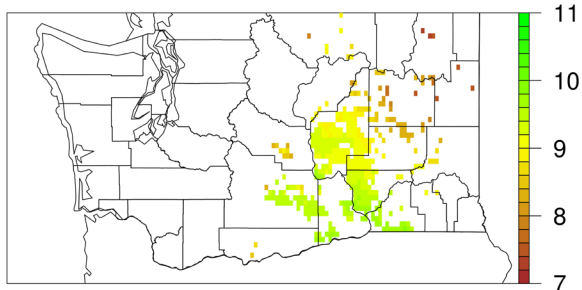
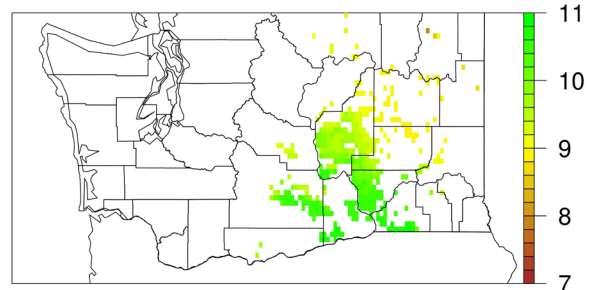


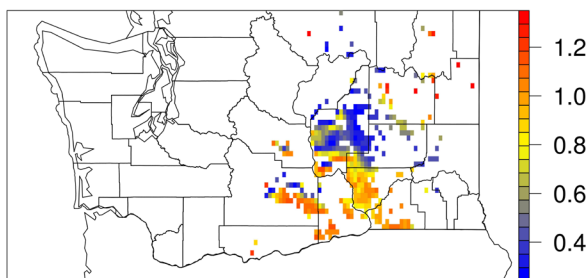
Historical Yield [Irrigated] (tonnes/hectare)



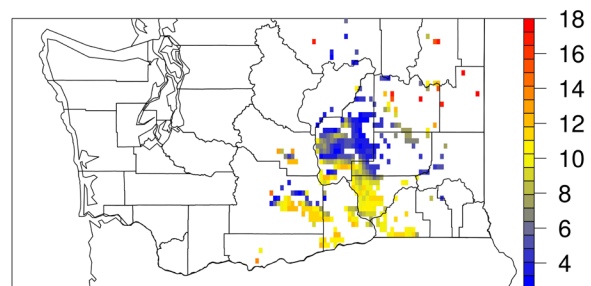
Future Yield [Irrigated] (tonnes/hectare)



Future Change in Yield [Irrigated] (tonnes/hectare)



% Change in Yield [Irrigated]



# MODELING ENVIRONMENTAL CHANGE: A GUIDE TO UNDERSTANDING MODEL RESULTS THAT EXPLORE THE IMPACTS OF CLIMATE CHANGE ON REGIONAL ENVIRONMENTAL SYSTEMS

By  
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## Introduction

Models come in many different forms—from a sand-and-gravel model of a watershed that sits on a tabletop, to a sophisticated hydrological model simulated using high-performance computing. While there are big differences between different modeling approaches, they are all alike in their aim to represent essential features of natural objects and phenomena. This guide focuses on process-based environmental models, particularly those used to model climate change impacts. This type of environmental modeling plays an increasingly important role in understanding the potential implications of environmental changes in the Pacific Northwest, other areas of the U.S., and the world at large (Mass et al. 2003; Lemos et al. 2012). This guide is designed to assist resource managers, planners, and others who are interested in using modeling results to better understand how environmental change and policy decisions may affect regional ecosystems, agriculture, and natural resource management as well as regional industries and populations. It is intended to help readers understand, interpret, and evaluate modeling results. A glossary is provided at the end of this publication to assist readers who are unfamiliar with some of the terms used in this guide.

Models are simplified representations of an object or a process (Box et al. 1978; Sterman 2002; Frigg and Hartman 2012). Statistician George Box famously wrote that, “essentially, all models are wrong, but some are useful” (Box et al. 1978). They are all “wrong” in the sense that they are simplifications of systems or processes existing in the real-world and thus by definition can never be perfect replicas of reality. However, models are tremendously *useful* because they can be instructive about the nature of real-world phenomena or systems (Sterman 2002). When applied and interpreted with care, models can capture the essence of a system or process and can provide reasonable

approximations of system behavior and projections of future conditions.

Many people are more familiar with laboratory and field experiments than with modeling and, therefore, they tend to trust experimental results, while they may be suspicious of modeling results. However, while experimental science is tremendously useful, it has some limitations. Assessing change over extended time periods or across a large spatial extent may be prohibitively expensive, or simply impractical to study using experiments alone (Steel et al. 2009a; Weisberg 2013). Modeling can play a central role in developing theories or explanations that describe how a system operates. Modeling also enables testing of a range of future scenarios (Lemos et al. 2012; Weaver et al. 2013). Furthermore, researchers can use models to isolate specific processes in order to better understand their role in the system as a whole (Frigg and Hartman 2012).

Modeling results are often most powerful when they move away from an approach focused on “prediction” towards an exploration of the range of possible futures we might find ourselves in (Lemos et al. 2012; Weaver et al. 2013). This approach shifts the focus to some different questions: Are planned or possible management or policy strategies “robust”—that is, do they perform well over the range of possible futures that are projected? What are key areas of vulnerability? If there are situations under which our current or planned management and policy strategies perform poorly, what can be done to minimize the negative impacts?

