean unsatisfied irrigation rate increases from 13 mm/y to 19 mm/y to 31 mm/y from the Historical to the RCP 4.5, and then to the RCP 8.5 scenario groups, an increase of 46% and 138% respectively. Using ensemble mean values avoids the large discrepancies from individual simulations. For example, the allocated irrigation rate at the 85 percentile varies from 789 mm/y in the Historical to 948 mm/y in the RCP4.5 to 1041 mm/y in the the RCP8.5 groups, and the unsatisfied irrigation rate at the 85 percentile varies from 20 mm/y in the Historical to 27 mm/yr in the RCP4.5 to 42 mm/yr in the RCP8.5 groups.

Figure 8: The annual amount of allocated irrigation water under 3 different scenario groups (Spatial Maps. Show mean, and 85 and 15 percent range for each scenario group)

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Figure 9: The annual amount of unsatisfied irrigation water under 3 different scenario groups (Spatial Maps. Show mean, and 85 and 15 percent range for each scenario group)

4. Discussion

4.1 Adopting stochastic weather generators with GCM output

The use of multiple GCM projections in combination with the stochastic weather generator to generate ensembles of future climate realizations offers some key advantages in assessing the potential future ramifications for coupled socio-hydrologic systems. The results are are broadly consistent with the GCM output, but also account for variability in climatic conditions as captured by a variety of GCMs while providing insights into local climatic perturbations

First, the method allows an unlimited number of future daily climate data with monthly statistics that are derived from multiple GCMs. In this way, the method avoids the deficiencies of using a single GCM or a simple mean of multiple GCMs that may lead to biased future projections, and avoids the deficiencies of limited number of GCMs that cannot provide enough reliable daily climate data for hydrologic models.

Second, stochastic weather generators (like WXGN) are a relatively computationally inexpensive method for generating daily climate variables needed by a diverse array of hydrologic and ecological models. They are also relatively easy to use and parameterize, making them amenable to a variety of different climate change assessment applications and techniques. The resulting ensemble of outputs generated with the corresponding ensemble of climate realizations used as input allow for a more sophisticated analysis of potential future impacts of climate change, both in terms of the central tendencies of change and potentially low-risk, high-consequence outcomes.

It should be added that the proposed method is not appropriate for all circumstances. The method we develop and apply here is most suitable for hydrologic and ecologic models that needs numerous sets of long-term daily climate inputs. For example, in our case study, we need daily hydrologic simulation to allow for real-time water rights allocations. The method may not be necessary for all conceptual modes or lump-sum models that only require rough water balance estimations.

Although the application of the stochastic weather generator to create ensembles of climate input to a socio-hydrologic model is methodologically straightforward, simulating an ensemble of climate realizations still requires a relatively large amount of computational time. This is particularly true for spatially distributed hydrologic models. There is, therefore, a need to balance larger ensembles against higher spatial resolutions when a spatially distributed model is being used.

4.2 The effects of climate change on regional scale hydrology and irrigation

Both temperature and precipitation are important climate variables that affect regional hydrology and irrigation demand. Temperature directly influences potential evapotranspiration and crop water demand (Figure 10, Figure 11). Under the same upstream inflow conditions, the allocated and unsatisfied irrigation water has a clear monotonic relationship with temperature across scenario groups. There is an increase of allocated irrigation amount with the increase of maximum temperature and minimum temperature. Although there is significant overlap between scenario groups, the overall trend of an increasing irrigation water demand and scarcity from historical conditions to RCP4.5 and RCP8.5 is evident.

The influence of precipitation on allocated and unsatisfied water is not as clear as that of temperature (Figure 12). In the Treasure Valley, over half of the precipitation happens in the non-irrigation season, and most of the irrigation water relies on diversion from streams and reservoirs. As such, precipitation change in the immediate region of the Treasure Valley is not as important as temperature change with regard to water demand and use. Instead, precipitation in the upper Boise River Basin that provides snowpack for irrigation water will exert a more significant influence on downstream water demand.

Figure 10 The scatterplot of the allocation irrigation amount and the unsatisfied irrigation amount with maximum and minimum temperature under three scenario groups. The solid dots indicate the mean values of each scenario group.

Figure 11 The annual amount of evapotranspiration rate under 3 different scenario groups

Figure 12 The scatterplot of the allocation irrigation amount and the unsatisfied irrigation amount with precipitation under three scenario groups. The solid dots indicate the mean values of each scenario group.

4.3 Future work

In illustrating the influence of climate change on the future water availability this work, does not consider population and land use change. Both of these factors will have

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

potentially significant influence on future water use in the region. Incorporating these potential land use changes would provide additional insight into changes to future water resources of the region. The present work also assumes that the input to the river system from the Upper Boise River Basin is captured by the observed flows in a typical year (calendar year 2012) in the Boise River. Despite these acknowledged limitations, this work illustrates the use of an ensemble-based method for climate change impact analysis that is of value in quantifying the central tendencies and variability about changes in future water use in a strongly coupled socio-hydrologic system.

5. Conclusions

This study develops an ensemble approach for creating daily climate realizations combining a stochastic weather generator and downscaled General Circulation Model (GCM) projections. The generated ensemble of climate data is then used to drive an integrated socio-hydrologic model using the Envision scenario-based modeling framework. In this way, the model captures both spatially explicit irrigation activities constrained by local water rights, and future changes in climate and their impact on atmospheric water demand in the region. We tested this model in a rapidly growing region of Idaho, USA. Results show that, on average, precipitation amount increases slightly and temperature increases significantly in future climate scenarios. Temperature increases are particularly pronounced in the RCP8.5 scenarios. The increase of temperature has direct influence on the increase of the allocated and unsatisfied irrigation amount, while the impacts of slightly increased mean annual precipitation (but increased interannual variability in mean annual precipitation) on water use are less obvious and more uncertain. The model also predicts spatial patterns in water allocation and scarcity and the ensemble approach allows us to identify regions within the study area that will be more prone to insufficient water supply in the future. Although the developed model is associated with some key simplifications that limit, for instance, the ability to draw inferences about future groundwater-surface water interactions, the approach presented here could be applied to more sophisticated modeling frameworks to elicit broader conclusions about system behavior. Moreover, the framework presented here is portable to other geographic settings where legal frameworks dictate the timing, amount, and priority of water use.

Author contributions: Bangshuai Han and Alejandro N. Flores designed this research and interpreted the results. Bangshuai Han conducted the research. Bangshuai Han prepared the manuscript with the help with Shawn G. Benner, Alejandro N. Flores, and get agreement for submission with all co-authors.

