Time of Emergence of Climate Change Signals in the Puget Sound Basin

Project Report

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Executive Summary

Because natural and human systems tend to be somewhat adapted to historical climate fluctuations, ecological and societal disruptions may occur when climate change causes local conditions to deviate significantly from the past. A key input to deciding and prioritizing actions on climate change, therefore, is information about when and where the distinctive trend due to climate change is projected to emerge from the noise of natural climate variability. Although this information can be gleaned from existing climate change scenarios, it has not been explicitly characterized for variables and spatial scales relevant to local decision-making and most climate change projections are reported without contextual information about the significance of projected changes relative to variability in past conditions. Multiple local climate change projections, based on different emission scenarios, global climate models and downscaling methods, increase the difficulty of identifying when and where the effects of climate change could matter.As a result, despite the wealth of downscaled climate change projections for the PNW, potential users of this information still struggle with interpreting multiple scenarios, finding information about projected changes in environmental conditions of relevance to their particular management concerns, or simply the technical challenges of extracting relevant information from the massive datasets available from climate data providers.

The Time of Emergence project enables a new look at future climate change from the point of view of when and where changes could matter compared to both typical variability in conditions and management sensitivity to those fluctuations. We combined climate statistics, engagement with policy and management entities, and data delivery platform development, to develop a new approach to climate change decision support based on the concept of "time of emergence" (ToE) for detectable change in management-relevant measures of the climate and environment for the US Puget Sound basin and Pacific Northwest (PNW). Variables for computation were selected in consultation with federal, state, and local decision-makers, who identified dozens of temperature-, precipitation-, hydrologic- and streamflow-related variables relevant to local management and operations, including proxies related to drought, energy, fish, floods, human health, infrastructure, streamflow, and water quality. ToE was computed for 35 types of variables (158 specific variables) using the "signal-threshold" method (Mauran 2013) and existing global, statistically- and dynamically-downscaled climate model outputs from Coupled Model Intercomparison Project phases 5 and 3 (CMIP5 and CMIP3) and existing simulations of regional hydrological change using the Variable Infiltration Capacity model. Analyses were performed at the resolution of the input datasets (i.e., 1/8- and 1/16-degree for gridded data) and spatially aggregated for WA, OR and ID counties and for 4^{th}-level (8-digit) hydrological unit codes (HUCs) in the PNW region.

In addition to databases of ToE results, intermediary computational outputs, and a library of maps for visualization of spatial variability in signal emergence, a final product is a prototype open online system designed to support evaluations of relative climate risks and efforts to prioritize preparatory action. The prototype tool enables users to visualize and compare the time of emergence of significant change for different variables and PNW locations and to explore the sensitivity of results to reasonable alternative choices about potential future conditions and management sensitivity.Users can explore the sensitivity of projected ToE to (1) user tolerance for change (low and high management sensitivity to climate fluctuations, triggered by the 10% and 40% most extreme historical conditions, respectively), (2) climate modeling uncertainty (represented by high and low emission scenarios; an ensemble of up to 21 global climate models, depending on input dataset; and statistically- and dynamically-downscaled regional projections), and (3) uncertainty in estimating the climate change trend. The prototype online tool is designed to provide scientific and technical information about the underlying methods, assumptions, datasets, and appropriate interpretation and application of ToE results, as well as guided tours of how a user might use the tool to support climate change decision-making, and supports user extraction and downloading of visualization products and underlying data.

The online tool is implemented in Drupal using the standard Drupal Content Management System, with custom modules to provide advanced filtering, user query, and dynamic visualization capabilities. The underlying database engine is MySQL, a standard open source database that powers both the underlying database for the Drupal site and a separate database that manages and serves the climate data. Designed as a prototype, the system can be expanded in the future to deliver additional ToE results (for different variables, input datasets, and/or user-selected analytical parameters), enhanced visualizations, or other features desired to enhance the user experience.

In the ToE project, we have reduced the burden for regional practitioners to access and interpret climate change projections by (1) downloading and formattingdownscaled model output, (2) using these projections to compute locally-specific, management-relevant variables, (3) evaluating the ToE for these variables under a range of plausible assumptions about future climate and management sensitivity to change, (4) developing syntheses of these results to indicate agreement across numerous global climate models, and for particular locations and levels of agreement, (5) producinga library of maps indicating spatial variability in both ToE and model agreement, and (6) developing a prototype online tool for exploring and accessing these results, in order to provide both novice and sophisticated users relatively easy entry into these complex and numerous datasets.By accurately representing the variability and uncertainty in projecting future climate, the prototype online tool enables user selection of the scenarios best fitting their decision context and risk tolerance. Combined with information about relevant response times, these results can be used to identify priority areas for more detailed analysis to support climate risk reduction. The flexible method of analysis, visualization and data delivery can be efficiently applied to new data sets as they emerge or are updated.

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1 Introduction

Because natural and human systems tend to be somewhat adapted to historical climate fluctuations, it is when climate change causes local conditions to deviate significantly from the past that ecological and societal disruptions may occur. A key input to deciding and prioritizing actions on climate change, therefore, is information about when and where the distinctive trend due to climate change is projected to emerge from the noise of natural climate variability. This type of information can be combined with information about local sensitivities, design standards or critical thresholds to help identify the relative need and priority for climate change adaptation activities.

Although information about the “time of emergence” for detectable change in management-relevant measures of the climate and environmentcan be gleaned from existing climate change scenarios, it has not been explicitly characterized for variables and spatial scales relevant to local decision-making. Multiple local climate change projections, based on different emission scenarios, global climate models and downscaling methods, increase the difficulty of identifying when and where the effects of climate change could matter. For many potential users, furthermore, useful climate change information is often hard to find, difficult to digest and compare, and rarely provided at spatial and temporal scales relevant to management.

Evaluating when and where climate change could matter requires information about the expected rate and plausible range of projected climate change – for specific locations and management-relevant environmental conditions, and knowledge of management sensitivity to change for specific systems and objectives.This effort combines climate statistics, engagement with policy and management entities, and data delivery platform development to develop a new approach to climate change decision support based on the concept of "time of emergence" (ToE) for detectable change in management-relevant measures of the climate and environment for the US Puget Sound basin and Pacific Northwest (PNW), with goals of:

- Consolidatingdisparate sources of climate change information
- Developing a flexible method of analysis, visualization and data delivery that can be efficiently applied to new data sets as they emerge or are updated
- Providing a variety of future scenarios in order to illustrate to the user community the existing range of uncertainty in projections of future climate
- Providinga tool useful for novice and sophisticated users – from those seeking general insights on how and where significant climate change could occur and wondering why there is a range of climate change projections, to those looking for a tool to support initial identification (or screening) of priority locations or issue areas in which to focus climate change risk reduction activities
- Raising awareness about complexities, uncertainties and limitations associated with projections of future climate

This report describes the *Methods* (Section 2) used to compute ToE for locally-specific, decision-relevant variables in the Puget Sound and Pacific Northwest(PNW) regions, including input datasets, selection of variables and locations for ToE analysis, analytical methods, and post-processing. It describes the *Web Delivery* (Section 3) of these results, including the user interface, navigation, selection options, and accompanying supporting information for exploring the variation of ToE results by location within the region, by variable, and as a result of different choices for parameters including emissions scenario, management sensitivity to change, estimated rate of climate change, and input dataset. Our *Strategy for Incorporating Uncertainty in Computing and Communicating ToE* is described in Section 4. Section 5, *Website Architecture*, describes the technical specifications of the prototype website, including its structure and framework, data engine, and user capabilities of data extraction and download. *Project Outputs* and *Data Archival* are described in Sections 6 and 7, respectively, while Section 8, *Moving Forward*, describes potential avenues of improvement or expansion of the prototype web tool.

2 Methods

2.1 Time of Emergence

In its simplest form, Time of Emergence (ToE) is a way of expressing the rate of climate change over time as compared to the range of past variability. The climate change signal is said to “emerge” when it becomes large compared to variability. Thus, three values need to be considered in computing the time of emergence of a variable: 1) the rate of change in the variable due to climate change 2) the range of past variability in the variable and 3) the threshold at which the change becomes large compared to variability. While there are well-established methods to compute each of these, they raise a number of issues that can substantially affect the results. Below we discuss how we selected the most appropriate method and how this choice affects the results of the study.

The ToE analysis is applied to management-relevant climate variables, which are described in the following section. These variables include values, such as the annual frequency of days with precipitation exceeding the historic 95% percentile, which must be computed from climate projection data of basic climate variables such as daily maximum/minimum temperature, precipitation, runoff, etc. This project focuses on regional-scale impacts and assessment, and so has used downscaled, daily time-step climate data for all variables. A variety of existing scenarios for future global and regional hydro-climatic conditions were used to compute ToE, including global, statistically- and dynamically-downscaled climate model outputs from Coupled Model Intercomparison Project phases 5 and 3 (CMIP5 and CMIP3) and existing simulations of regional hydrological change using the Variable Infiltration Capacity model. The selection and sources of these input datasets are described below, along with the methods to select and derive the management-variables used in the Time of Emergence analysis (Figure 1).

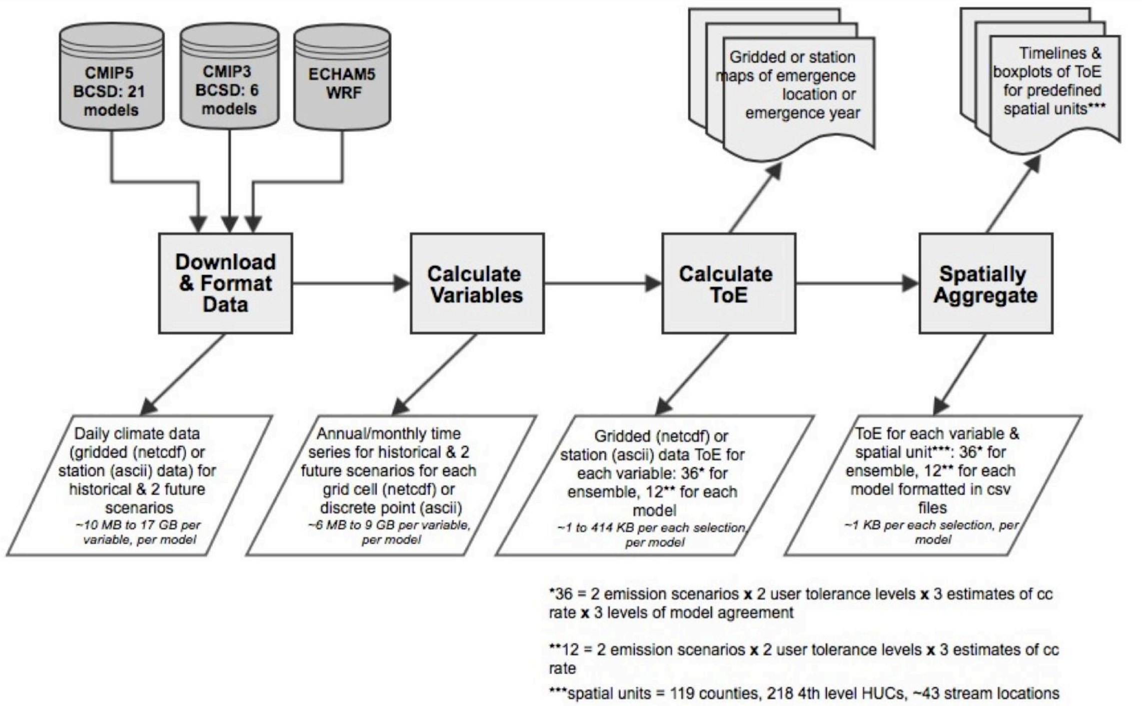

Figure 1. Flow chart indicating data sources, analytical steps, and outputs for Time of Emergence Analysis.

2.2 Climate Data Sets

2.2.1 Global Models

The Coupled Model Intercomparison Project (CMIP, e.g., Taylor et al. 2012, http://cmip-pcmdi.llnl.gov/cmip5/) has organized international global climate model centers to support the Intergovernmental Panel on Climate Change (IPCC) assessments with simulations of the past and future climate. The CMIP provides a standard experimental protocol for coupled atmosphere-ocean general circulation model simulations, and we use global model simulations exclusively from CMIP experiments. There are two generations of the Coupled Model Intercomparison Project currently in use, CMIP3 (used in the IPCC Fourth Assessment Report (AR4)) and CMIP5 (IPCC AR5) (there was no CMIP4). The global models have been extensively studied and compared to observations over the PNW region for CMIP3 (Mote and Salathé, 2010)and CMIP5 (Rupp et al, 2014) simulations. Given this thorough documentation of model performance and the published guidance that choosing a large model ensemble is more reliable than attempting to select only a few top models (Mote and Salathé, 2010), we have opted to perform the ToE analysis for all global model results available for the PNW (after appropriate downscaling or hydrologic simulations; see below). The final data delivery products allow users to visualize the contributions of individual models to the ensemble results.

Because downscaled scenarios and derived hydrologic products from CMIP5 are only now becoming available and because there has been no conclusive evaluation of relative quality of CMIP5 and CMIP3 for the PNW, we used results based on both CMIP3 and CMIP5 global model simulations as described below. Where resources limited the delivery of results (via the prototype online tool described below), we prioritized results based on the CMIP5 global simulations, where available, in recognition of the strong interest from the stakeholder community in focusing on the more recent simulations.

For both CMIP3 and CMIP5, we have selected a "High" (RCP8.5 and SRES A1B) and "Low" (RCP4.5 and SRES B1) emissions scenario (RCP4.5 and RCP8.5 for CMIP5, Van Vuuren et al, 2011, or SRES B1 and A1B for CMIP3, Nakicenovic and Swart 2000). The "High" scenario is based on rapid greenhouse gas emissions with little to no mitigation strategies and "business as usual" approach to energy usage, which implies an earlier ToE estimate due to greater effects of climate change; "Low" is based on lower emissions, a high level of mitigation strategies, and use of alternative energies, and implies a later ToE estimate. The two sets of emissions scenarios (RCP and SRES scenarios) are noted for the user since ToE results are provided from a suite of different underlying climate data sets derived from CMIP5 and CMIP3, respectively.

2.2.2 Downscaling and Hydrologic Modeling

The data used for the ToE analysis have been derived from downscaled global climate model simulations using the Bias-Corrected Statistical Downscaling (BCSD) approach (Tohver et al. 2014; Reclamation 2013) for both CMIP3 and CMIP5 scenarios. This downscaling method and data products are well established (Hamlet et al 2013), and the downscaled CMIP3 data have been widely used in climate impacts studies (Tohver et al, 2014). The BCSD results provide daily Tmin, Tmax, and precipitation data on a high-resolution latitude-longitude grid over the region. For this project, we have used downscaled climate data for the simulated time period 1950-2100. This period includes 50 years of 20th century climate to establish the historic climate variability and then extends through the 21st century to project the climate change signal. The downscaled scenarios have additionally been used as input for hydrologic simulations using the VIC hydrologic model (Reclamation 2013). The VIC model is well-established, and simulation output has been widely used in climate impacts studies (Tohver et al, 2014; Salathé et al 2014). The VIC simulations provide spatially distributed hydrologic variables on the fine-scale latitude-longitude grid as well as streamflow volumes routed to specific river locations. The management-relevant climate variables described below were then computed from these downscaled and hydrologic data.