This guide will provide some key concepts to increase decision-makers’ understanding and interpretation of model results. Attention is given to the importance of asking questions such as: What specific systems are being modeled? What data are inputs into the model? Over what domain and at what scale is the model designed to provide outputs? What assumptions are used in the design of the model and in the scenarios

being modeled? If there are competing models, how do they differ? What sources of uncertainty exist in the model, and how is uncertainty handled in the model outputs?

In several places in this guide, concepts are illustrated using examples from the 2011 Columbia River Basin Long-Term Water Supply and Demand Forecast (CRB Forecast), which was completed by Washington State University researchers in collaboration with the Washington State Department of Ecology (Yorgey et al. 2011; Adam et al. 2012). The project evaluated the impacts of climate change, regional and global economic conditions, and state-level management actions on future surface water supply and demand across the Columbia River basin. In this guide, the focus will be on the lessons relevant to understanding the results obtained from process-based environmental models, rather than the specific results of the CRB Forecast. Readers who are interested in the results of the CRB Forecast should review the summary report (Yorgey et al. 2011) and the technical report (Adam et al. 2012), which can be found at <http://www.ecy.wa.gov/programs/wr/cwp/forecast/forecast.html>.

## Process-Based Modeling

### What is a process-based model?

Most earth system models that decision-makers are likely to encounter can be classified as process-based models. Process-based models directly capture the most fundamental scientific features and relationships of the system being modeled, representing them mechanistically. This enables the modeler to understand causal relationships between system components (e.g., A leads to B). In contrast, empirical models, such as statistical models, generally rely on observation of external characteristics of the system and inductive reasoning (inference) to determine probable relationships between system components and represent those relationships



mathematically (Thakur 1991; Fritts et al. 1991).

### How are process-based models developed?

Process-based models are typically developed beginning with understanding the important components in a system, relationships between the components, and then representing them numerically. For example, a process-based model could simulate infiltration, or seepage of rainwater into soil, by mathematically representing how water moves through specific soil types according to characteristics that have been experimentally studied and defined, such as soil texture, relative proportion of organic matter, and depth of soil layers.

Multiple process-based models can also be linked to represent an integrated system. In the CRB Forecast, two process-based models were linked—a hydrology model (the Variable Infiltration Capacity model, VIC) and a cropping-systems model (CropSyst). These two linked models were then used to forecast future water supply and crop water demand.

Modeling happens progressively: researchers construct a model, they analyze and refine the properties and dynamics of the model, they assess the relationship between the model and reality, and they may apply the model with the intention of developing a better understanding of real-world systems (Weisberg 2007). These stages are iterative. Model application often leads to new questions and exposes gaps in scientific understanding, pointing to the need for additional experimental studies or further model development.

Following model development and parameterization, the model must be evaluated before it can be used to address questions about future change under new conditions. One component of evaluation is comparison of model outputs against independent observations of the real-world that are not already

incorporated into the model. For example, a hydrologic model can be evaluated by comparing modeled streamflow with observed streamflow. However, it is important that the model is evaluated specifically for the research question under investigation. For example, if a hydrologic model is being run to forecast frequency of extreme high or low streamflow events in an altered future climate, then the model should be evaluated for its ability to capture extreme historical events, not just mean historical hydrologic behavior.

### How do regional environmental models represent climate change?

Regional environmental models generally are weather-driven, meaning they explore how weather (e.g., precipitation and temperature) affects other environmental processes. These models represent climate change impacts by considering different projections of future climate as model inputs. These projections are obtained from global climate models that simulate oceanic and atmospheric conditions. These models are technically called general circulation models (GCMs). There are dozens of widely used GCMs, each drawing on specific baseline data and algorithms, and each with a unique structure for linking model components (IPCC 2013). Each GCM is run using multiple emissions scenarios, or assumptions about future greenhouse gas emissions. This results in multiple future climate projections, each representing a GCM run under a particular emissions scenario.

Global climate projections from GCMs provide information at a coarse spatial resolution and have limited utility in regional studies because they do not have sufficient detail to capture important drivers of regional climate. To address this limitation, projections of future climate are typically downscaled to a smaller, finer spatial scale for use in regional environmental models. This is done by fine-tuning the relevant portion of the global climate

### Where do emissions scenarios come from?

To help make results from various projects comparable, the Intergovernmental Panel on Climate Change (IPCC) defined a standard set of emissions scenarios that are commonly used. The approach to modeling future emissions continues to evolve, and in the 5th IPCC Assessment Report analyses are based on Representative Concentration Pathways (RCPs) (IPCC 2014). RCPs are a set of future greenhouse gas concentration trajectories, which do not assume specific policy and technology development scenarios (IPCC 2014).

projections based on understanding of regional climatic drivers (Abatzoglou and Brown 2012). In the process of downscaling, adjustments are made to the outputs from general circulation models to better capture local forces, such as the rain shadow effect from the Cascade Range (Mote and Salathe 2010). Figure 1 provides a conceptual illustration of how a GCM output could be downscaled for use in projecting climate change impacts for the western United States.

### Why are multiple climate projections typically used?

In assessing the regional impacts of climate change, it is important to consider multiple downscaled regional projections (based on multiple GCM and emissions-scenario combinations) because we cannot predict future climate with certainty. The CRB Forecast utilized five different climate change projections. These projections were selected from the 21 Coupled Model Intercomparison Project Phase 3 (CMIP3) general circulation models because they captured the full range of temperature and precipitation changes for the 2030s, as indicated by a separate analysis (Mote and Salathe 2010).