ACKNOWLEDGMENTS

This work was supported by grants from the National Science Foundation (NSF) Idaho Established Program to Stimulate Competitive Research (EPSCoR) under award number IIA-1301792, NSF CAREER Award EAR-1352631, and Ball State University new faculty start-up fund under award number 120198. We would like to thank Dr. Javier M. Osorio Leyton from Texas A&M for the help with WXGN, and Dr. Katherine Hegewisch from University of Idaho for the MACA data collection. We also thank the Envision team from Oregon State University for the help with the hydrologic model construction and debugging. Data associated with this manuscript has been permanently archived and made public with DOI: https://doi.org/10.18122/B20133.

List of Tables

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Discussions

List of Figures

Table 1 CMIP5 models used in this study for downscaled climate data and the model development centers

Model	Development Center
BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University, China
CanESM2	Canadian Center for Climate Modeling and Analysis
CNRM-CM5	National Center of Meteorological Research, France
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Center of Excellence, Australia
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory, USA
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA
IPSL-CM5A-LR	Institut Pierre Smon Laplace, France
IPSL-CM5A-MR	Institut Pierre Smon Laplace, France
IPSL-CM5B-LR	Institut Pierre Smon Laplace, France
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute of Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
MRI-CGCM3	Meteorological Research Institute, Japan

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Table 2 13 climate variables summarized from GCMs for WXGN use to generate ensemble of daily climate realizations

Variable	*Description*
PRECIP	Average monthly precipitation
TMAX	Average monthly maximum air temperature
TMIN	Average monthly minimum air temperature
PWD	Monthly probability of wet day after dry day
PWW	Monthly probability of wet day after wet day
DAYP	Average number days of rain per month days
RAD	Average monthly solar radiation
SDMX	Monthly average standard deviation of daily maximum temperature
SDMM	Monthly average standard deviation of daily minimum temperature
SDRF	Monthly standard deviation of daily precipitation
SKRF	Monthly skew coefficient for daily precipitation
RH	Monthly average relative humidity (fraction)
WS	Average monthly wind speed

Table 3 Datasets used and the source link in the study

Input Data	***Data Source***	***Year***	***Use in Model***	***Link***
Streams	NHDPlus	2012	Build stream network and flow routing	http://www.horizon-systems.com/nhdplus/NHDPlusV2_17.php
Land use/land cover	National Landcover dataset (NLCD)	2011	Evaportranspirtaion	http://www.mrlc.gov/nlcd2011.php
Water Rights	Idaho Department of Water Resources (IDWR)	2010	Irrigation (Watermaster)	http://www.idwr.idaho.gov/ftp/gisdata/Spatial/WaterRights
Major climate variables	National Climatic Data Center (NCDC)	1981-2014	Climate input	http://www7.ncdc.noaa.gov/CDO/cdodata.cmd
Solar radiation	National Renewable Energy Laboratory (NREL)	1981-2010	Climate input	http://rredc.nrel.gov/solar/old_data/nsrdb/
Reservoir Inflow	Hydromet Pacific Northwest Region	2012	Inflow boundary	http://www.usbr.gov/pn/hydromet/arcread.html

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

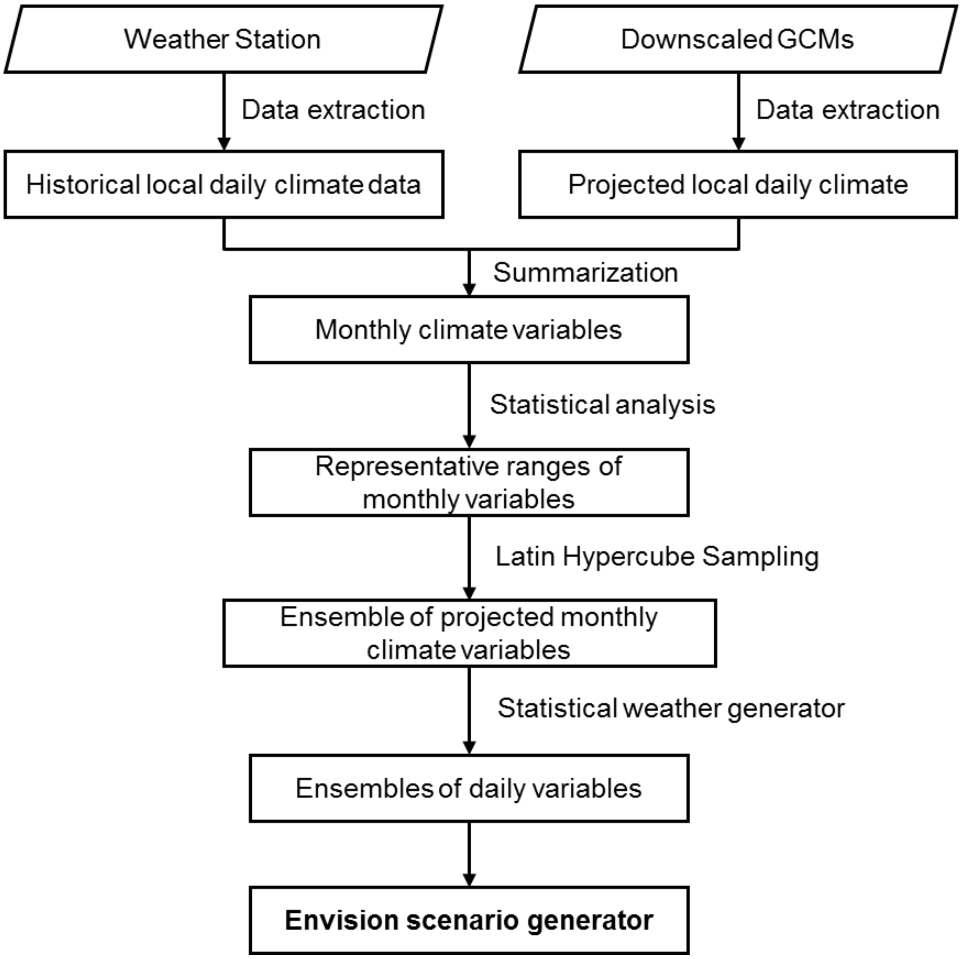


Figure 1 The flow chart of climate data generation. Daily climate data was extracted from weather stations (historical) and downscaled GCMs (projection of RCP4.5 and RCP8.5). The data were then summarized to get monthly climate variables which were then statistically analyzed to get the representative ranges (25% to 75%). Future projections of the monthly climate variables were generated using a Latin Hypercube Sampling. Then Ensembles of daily variables were generated using statistical weather generator (WXGN). These data (210 sets of 30-yr daily climate data) were then employed as input for Envision running to drive the integrated hydrologic model.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