The primary BCSD data set is based on the CMIP5 global climate model project and obtained from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections project (Maurer et al, 2007; Reclamation 2013;http://gdo-dcp.ucllnl.org/downscaled_cmip_projections). Downscaling was performed to a 0.125° latitude-longitude grid (~12km by ~12km). Selection of a subset of 21 global climate system models from this dataset (Table 1), which we shall refer to as BCSD5, was based on the following criteria: coupled models using standard component models, i.e., component models that have subsequent versions and have been well documented in the metadata and literature (rather than, e.g., CHEM or perturbed physics component models); choice of a single model implementation rather than multiple versions of models from specific modeling centers; models for which simulations were available using both RCP4.5 and RCP8.5; models for which VIC simulations were available using the downscaled projections as input; and all global climate models that were used for the CMIP3-derived dataset described below.

Although VIC model simulations using BCSD5 have been completed and routed streamflow output is available (Reclamation 2013), no gridded hydrologic variables are currently available from this dataset. Consequently, we also incorporated both downscaled climate variables and VIC hydrologic simulations from earlier BCSD downscaling of six CMIP3 global models to a 0.0625° grid (~6km by ~6km) (Tohver et al. 2014, http://warm.atmos.washington.edu/2860/); these data are referred to as BCSD3.

The BCSD5 and BCSD3 downscaled global climate model simulations used in this analysis could be termed 'ensembles of opportunity' since the ensemble members have not been specifically designed to span the full possible range of uncertainty. There is no weighting or bias correction; each model is assumed to be independent of the others in the ensemble. An 'ensemble of opportunity' is comprised of models with generally similar structures (forcings, spatial resolution (e.g., truncation level in spectral space), etc.) because they were usually developed at the same time for the same reasons (i.e., IPCC reports). However they will likely have different parameter choices and calibration histories (Stephenson et al. 2012).

Table 1. List of climate models and their organizational affiliations used in this analysis.

Model	Organization	Dataset
ACCESS1-0	Commonwealth Scientific and Industrial Research Organization/ Bureau of Meteorology, Australia	CMIP5
BCC-CSM-1-1	Beijing Climate Center, China Meteorological Administration, China	CMIP5
BNU-ESM	Beijing Normal University, China	CMIP5
CANESM1	Canadian Centre for Climate Modelling and Analysis, Canada	CMIP5
CCSM4	National Center for Atmospheric Research, University Corporation for Atmospheric Research, USA	CMIP5
CESM1-BGC	National Center for Atmospheric Research, University Corporation for Atmospheric Research, USA	CMIP5
CMCC-CM	Euro-Mediterranean Center on Climate Change, Italy	CMIP5
CNRM-CM5	National Centre for Meteorological Research, France	CMIP5
CSIRO-MK3-6-0	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Center of Excellence, Australia	CMIP5
FGOALS-G2	Laboratory of Numerical Modelling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, China	CMIP5
GFDL-CM3	National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory, USA	CMIP5
GFDL-ESM-2G	National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory, USA	CMIP5
GISS-E2-R	National Aeronautics and Space Administration Goddard Institute for Space Studies, USA	CMIP5
HADGEM2-ES	Meteorological Office Hadley Center, UK	CMIP5

INMCM4	Institute for Numerical Mathematics, Russian Academy of Sciences, Russia	CMIP5
IPSL-CM5A-MR	Dynamical Meteorology Laboratory at the Pierre-Simon Laplace Institute, France	CMIP5
MIROC5	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies/Japan Agency for Marine-Earth Science and Technology, Japan	CMIP5
MIROC-ESM	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies/Japan Agency for Marine-Earth Science and Technology, Japan	CMIP5
MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	CMIP5
MRI-CGCM3	Meteorological Research Institute, Japan Meteorological Agency, Japan	CMIP5
NORESM1-M	Norwegian Climate Center, Norway	CMIP5
CCSM3	National Center for Atmospheric Research, University Corporation for Atmospheric Research, USA	CMIP3
CGCM3.1	Canadian Centre for Climate Modelling and Analysis, Canada	CMIP3
CNRM-CM3	National Centre for Meteorological Research, France	CMIP3
ECHAM5	Max Planck Institute for Meteorology, Germany	CMIP3
ECHO-G	Meteorological Institute of the University of Bonn (Germany), Institute of KMA (Korea)	CMIP3
PCM1	Los Alamos National Laboratory, the Naval Postgraduate School, the US Army Corps of Engineers' Cold Regions Research and Engineering Lab, and the National Center for Atmospheric Research, USA	CMIP3

Finally, for comparison purposes, we have also included results from a single regional climate model simulation using the Weather Research and Forecast (WRF) mesoscale model forced by an ECHAM5 global model simulation from the CMIP3 project (Salathé et al 2014). The WRF output has been spatially downscaled to the same 0.0625-degree grid as the BCSD3 dataset and used for VIC simulations to provide hydrologic data. The WRF model will give different results from statistical downscaling in locations where fine-scale feedbacks or terrain effects can alter the simulated climate change signal. By design, the BCSD downscaling preserves the magnitude and direction of the climate change signal in temperature and precipitation provided by the global model while removing systematic biases due to unresolved terrain features. WRF explicitly represents high-resolution processes, such as orographic precipitation, mesoscale weather systems, and land-atmosphere feedbacks. These processes can produce localized responses to climate change that are not represented in global models. For example, snow-albedo feedbacks can amplify warming on the margins of the snowpack (Salathé et al 2008) and precipitation trends can differ on windward and lee slopes of terrain (Salathé et al 2010). The simulation used here has been extensively evaluated against observations (Dulière et al 2011) and applied in other climate impacts studies (Salathé et al 2014).

In summary, we have used the following downscaled and hydrologic data:

1. Daily Tmax, Tmin, and precipitation from the CMIP5 BCSD on a 0.125-degree latitude-longitude grid for 21 global climate models (BCSD5).
2. Daily Tmax, Tmin, precipitation, and spatially-distributed hydrologic variables (*e.g.* runoff, evapo-transpiration) derived from the CMIP3 BCSD on a 0.0625-degree using VIC for 6 global climate models (BCSD3).
3. Daily Tmax, Tmin, precipitation, and spatially-distributed hydrologic variables (*e.g.* runoff, evapo-transpiration) derived from the CMIP3 ECHAM5 WRF using VIC (ECHAM5-WRF).
4. Daily streamflow volume at specified river locations derived from the CMIP5 BCSD using VIC for 21 global climate models (BCSD5).
5. Daily streamflow volume at specified river locations derived from the CMIP3 BCSD using VIC for 6 global climate models (BCSD3).

Global climate model simulations downscaled for the PNW using the Multivariate Adaptive Constructed Analogs (MACA) statistical downscaling method (Abatzoglou and Brown 2012) became available during the course of this project and are perhaps better suited for some specific applications. Nevertheless, due to the preliminary nature of these data and lack of quality assurance, we have not incorporated MACA results in this study.

Because version control issues for data are important to note, the data provenance for all daily data used in this analysis is given below in Table 2.

Table 2. Data provenance

Daily Variables	Dataset	Date of Download	Source	Reference
Tavg, Tmax, Tmin, Prcp	BCSD5	6-13-2014 through 6-18-2014	http://gdo-dcp.ucllnl.org	Thrasher et al, 2013
Tavg, Tmax, Tmin	BCSD3	10-23-2014	Internal CIG database	Hamlet et al, 2010
Tavg, Tmax, Tmin, Prcp, Baseflow, ET, PET, Runoff, Soil moisture, SWE	ECHAM 5-WRF	11-04-2014	Internal CIG database	Salathé et al, 2010
Prcp, Baseflow, ET, PET, Runoff, Soil moisture, SWE	BCSD3	9-25-2014 through 10-01-2014	Internal CIG database	Hamlet et al, 2010
Q from Station Data	BCSD5	7-17-2014 through 12-03-2014	http://gdo-dcp.ucllnl.org	Thrasher et al, 2013
Q from Station Data	BCSD3	8-13-2014 through 12-03-2014	http://warm.atmos.washington.edu/2860	Hamlet et al, 2010

2.3 Variables and locations for ToE analysis

2.3.1 Calculation

Management-relevant climate variables were computed from the primary climate and hydrologic datasets described above to support the ToE calculations described below. These climate variables are a time-series of yearly values at each grid cell or river station location for each downscaled global climate model simulation. Depending on the specific climate variable, these may be annual values or variables computed only for days in a given calendar month or season. These intermediate data have been archived and are available for other applications (see Section 6, Project Outputs).

Over 30 types of management relevant climate variables were computed and analyzed for this project as listed in Table 3; many for multiple periods (e.g., months or seasons).

All variables were calculated from daily values. Monthly or annual average variables were calculated from daily data and averaged for a specified time period (e.g., monthly, seasonal, annual, etc), or the daily min/max was determined for a specified season. Frequency variables were calculated based on number of days, or consecutive days, over a percentile or fixed value for the specified time period.

For percentile-based variables, such as “Number of days with 24-hour precipitation exceeding historical 90th percentile, October-March”, the historical period of 1950-1999 (1970-1999 for ECHAM5-WRF, since the WRF simulation time series is only available for 1970-1999 and 2010-2069) was used to construct the reference percentiles. Then a count of the number of days, or of consecutive days, exceeding the threshold was calculated for the full time period. The choice of historical reference period was based on the assumption that management tends to be “generally” adapted to historical climate fluctuations, and that this historical period is relatively long for management related to operations and planning of large infrastructure. Because the appropriate reference period will differ by user and management context, we note the reference period used in online delivery of ToE results (described below) and suggest that future efforts consider providing users the opportunity to explore the implications of choosing different reference periods.

Table 3. Variables analyzed for Time of Emergence: source and resolution of relevant input datasets.

Climate variable	**Data set**	**Grid spacing or station data**
Temperature, each calendar month	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with daily maximum temperature above 65°F (18.3°C), each calendar month (Mar-Nov)	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with daily average temperature below 25°F (–3.9°C), winter (Dec-Feb)	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with daily average temperature above 68°F (20°C), spring (Mar-May) and fall (Sep-Nov)	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with daily maximum temperature above 90°F (32.2°C), annual	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with daily maximum temperature at or above 80°F (26.7°C), spring-summer (21 April- 21 August)	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of daytime heat waves (3 consecutive days with daily maximum temperature above historical 99th percentile), annual	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of nighttime heat waves (3 consecutive days with daily minimum temperature above historical 99th percentile), annual	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Precipitation, each calendar month	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Precipitation, fall (Oct-Dec), winter (Jan-Mar), spring (Apr-Jun), and summer (Jul-Sep)	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with 24-hour precipitation exceeding historical 90th percentile, October-March	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with 24-hour precipitation exceeding historical 95th percentile, October-March	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5)

		1/16-degree (BCSD3, WRF)
Number of days with 24-hour precipitation exceeding historical 99th percentile, October-March	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with 24-hour precipitation exceeding 2 inches (50.8 mm), annual	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Maximum 48-hour precipitation accumulation, annual	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Maximum 24-hour precipitation accumulation, annual	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of days with 24-hour precipitation equal to 3 inches (76.2 mm) or more, annual	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Number of wet sequences (18-day cumulative precipitation exceeding 3.5 inches (88.9 mm)), October-March	BCSD5, BCSD3, ECHAM5-WRF	1/8-degree (BCSD5) 1/16-degree (BCSD3, WRF)
Runoff, annual	BCSD3, ECHAM5-WRF	1/16-degree
Runoff, each calendar month	BCSD3, ECHAM5-WRF	1/16-degree
Dryness ratio (fraction of input precipitation lost to evapotranspiration), each calendar month	BCSD3, ECHAM5-WRF	1/16-degree
Potential evapotranspiration (PET), each calendar month	BCSD3, ECHAM5-WRF	1/16-degree
Actual evapotranspiration (AET), each calendar month	BCSD3, ECHAM5-WRF	1/16-degree
Soil moisture, each calendar month	BCSD3, ECHAM5-WRF	1/16-degree
Snow water equivalent (SWE), each calendar month	BCSD3, ECHAM5-WRF	1/16-degree
Coefficient of variation of runoff, annual	BCSD3, ECHAM5-WRF	1/16-degree
Highest spring runoff date	BCSD3, ECHAM5-WRF	1/16-degree
Streamflow, each calendar month	BCSD5, BCSD3	~100 stations
Maximum daily streamflow per year	BCSD5, BCSD3	~100stations
Maximum daily streamflow, each calendar month	BCSD5, BCSD3	~100stations
Minimum daily streamflow, each calendar month	BCSD5, BCSD3	~100stations
Number of flood flows per year	BCSD5, BCSD3	~100stations
Number of 7-day low flows per year	BCSD5, BCSD3	~100stations

Number of low flows per year	BCSD5, BCSD3	~100stations
Lowest mean streamflow for 30 consecutive days per year	BCSD5, BCSD3	~100stations

2.3.2 Variable selection

Identifying a list of candidate variables for time of emergence analysis involved consideration of:

- The potential impacts caused by climate change (such as droughts, floods, human health, energy supply, water availability, fish survival) that could have implications for stakeholders' planning, management, operations or regulatory responsibilities.
- The underlying hydro-climatic drivers of these climate change impacts.
- Stakeholders' existing or anticipated vulnerabilities, concerns and priorities as climate changes.
- How stakeholders are addressing or plan to address the issues or potential impacts related to climate change.

In addition to informal consultation with U.S. Environmental Protection Agency (USEPA) and U.S. Army Corps of Engineers (USACE), a desktop review of existing literature and available online information was carried out, which included:

- Peer-reviewed publications on the projected changes in climate and the associated impacts across the Pacific Northwest domain (e.g., Bonfils *et al.*, 2008, Markoff and Cullen, 2008).
- Information prepared by, and for, specific stakeholders: goals and strategies (e.g., climate action plans such as the 2007 King County Climate Plan and WSU, 2011), official and unofficial documents (e.g., technical, annual, research reports, such as Snover *et al.*,2010, and Hamlet, 2011, and presentations), climate change-related studies (e.g., impacts and vulnerability assessments such as Mote *et al*., 2012, and Turner and Brekke, 2011), regulatory standards, guidelines and mandates (e.g., EPA Region 10 Guidance for Pacific Northwest State and Tribal Temperature Water Quality Standards).