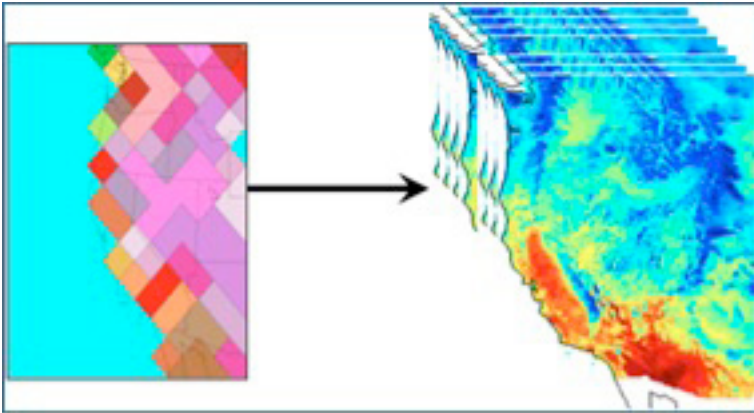


Figure 1. The image on the left provides a conceptual illustration of GCM output cropped to show the western United States. The image on the right illustrates the same output downscaled for study of regional climate change impacts. (Figure courtesy of John Abatzoglou, University of Idaho)

### Why do model inputs and domain matter?

Process-based models normally use a wide range of input data, including data on historical and future climate, soils, crops, land cover, and management. Limitations on available data are one important group of limitations on the results that can be generated by a model (Steel et al. 2009a).

It is essential to identify and understand a model’s domain, or the temporal and spatial range that it was designed to examine. Process-based models represent important components and relationships in a system mechanistically; therefore, they can be applied to contexts outside the range of data that was used to calibrate the model. This differs from empirical models, which are typically less reliable outside of the spatial and temporal range in which they were developed and calibrated (Meadows and Robinson 2002). This is one reason that process-based models are the primary model type used for climate change impact studies. However, it is important to understand that under changing conditions new processes may emerge as dominant that are not adequately represented in the model, thus limiting the model’s ability to accurately project future conditions.

### Why is understanding scale essential?

Depending on the systems being investigated and the specific questions being asked, entirely different spatial scales of analysis may be appropriate. For example, many regional-scale, land surface models, including the VIC hydrology model used in the CRB Forecast, represent processes at a 6 km

x 6 km grid cell resolution. In the case of a variable that is spatially “mixed” or “patchy” at this scale, variability is represented statistically.

A hypothetical example illustrates how the VIC model might deal with soil type, which is mixed, or patchy, at a 6 km x 6 km grid cell resolution (Figure 2). The spatial distribution of three soil-type classes can be seen in the grid cell shown in Figure 2a. The VIC model treats within-grid cell variability statistically, or implicitly. In other words, the model uses the information that 1/5<sup>th</sup> the grid cell area is soil-type yellow, 1/5<sup>th</sup> is soil-type green, and the remaining 3/5<sup>th</sup> is soil-type grey. The model does not take into account the exact spatial location of a given soil type within the grid and does not distinguish between the five hypothetical spatial distributions of soil types in Figure 2b. A model such as the VIC hydrology model, which accounts for sub-grid cell spatial variation implicitly, may thus be ineffective in explaining very localized patterns of soil infiltration rates, even though it effectively simulates infiltration in the larger

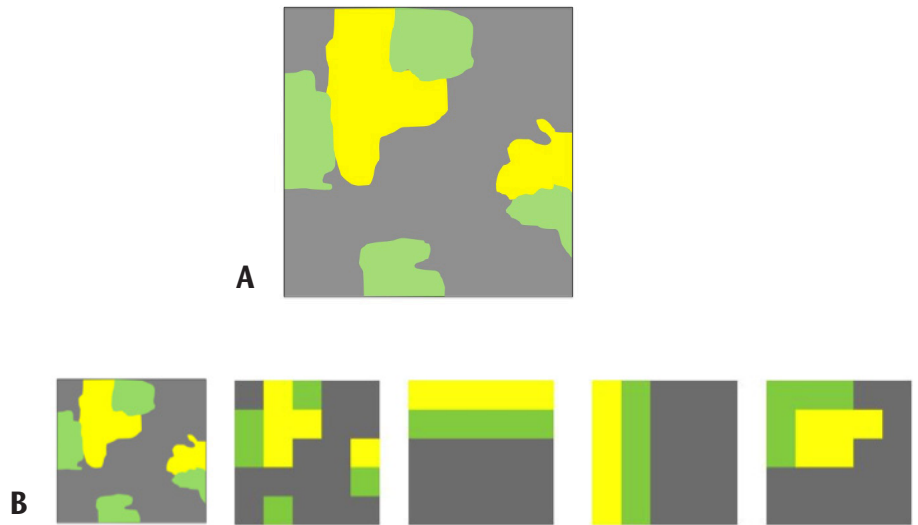


Figure 2. A conceptual illustration of how the VIC model handles variation in soil type within a grid cell. Figure 2a shows the spatial distribution of soil types in a hypothetical 6 km x 6 km grid cell where 1/5<sup>th</sup> the grid cell area is soil type “yellow,” 1/5<sup>th</sup> is soil type “green,” and the remaining 3/5<sup>th</sup> is soil type “grey.” The VIC hydrology model handles sub-grid cell variability implicitly, meaning the multiple spatial configurations of soil types shown in Figure 2b are indistinguishable. Under a spatially implicit treatment, the relative proportions of features within a grid cell are accounted for but their exact spatial location is not.

watershed unit (Seyfried and Wilcox 1995).