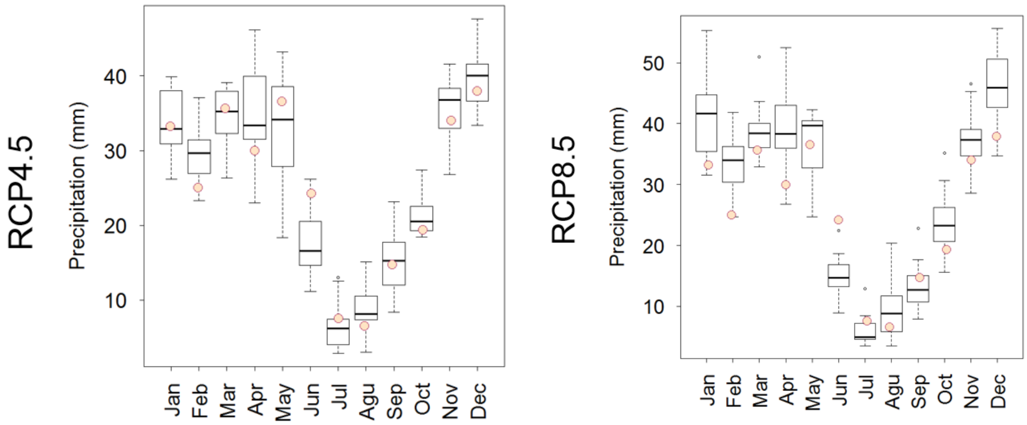
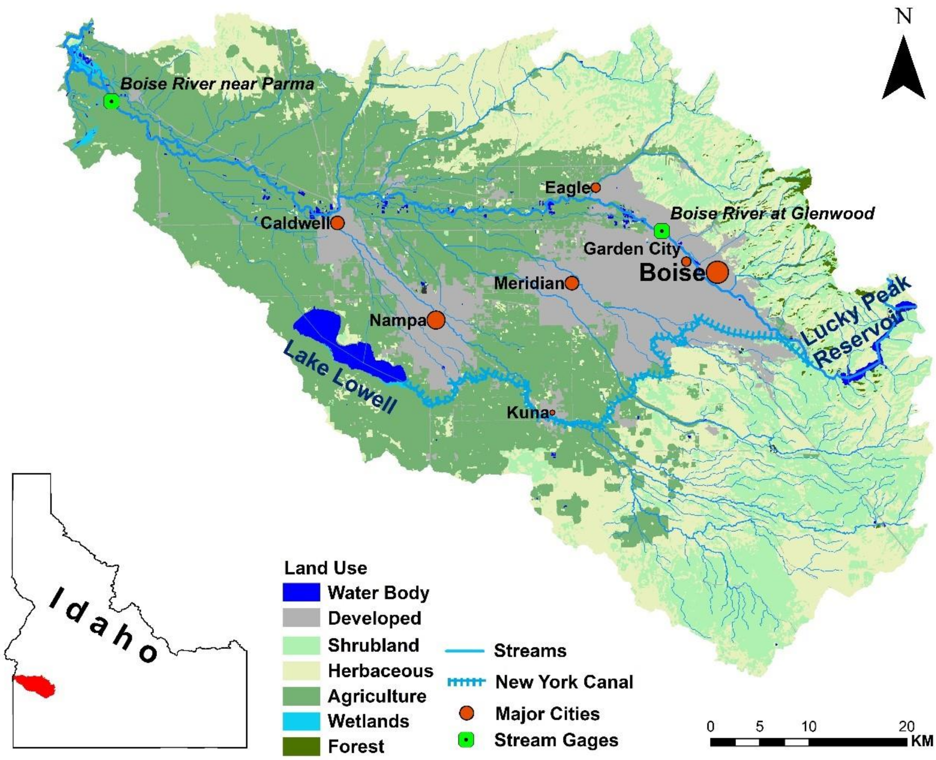


Figure 2 Boxplot of monthly climate variables over 11 selected GCMs, using only precipitation as an example. Boxplot of all variables are included in Appendix A. The circles indicate the historical monthly precipitation. The large variance indicates that an ensemble of climate realizations are necessary to capture the variations of future climate change. See Appendix A for boxplot of all monthly climate variables.



731

732 ***Figure 3 Study area: the Treasure Valley***

733

734

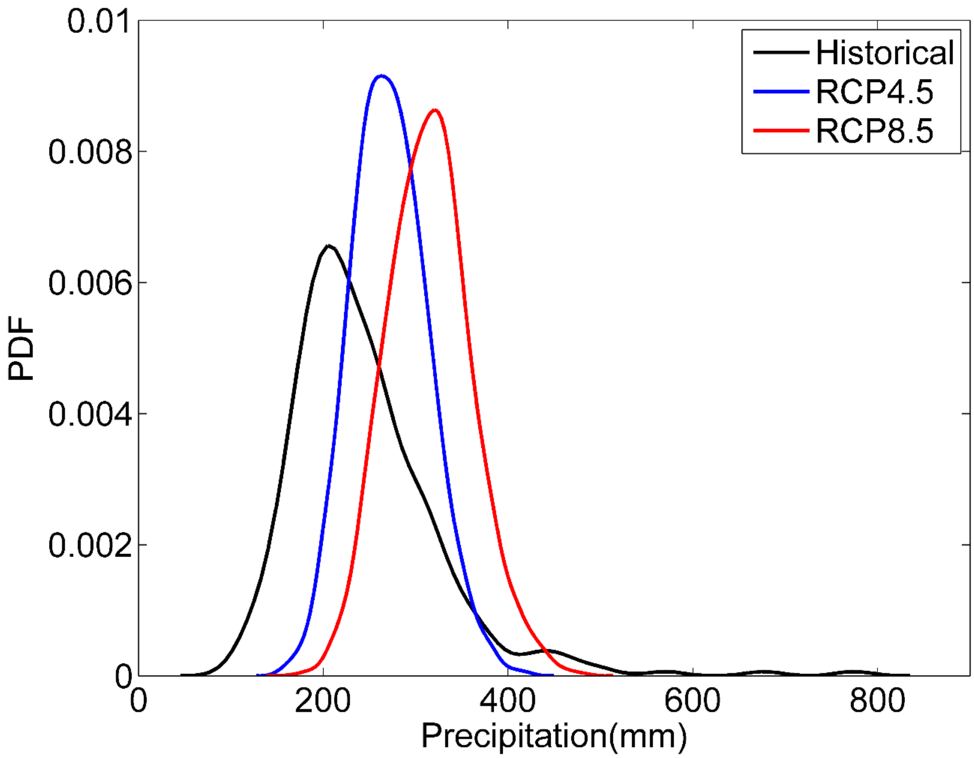


Figure 4 The probability density function of the annual precipitation used to drive the hydrologic model.