These efforts led to the compilation of a candidate list of ~35 hydro-climatic variables (e.g., monthly mean temperature, precipitation and runoff), and proxies for extreme events (e.g., heatwaves, droughts, floods) for subsequent time of emergence analysis. These variables were considered to be of interest to stakeholders, sensitive to climate change, and ready for analysis on the basis of data availability and accessibility. Subsequent stakeholder consultation through a variety of engagement mechanisms was used to refine the list of variables for analysis.

The initial stage of stakeholder engagement involved developing a brief project description that outlined the motivation and goal of the project, along with the potential for participants to influence outcomes. This project description was circulated via email in December 2013 to 28 regional stakeholders known to be actively engaged in climate change-related issues, and with whom the Climate Impacts Group had an established relationship, to facilitate more rapid response. These included the following entities:

- Federal agencies: USEPA, USACE, U.S. Department of Interior Bureau of Reclamation (USBR), U.S. Forest Service (USFS)
- State agencies: Washington State Departments of Health (WADOH), Ecology, Natural Resources, Transportation (WSDOT), Emergency Management Division (EMD), and the Puget Sound Partnership (PSP)
- Local agencies: King County, City of Seattle
- Tribes: Swinomish, Puyallup, Tulalip

Subsequent one-on-one conversations were conducted with seven of the stakeholders via phone and/or in person. These included USEPA and USACE, WADOH, WAEMD, King County, Seattle City Light and tribal entities. This subset of entities was selected because they span the anticipated climate change impacts mentioned above.

The candidate list of 35 hydro-climatic variables was distributed by email to eleven stakeholders in February and March 2014 for comment and feedback. These include

USEPA, USACE, USBR, WADOH, Ecology, WSDOT, EMD, PSP, King County, Seattle City Light and the Swinomish, Puyallup, Tulalip. These technical users of climate change information were chosen because their activities and operations span the potential range of climate change impacts in the Pacific Northwest region. Additional variables suggested by stakeholders were incorporated to the original list, generating a total of 65 variables.

The final set of variables for analysis (Table 4) were either directly provided in the downscaled climate and hydrology datasets described above or could be derived from these data using techniques established in the literature.

The first step in prioritizing variables for analysis involved eliminating those unsuited to a time of emergence analysis due to inadequate data or high uncertainty in the climate projections. For instance, variables related to wind, ocean acidification and sea surface temperature have been excluded from this analysis. Similarly, variables related to wildfire risk have also been excluded due to the complication and high uncertainties in identifying and simulating conditions favorable for fire occurrence. A few variables that were location-specific or relevant to only one or two stakeholders were also given a low priority. Some variables were excluded due to computational infeasibility, given the chosen method for time of emergence computation (see section below on "Computing Time of Emergence"). Requested variables that were excluded from the analysis are listed in Table 5.

Table 4. Variables analyzed for Time of Emergence, with requesting stakeholder(s) identified. "CIG" indicates variables identified for analysis by the Climate Impacts Group, based on the desktop review process described above.

Variable	Source
Temperature, each calendar month	CIG
Number of days with daily maximum temperature above 65°F (18.3°C), monthly March-November	Seattle City Light
Number of days with daily average temperature below 25°F (–3.9°C), winter (Dec-Feb)	Seattle City Light
Number of days with daily average temperature above 68°F (20°C), spring (Mar-May) and fall (Sep-Nov)	Seattle City Light

Number of days with daily maximum temperature above 90°F (32.2°C), annual	Seattle City Light
Number of days with daily maximum temperature at or above 80°F (26.7°C), spring-summer (21 April- 21 August)	Puget Sound Clean Air Agency
Number of daytime heat waves (3 consecutive days with daily maximum temperature above historical 99th percentile), annual	Seattle City Light
Number of nighttime heat waves (3 consecutive days with daily minimum temperature above historical 99th percentile), annual	Seattle City Light
Precipitation, each calendar month	CIG
Precipitation, fall (Oct-Dec), winter (Jan-Mar), spring (Apr-Jun), and summer (Jul-Sep)	USACE
Number of days with 24-hour precipitation exceeding historical 90th percentile, October-March	CIG
Number of days with 24-hour precipitation exceeding historical 95th percentile, October-March	CIG
Number of days with 24-hour precipitation exceeding historical 99th percentile, October-March	CIG
Number of days with 24-hour precipitation exceeding 2 inches (50.8 mm), annual	Seattle Public Utilities
Maximum 48-hour precipitation accumulation, annual	USACE
Maximum 24-hour precipitation accumulation, annual	USACE
Number of days with 24-hour precipitation equal to 3 inches (76.2 mm) or more, annual	USACE
Number of wet sequences (18-day cumulative precipitation exceeding 3.5 inches (88.9 mm)), October-March	City of Seattle
Runoff, annual	CIG
Runoff, each calendar month	CIG
Dryness Ratio (fraction of input precipitation lost to evapotranspiration), each calendar month	USEPA
Potential evapotranspiration (PET), each calendar month	USEPA
Actual evapotranspiration (AET), each calendar month	USEPA
Soil moisture, each calendar month	CIG
Snow water equivalent (SWE), each calendar month	USEPA
Coefficient of variation of runoff, annual	USACE
Highest spring runoff date	USEPA / USACE
Streamflow, each calendar month	USACE
Streamflow center of timing	USEPA
Maximum daily streamflow per year	CIG
Maximum daily streamflow, each calendar month	CIG
Number of flood flows per year	USACE
Number of 7-day low flows per year	King County
Number of low flows per year	USACE
Lowest mean streamflow for 30 consecutive days per year	King County

Table 5. Variables excluded from the analysis

Variable	Source	Reason
Number of days with daily maximum temperature above 65°F (18.3°C), January, February, December	Seattle City Light	High variance or no historical record of occurrence in Puget Sound / WA
Number of days with daily maximum temperature below 65°F(18.3°C), each calendar month	Seattle City Light	Every day in historical record fits criteria
Number of days with daily average temperature above 86°F (30°C), summer (Jun-Aug)	Seattle City Light	High variance or no historical record of occurrence in Puget Sound / WA
Number of days with daily maximum temperature above 100°F (37.8°C), annual	USEPA	High variance or no historical record of occurrence in Puget Sound / WA
Number of drought months, annual	USACE	Variable would be 0-12, which is not methodologically suited for this analysis \
Snowmelt Fraction (Fraction of streamflow contributed by snowmelt) , each calendar month	USEPA	Variable not directly available in hydrologic model output
Low Flow Sensitivity	USEPA	Variable not directly available in hydrologic model output
Annual frequency of 7-day moving avg daily maximum stream temperature above 60°F (16°C), 64.4°F (18°C), 71.6°F (22°C), 75.2°F (24°C)	USEPA	Variable not directly available in hydrologic model output
Time lag between stream temperature maxima (Tmax_w) & stream flow minima (Qmin)	USEPA	Variable not directly available in hydrologic model output
[%change in streamflow] / [%change in precipitation], each calendar month	USACE	Requires new cross-walking between routed hydrologic model output (point values) and downscaled precipitation data (gridded)
Maximum 6-hr wind speed	Seattle City Light	High uncertainty in the projections
Frequency of days with high (>30 mph or >40 mph) wind	Seattle City Light	High uncertainty in the projections
Date of first fire	WADOH	High uncertainty associated with projecting fire dates; no timeseries projection of this variable available
Date of end of fire season	WADOH	Same as above
Acres burned	WADOH	No timeseries projection of this variable available
pH at Tatoosh Is. and in Puget Sound	WADOH	No data available
Sea-surface temperature at Tatoosh Is. and in Puget Sound	WADOH	No data available

2.3.3 Selection of streamflow locations for analysis

Because available resources precluded the analysis of ToE streamflow variables for all available streamflow locations (70 for the BCSD5 dataset; 297 for the BCSD3 dataset), a subset of ~100 locations (~50 from each dataset; Figure 2)was selected for analysis using the following criteria:

1. Locations common to both datasets (i.e., within 5 km)
2. Locations close to (~50 km) the Puget Sound Basin
3. Locations showing diversity in watershed type, for example, rain dominant vs. snow dominant

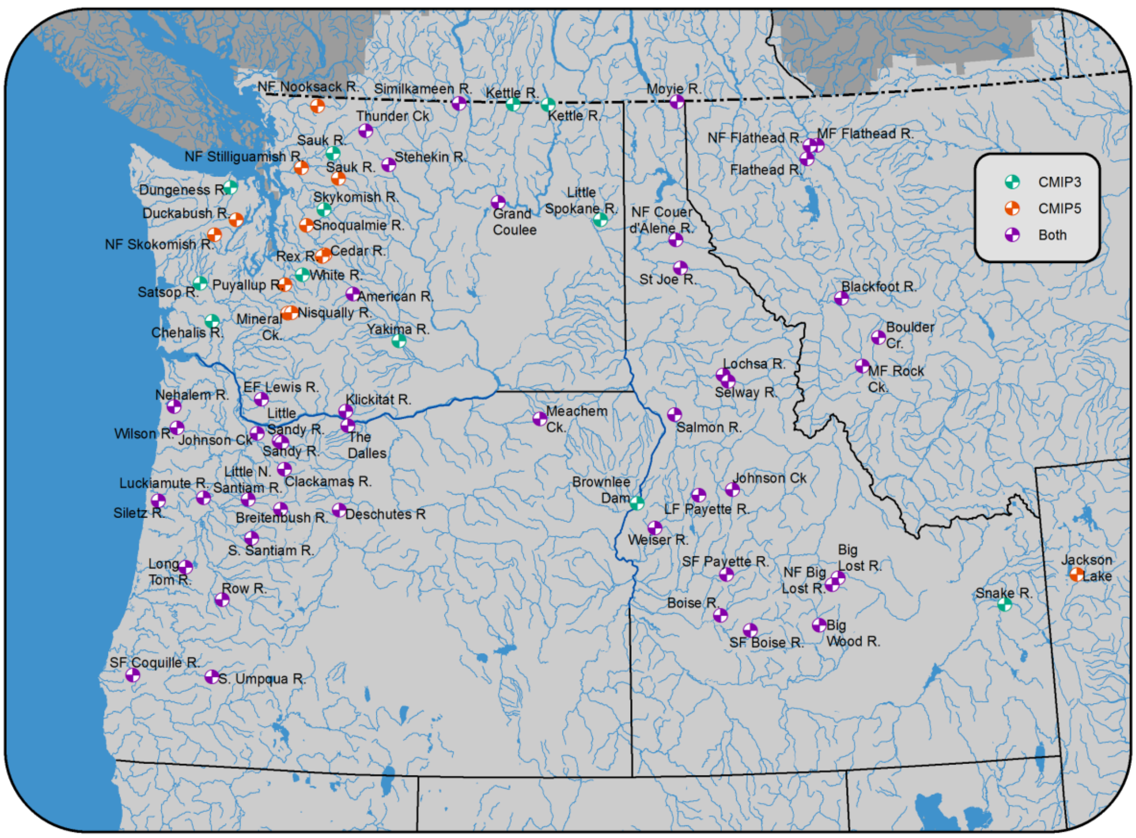

Figure 2. Streamflow locations for Time of Emergence analysis of streamflow-related variables listed in Table 8. CMIP3 and CMIP5 indicate source datasets described in the text as BCSD3 and BCSD5, respectively.

2.4 Computing Time of Emergence

The Time of Emergence for the time series of a climate variable is the point in time when the systematic, long-term change of the variable emerges from historic variability. There are several approaches in the literature for computing ToE, each with advantages and disadvantages for this project. We were guided in our selection to choose an approach that clearly communicated what emergence would imply for managing climate change and that was well-suited to the management-relevant climate variables we analyzed. There are three approaches in particular that we considered:

1. *Signal to Noise.* From the time series of a climate variable, the time varying climate signal, $s(t)$, is estimated as the long term monotonic change in the variable. The noise, N, is based on the range of variability (e.g. the standard deviation) over some historic time period. The time of emergence is then found at the time t when $s(t)/N$ exceeds some value, typically 1 or 2. (See Hawkins and Sutton 2012)
2. *Exceedence Threshold.* The upper limit for the climate variable is set based on some historic reference period. The time of emergence is set as the time when a selected number of consecutive years exceed this threshold, for example 3 years, 11 years, or all years. (See Mora 2013)
3. *Signal Threshold.* A climate signal is defined by a linear fit to the time series of the climate variable. The time of emergence is set where this line crosses a predefined threshold for emergence. (See Maraun 2013)

We have selected method #3 due to the clarity of communicating the management implications of the emergence threshold and the robustness of the method for a wide variety of climate variables. A key consideration is that for this project, we interpret the Time of Emergence as the time when the change of a variable becomes substantial enough to affect management decisions. In the signal-to-noise paradigm (*i.e.,* #1 above), the emphasis is on detection – the time when the change in a variable is statistically significant as compared to random noise. In the *Signal Threshold* method, the adjustable parameters and the error interpretation have more obvious connections to management considerations.

The emergence thresholds in this study reflect the boundaries of the envelope of adaptability to changes in the climate and are selected as a range of historical variability (Figure 3). The threshold is user-selected to accommodate risk tolerance with upper and lower bounds encompassing 90 or 60 percent of the observed variability for 1950-1999. The 60% envelope reflects a narrower range of adaptability, with a lower bound at 20th and upper bound at the 80th percentiles of historic variability. This narrower envelope can represent a system or management context that is relatively highly sensitive to climate change. The 90% envelope indicates a wider range of adaptability, with bounds at the 5th and 95th percentiles. This wider envelope represents a system that is relatively insensitive to climate change. These emergence thresholds (5th, 20th, 80th and 95th percentiles of historical variability) are calculated for each model at each grid cell (for the period 1950-1999 for BCSD5 and BCSD3 and 1970-1999 for ECHAM5-WRF). The climate signal may be either negative or positive and therefore emerge by crossing out of the envelope at either its upper or lower bound. Consequently, we distinguish between the emergence of a positive or negative trend. For some variables, the different models may not agree on the direction of the trend at a given location, and a single model may give positive or negative trends at different locations or times of the year.

The linear climate signal is calculated for low and high future emission scenarios (RCP4.5 and RCP8.5 for CMIP5, Van Vuuren et al, 2011, or SRES B1 and A1B for CMIP3) using the slope from a least squares regression model added to the climatological baseline for the period 1981-2010, corresponding to the period used by NOAA/NCDC for climate normals. To incorporate uncertainty in extracting the climate change signal from a single model realization, we consider the 90percent confidence interval in the computed slope. The confidence interval is computed as the standardized error in the slope based on a Student’s t-test. This error term is then added and subtracted from the calculated slope to obtain an upper and lower bound to the climate signal. ToE is then found as the year at which the linear signal crosses the predefined thresholds. All calculations are done at each grid cell of the downscaled data domain. Thus, *for each downscaled climate model and each grid cell, we obtain **twelve** ToE values* corresponding to the central, lower, and upper estimate of the climate signal, the two emergence thresholds, and two emissions scenarios.