Just as a model designed to simulate watershed-scale patterns may not be able to project what will happen on a particular field, a model designed to understand a small-scale process cannot always be used to understand region-wide impacts. For example, a field-scale model used to assess the loss of nitrogen from a particular crop rotation with a specific set of soils cannot be applied to a larger region unless input data is available for all other land-cover classes and soil types in the study area. Even if the necessary input data were available, this “up-scaling” of a field-scale model may be infeasible because of the computing power and time required. Also, the dominant processes may be different at different scales. Thus, in moving from one scale to another, it is necessary to make sure that the model adequately represents processes dominant at the relevant scale.

The scale at which model outputs are presented influences how modeling results can be used. Results shown at one scale can mask variability at a smaller scale. For example, the CRB Forecast was designed to understand the impacts of water supply and demand at the Water Resource Inventory Area (WRIA) level in addition to the basin-wide scale, because WRIs are important for managing water resources within Washington State. Figure 3 shows projected water supply within the entire Columbia River basin and within the Yakima River basin. At the Columbia basin scale in the 2030s, water supply is projected to be more than enough to meet out-of-stream demands (Figure 3a), but at a watershed scale it can be seen that during certain times of the year, water supply in the Yakima basin is projected to be insufficient to meet out-of-stream demands (Figure 3b).

Understanding temporal scale is also important to interpreting modeling results correctly. The monthly timescale of the results shown in Figure 3b provides important

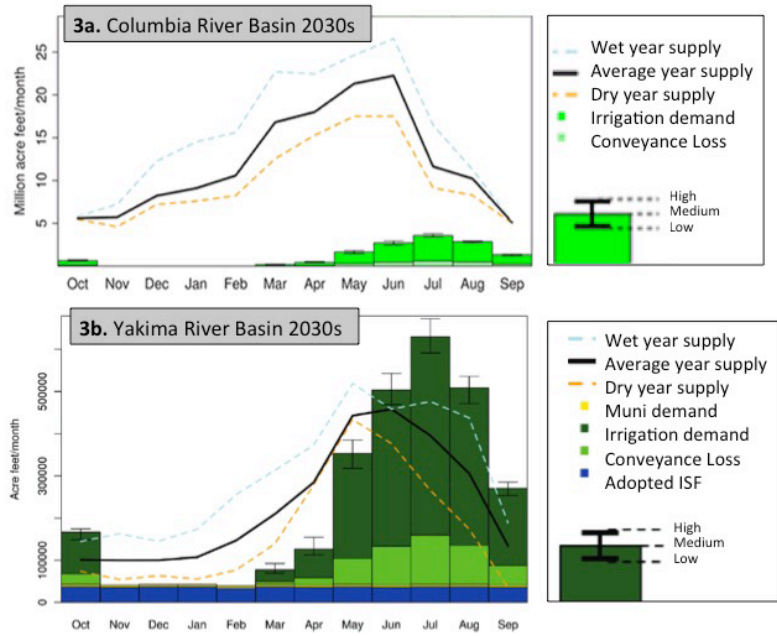


Figure 3. Comparison of surface water supply, surface water irrigation demands, and municipal water demand in the Columbia River basin (a) and the Yakima River basin (b) for the 2030s decade, based on the median climate change projection considered. When comparing the two figures, note that Figure 3a does not show instream demands, whereas Figure 3b does (blue).

**How are water supplies and water demands defined within the results from the CRB Forecast?**

Water supplies reflect water supply generated within the watershed, including current major reservoir operations. Surface water irrigation demand is shown at the point where water is applied to crops. It will thus include water that will actually be used by plants, as well as on-field losses based on irrigation type. Irrigation demand is calculated based on a crop mix determined by a “baseline” economic scenario (medium growth in the domestic economy and in international trade). Conveyance losses (water lost from the system as water is transported to the point of application) are estimated separately. Instream flow requirements (in blue) are based on federal flow targets.

information about potential shortages that would not be evident if the results were shown at an annual timescale.

**What are some important sources of uncertainty in process-based environmental models?**

Model projections are not exact descriptions of what will happen; there is always some degree of uncertainty associated with them (Smith and Stern 2011). Uncertainty

can be due to incomplete knowledge of a system, which can be reduced with further experimental study. Uncertainty can also be due to inherent variability in a system (Walker et al. 2003). It is not possible to quantify all forms of uncertainty; some expressions of what is unknown can only be stated qualitatively. However, when environmental modelers discuss uncertainty they are often referring to only the kind of uncertainty that can be quantified, in other words, the range of model outputs which have mathematical

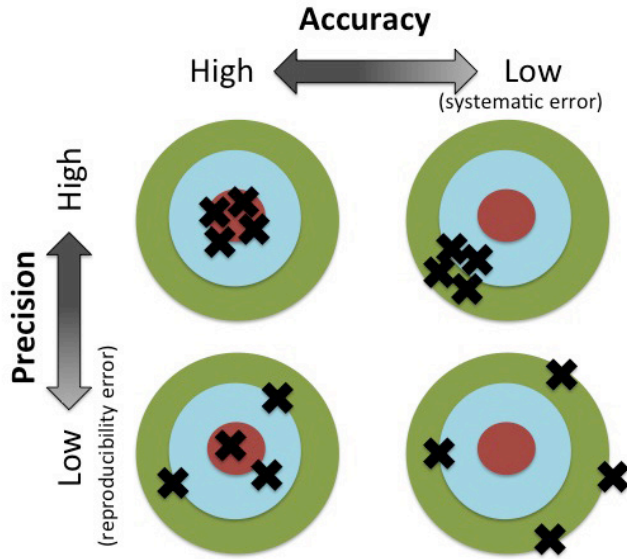


Figure 4. Precision and accuracy of model inputs are important factors in determining the certainty of model outputs.

probabilities assigned to them (Walker et al. 2003; Hawkins and Sutton 2010).