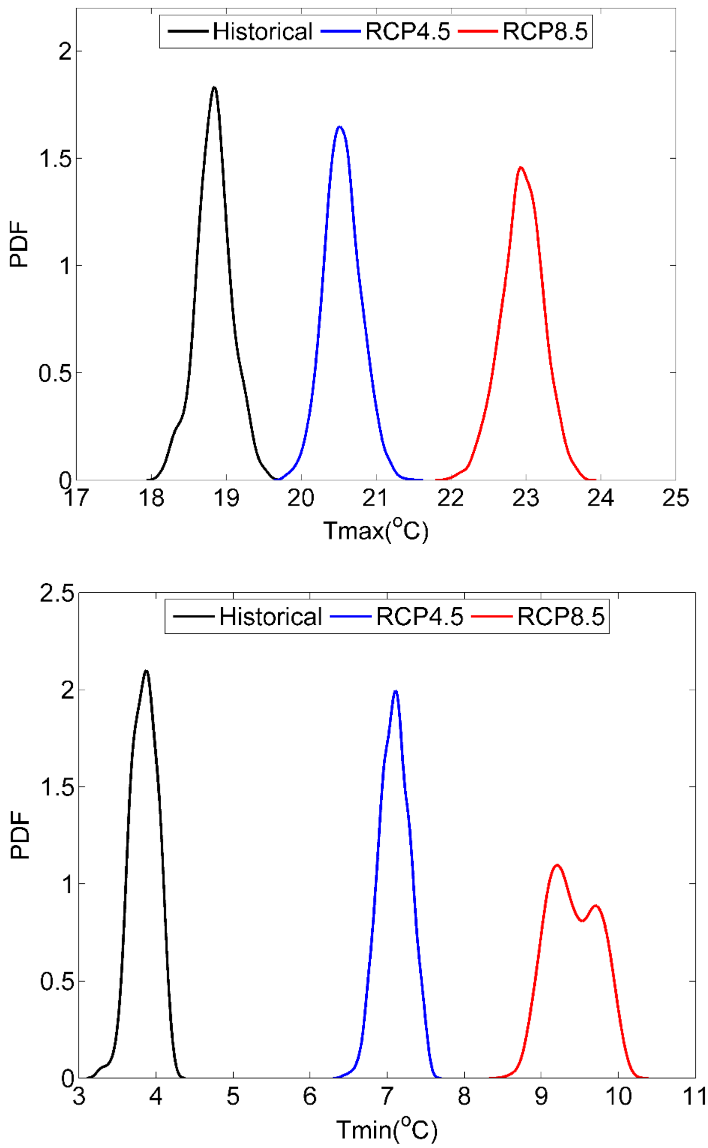


Figure 5 The annual maximum (Tmax) and minimum (Tmin) temperatures used to drive the hydrologic model.

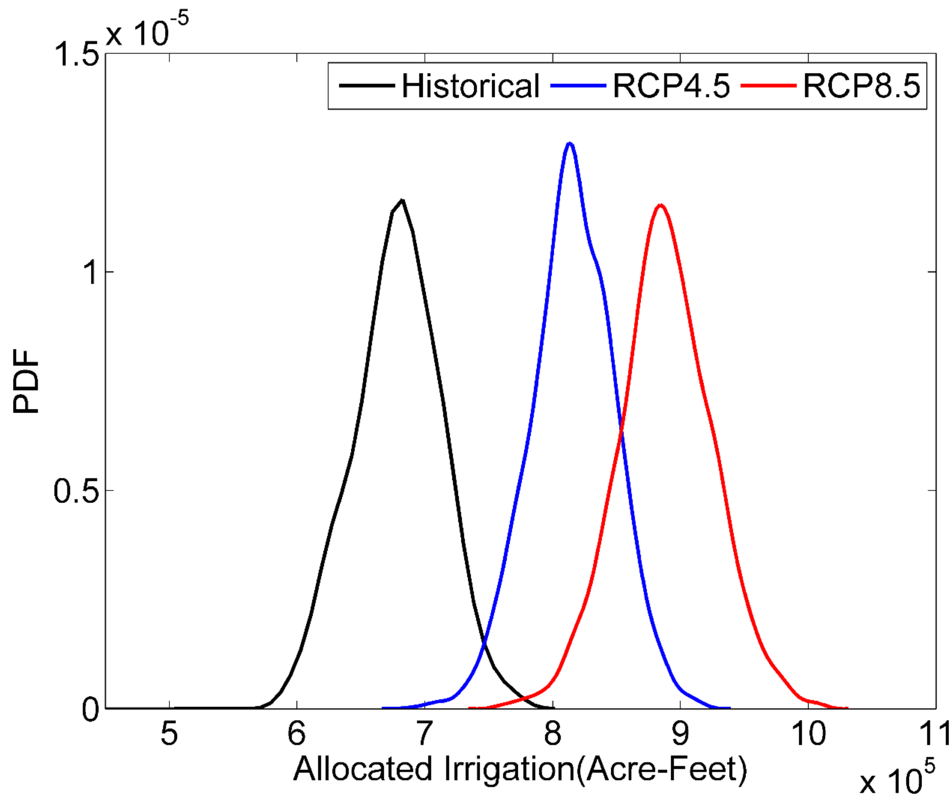


Figure 6 The annual amount of allocated irrigation water under 3 different scenario groups (Line figure. Show mean, and 85% and 15% range for each scenario group)