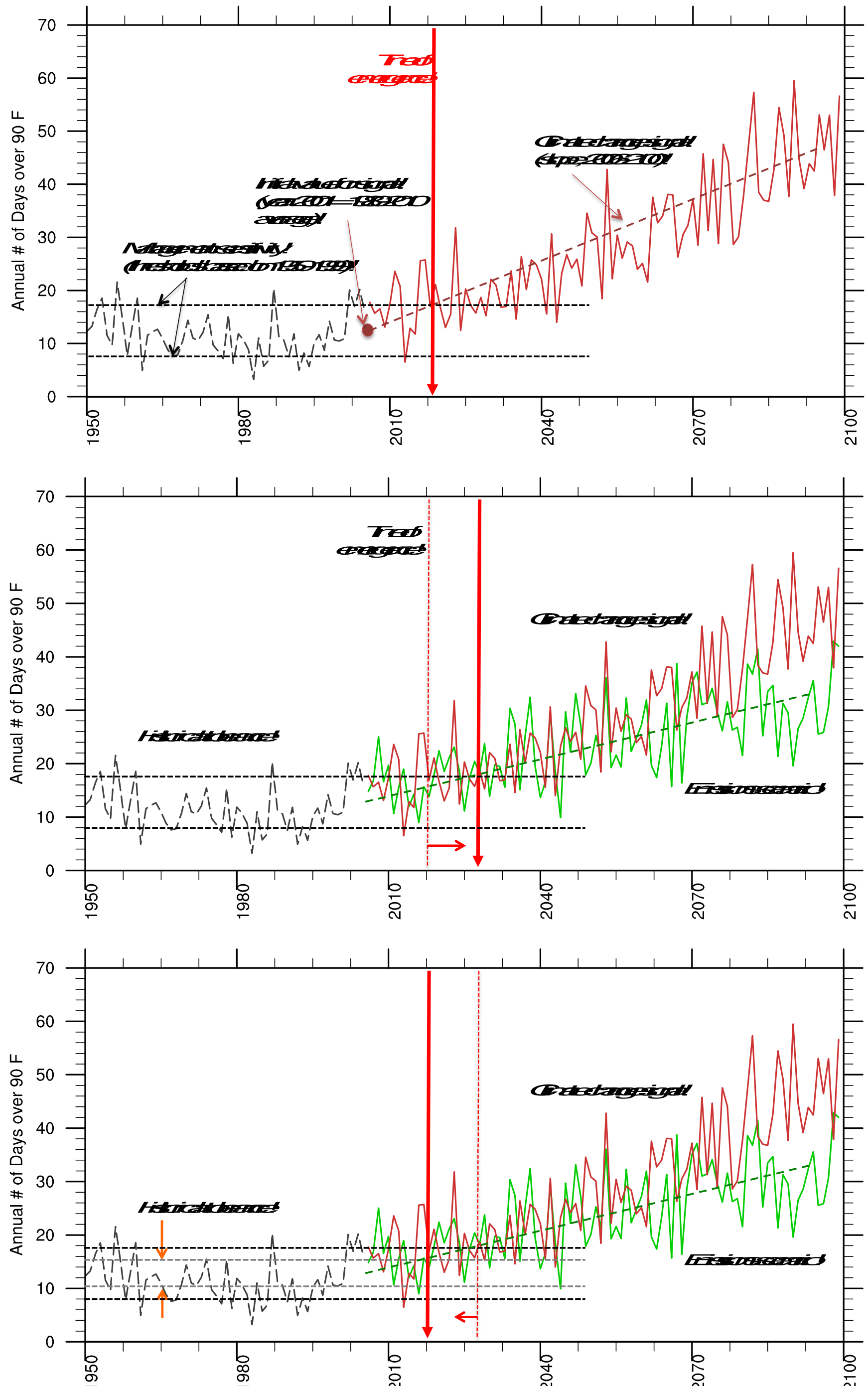

Figure 3. Figurative depiction of computation of Time of Emergence using the *Signal Threshold* method for a specific variable (in this case, annual number of days warmer than 90 degrees F) at a single grid cell for output derived from a single global model. (Top) Time of Emergence is calculated as the year when the climate change signal (the slope from a least-squares regression model of the simulated variable for 2006-2100 added to the climatological baseline for the period 1981-2010) crosses the threshold for emergence (the 5th or 95th percentile of observed

variability for 1950-1999). (Middle) A lower emissions scenario (e.g., RCP4.5 instead of RCP8.5) results in later emergence due to a smaller climate change signal. (Bottom) Lower management tolerance for change (i.e., higher management sensitivity) results in an earlier ToE due to lower thresholds for emergence.

All models will emerge for an arbitrarily high year, even with a near-zero signal, but such high ToE values would not be meaningful. Thus, we flag any model that has not emerged by 2100 for a particular combination of threshold and slope as “non-emergent”.

This method is applied to all climate models in the ensemble, 21 for BCSD5 and 6 for BCSD3. To represent the ensemble consensus, we select the median ToE across the ensemble for each grid cell. The median ToE indicates the year at which 50% of the models have emerged. To understand ensemble spread in ToE, for each grid cell we also calculate the year at which 25 and 75% of all models in the ensemble have ‘emerged’. For example, if 16 of the models in the 21-model BCSD5 ensemble have emerged by 2060 at a particular grid cell, the ToE for 75% model agreement is set to 2060 at that grid cell.

We are calculating ToE for a wide variety of climatological variables, and the methodology used in this analysis may not be entirely appropriate to for all variables. An example is in computing the ToE for the time series of the number of days per year when a climate variable exceeds a particular threshold. If this threshold is never exceeded in the historical period, then the emergence threshold is zero, and any occurrence in the future will yield a ToE in the first year, 2001. In this case, an approach like that used in Mora (2013) might be appropriate, where the emergence is taken as the third occurrence of this exceedance. Nevertheless, the emergence of an event that has not occurred historically is difficult to discuss quantitatively, and in this case we flag the variable as non-emergent.

Another difficulty occurs for variables where the projected range of variability from a model is very large, so that the sign of the trend in the variable is uncertain. Thus, the lower and upper bounds to the signal (trend) produce emergence of the variable in different directions. For example, we might find a variable that emerges with a positive trend, but where the confidence interval for the computed slope indicates the possibility of an emergence with negative trend. This result generally indicates a high degree of uncertainty in computing the projected climate signal in a given variable and would be reflected in visualizations or other reporting of uncertainty in ToE. For reporting of ToE at different levels of global climate model agreement, if a grid cell showed less than 60% agreement in direction of trend, the median cell value for the ensemble was not calculated and we flag the variable as non-emergent in that grid cell (Table 6).

Table 6. Definitions of "non-emergent" variables used in computing ToE for individual locations and spatially-aggregated results.

Reasons for flagging a variable as "non-emergent" at a specific location (grid cell or stream location)

- No emergence by 2100 for a particular combination of threshold and slope for a specific input model
- No occurrence (i.e., exceedance of the threshold) during the historical reference period for a specific input model
- Less than 60% agreement in direction of climate change signal among ensemble of input models

Reasons for flagging a variable as "non-emergent" for spatially-aggregated ToE results

- Less than 60% of the grid cells in the selected spatial unit show emergence by 2100
- Disagreement over direction of climate change signal among grid cells in the selected spatial unit showing ToE emergence prior to 2100

To test the method, we first applied the ToE computation to global fields of standard extreme climate indices computed by the Expert Team on Climate Change Detection and Indices (ETCCDI). This suite of indices provided an opportunity to test the robustness of the method with variables that have substantially different climate sensitivities from each other and across the globe. Results from this analysis will be reported in a publication now in draft form, which constitutes one of the publications resulting from this project. Regional results from this test dataset show robust model agreement that for PNW temperature-based extremes, ToE is likely in the next 50 years. For precipitation-based extremes, ToE projections are later, but there is good general agreement in direction of change for ToE calculations.

2.5 Post processing

2.5.1 Spatial Aggregation

Aggregation from grid cell data to spatial units was requested by stakeholders, and we selected two aggregation units: 1) Counties in WA, OR, and ID and 2) 4th-Level (8-digit) hydrological unit codes (HUCs). These spatial units were chosen in part because they are spatially small enough to provide useful results. Due to the high spatial resolution of the gridded data and topographic heterogeneity across the PNW, a spatial unit significantly larger than a typical county would encompass too wide a range of model agreement in date of ToE and disparities in the direction and magnitude of the climate trend.

Spatial aggregation was first done for each variable, scenario, tolerance level, confidence level, and model. To ensure that the aggregated results reasonably reflect the Time of Emergence within the spatial unit, two criteria had to be met prior to areal averaging, i.e.,:

1. The signal has emerged by 2100 in at least 60% of the grid cells in the selected spatial unit
2. All grid cells with valid ToE dates in the selected spatial unit agree in direction of trend.

If both of the above mentioned criteria are met, data were aggregated across the spatial unit. If either of the above criteria was not met, the value for that spatial unit would be returned as “0”, indicating an invalid or non-emergent result (Table 6).

After the areal average is done for each variable, scenario, tolerance level, confidence level, and model, model agreement was calculated for each variable, scenario, tolerance level, and confidence level at each spatial unit. This was done to represent the ensemble consensus for the spatial unit. As with the gridded results, to understand ensemble spread in ToE, we calculated the year at which 25, 50, and 75% of all models in the ensemble have ‘emerged’. For example, 16 of the models in the 21-model BCSD5 ensemble have emerged by 2060 for a given spatial unit, the ToE for 75% model agreement is set to 2060.

3 Web delivery

3.1 Introduction

The Time of Emergence tool is an interactive web-based platform developed to support climate change risk assessment and decision-making by providing user-friendly access to time of emergence results. The tool is designed to enable users to explore when and where climate change could matter, to support prioritization of preparatory action to reduce climate risks or climate impacts. The tool is also intended to help engender deeper understanding among users of the existing range in assessments of the location and timing of significant climate impacts, and the sensitivity of such results to reasonable alternative choices about potential future conditions and user sensitivity to change. This section describes the tool as designed. Website specifications are described in a following section. Website elements implemented as of 31 December 2014 can be viewed at http://toe.cloudapp.net/welcome.

3.2 Organization

The Time of Emergence tool (Figure 4) enables the user to:

- **EXPLORE** the time of emergence of decision-relevant climate change by locale or by variable, and the sensitivity of such results to reasonable alternative choices about potential future conditions and user sensitivity to change
- **READ** about the "Time of emergence" concept and methodology.
- **TOUR** around the tool through examples.

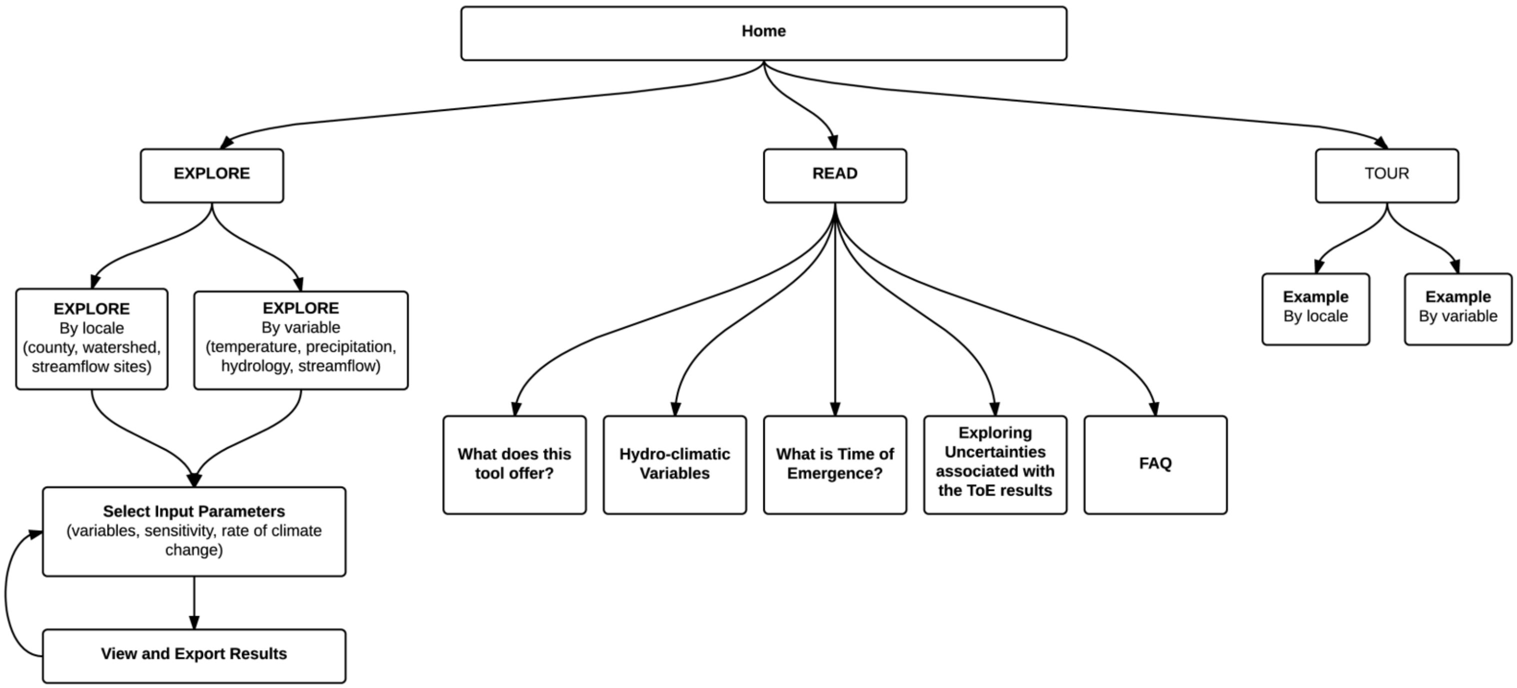

Figure 4. Organization of the prototype Time of Emergence online tool.

3.3 User exploration of time of emergence results

The “explore” section of the prototype online tool allows the user to view the time of emergence of decision-relevant climate change by locale or by variable, and to explore the sensitivity of the results due to the associated uncertainties, based on the methodology and models applied. This occurs through a series of user-oriented queries as illustrated in Figure 5 and described below.