Model uncertainty is related to the precision and accuracy of model outputs. Precision is concerned with the amount of random error, or “noise” in the data, while accuracy is concerned with the amount of error that is consistent, meaning that it

always shifts the results in the same direction (Figure 4). The precision and accuracy of model *inputs*, the scale of modeling, and the internal modeling equations all contribute to determining the precision and accuracy of model *outputs*. Precision and accuracy should be evaluated with respect to the proposed uses of model outputs; it is possible for outputs to be precise and accurate

enough for some uses, but not for others (Steel et al. 2009b).

It is also possible for a model to predict one process or feature well but not others (Steel et al. 2009b). For example, projections of average precipitation patterns are generally more uncertain than average temperature projections because precipitation is governed by a wider range of factors, including local topography and wind direction (Christensen et al. 2008; Steel et al. 2009a). Making predictions about extreme precipitation or temperature events is more difficult than predicting averages or events that occur frequently (Steel et al. 2009a). Figure 5 shows projected future changes in annual and seasonal temperature and precipitation in the Pacific Northwest and illustrates the greater uncertainty associated with precipitation projections. At an annual scale, there is even some uncertainty around the direction of change in precipitation, whereas all temperature projections point to warmer temperatures.

Some key sources of uncertainty in process-based models that explore

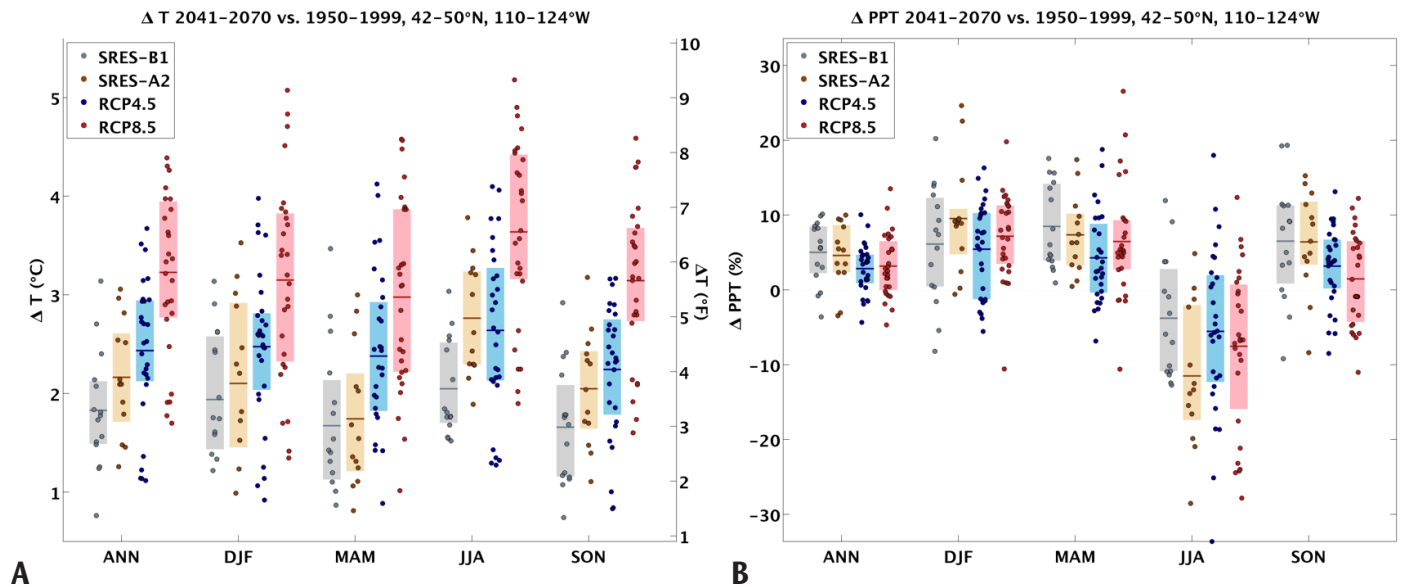


Figure 5. Projected annual and seasonal changes in (a) temperature and (b) precipitation for 2041–2070 compared to 1950–1999 averaged across the Pacific Northwest (42°–50° N, 110°–124° W), calculated from the CMIP3-SRES and CMIP5-RCP simulations. Four different emissions scenarios (B1, A2, RCP 4.5, and RCP 8.5) are shown. Each symbol represents one simulation by one model (where more than one simulation is available, only the first is shown). The shaded boxes indicate the interquartile range (25<sup>th</sup> to 75<sup>th</sup> percentiles). Means are indicated by the thick horizontal line in the boxes. (Figure used with permission from Mote, Abatzoglu, and Kunkel 2013.)

climate change impacts on regional environmental systems include uncertainty related to emissions scenarios (and general uncertainty about human behavior and decision making in the future), structure and parameterization of GCMs and regional environmental models, the downscaling approach, and the inherent internal variability of systems. Some of these factors may be explicitly addressed or shown in results, while others may not.