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Discussions

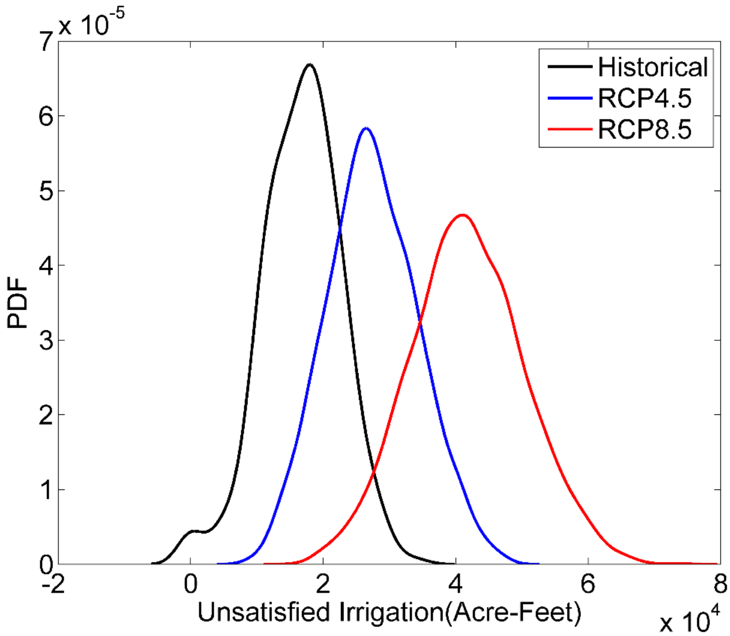


Figure 7 The annual amount of unsatisfied irrigation water under 3 different scenario groups

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

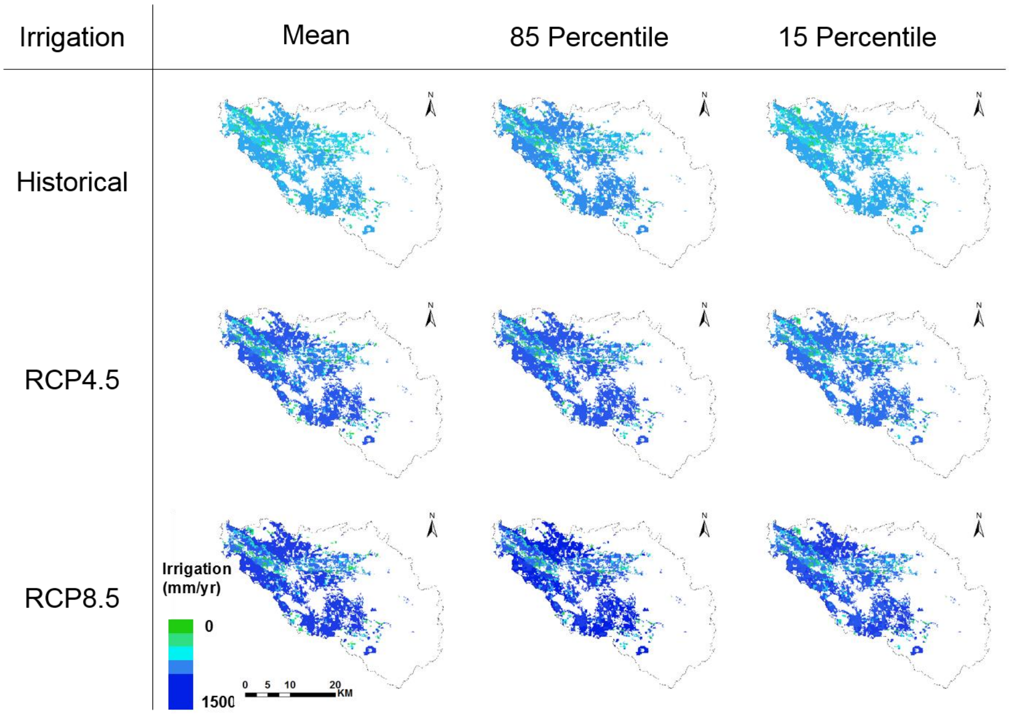


Figure 8 The annual amount of allocated irrigation water under 3 different scenario groups (Spatial Maps. Show mean, and 85 and 15 percent range for each scenario group)

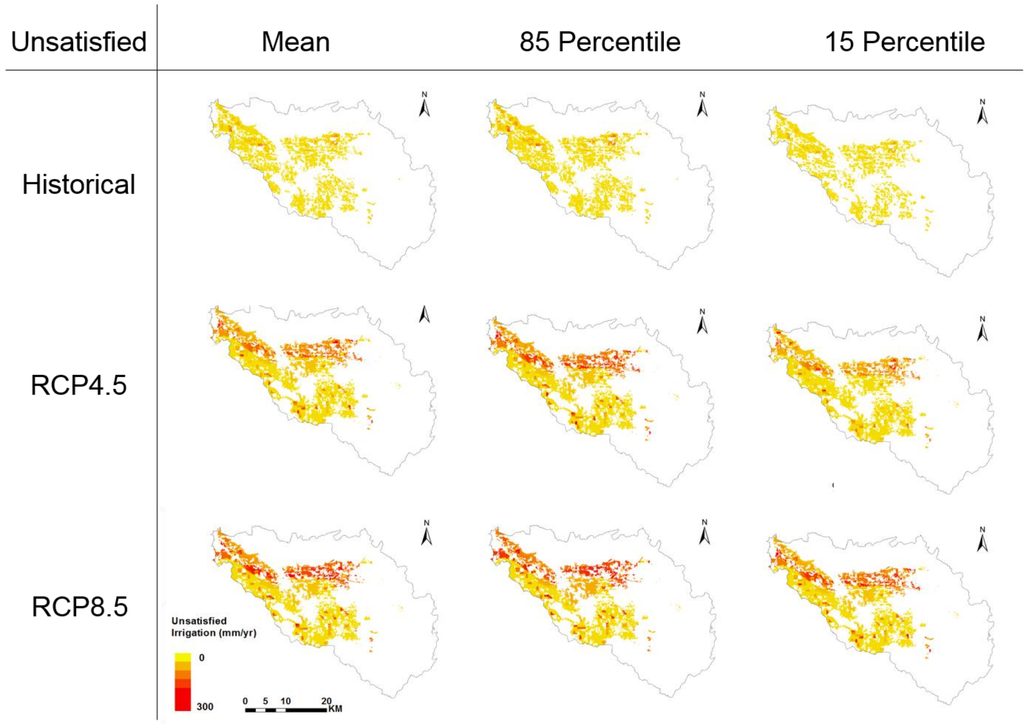


Figure 9 The annual amount of unsatisfied irrigation water under 3 different scenario groups (Spatial Maps. Show mean, and 85 and 15 percent range for each scenario group)