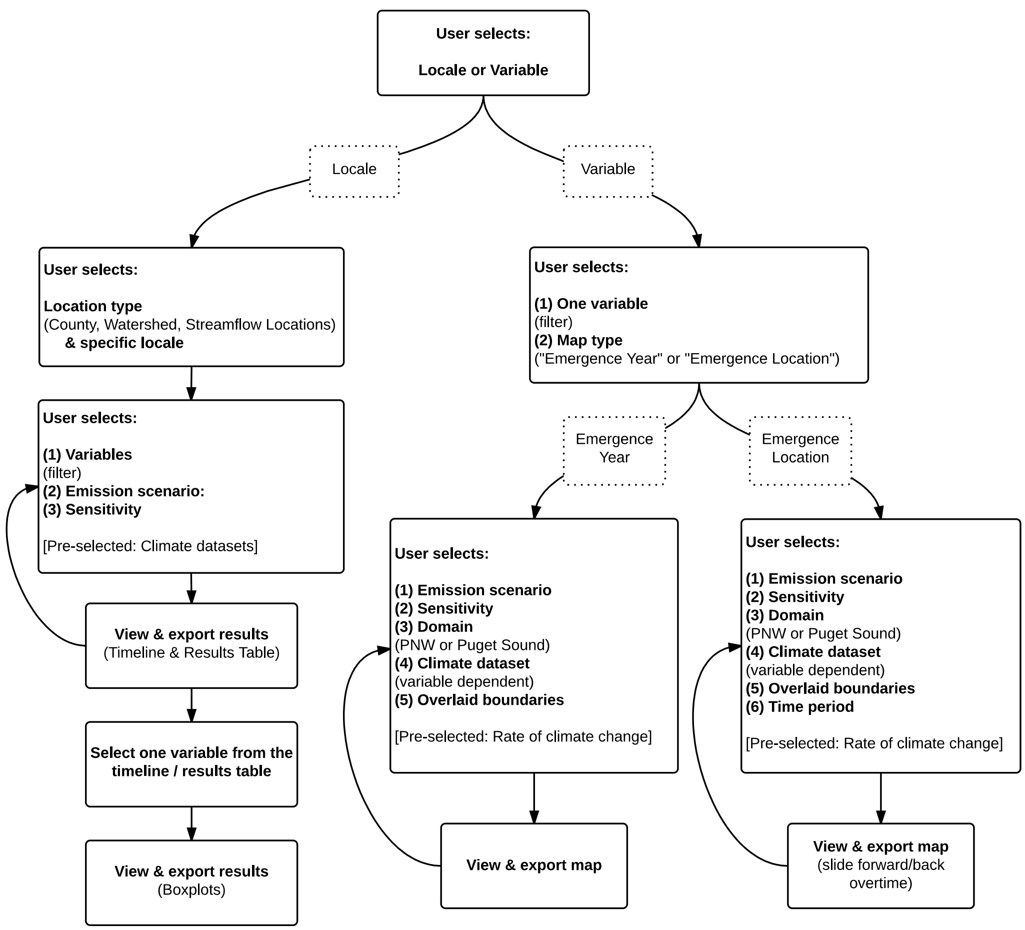

Figure 5. Organization of the “Explore” section of the prototype Time of Emergence online tool.

3.3.1 Explore by locale

In this part of the tool (the left branch in Figure 5), the user can explore the question: *Which type of changes could occur first?,* by comparing ToE results for a set of variables in a specific sub-domain (county, watershed, stream location) within the Pacific Northwest. This part of the tool also helps the user evaluate *How uncertain are these projections?,* by exploring how the results change under different assumptions about potential future change and the ability of the management system to cope with that change.

3.3.1.1 User selection of locale, variables, analytical parameters

The user can select a particular location of interest (county, watershed (4th-level (8-digit) hydrologic unit code) or streamflow site) within the Pacific Northwest (Washington, Oregon, Idaho, and the British Columbia portion of the Columbia River basin) for which to compare results for two or more hydro-climatic variables. The user selects the hydro-climatic variables of interest, either from a drop-down list of all available variables, or using a filtering tool that generates a shorter list of variables within specified categories. The available filter options are listed in Table 7; the categorization of variables by filter category is shown in Table 8.

Table 7. Variable Filter Options

Theme	Related Impact	Type
• All • Air Temperature • Precipitation • Hydrologic • Streamflow	• All • Drought • Energy • Fish • Flood • General • Human health • Infrastructure • Streamflow • Water quality	• All • Average • Extreme • Monthly or seasonal • Annual

Table 8. Categorization of Variable

Theme	Descriptor	Impact	Timescale	Variable name
Air temperature	Average	Human health	Monthly	Temperature, each calendar month
Air temperature	Extreme	Human health / Energy supply	Monthly	Number of days with daily maximum temperature above 65°F (18.3°C), March-November
Air temperature	Extreme	Human health / Energy supply	Seasonal	Number of days with daily average temperature below 25°F (–3.9°C), winter (Dec-Feb)
Air temperature	Extreme	Human health / Energy supply	Seasonal	Number of days with daily average temperature above 68°F (20°C), spring (Mar-May) and fall (Sep-Nov)
Air temperature	Extreme	Human health / Energy supply	Annual	Number of days with daily maximum temperature above 90°F (32.2°C), annual
Air temperature	Extreme	Human health / Energy supply	Seasonal	Number of days with daily maximum temperature at or above 80°F (26.7°C), spring-summer (21 April-21 August)
Air temperature	Extreme	Human health / Energy supply	Annual	Number of daytime heat waves (3 consecutive days with daily maximum temperature above historical 99th percentile), annual
Air temperature	Extreme	Human health / Energy supply	Annual	Number of nighttime heat waves (3 consecutive days with daily minimum temperature above historical 99th percentile), annual
Precipitation	Average	Water availability	Monthly	Precipitation, each calendar month
Precipitation	Average	Water availability / Flood / Fish	Seasonal	Precipitation, fall (Oct-Dec), winter (Jan-Mar), spring (Apr-June), summer (Jul-Sept)
Precipitation	Extreme	Flood / Fish / Landslide	Seasonal	Number of days with 24-hour precipitation exceeding historical 90th, 95th and 99th percentile, October-March
Precipitation	Extreme	Flood / Fish /	Annual	Number of days with 24-

		Landslide		hour precipitation exceeding 2 inches (50.8 mm), annual
Precipitation	Extreme	Flood / Fish / Landslide	Annual	Maximum 48-hour precipitation accumulation, annual
Precipitation	Extreme	Flood / Fish / Landslide	Annual	Maximum 24-hour precipitation accumulation, annual
Precipitation	Extreme	Flood / Fish / Landslide	Annual	Number of days with 24-hour precipitation equal to 3 inches (76.2 mm) or more, annual
Precipitation	Extreme	Flood / Fish / Landslide	Seasonal	Number of wet sequences (18-day cumulative precipitation exceeding 3.5 inches (88.9 mm)), October-March
Hydrologic	Average	Water availability	Annual	Runoff, annual
Hydrologic	Average	Water availability / Flood / Fish	Monthly	Runoff, each calendar month
Hydrologic	Average	Drought / Water availability / Water quality	Monthly	Dryness Ratio, each calendar month
Hydrologic	Average	Drought / Water availability / Water quality	Monthly	Potential evapotranspiration (PET), each calendar month
Hydrologic	Average	Drought / Water availability / Water quality	Monthly	Actual evapotranspiration (AET), each calendar month
Hydrologic	Average	Drought / Landslide	Monthly	Soil moisture, each calendar month
Hydrologic	Average	Water availability	Monthly	Snow water equivalent (SWE), each calendar month
Hydrologic	Extreme	Water availability	Annual	Coefficient of variation of runoff, annual
Hydrologic	Extreme	Flood / Fish	Annual	Highest spring runoff date
Streamflow	Average	Water availability / Water quality	Monthly	Streamflow, each calendar month
Streamflow	Average	Water availability	Annual	Streamflow center of timing
Streamflow	Extreme	Flood / Fish	Annual	Maximum daily streamflow per year
Streamflow	Extreme	Flood / Fish	Monthly	Maximum daily streamflow, each calendar month
Streamflow	Extreme	Flood / Fish	Annual	Number of flood flows per year

Streamflow	Extreme	Drought / Water availability / Water quality / Fish	Annual	Number of 7-day low flows per year
Streamflow	Extreme	Drought / Water availability / Water quality / Fish	Annual	Number of low flows per year
Streamflow	Extreme	Drought / Water availability / Water quality / Fish	Annual	Lowest mean streamflow for 30 consecutive days per year

The user can then select the input parameters necessary for calculating ToE – i.e., emissions scenario, estimated rate of climate change and management sensitivity – or to accept the system defaults (*high* emissions, *low* sensitivity, *moderate* rate of change). Specifically, the user can select the input parameters for:

- **Emission Scenario**
  The user can select a “High” (RCP8.5 and SRES A1B) or “Low” (RCP4.5 and SRES B1) emissions scenario. “High” implies an earlier ToE estimate due to greater effects of climate change; “Low” implies a later ToE estimate due to smaller effects. The two sets of emissions scenarios (RCP and SRES scenarios) are noted for the user since ToE results are provided from climate data sets derived from CMIP5 and CMIP3, respectively. The user can find more details about the definition and selection of emission scenario in the “read” section of the website.
- **Management Sensitivity**
  The user can select a “High” or “Low” level of management sensitivity to past hydro-climatic fluctuations or extreme events. “High” sensitivity represents a management system that would experience negative impacts during the most extreme 40% of conditions that occurred for the variable of interest during the 1950-1999 reference period. “Low” sensitivity represents a system that would experience negative impacts during only the most extreme 10% of conditions. Therefore, “High” sensitivity leads to an earlier ToE estimate due to less tolerance for extreme conditions; “Low” leads to a later ToE estimate due to higher tolerance.

- **Estimated Rate of Climate Change**
  The user can choose to view results based on a "Faster", "Central" or "Slower" estimate of the rate of climate change. This describes the rate of climate change estimated from any particular global climate model (i.e., the calculation of the slope of the climate change signal, as described above). "Fast" implies an earlier ToE estimate due to more rapid climate change; "Slow" implies a later ToE estimate due to less rapid climate change; and, "Central" implies a ToE estimate roughly centered between "Fast" and "Slow" due to moderate climate change. For each global climate model, the values provided are within the 90% confidence range, i.e., there is a 5% chance that the true rate of climate change could occur faster than the "Fast" rate, and there is a 5% chance that the true rate could occur slower than the "Slow" rate.

All results for temperature, precipitation and streamflow-related variables available through this part of the tool were derived from the BCSD5 dataset; (gridded) hydrologic results were derived from BCSD3.

In both the "Read" section of the online tool and the User Guide, we provide guidance on using information about specific management contexts and risk tolerance to choose parameters and interpret ToE results, as outlined in Table 9.

Table 9. Guidance on Input Parameter Selection

	Lower Risk Tolerance	**Higher Risk Tolerance**
Emission Scenario	High (RCP8.5 or SRES A1B)	Low (RCP4.5 or SRES B1)
Management sensitivity	High (impacts triggered by most extreme 40% of past (1950-1999) conditions)	Low (impacts triggered by most extreme 5% of past (1950-1999) conditions)
Rate of Climate Change	Fast (earlier ToE)	Slow (later ToE)
Model Agreement *EXPLORE by Variable* only	Low (25%)	High (75%)

3.3.1.2 Visualization of results

After entering the selections described above, the online tool dynamically generates and delivers a graphical visualization and tabular summary of ToE results for the specified location, variables, and analytical parameters. A timeline graphically depicts the sequence of occurrences between 2000 and 2100 of the central estimates of the time of emergence (denoted by the multi-model median value) for the selected variables across all the global climate models examined (Figure 6). Due to space constraints, shortened variable names are displayed on the timeline. Succinct information about interpreting the timeline results will be displayed onscreen; more details are provided in both the “Read” section of the online tool and the User Guide.

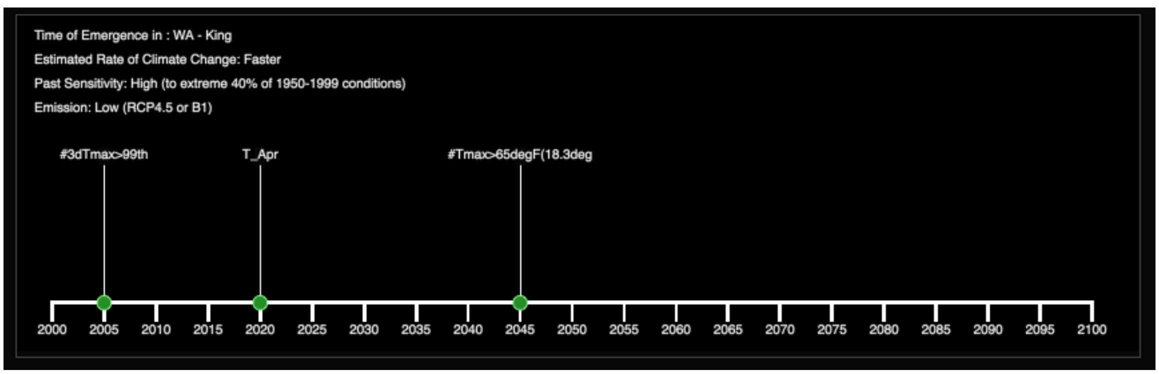

Figure 6. Sample timeline from the prototype online tool showing multi-model median ToE for (left to right) average April temperature, annual number of daytime heat waves (three consecutive days with daily maximum temperature above historical 99th percentile), and number of days in July with daily maximum temperature above 65 degrees F. Results are shown for King County for Low emissions, High sensitivity, Faster rate of change, from the BCSD5 dataset. Both the image (PNG format) and data (CSV format) are easily available for export by the user, via the onscreen Export buttons.

In addition to the multi-model median ToE shown in the timeline, the online tool dynamically generates a tabular summary of the plausible range of ToE results for each variable depicted on the timeline (Figure 7). The ranges represent the central 50% of the range of emergence dates projected by the ensemble of climate models considered. That is, based on uncertainty in simulating future climate (represented by the multi-model ensemble), there is a 50% chance that this range indicates the time when future conditions are projected to deviate from those experienced in 1950-1999, for the displayed variables according to the selected emission scenario, past sensitivity and rate of climate change. (There is a 25% chance that emergence will occur earlier than indicated, and a 25% chance that it will occur later than indicated.)

Projected Range of Time of Emergence for King County under RCP4.5

Hydro-climatic Variable	ToE Range	Direction of Change
T_Apr	2035 - 2060	Increasing
#3dTmax>99th	2020 - 2035	Increasing
P_Oct	0 - Beyond 2100	Increasing
Pwet>99th	2100 - Beyond 2100	Increasing
#Tmax>65degF(18.3deg	2060 - 2080	Increasing

Figure 7. Sample results table from the prototype online tool showing the central 50% of the multi-model projected range of ToE for (top to bottom) average April temperature; annual number of daytime heat waves (3 consecutive days with daily maximum temperature above historical 99th percentile); average October precipitation; number of days during October-March with 24-hour precipitation exceeding historical 99th percentile; and number of days in July with daily maximum temperature above 65 degF. Results are shown for King County for Low emissions, High sensitivity, Faster rate of change, from the BCSD5 dataset.

