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Climate consoles: Pieces in the puzzle of climate change adaptation

Dominique Bachelet[a,*], Mike Gough[b], Tim Sheehan[b], Barry Baker[b], Ken Ferschweiler[b], James Strittholt[b]

[a] Dept of Biological and Ecological Engineering, Oregon State University, Corvallis, OR 97333, USA
[b] Conservation Biology Institute, Corvallis, OR 97331, USA

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ABSTRACT

Conservation Biology Institute (CBI) has been developing web applications to centralize and serve credible and usable information that allows natural resource managers, as well as the general public, to better understand the challenges posed by on-going environmental change. In particular CBI has designed a series of climate consoles that provide natural resource managers the most recent 5th Climate Model Intercomparison Program (CMIP5) climate projections, landscape intactness, and soil sensitivity for a series of reporting units over the western United States. The publically available web sites were refined based on feedback from a variety of users. In this paper, we describe each of the tools developed as open-source applications and provide details of their infrastructure in the hope they can be used and possibly modified by a wider audience. They were designed to be used as stepping-stones towards planning effective climate change adaptation strategies.

1. Introduction

Climate change is projected to affect ecosystems across the country but the extent and direction of potential changes is subject to much uncertainty particularly with regard to water budgets. Managing ecosystems for future resilience requires collaboration, innovation and effective communication. The Council on Environmental Quality (CEQ) developed standard "Federal Agency Climate Change Adaptation Planning Implementing Instructions" in 2011, requiring the head of each federal agency to develop a climate change adaptation policy, increase understanding of how the climate is changing, apply understanding of climate change to agency missions and operations, develop, prioritize, and implement actions; and evaluate and learn (CEQ, 2011). These instructions have triggered a variety of responses among agencies (Archie et al., 2012). The Bureau of Land Management for example, has used Rapid Ecoregional Assessments to better understand vulnerability and inform management efforts.

Scientists have responded to the need for addressing climate change and assessing vulnerability and adaptive response by providing an assortment of information sources – everything from guidebooks and reports to data repositories to carbon calculators and modeling tools – and multitudes of workshops where powerpoint presentations by experts left little time for social exchange. Most of the information has not been provided with practical guidance to managers who have limited funding and time to interpret and incorporate the available material into planning and implementation documents. Conversely, there is little guidance for scientists to develop climate change-related tools for the management community; consequently, many tools are not considering management needs and priorities (Kemp et al., 2015).

To fill the primary need for readily accessible spatial datasets in a collaborative and transparent environment, the first step towards working towards effective climate adaptation strategies, the Conservation Biology Institute (CBI) has been developing a series of web applications and using iterative feedback from stakeholders to improve them. These web sites aim to centralize and serve credible and usable information that allows natural resource managers, as well as the general public, to better understand the challenges posed by on-going environmental change and help them design effective management strategies.

Abbreviations: BLM, Bureau of Land Management, US Federal Agency in the Dept of Interior; CMIP5, 5th Climate Model Intercomparison Program; HUC5, Hydrological Unit Code 5; LCC, Landscape Conservation Cooperative; RCP, Representative Concentration Pathway; RCP 8.5, "RCP8.5 is a so-called 'baseline' scenario that does not include any specific climate mitigation target. The greenhouse gas emissions and concentrations in this scenario increase considerably over time, leading to a radiative forcing of 8.5 W/m^2 at the end of the century."; MC2, acronym for the 2nd version a Dynamic Global Vegetation Model based originally on the linkage between the MAPSS biogeography model and the Century biogeochemical model

* Corresponding author.
E-mail addresses: bacheled@oregonstate.edu (D. Bachelet), mike.gough@consbio.org (M. Gough), tim@consbio.org (T. Sheehan), barry.baker@consbio.org (B. Baker), ken@consbio.org (K. Ferschweiler), stritt@consbio.org (J. Strittholt).