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

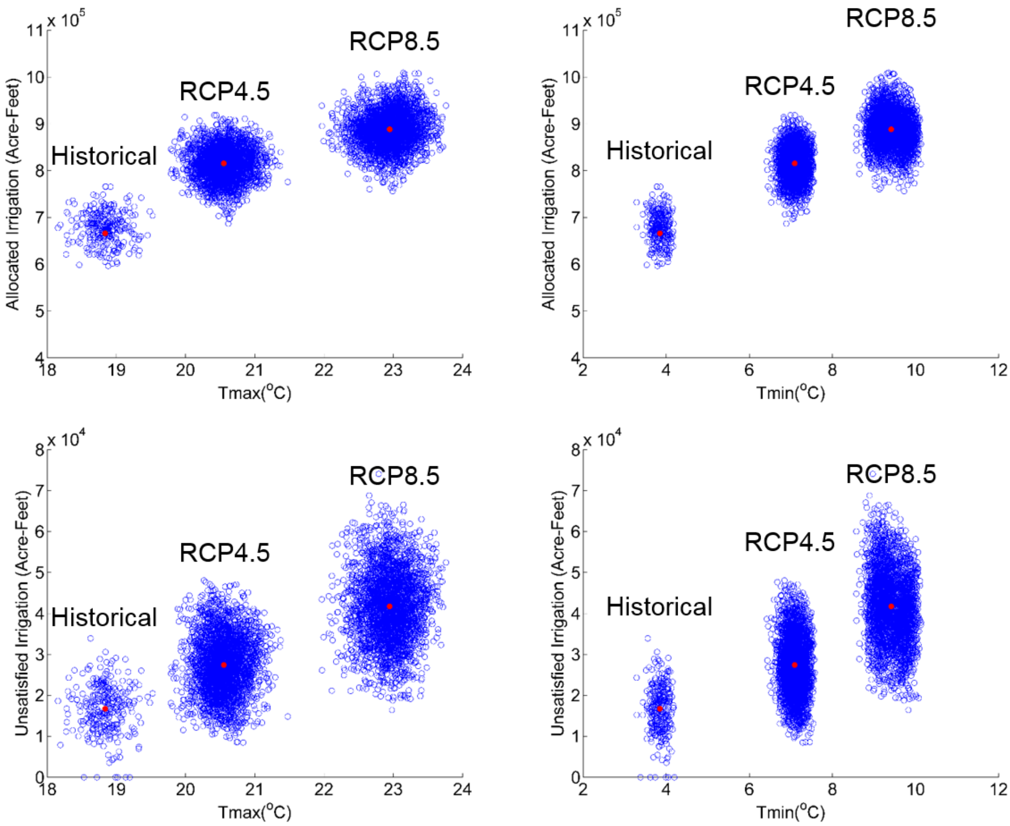


Figure 10 The scatterplot of the allocation irrigation amount and the unsatisfied irrigation amount with maximum and minimum temperature under three scenario groups. The solid dots indicate the mean values of each scenario group.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

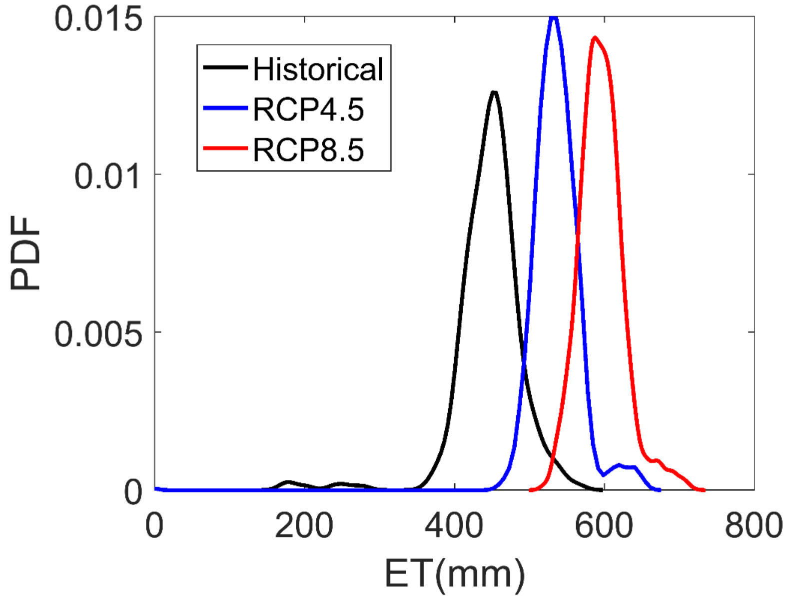


Figure 11 ***The annual amount of evapotranspiration rate under 3 different scenario groups***

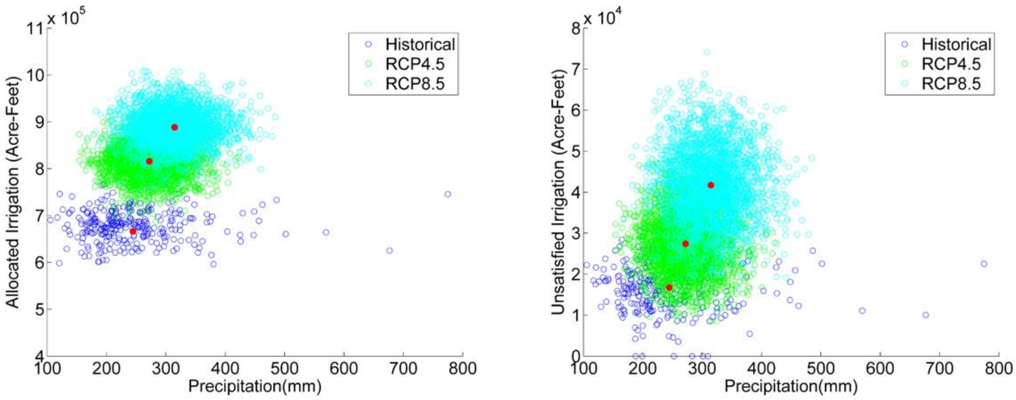


Figure 12 The scatterplot of the allocation irrigation amount and the unsatisfied irrigation amount with precipitation under three scenario groups. The solid dots indicate the mean values of each scenario group.

References:

Abatzoglou, J. T., and T. J. Brown (2012), A comparison of statistical downscaling methods suited for wildfire applications, *International Journal of Climatology*, *32*(5), 772-780.

Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological applications and modelling. International Journal of Climatology, 33(1), 121-131.

Ashfaq, M., L. C. Bowling, K. Cherkauer, J. S. Pal, and N. S. Diffenbaugh. "Influence of climate model biases and daily-scale temperature and precipitation events on hydrological impacts assessment: A case study of the United States." *Journal of Geophysical Research: Atmospheres (1984–2012)* 115, no. D14 (2010).

Bolte, J. P., D. W. Hulse, S. V. Gregory, and C. Smith (2006). Modeling biocomplexity–actors, landscapes and alternative futures. *Environmental Modelling & Software* 22, no. 5: 570-579.

Bosher, L., P. Carrillo, A. Dainty, J. Glass and A. Price (2007). Realising a resilient and sustainable built environment: towards a strategic agenda for the United Kingdom. Disasters, 31(3), pp.236-255.

Bouzaher, A., J. F. Shogren, D. Holtkamp, P. W. Gassman, D. Archer, P. G. Lakshminarayan, A. L. Carriquiry, and R. Reese (1994), Agricultural Policies and Soil Degradation in Western Canada: An Agro-Ecological Economic Assessment, Report 2: The Environmental Modeling System, Center for Agricultural and Rural Development (CARD) at Iowa State University.

Cai, W., S. Borlace, M. Lengaigne, P. Van Rensch, M. Collins, G. Vecchi, A. Timmermann, A. Santoso, M.J. McPhaden, L.Wu and M.H. England (2014). Increasing frequency of extreme El Niño events due to greenhouse warming. *Nature climate change*, *4*(2), pp.111-116. doi:10.1038/nclimate2100.

Chen, H., X. Chong-Yu, and G. Shenglian (2012), Comparison and evaluation of multiple GCMs, statistical downscaling and hydrological models in the study of climate change impacts on runoff, *Journal of Hydrology.* Volumes *434–435*, 36–45.

Chen, J., François P. B., and R. Leconte (2010). A daily stochastic weather generator for preserving low-frequency of climate variability. *Journal of hydrology* 388.3: 480-490.

Dominguez, F., J. Cañon, and J. Valdes (2010), IPCC-AR4 climate simulations for the Southwestern US: the importance of future ENSO projections. Climatic Change 99, no. 3: 499-514. DOI: 10.1007/s10584-009-9672-5.

Dosio, A., and P. Paruolo (2011). Bias correction of the ENSEMBLES high-resolution climate change projections for use by impact models: evaluation on the present climate. *Journal of Geophysical Research: Atmospheres*116.D16.

Fildes, R., and N. Kourentzes (2011). Validation and forecasting accuracy in models of climate change. *International Journal of Forecasting*27, no. 4: 968-995. https://doi.org/10.1016/j.ijforecast.2011.03.008.

Flecher, C., P. Naveau, D. Allard, and N. Brisson (2010). A stochastic daily weather generator for skewed data. *Water Resources Research* 46, no. 7.

Fordham, D. A., Wigley, Tom M.L., and B. B. W. (2011), Multi‐model climate projections for biodiversity risk assessments, *Ecological Applications*, *21*(8), 3317-3331.

Forsythe, N., H. J. Fowler, S. Blenkinsop, A. Burton, C. G. Kilsby, D. R. Archer, C. Harpham, and M. Z. Hashmi (2014), Application of a stochastic weather generator to assess climate change impacts in a semi-arid climate: The Upper Indus Basin, *Journal of Hydrology*, *517*, 1019-1034.

Fowler, H. J., S. Blenkinsop, and C. Tebaldi (2007), Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling, *International journal of climatology*, *27*(12), 1547-1578.

Frei, C., J. H. Christensen, M. Déqué, D. Jacob, R. G. Jones, and P. L. Vidale (2003), Daily precipitation statistics in regional climate models: Evaluation and intercomparison for the European Alps, *Journal of Geophysical Research: Atmospheres*, *108*(D3).

Giorgi, F., C. Jones and G.R. Asrar. (2009). Addressing climate information needs at the regional level: the CORDEX framework. World Meteorological Organization (WMO) Bulletin, 58(3), p.175.

Han, B., Benner, S. G., Bolte, J. P., Vache, K. B., and Flores, A. N. (2017). Coupling biophysical processes and water rights to simulate spatially distributed water use in an intensively managed hydrologic system, Hydrol. Earth Syst. Sci., 21, 3671-3685, https://doi.org/10.5194/hess-21-3671-2017.

Hansen, J., M. Sato, and R. Ruedy (2012), Perception of climate change. *Proceedings of the National Academy of Sciences* 109.37: E2415-E2423.

Hayhoe, H. N., and D. W. Stewart (1996), Evaluation of CLIGEN and WXGEN weather data generators under Canadian conditions, *Canadian Water Resources Journal*, *21*(1), 53-67.

Ivanov, V. Y., R. L. Bras, and D. C. Curtis (2007). A weather generator for hydrological, ecological, and agricultural applications. *Water resources research* 43.10.

Kay, J. E., C. Deser, A. Phillips, A. Mai, C. Hannay, G. Strand, J. M. Arblaster, S. C. Bates, G. Danabasoglu, and J. Edwards (2015), The Community Earth System Model (CESM) large ensemble project: A community resource for studying climate change in the presence of internal climate variability, *Bulletin of the American Meteorological Society*, *96*(8), 1333-1349.

Kilsby, C. G., P. D. Jones, A. Burton, A. C. Ford, H. J. Fowler, C. Harpham, P. James, A. Smith, and R. L. Wilby (2007), A daily weather generator for use in climate change studies, *Environmental Modelling & Software*, *22*(12), 1705-1719.

Klos, P.Z., T.E. Link, and J.T. Abatzoglou (2014). Extent of the rain-snow transition zone in the western US under historic and projected climate. *Geophysical Research Letters*, *41*(13), pp.4560-4568. **DOI:** 10.1002/2014GL060500.

Marston, L. and X. Cai (2016). An overview of water reallocation and the barriers to its implementation. Wiley Interdisciplinary Reviews: Water, 3(5), pp.658-677.

Mikhail A. Semenov, E. M. B. (1997), Use Of A Stochastic Weather Generator In The Development Of Climate Ch, *Climate Change*, *35*(4), 397-414.

P. Racsko, L. S. (1991), A serial approach to local stochastic weather models, edited.

Petrich, C. R. (2004), *Treasure Valley hydrologic project executive summary*, Idaho Water Resources Research Institute.