The user can explore the effects of uncertainty in the analytical parameters by selecting different options for emission scenario, management sensitivity and rate of climate change in the onscreen query dialog box at any time, clicking the *Submit* button, viewing the dynamically-updated results in the timeline and table, and downloading the updated image and data files.

For more detailed information about the effects on estimated ToE of alternative choices about analytical parameters for any specific variable, the user can generate a database query by clicking on any one of the hyperlinked hydro-climatic variable names in the table. The prototype online tool dynamically generates a set of figures illustrating the spread of the results arising from the different global climate models, emission scenarios, past fluctuations and rates of climate change.

The resultant boxplots (Figure 8) illustrate the effects of uncertainties associated with:

1. Rate of climate change, estimated from each global climate model simulation – represented by the three colors. The rate of change for each model falls within this range with 90% confidence and reflects statistical uncertainty.
2. Climate modeling, estimated using output from different global climate models – represented by the horizontal spread of dots. Each model should be considered equally probable, and the range reflects uncertainties in modeling the climate system.
3. Future emissions, estimated using two emissions scenarios – represented by the left and right panels. These scenarios depend on specific policy actions and represent uncertainty in future societal choices.
4. Definition of the threshold for emergence of significant climate change, estimated using two levels of management sensitivity to past climate fluctuations – represented by the top and bottom panels. These choices reflect uncertainty in the vulnerability of human and natural systems to past and future climate fluctuations.

In each of the four sub-plots:

- The top (purple) box indicates the middle 50% of ToE projections from the global climate models used in the analysis (indicated by the dots), using the faster or higher-end estimates of the rate of change from each climate model.
- The middle (green) box indicates the middle 50% of ToE projections from the global climate models used in the analysis (indicated by the dots), using the central estimate of the rate of change from each climate model.
- The bottom (orange) box indicates the middle 50% of ToE projections from the global climate models used in the analysis (indicated by the dots), using the slower or lower-end estimates of the rate of change from each climate model.

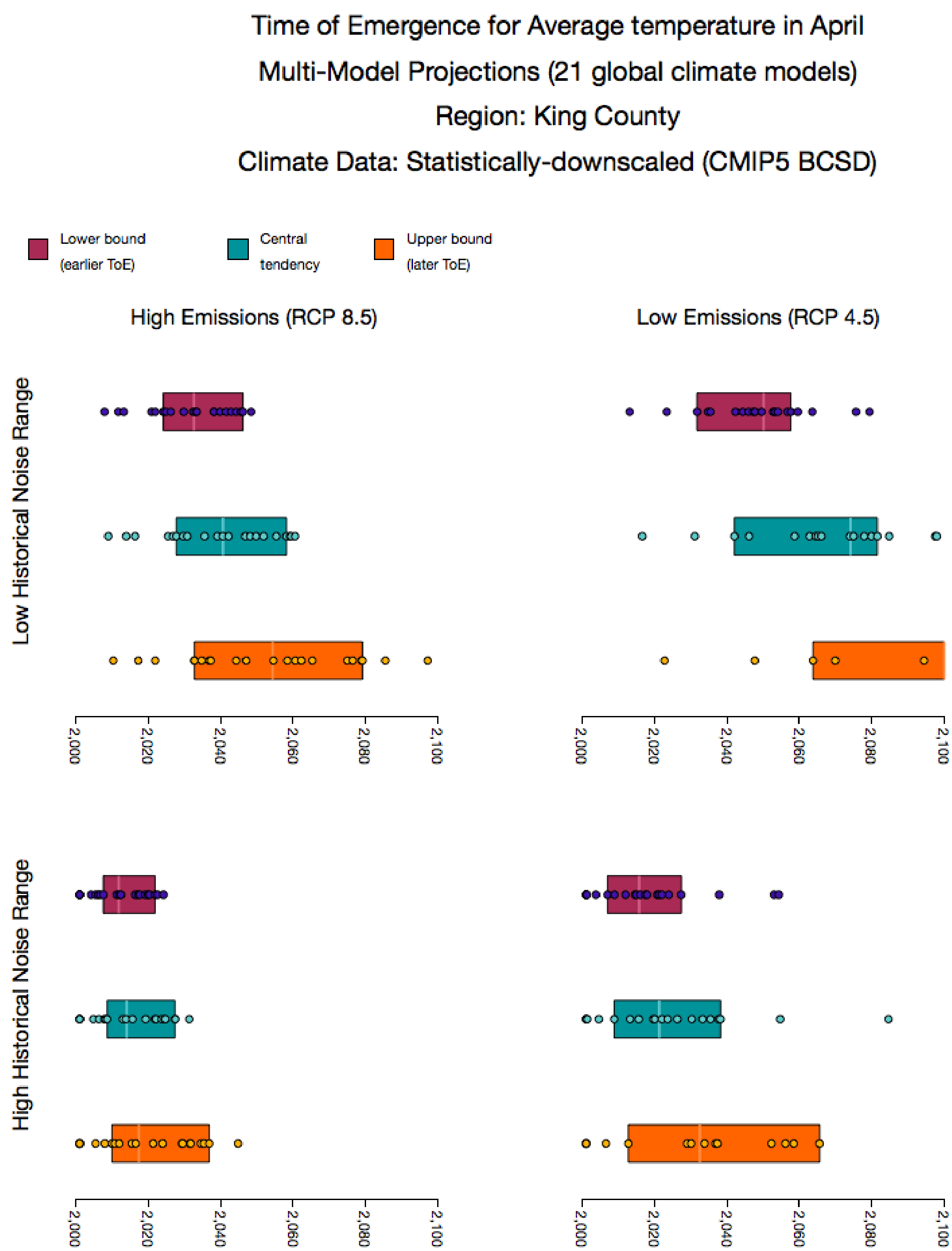

Figure 8. Sample boxplots from the prototype online tool showing ToE for average April temperature projected by each model simulation. Results from the BCSD5 dataset are shown for King County. Left and right panels: High and Low emissions, respectively; Top and bottom panels: Low and High sensitivity, respectively; Three colors: estimated fast, central, and slow rate of climate change, represented by purple, green and orange, respectively.

Both the image (PNG format) and data (CSV format) will be easily available for export by the user, via the onscreen *Export* buttons.

3.3.2 Explore by variable

In this part of the tool (the right branch in Figure 5), the user will be able to explore the question: *Where could changes occur first?,* for a specific variable of interest – across either the entire Pacific Northwest domain or within the Puget Sound basin. This part of the tool will also help the user evaluate *How uncertain are these projections?,* by exploring how the results change under different assumptions about potential future change and the ability of the management system to cope with that change.

3.3.2.1 User selection of locale, variables, analytical parameters

The user will be able to select a variable of interest (from the entire list, or a subset generated using the filtering tool described above) and to specify the type of map visualization desired.

The user will be able to select one of two map types to view:

- Year of Emergence – showing the average (multi-model median) time when future conditions are projected to deviate from those experienced in 1950-1999 (for grid cells with at least 60% agreement among global climate models in the direction of the climate change signal; multi-model median is computed using the subset of models that agree on trend direction).
- Emergence locations – showing places where global climate models project future conditions to deviate from those experienced in 1950-1999, for a moderate rate of climate change and a user-specified future time period (by 2025, 2050, 2075 and 2100), according to three levels of global climate model agreement (25%, 50%, 75%).

The user will also be able to select the geographic domain of interest (the Puget Sound basin or the Pacific Northwest (states of WA, OR, ID and the BC portion of the Columbia River basin)), emissions scenario and management sensitivity (as described above), climate dataset (Table 11), and desired boundaries for maps overlay (state, county, or watershed (4th-level (8-digit) HUC). Because uncertainty in the estimated rate of climate change is unlikely to affect the spatial pattern of ToE, all maps were developed using the central estimate for the rate of climate change.

Table 11. Climate Data Source Options for Maps of *Emergence Year* and *Emergence Location*.

Temperature & Precipitation Variables	**Hydrology Variables**	**Streamflow Variables**
BCSD5 ECHAM5-WRF	BCSD3	BCSD5 BCSD3

3.3.2.2 Visualization of results

After entering the selections described above, the prototype online tool will query a catalog of pre-generated images and displays the map corresponding to the user's selection (Figures 9 and 10). Succinct information about interpreting the maps will be displayed onscreen; more details are provided in both the "Read" section of the online tool and the User Guide. The images (PNG format) are easily available for export by the user.

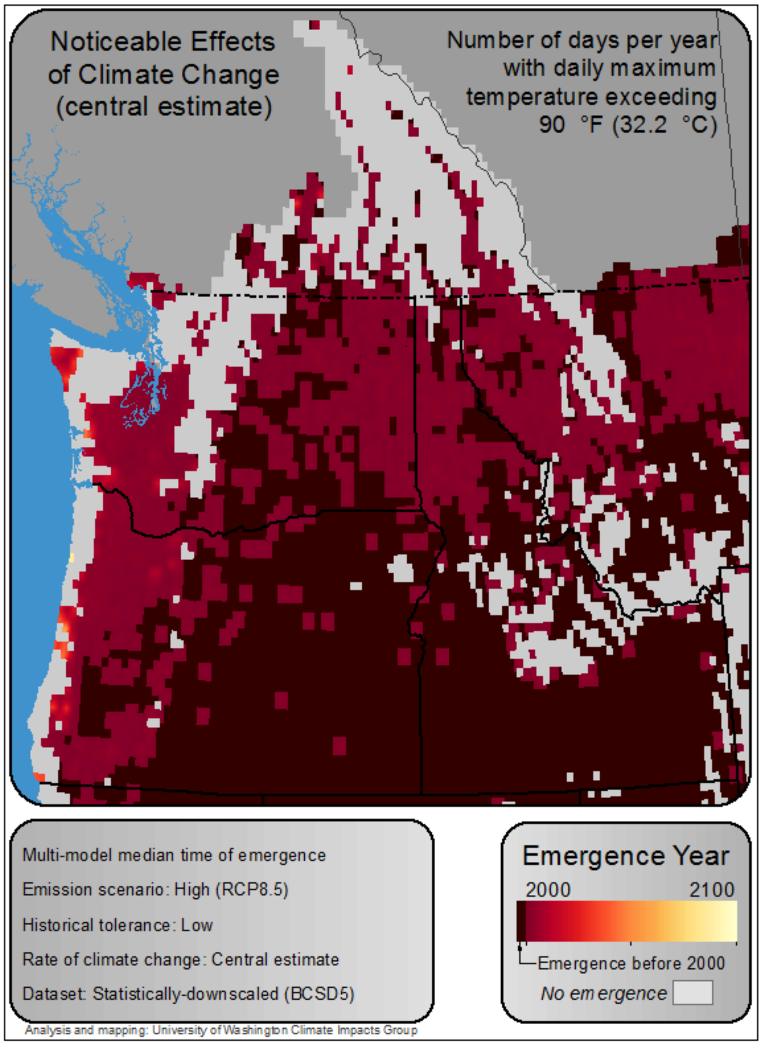

Figure 9. Sample map of "Year of Emergence", depicting where and when there is projected to be noticeable differences in number of days per year with daily maximum temperature exceeding 90°F (32.2°C) compared to 1950-1999, for a moderate rate of climate change, high emissions scenario and high management sensitivity, according to the BCSD5 climate data source. Results are shown for the multi-model median ToE across the 21 global climate models examined at each grid cell in the domain. At each grid cell, therefore, the indicated date represents when 50% of the 21 global climate models examined project the climate change signal to have emerged for the given set of analytical parameters.

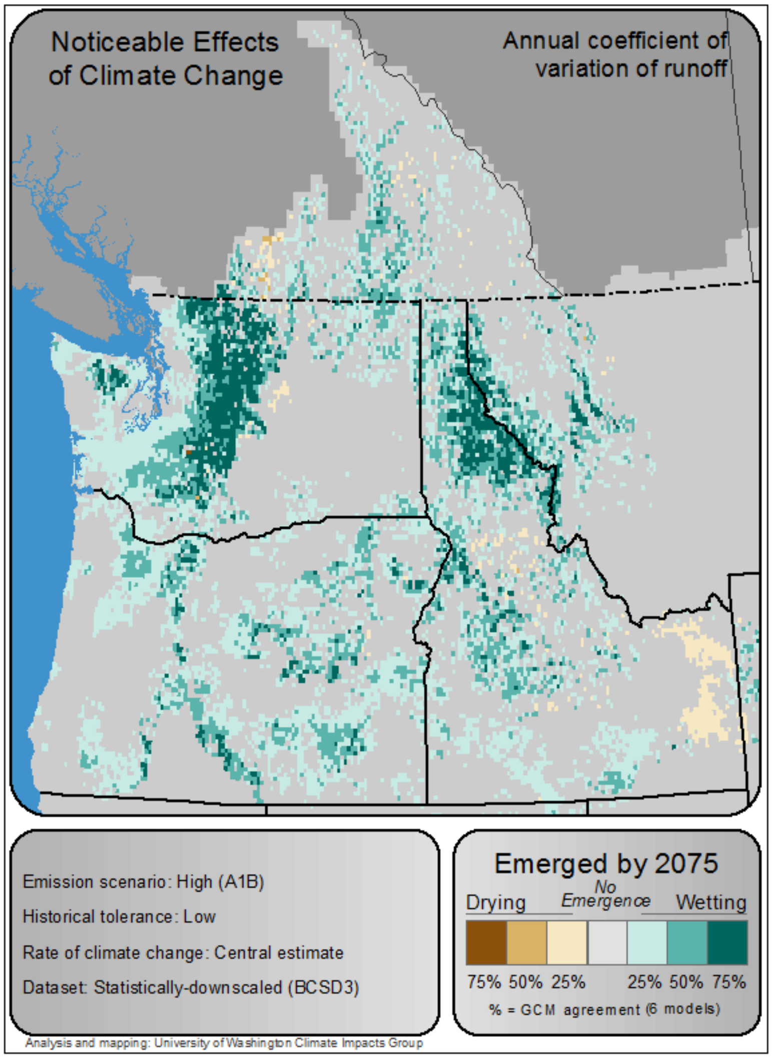

Figure 10. Sample map of "Emergence Locations", depicting where there are projected to be noticeable differences in the annual coefficient of variation of runoff by 2075 compared to that experienced in 1950-1999, for a moderate rate of climate change, high emissions scenario and high management sensitivity, according to the BCSD3 climate data source. The different shadings indicate where 25%, 50% and 75% of the global climate models examined agree that the signal will have emerged by 2075.