There are several sources of uncertainty in the results of the CRB Forecast, and only some of these sources are illustrated graphically. For example, there is uncertainty caused by limitations in the scientific understanding of climate drivers and the ability to model those drivers perfectly. In other words, there is uncertainty about which climate projection (downscaled GCM plus emissions scenario) will most closely represent future conditions. In an

example from the Yakima River basin portion of the CRB Forecast, projected water supply is represented with a green cloud (Figure 6). This green cloud represents the range of results for monthly surface water supply in the 2030s for the set of projections examined. Meanwhile, these results do not explicitly show uncertainties related to future policy actions.

Uncertainty due to inter-annual variability is also addressed in the CRB Forecast. Because water supply varies from one year to the next, some years are inherently wetter than others. After discussions with water managers, modelers working on the CRB Forecast chose to handle this uncertainty by showing water supply during a year with average streamflow, as well as a particularly wet year (defined as being in the 80<sup>th</sup> percentile for water supply, meaning a year when annual streamflow was higher than 80% of the years on record) and a particularly dry year (defined as the

20<sup>th</sup> percentile). Water supply during a dry, average, and wet year are shown in the three parts of Figure 6.

### How do assumptions made in the modeling process influence outputs?

All models make assumptions (Peterson et al. 2003). Decision-makers who are looking at model outputs need to understand the assumptions built into a model. Within the CRB Forecast, there were many assumptions built into the scenarios that were examined for the 2030s decade. One important assumption, which impacts surface water availability estimates, relates to the separation of water demands into those met by surface water sources versus groundwater sources. An approximate split percentage between ground and surface water was assumed. While researchers understood that this assumption was likely an inaccurate representation of reality, a better characterization of the sources was not possible because of time, resource, and data constraints.

Assumptions are also frequently found in scenarios, or storylines about a set of future conditions and trends. Scenarios are frequently used in models that look at coupled human—ecological systems to explore modeled possible future conditions (Peterson et al. 2003; Weisberg 2013). A single model can be used to explore multiple scenarios. Generally, it is only possible to generate a relatively small number of scenarios because of limited computing and analytical power, as well as limitations on the time that modelers can reasonably invest in running scenarios. Thus, it is important to invest time to clearly define a set of meaningful scenarios that encompass likely future conditions.

Analyzing how results change as assumptions change can also provide insight into the mechanisms that are driving the results, a process sometimes referred to as sensitivity analysis. For example, different assumptions about economic growth

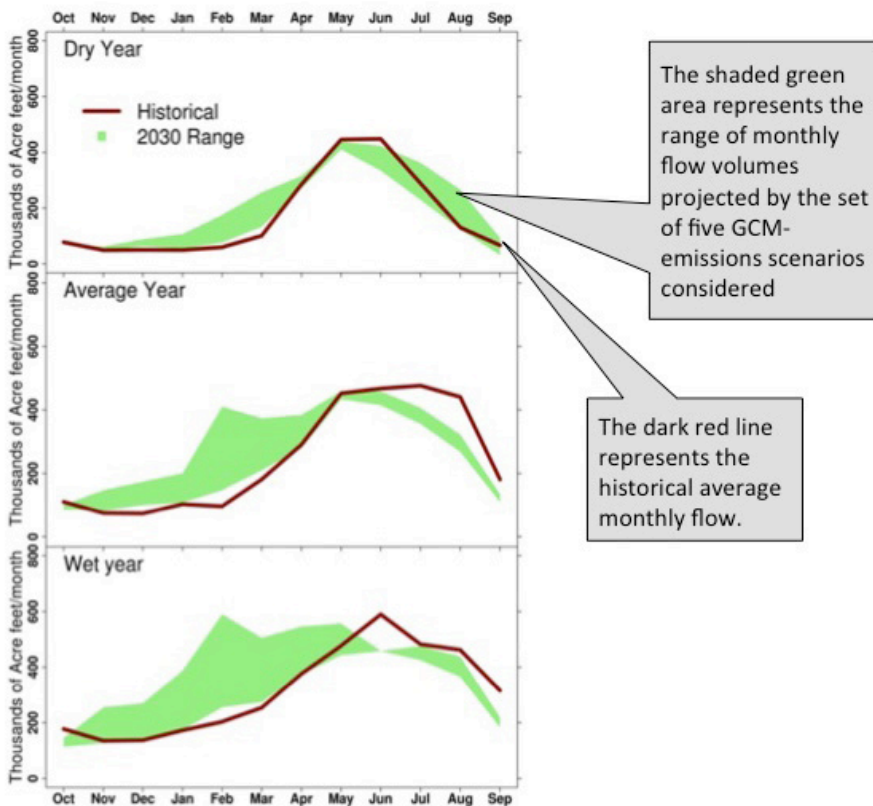


Figure 6. Modeled historical (1997–2006) surface water supply and 2030s water supply generated within the Yakima River basin for a range of flow conditions. Supply includes current major reservoir operations, and is defined as in the text box associated with Figure 3.

and future crops to be grown in the region were tested in the CRB Forecast. The baseline water demand scenario (shown earlier in Figure 3) was generated using an assumption that changes in crop mix would occur over time, and that these changes would be the result of medium (most likely) domestic economic growth and medium growth in international trade. Researchers also varied these assumptions by constructing low and high economic growth scenarios, and comparing the impacts of these different assumptions on water demand (Figure 7). As Figure 7 indicates, the impact on water demand in the Yakima Basin is slight even if the economic situation is considerably different than the “medium” scenario.