Qian, B., S. Gameda, H. Hayhoe, R. De Jong, and A. Bootsma (2004), Comparison of LARS-WG and AAFC-WG stochastic weather generators for diverse Canadian climates, *CLIMATE RESEARCH.*, *26*(3), 175-191.

Richardson, C. W. (1981), Stochastic simulation of daily precipitation, temperature, and solar radiation, *Water Resources Research*, *17*(1), 182-190.

Richardson, C. W., and D. A. Wright (1984), WGEN: A model for generating daily weather variables, edited, US Department of Agriculture, Agricultural Research Service Washington, DC, USA.

Semenov, M. A., and E. M. Barrow (1997). Use of a stochastic weather generator in the development of climate change scenarios. *Climatic change* 35.4: 397-414.

Stocker, T. F. (2014), Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change. *Cambridge University Press*. Cambridge, England

Tarlock, A.D., (2000). Prior appropriation: Rule, principle, or rhetoric. *N.D.L. Rev.*, 76, p.881.

Urban, S. M., and C. R. Petrich (1996), water budget for the Treasure Valley aquifer system, *Treasure Valley Hydrologic Project Research Report, Idaho Department of Water Resources, Boise, Idaho*.

Vano, J.A., B. Nijssen and D.P. Lettenmaier (2015). Seasonal hydrologic responses to climate change in the Pacific Northwest. *Water Resources Research*, *51*(4), pp.1959-1976. DOI: 10.1002/2014WR015909

Wilby, R. L., and T. M. L. Wigley (1997), Downscaling general circulation model output: a review of methods and limitations.

Wilks, D. S (2010). Use of stochastic weathergenerators for precipitation downscaling. *Wiley Interdisciplinary Reviews: Climate Change* 1.6: 898-907.

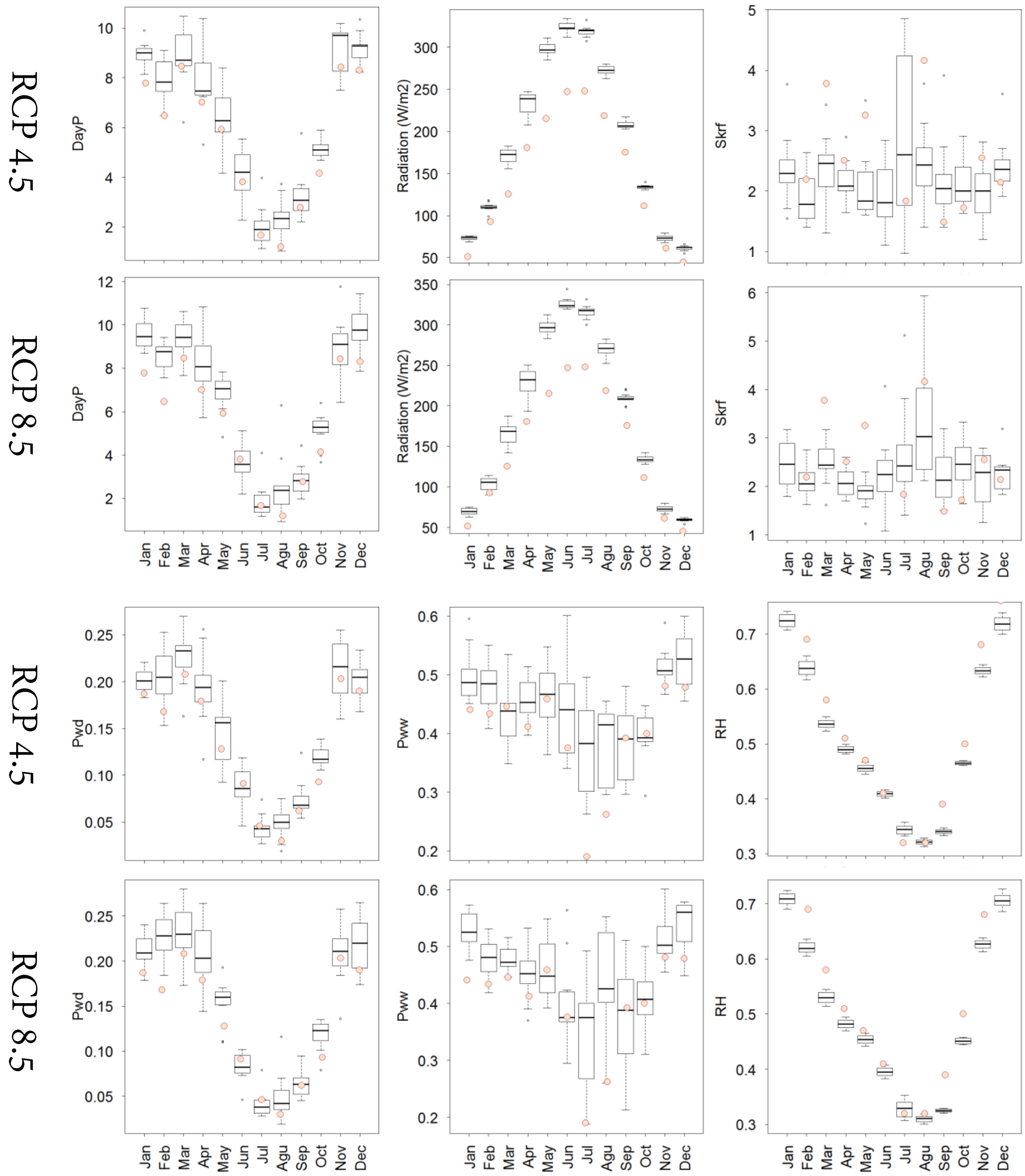
Will, R. E., M. W. Stuart, Z. B. Chris, and C. H. Thomas. (2013) Increased vapor pressure deficit due to higher temperature leads to greater transpiration and faster mortality during drought for tree seedlings common to the forest–grassland ecotone. *New Phytologist* 200, no. 2: 366-374. DOI: 10.1111/nph.12321.

Xu, C.Y. (1999), From GCMs to river flow: a review of downscaling methods and hydrologic modelling approaches. *Progress in Physical Geography: Earth and Environment.* 23 (2): 229-249. https://doi.org/10.1177/030913339902300204.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

Appendix A: *Boxplot of monthly climate statistics (12 variables) of 11 selected GCMs. The circles indicate the historical monthly average.*



Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-140
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 9 May 2018

Hydrology and Earth System Sciences
Open Access
Discussions

916