3.4 Read

This section will provide a brief description of the prototype online tool, as well as scientific and technical information on:

- The available hydro-climatic variables, how they were identified, defined, and calculated

- The concept of "Time of emergence" of climate change, including the methodology applied to determine the "Time of Emergence", its relevance and usage
- Uncertainties associated with the "Time of Emergence" results, including those arising from climate modeling, and Time of Emergence estimation

The "read" section also provides a catalog of frequently asked questions and responses, to provide the interested user more details about the underlying methods, assumptions, datasets, interpretation, and application of the ToE results. The following subjects are covered within the FAQ:

Use of Products and User Interface

- Does this tool provide all the information I need?
- Are there other climate change decision-support tools available?
- How should I use the maps?
- Am I able to reproduce and publish maps and images from this tool?
- How do I acknowledge use of the products available from the tool?

Use of Findings from this ToE Analysis

- Climate change projections are already available for many variables. What added value is provided by the ToE analysis?
- Why are there different rates of climate change in different places and for different variables?
- Which emission scenario, sensitivity, rate of climate change, or model agreement, should I choose?
- What is "GCM agreement"?
- Does the "percentage of GCM agreement" translate to the "likelihood", or "probability", of something occurring in future (reality)?
- Why is the "likelihood", or "probability", of something occurring in future not estimated?

- Why are the results simply presented as “GCM agreement”, and why have no other more sophisticated statistical methods have been applied?
- Given the uncertainties in the climate projections, are projections of the ToE of climate change still useful for planning purposes?
- What is the baseline period for defining the historic tolerance (“noise”) component in this ToE analysis?
- How is the climate change signal defined in this ToE analysis?
- Are all the modeling uncertainties accounted for in this ToE analysis?
- What are some of the main assumptions associated with the climate projections presented in this tool?
- Are the GCMs used weighted when generating ensemble results?
- Why are the results from a single projection (e.g., emission scenario, GCM) not available?
- Why is the multi-model average value represented by the median rather than the mean?
- Why are the most extreme values of the ensemble not provided in the results?
- Why is the exact year and location (at the grid cell scale) of the time of emergence not provided?

Science and Modeling

- What is a climate projection, or a climate simulation?
- What is the difference between a “climate projection“ and a “climate prediction”?
- What are observations or observed data?
- What is an emission scenario?
- What is radiative forcing?
- What is a climate model?
- What is downscaling?
- What is a multi-model ensemble?
- What is uncertainty in climate projections?
- What is modeling uncertainty?

- What methodology was used to generate Potential Evapotranspiration in the VIC model?

3.5 Tour

This section will provide two examples of how a user might use the tool to support climate change decision-making: one for “EXPLORE by locale” and one for “EXPLORE by variable”. These guided tours demonstrate how a user might navigate the tool to generate customized results and images, what input parameters one might select, and the interpretation of the results.

4 Incorporating Uncertainty in Computing Time of Emergence

There are many caveats to using climate models and climate model projections, and it is necessary to address the issue of 'uncertainty' in particular. From the literature, uncertainty in global climate change projections is described as a measure of variation among model projections due to emissions scenario used, model response/sensitivity, and natural variability (Hawkins and Sutton 2009). For local projections, uncertainty also results from downscaling and subsequent impacts modeling, such as hydrologic simulations to develop projections for future hydrologic conditions. For this project, uncertainty also arises from numerical probability assessments, which exists due to our methods of calculating time of emergence (ToE) of the climate change signal. This type of uncertainty is usually examined through error statistics and confidence estimates (Katz et al. 2013). Here we discuss each component of uncertainty in turn.

A primary limitation in understanding uncertainty in climate projections compared to weather or seasonal (e.g., ENSO) forecasting is that we cannot produce calibrated probability estimates based on past performance. For example, in weather forecasting, a forecast of an 80% chance of an event can be interpreted as meaning: In the past ten times when a similar model outcome was obtained, the forecasted event occurred eight times. Thus, if a user consistently followed this forecast guidance, 20% of the time they would have made the wrong choice. In the case of climate projections, we cannot use this sort of interpretation -- even when similar numerical values could be computed. In particular, the uncertainty in emissions scenario depends on societal choices that cannot be given a reasonable statistical interpretation. Instead, we recommend that the source of uncertainty be made clear with statements like *80% of the models show ToE before this date* or *the ToE is in a given time interval, based on a 90% confidence estimate of the climate trend*.

The uncertainty due to emission scenario used cannot be eliminated, as future socio-economic conditions are unknown, but we can examine multiple emission scenarios to look at a range of possible future outcomes. We examined this type of uncertainty by using both the RCP4.5 and RCP8.5 emission scenarios used in CMIP5, and the SRES B2 and A1B emission scenarios used in CMIP3. The selection of these scenarios was based on the combination of availability of simulations based on specific scenarios, and the desire to span the range of available scenarios. Certain scenarios in both CMIP3 and CMIP5 were given higher priority by the IPCC, which limited the number of available climate models for each climate variable (Meehl et al. 2009; Taylor et al. 2012). This prioritization of scenarios by the IPCC reflects a subjective assessment of the estimated likelihood of projected socioeconomic development and potential mitigation measures (Rogelj et al. 2012), and as such may limit the range of uncertainty illustrated because of emission scenario used.

Global climate model response to a specific emissions scenario, or 'structural' uncertainty, arises from an incomplete understanding of the climate system and the response of particular climate variables to greenhouse gas forcing. This uncertainty is reflected in the spread across different climate models in their projected sensitivity of the climate to greenhouse gas forcing. Some researchers suggest this type of uncertainty, particularly for global average temperature, is becoming smaller as modeling centers evaluate and improve their model components (Knutti and Hegerl, 2008; Knutti et al. 2013). Nevertheless, at the regional scale and for variables such as precipitation, the magnitude and even the sign of changes varies among models. Since we are using a suite of 6-21 climate models, depending on downscaling methods and the choice of climate variable (e.g., precipitation, runoff, streamflow, etc.), model response uncertainty substantially affects our results. Weighting models depending on their performance in simulating the historic, observed climate is one option for resolving this uncertainty. Past performance, however does not necessarily equate with realistic climate sensitivity, and weighted ensemble averaging in practice makes little difference when a large ensemble is used (Mote and Salathé 2010). Given the strong similarities between models developed at the same institution, between models with shared model component versions, and between subsequent model versions, there is not a strong assumption of model independence (Masson and Knutti, 2011). However, results from Gleckler et al. 2008, show that the 'mean model', or the model ensemble average from the CMIP3 archive, consistently outperforms all other models in multiple performance metrics. For the PNW, Rupp et al. (2013) have shown similar results in that there is no one model that consistently outperforms all other models in multiple performance metrics. Thus, we intend to provide results from a relatively large group of models so as to highlight and quantify this uncertainty for the user. Also note that the "extreme" simulations *are* plausible – ensemble mean only indicates best estimate of central value, not actual year-to-year climate. We provide results representing a range of potential futures in order to enable user selection of the scenario most appropriate for their risk tolerances (users that are highly risk averse might consider the scenario indicating the largest change, while those that are risk tolerant may consider the least change scenario).

Downscaling may compound model response uncertainty. Statistical downscaling methods are computationally efficient, which allow them to generate output from many models and multiple realizations, but are based on the assumption of statistical stationarity and cannot simulate changes in regional feedbacks. Multiple methods for statistical downscaling are currently in use, with little evidence and less consensus regarding their relative quality. Dynamical downscaling yields higher spatial resolution and can better incorporate regional features and processes, which are important for variables of importance to regional stakeholders, but they are strongly dependent on the lateral boundary conditions and the methods used to constrain the regional climate model to the coarser spatial scale parent global model. Essentially, errors in the global models are retained and potentially amplified by dynamical downscaling (Feser et al. 2011). Global climate model response uncertainty is unlikely to be resolved by the use of downscaled model output in this analysis. For this project, therefore, we have used downscaled climate model output from multiple sources, in order to portray this source of uncertainty. The analytical methods and online delivery mechanisms have been designed to enable ready uptake, analysis and delivery of ToE results derived from additional datasets as they become available.

Uncertainty arising from natural variability is largely inevitable, due to the inherent chaotic nature of spatial and temporal climate variability. Natural variability can create short-term and localized trends that do not correspond to the forced climate response to greenhouse gas emissions. The dominant modes of natural variability are well recognized, but models vary in their ability to correctly simulate the phase and amplitude of these modes as well as the strength and location of teleconnections (Polade et al.

2013). The ideal way to examine uncertainty from natural variability from climate model simulations, recognizing the limitations of current model ability to simulate such variations, would be to use multiple realizations from each model (Deser et al. 2014). Since internal variability is not coherent across the ensemble while the forced climate response is, the two effects can be distinguished. This approach, however, is beyond the scope of this project. Changes in projected (forced and internal) variability may be analyzed by statistical means. Natural variability contributes to uncertainty in the estimated signal found as a linear fit to the simulated variable, which we do consider. Therefore although uncertainty from natural variability will contribute to the uncertainties indicated by the results, it will not be explicitly resolved at this time.

Uncertainty can also arise from the calculation of ToE itself for a given climate variable. Calculation of ToE requires a number of assumptions, e.g., about (1) the appropriate analytical method (e.g., the "threshold" vs. the "signal:noise" approach), (2) the length of (and data source for) the historical baseline against which ToE will be calculated, (3) the definition of "emergence", i.e., the threshold of the historical data (for the threshold method) at which "emergence" occurs, and (4) error in the calculation of the signal, i.e., the slope of the linear fit to the simulated data for the threshold method. In this effort, we address these uncertainties by (1) providing results from only the "threshold" method, recognizing that this method is well suited to most of the extreme variables of interest to stakeholders, but acknowledging to the user that other methods might provide slightly different results, (2) providing results derived from ToE calculations using one historical baseline period (1950-1999), but acknowledging to the user that other time periods might provide slightly different results, (3) allowing the user to select the threshold of emergence from a pre-determined suite of options, and (4) providing information about the statistical significance of projected trends.

To summarize, we incorporate each of these uncertainties in our ToE analysis as follows:

1) *Uncertainty in future greenhouse gas emissions that force climate change*. This is an inherent uncertainty in what the future will be like in terms of human society. It is dealt with by choosing multiple scenarios, SRES in CMIP3 and RCP in CMIP5. ToE

results are computed for both a low (SRES_B1/RCP_4.5) and high (SRES_A1B/RCP_8.5) emissions scenario for all variables and datasets.

2) *Uncertainty in the sensitivity of the climate to the projected forcing*. This uncertainty includes both unsettled scientific issues (cloud feedback, ocean heat uptake) and technical difficulties in modeling the climate system computationally. It is dealt with by using an ensemble of climate models that make different, but equally justified, choices in representing the climate. ToE is computed for each model and the range of model agreement establishes a confidence interval for ToE relative to model uncertainty.
3) *Uncertainty in downscaling global climate change projections to the regional scale*. This is another scientifically-unsettled source of uncertainty. We address this by providing results from two statistically-downscaled datasets (BCSD5 and BCSD3) and one dynamically-downscaled dataset (WRF3) and by designing both the analytical methods and online delivery mechanisms to enable efficient incorporation of additional datasets as they become available.
4) *Uncertainty in management sensitivity to climate change*. This is a basic question of how sensitive a particular societal or natural system is to changes in the climate. The answer will vary for different systems depending on their capacity to adapt to change. This uncertainty is incorporated in the ToE calculation through the user-selected level of management sensitivity to change.
5) *Uncertainty in statistically estimating the climate change signal*. The projected future time series of a climate variable (for example temperature) typically includes a steady trend and fluctuations around that trend (both stochastic and cyclic). The steady trend is assumed to be the climate system response to external greenhouse gas forcing and the fluctuations result from the various modes of internal climate variability. Estimating the trend from the time series is a statistical challenge subject to uncertainty. In computing the trend, one can place the true slope within statistical confidence limits depending on the strength of the trend compared to the variance in the data using a Student's t test. Thus, ToE can be computed from each model using a high, central, or low value for the signal based on the confidence interval for the computed trend.

Thus, we have computed ToE many times for each climate variable in order to span each dimension of uncertainty. In the first and fourth cases, higher and lower bounds are selected; in the second case, an ensemble of up to 21 models is used; in the third case, three different input datasets were used; in the fifth case, we use a central estimate with upper and lower bounds. Depending on a user's risk tolerance and perception of uncertainties, either earlier or later Time of Emergence can be obtained by choosing the appropriate combination of these uncertainty ranges across these dimensions. The following selections would result in a high estimate of ToE (*i.e.,* late emergence) for a specific climate variable:

- Selecting a *low emissions scenario* would represent a best-case scenario of low forcing on the climate system and a later ToE as compared to a high-emissions scenario.
- Requiring *high model agreement*, for example, taking ToE as the date where 75% of the models project emergence.
- Applying a *high threshold* for emergence, indicating low sensitivity to change in the variable.
- Using the *lower estimate of the climate trend* would assume the slowest probable rate of climate change.

The web site and visualization tools produced by this project attempt to incorporate all these sources of uncertainty into the results in a way that is intended to match a user's risk perception and allow interactive exploration of uncertainty. Table 12 summarizes how each source of uncertainty is treated in the analysis of ToE, and how each is incorporated into the user experience.

Table 12. Analytical treatment and user experience in the prototype web tool for each component of uncertainty associated with determining Time of Emergence (ToE).

Source of Uncertainty	**Analytical Approach**	**User Experience**
Future greenhouse gas emissions	Calculate ToE using projections based on both "High" (RCP8.5 and A1B) and "Low" (RCP4.5 and B1) emissions scenarios	For timelines, summary tables and maps: Allow users to filter ToE results by greenhouse gas scenario In boxplots: Show effects of two greenhouse gas scenarios for ToE results
Climate model disagreement	Calculate ToE using all available global climate model projections available for a particular dataset • 21 GCMs, BCSD5 (temperature, precipitation, streamflow-related variables) • 1 GCM, WRF3 (temperature, precipitation, hydrologic, streamflow-related variables) • 6 GCMS, BCSD3-VIC (temperature, precipitation, hydrologic, streamflow-related variables) *Note.* For variables where different models indicate different directions for the climate change signal, the signal direction is identified as the direction projected by 60% or more of the models. ToE results are computed and reported using only that subset of (60% or more) of models.	In timelines: indicate multi-model median ToE In summary tables: report central 50^{th} percentile ToE range In boxplots: show (graphically) multi-model median ToE, $25\text{-}75^{th}$ percentile ToE range, and individual GCM results In maps of *Emergence Year*: show multi-model median ToE In maps of *Emergence Location* (by year): show locations with 25, 50, 75% model agreement that emergence has occurred
Downscaling	Calculate ToE using both statistically- (BCSD5 and BCSD3) and dynamically-downscaled (WRF3) datasets	For maps of *Emergence Year* and *Emergence Location*: Allow users to filter ToE results by downscaling method (see Table 9) Notify users that the ToE results derived from the dynamically-downscaled dataset (which reflects input from a single global climate model run), is not directly comparable to the results derived from the *ensemble* of statistically-downscaled global climate models.
Natural climate variability	For contribution of natural variability to uncertainty in the estimated climate change signal, see "Error in Calculation of Climate Change Signal", below.	Alert users (in online documentation) to this source of currently unexplored uncertainty.