**How can process-based models provide insight into the factors that may contribute to future outcomes?**

One of the strengths of process-based models is that they can be used to isolate the factors contributing to future changes. Building on work completed in the CRB Forecast, researchers projected changes in agricultural yield for dryland winter wheat and irrigated winter wheat under future climate change. Figure 8 breaks down the total projected yield change into a number of climate-change related components. The bars on the far right show the combined yield impacts projected from changes in precipitation, temperature, and carbon dioxide enrichment (which can benefit the growth of some crops). To the left of this, the impact of precipitation, temperature, and carbon dioxide are shown separately.

Under climate change, dryland winter wheat yields would be positively impacted by an earlier start of the growing season coupled with increases in early season precipitation. Temperature, precipitation, and carbon dioxide enrichment are all projected to increase yield by relatively equal proportions. In contrast, irrigated winter wheat yields would not change drastically. Looking

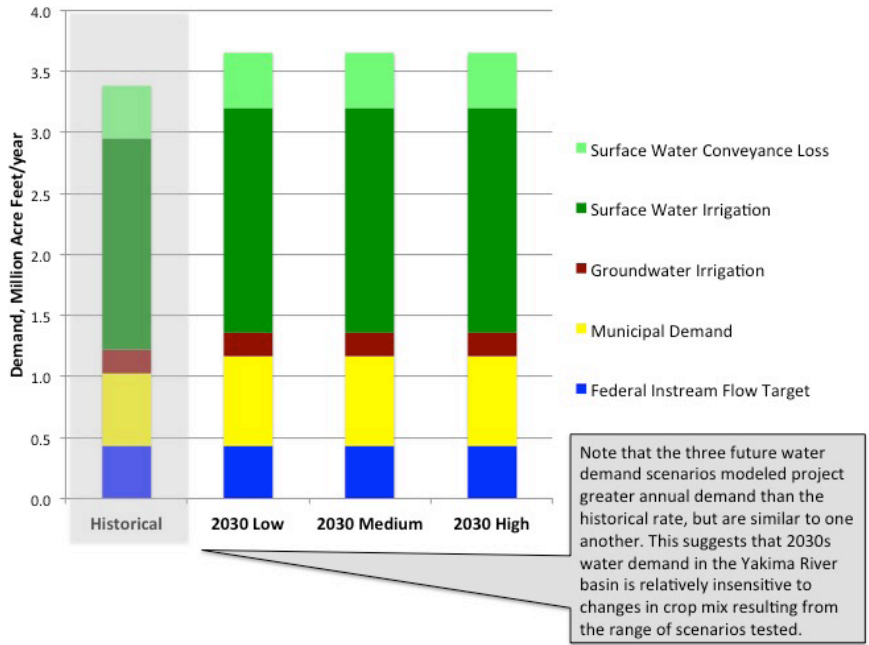


Figure 7. Modeled historical (1977–2006) and 2030s demand for irrigation water, municipal water, and instream flow in the Yakima River basin under average flow conditions, and under the middle climate change scenario considered. Forecast 2030s water demands are shown for a crop mix that results from three economic scenarios: low, medium, and high growth in the domestic economy and international trade. Water demands are defined as described in the text box associated with Figure 3.

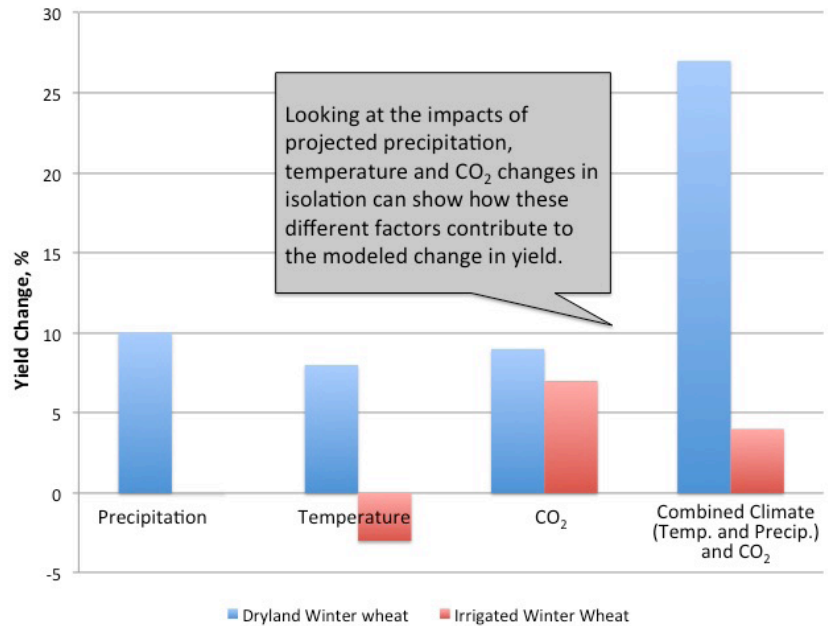


Figure 8. Percentage change in average Washington State yields of non-irrigated winter wheat and irrigated winter wheat between the historical (1977–2006) and future (2030s) time period. Effects are broken out to show impact of changes in precipitation, temperature, carbon dioxide (CO<sub>2</sub>), and combined impacts of climate and carbon dioxide.

at the various components, yields would not be affected by projected changes in regional precipitation, which makes sense since the crop is irrigated. Meanwhile, yields are projected to be reduced a small amount by increased temperatures. This negative impact on yield is counterbalanced by the positive impact of increased carbon dioxide fertilization.