	Exploration of uncertainty from natural variability in climate model simulations is not explored at this time.	
Method for calculating ToE	Calculate ToE using only the *Signal Threshold* method (e.g., Maraun 2013), due to the clarity of communicating the management implications of the relevant computational parameters (i.e., the emergence threshold) and the robustness of the method for a wide variety of climate variables (see Section 2.4, above)	Notify users in online documentation that, although well suited to most of the extreme variables of interest to stakeholders, other computational methods might provide slightly different results.
Management sensitivity to (or tolerance for) climate fluctuations	Calculate ToE using two definitions of management sensitivity: "High" (negative impacts triggered by the most extreme 40% of conditions during the 1950-1999 reference period) and "Low" (negative impacts triggered by the most extreme 10% of conditions).	For timelines, summary tables and maps: Allow users to filter ToE results by management sensitivity In boxplots: Show effects of two levels of management sensitivity for ToE results
Historical baseline to which fluctuations are compared	Calculate ToE using only the 1950-1999 historical reference period.	Notify users in online documentation that alternative definitions of historical reference period could affect ToE results
Error in calculation of climate change signal	Calculate ToE using three values for the estimated rate of climate change (i.e., the slope of the simulated climate change signal) – the central estimate and "low" and "high" estimates defining the 90% confidence range (i.e., there is a 5% chance the slope is above the faster rate and a 5% chance it is below the slower rate)	For timelines and summary tables: Allow users to filter ToE results by estimated high/medium/low rate of climate change In boxplots: Show effects of different assumptions about rate of climate change for ToE results

5 Website Architecture

5.1 Overall Architecture

The Time of Emergence Prototype website provides the capability to query, retrieve and extract Time of Emergence results computed by the Climate Impacts Group. The developed system leverages existing open source frameworks that provide basic website navigation constructs, augmented with custom development to enable the requested data flows, and visualizations as identified by project stakeholders. This approach enables targeting of scarce resources on specific needs of the project, while leveraging generally accepted web development approaches and capabilities of the underlying framework.

5.2 Underling Framework

The underlying framework of the site consists of several components. The core functional elements (authentication, content management file handling, etc.) are handled through the standard Drupal Content Management System (CMS). This system is widely deployed and used by such entities as UW.edu and WhiteHouse.gov. Additional custom modules were developed to provide the advanced filtering capability, and serve up the requested visualizations. The customizations have been developed using standard Drupal programming practices and coding conventions (https://www.drupal.org/coding-standards).

5.3 Data Engine

The underlying database engine for the site is MySQL, a standard open source database used in many web applications. This database engine powers both the underlying database for the Drupal site, which controls logic for items such as user management and navigation, as well as a separate database which manages and serves the climate data. This separation is seamless to the end user as the system internally handles switching between the two data sources.

This separation allows system administrators to handle standard Drupal management and automated upgrade protocols, while providing undisturbed access to the data. This also makes it easier for migration of the results to another system, should that become necessary.

Information about Drupal API's and schema can be found on Drupal.org (https://api.drupal.org/api/drupal).

Detailed schema for the climate data can be found in Appendix A.

5.4 Data Extraction / Download

There are two types visualizations on the site, on demand and pre-generated.

The timeline and boxplot visualizations are generated on demand, based on input from the user and the available underlying data. The generated images themselves and the underlying data can be downloaded, the latter extracted to industry standard CSV format for easy sharing and transfer of the data.

The pre-generated map data is represented as images that the user will be able to download using a standard right or ctrl click.

5.5 Hosting Environment and Installation instructions

5.5.1 Hosting

For development the system was installed on a standard open source LAMP stack framework, (Linux, Apache, MySQL, PHP) which was hosted on the Microsoft Azure cloud hosting service. The delivered code will consist of the system files, custom code, as well as two database snapshots (Drupal core, and custom TOE data databases). This will be delivered either through the online source control repository (https://github.com/WebDataScience/cwds-time-of-emergence) or as a compressed file.

5.5.2 Installation

An industry professional with moderate exposure to LAMP stack and Drupal development will be able to deploy the site to any standard LAMP based system.

6 Project Outputs

The following are outputs of the Time of Emergence project described here.

1. **Project report**, detailing project input and output datasets, methodology for calculating and visualizing Time of Emergence, approach to stakeholder engagement, and the user interface/navigation and technical specifications of the prototype Time of Emergence website.

2. **Results database.** As indicated in Figure 1, development of ToE results for online delivery is a multi-step process resulting in a series of intermediary results datasets. In addition to the results delivered through the prototype web tool, the following intermediary datasets have been archived at the University of Washington.
   a. Time series of variables used in ToE analysis: annual/monthly timeseries for historical and two future scenarios for each grid cell (netcdf) or discrete point (ascii)
   b. Year of emergence for each variable/parameter combination: gridded (netcdf) or station (ascii) date of emergence showing 12 values for each global climate model (2 emission scenarios x 2 levels of management sensitivity x 3 estimates of climate change rate) and 36 values for each ensemble of global climate models (2 emission scenarios x 2 levels of management sensitivity x 3 estimates of climate change rate x 3 levels of model agreement)
   c. Spatially aggregated ToE results: ToE for each variable and spatial unit (119 counties, 218 4th-level (8-digit) HUCs, ~100 stream locations), with 12 values for each global climate model (2 emission scenarios x 2 levels of management sensitivity x 3 estimates of climate change rate) and 36 values for each ensemble of global climate models (2 emission scenarios x 2 levels of management sensitivity x 3 estimates of climate change rate x 3 levels of model agreement)

3. **Maps library.**
   a. Gridded maps of emergence year and emergence location for 127 variables, with 20 maps for each variable (2540 maps total).
   b. Discrete point data of station maps of emergence year for 30 variables for ~100 stream locations (all on 1 map) for 2 datasets, with 20 maps for each variable (120 maps total).

4. **Prototype web tool.** As described above, the Time of Emergence Prototype website provides the capability to query, retrieve and extract ToE results.

5. **User guide.** A brief manual designed to help the user navigate the prototype Time of Emergence website, conduct customized queries of ToE results, and use the outputs meaningfully.

7 Data Archival

All datasets will be preserved and archived at the University of Washington in perpetuity. We expect other organizations, USACE in particular, will mirror these archives to further assure data protection. The Climate Impacts Group has access to a variety of data archive facilities at the University of Washington including local storage on RAID servers maintained by the Department of Atmospheric Sciences, which are accessible over the internet to research collaborators. The local RAID servers will be used for data distribution and for active data analysis. The UW maintains a central archive system (lolo) https://depts.washington.edu/uwtscat/archivestorage where we will archive data products. All data stored to the archive system are duplicated to tape at two separate backup centers in the Seattle area. Archiving to this system will ensure the long-term preservation of project results.

8 Moving Forward

The prototype online tool developed through the Time of Emergence project enables a new look about future climate change from the point of view of when and where changes could matter compared to both typical variability in conditions and management sensitivity to those fluctuations. Despite the wealth of downscaled climate change projections for the PNW, potential users of this information still struggle with: interpreting multiple scenarios, finding information about projected changes in environmental conditions of relevance to their particular management concerns, or simply the technical challenges of extracting relevant information from the massive datasets available from climate data providers. We have reduced this burden for users by (1) accessing, downloading and formatting downscaled model output, (2) using these projections to compute locally-specific, management-relevant variables, (3) evaluating the ToE for these variables under a range of plausible assumptions about future climate and management sensitivity to change, (4) developing syntheses of these results to indicate agreement across numerous global climate models, and for particular locations and levels of agreement, and (5) developing and producing maps indicating spatial variability in both ToE and scenario agreement, and (6) developing a prototype online tool for exploring and accessing these results, in order to provide both novice and sophisticated users relatively easy entry into these complex and numerous datasets. The flexible method of analysis, visualization and data delivery can be efficiently applied to new data sets as they emerge or are updated.

Several potential avenues of improvement or expansion of the tool have emerged during its development and piloting that may be useful to consider. In this section we describe potential pathways for expanding and improving the tool, specifically: incorporating more input datasets, computing ToE for additional locally-specific, management-relevant variables, expanding the geographic domain covered by the ToE approach, and enhancing visualization and online delivery of ToE results.

For future analysis we would like to include additional statistically and dynamically downscaled model output, which would offer the means to examine climate change across the PNW at fine spatial scales ($1/8^{th}$ degree resolution or less) needed for climate change decision support in management-relevant measures of the climate and environment for the PNW. The Multivariate Adaptive Constructed Analogs (MACA) statistically downscaled climate model dataset has exhibited great skill in reproducing the spatial and temporal variability of PNW climate, when compared to observations for the 20^{th} century (Abatzoglou and Brown, 2012). MACA is derived from the Coupled Model Intercomparison Project phase 5 (CMIP5), is available at a daily time-step and a higher spatial resolution (~6km) than that of the BCSD datasets and has only recently become available. While data management/storage has been an issue throughout this analysis, we recently received +20 TB of space on the Amazon Web Server, which can potentially speed up the pace with which variables and ToE for each variable is calculated. Adding the MACA dataset to our analysis would be straightforward and would greatly enhance the web tool's ability to compare results across datasets.

Also, the Weather and Research Forecasting model (WRF) has been run with forcings from various CMIP3 and CMIP5 models. At present we have incorporated ToE results from one WRF simulation, but additional runs would also be easy to incorporate into existing results, establishing a larger regional climate model ensemble.

As additional projections of PNW climate change become available, or additional user needs identified, ToE could be computed for additional management-relevant variables. One of the most widely requested variables for which the necessary input data do not exist was PNW stream temperature. Multiple research groups are currently working to project future stream temperature under climate change – if these efforts produce timeseries of stream temperature suitable for ToE analysis, this gap could be filled. Many stakeholders also requested information about projected changes in wind and lightning, which could now be examined using dynamically-downscaled model output from WRF simulations.

There is also potential to expand the present geographical domain from the current focus on the Puget Sound basin and PNW to cover the western United States or even the entire coterminous US. The BCSD datasets that have been used in this study cover these broader areas (western US for BCSD3; coterminous US for BCSD5) as does MACA (coterminous US), and a further-reaching spatial analysis would simply utilize the existing code from the established methodology. This would result in a larger set of spatial units (e.g., more counties and HUCS) to which to compare the existing results.

The number of stream gauge stations used in this study could also be expanded. Of the 297 stream locations in the BCSD-CMIP3, we have analyzed only ~50. Additional stream locations would enhance future analysis and would not require additional ToE code development.

While the prototype online ToE tool is designed to provide useful and useable information for both novice and sophisticated users of climate change information, additional tool development could enhance the user experience, providing additional interpretive information and enhanced connectivity between different visualization products. For example, what sort of *intermediate step* (text, or visuals) would help the novice user successfully transition between the timeline and boxplot visualizations, which are significantly different in terms of levels of detail and complexity? How could the location-specific results, such as the timeline or boxplots, be effectively connected to the regional maps of variation in a single variable? What kinds of adjacent visual comparisons of ToE results based on different analytical assumptions would be most useful to users? Future development could add capabilities for users to comment on specific visualizations, or to save jobs for future viewing. Knowing that these may be of interest, we built “breadcrumbs” tracking user navigation and choices into the prototype site, so as to enable easy establishment of the functionality for saving jobs in the future.

The ToE analysis and online delivery described here used a pre-determined set of values for the analytical parameters necessary for ToE computation (management sensitivity, historical reference period, level of statistical certainty in the computation of the climate change signal). While users can explore how these pre-determined values affect the date of expected emergence, users cannot currently explore ToE for additional parameter values of interest. Future work could expand the pre-determined values for the analytical parameters or apply these methods for ToE computation to develop a fully-dynamic online application for exploring ToE for any user-specified parameter value.

Even more exciting tool development could involve the development of scripts to enable automated ToE analysis of user-provided (correctly formatted) input datasets.

As the prototype online tool is increasingly tested within both USACE and EPA and the broader PNW climate user community, formal evaluation of user experience, tool navigability and understandability, and applicability of ToE results in management and planning contexts, could provide valuable insights for prioritizing future development efforts.

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10 Appendix A: Climate Database Schema

Variable Data:

```
CREATE TABLE `SCEN1_DATA` (
  `VARIABLEID` varchar(10) DEFAULT NULL,
  `TOE` int(11) DEFAULT NULL,
  `CHANGEDIR` int(11) DEFAULT NULL,
  `GCM` varchar(50) DEFAULT NULL,
  `REGION` varchar(50) DEFAULT NULL,
  `EMISSCENARIO` varchar(20) DEFAULT NULL,
  `DATASET` varchar(20) DEFAULT NULL,
  `BASELINE` varchar(100) DEFAULT NULL,
  `EMERGTHRES` int(11) DEFAULT NULL,
  `SIGNALCONFIDENCE` int(11) DEFAULT NULL,
  `MODELAGREEMENT` varchar(10) DEFAULT NULL
) ENGINE=InnoDB DEFAULT CHARSET=latin1;
/*!40101 SET character_set_client = @saved_cs_client */;
```

Scenario Data:

```
CREATE TABLE `TOE_DATA` (
  `THEME` varchar(20) DEFAULT NULL,
  `AVERAGEEXTREME` varchar(20) DEFAULT NULL,
  `IMPACT` varchar(50) DEFAULT NULL,
  `VARIABLEID` varchar(10) DEFAULT NULL,
  `VARIABLEDEF` varchar(250) DEFAULT NULL,
  `VARIABLEMONTH` int(11) DEFAULT NULL,
  `VARIABLENAME` varchar(250) DEFAULT NULL,
  `VARIABLESHORTNAME` varchar(20) DEFAULT NULL
) ENGINE=InnoDB DEFAULT CHARSET=latin1;
/*!40101 SET character_set_client = @saved_cs_client */;
```

Region Data:

```
CREATE TABLE `region_detailsV1` (
  `region_name` varchar(100) NOT NULL,
  `state_abbr` varchar(50) NOT NULL,
  `subregion_id` varchar(10) NOT NULL,
  `subregion_name` varchar(100) NOT NULL
) ENGINE=InnoDB DEFAULT CHARSET=latin1;
/*!40101 SET character_set_client = @saved_cs_client */;
```

Region Mapping:

```
CREATE TABLE `region_masterV1` (
  `region_id` varchar(10) NOT NULL,
  `region_name` varchar(100) NOT NULL
) ENGINE=InnoDB DEFAULT CHARSET=latin1;
/*!40101 SET character_set_client = @saved_cs_client */;
```

State Mapping:

```
CREATE TABLE `state_masterV1` (
  `state_id` varchar(10) NOT NULL,
  `state_abbr` varchar(50) NOT NULL
) ENGINE=InnoDB DEFAULT CHARSET=latin1;
/*!40101 SET character_set_client = @saved_cs_client */;
```