## Conclusion

While no model can perfectly predict the future, models are vitally important in helping us understand the range of possible environmental conditions we may encounter. They can also help us assess how well existing or proposed management strategies and policies might perform under different future conditions. The information gained from models complements the information gained from experiments, and both can inform our understanding of complex real-world objects and processes. Using information from models can help effectively address regional environmental change, thus enhancing the resiliency of communities and industries.

Collaboration between scientists and private and public decision-makers can help ensure that modeling applications are relevant to real-world concerns. Scientists can do their part in this collaboration by engaging with stakeholders throughout the model development process, and by effectively helping stakeholders become more knowledgeable about the processes and uses of environmental modeling. The quality and effectiveness of these collaborations is improved when private and public decision-makers become more knowledgeable and more comfortable with environmental modeling. Additionally, as resource managers learn more about the considerations and the constraints that modelers must respond to, they can more effectively engage with modelers to ensure that environmental models provide the most decision-important information.

This collaboration will enhance the utility and applicability of models for supporting decision-making in the context of complex environmental problems.

## Glossary of Terms

**accuracy**—A measure of how close the average of repeated predictions are to the truth.

**algorithm**—A procedure or set of rules to be followed in problem-solving operations.

**downscaling**—The process of converting something at a larger scale or spatial extent to a finer scale.

**empirical**—Something that is verifiable by observation or experience, rather than theory or pure logic alone.

**evaluation**—In this context, the process of testing model output. There are multiple ways a model can be evaluated, one of which is a comparison of model output against independent real-world observations.

**forecast**—An estimate of what is likely to happen in the future. A forecast can be thought of as a “best” prediction made with a particular technique or representation of current conditions.

**General Circulation Model (GCM)**—IPCC (2013) defines GCMs as mathematical models representing physical processes in the atmosphere, ocean, ice masses, and land surface used to simulate the effects of increasing greenhouse gas concentrations on the global climate system. GCMs depict the global climate system as a coarse resolution three-dimensional grid over the globe. Up to 30 vertical layers are considered in the ocean and 10 to 20 vertical layers are considered in the atmosphere. Each grid cell has a typical horizontal resolution between 250 and 600 km. Land use and water resource management decisions generally need to be made at a much finer resolution than this and hence the need to downscale GCM output arises.

**grid cell resolution**—See “resolution.”

**inductive reasoning**—Also referred to as “bottom-up logic,” or reasoning about what is probable based on what can be observed. This is in contrast to deductive reasoning, or “top-down logic,” which is based on application of general principles to understand a specific case.

**inputs**—Data that are “fed” into a model.

**mean**—The average of a set of values calculated as the sum of the values divided by the number of values in the set.

**model**—A representation of an object, process, or relationship.

**outputs**—Results from a model, may also be referred to as “model projections.”

**parameterization**—The process of deciding and defining the parameters, or measurable attributes, necessary for a complete description of an object or process that is being modeled.

**percentile**—A statistical measure indicating the value below which a given percentage of observations in a group of observations fall. For example, an 80th percentile annual stream flow value of 300 cubic feet per second (cfs) at a particular location indicates that 80% of the annual streamflow values at that location are lower than 300 cfs.

**phenomenon (plural, phenomena)**—An observed fact or situation, especially one whose cause or explanation is in question.

**precision**—A measure of how close repeated predictions are to each other.

**prediction**—An estimate of what is likely to happen in the future based on what is known today.

**process-based model**—A model based on mathematical representation of the physical relationships in the system being modeled.

**projection**—The extension of particular predictions under particular conditions. Projection allows for defining a range of conditions that might influence the prediction, creating “if this, then that” types of statements.

**resolution**—In this context, model resolution is the smallest spatial unit in which model input is prepared and model output is delivered.

**qualitative**—Relating to or measured by the qualities or descriptive attributes of something, rather than quantity.

**quantitative**—Relating to or measured by quantity, rather than quality.

**scale**—The space or time unit of discussion. Examples of time scales include decadal, annual, monthly, or daily. Examples of spatial scales include grid cell, field, watershed, county, state, region, or country.

**scenario**—A description of plausible alternative futures (actions or reactions), or changes in conditions. Scenarios provide an indication of possible futures, but not definitive probabilities.

**sensitivity analysis**—An assessment of how much a change in one input affects one or more model outputs.

**spatial**—Of or relating to space.

**statistical model**—A model that identifies and generalizes relationships from data, describing how one or more variables are probabilistically related to one or more other variables. For example, a statistical model could describe the relationship between temperature and soil moisture; these factors are related probabilistically because warmer temperatures tend to lead to increased surface evaporation, but temperature is not the only factor that determines soil moisture.

**temporal**—Of or relating to time.

**uncertainty**—A lack of certainty, in this case often in describing a future

outcome. Uncertainty can arise from a variety of causes, including limitations in our scientific understanding of natural systems and the ability to model them perfectly, limitations in the accuracy and precision on input data, or random variability in the system.

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