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2. Background and use cases

In 2013 CBI worked with Utah's Division of Wildlife Resources (DWR) and the Bureau of Land Management (BLM) to develop decision support models that would inform current conservation initiatives in Utah and throughout the Colorado Plateau ecoregion. Based on earlier Rapid Ecoregional Assessment work, CBI updated terrestrial landscape and aquatic intactness models for the Colorado Plateau ecoregion as well as the habitat profiles for a number of identified conservation elements of interest (largely native species and communities). In order to facilitate sharing those results with the stakeholders, the Environmental Evaluation Modeling System (EEMS) was designed to display the intactness models and climate exposure (Sheehan and Gough, 2016).

The Desert Renewable Energy Conservation Plan (DRECP) is part of California's renewable energy planning efforts (www.drecp.org). It is designed to ensure effective protection and conservation of desert ecosystems while allowing for appropriate development of renewable energy projects. The plan encompasses ~22.5 million acres of federal and non-federal California desert land. CBI provided science support for this ambitious planning process including developing and maintaining the DRECP Gateway (https://drecp.databasin.org), which includes a range of spatial datasets and model results as well as applications such as the climate console. CBI developed the Climate Console for the California Energy Commission (CEC) to perform two important functions: (1) present and share the climate data used by the Renewable Energy Action Team to support Plan development, and (2) provide information important to its effective implementation as an adaptive management strategy.

Soon after, the CEC decided to expand and update the climate console to include the entire State of California. Consequently CBI is now providing science and technical support to assist the California Energy Commission (CEC) in planning the state's future energy needs, which includes achieving aggressive renewable energy goals with minimal damage to natural systems. As a subset of the work, CBI is supporting the Renewable Energy Transmission Initiative 2.0 (RETI). RETI, according to the CEC, "is an open, transparent, and science-based process that will explore the abundant renewable generation resources in California and throughout the West, consider critical land use and environmental constraints, and identify potential transmission opportunities that could access and integrate renewable energy with the most environmental, economic, and community benefits." When the application was released, CBI completed a series of ~40 phone interviews (Strittholt, pers. comm.) to ensure the California Climate Console was meeting the goals of the CEC and its stakeholders and to update it as needed following the most relevant users' recommendations.

In the mean time CBI received funding from the BLM to design a similar tool that would serve climate change information to natural resource managers pursuing conservation goals for the sage grouse habitat conservation and restoration in eastern Oregon and western Idaho. In collaboration with Oregon State University, project staff completed a series of phone surveys on the usefulness and usability of existing web sites with instantaneous feedback from practitioners (Brown and Bachelet, 2017). Survey results helped revise the DRECP and California Climate Console (for which specifically there was another on-going phone survey) and start the development of a sagebrush-focused console. The goal was to deliver graphics with relevant spatial and temporal scales, unambiguous terminology, intuitive to natural resource managers and planners to help visualize abiotic threats in sagebrush dominated lands. A few months later the Sagebrush console was publically released and reviewed through a new round of phone interviews among Great Basin federal lands managers. Furthermore two workshops (12/07/16 in Boise ID and 02/16/17 in Lakeview OR) brought together scientists, web developers and practitioners to discuss strengths and weaknesses of the tools as well as bring requests for new features or new tools. The results from these two workshops are the subject of another journal article by a social scientist working with the team.

The USA also include a great number of natural areas protected at different levels including National Parks, Wildlife Refuges, National Monuments and many others. Since 1998 CBI has managed a national protected areas dataset (the Protected Areas dataset for the conterminous US or PAD-US, CBI Edition) that provides standardized information on land ownership, management designations, and conservation status across the country. Protected area networks play a fundamental role in regional conservation and climate change is believed to be one of the greatest threats to these natural landscapes. But are all protected areas equally threatened by a changing climate? A group of western Landscape Conservation Cooperatives (LCCs), including California, Great Basin, Great Northern and North Pacific, believed that if resource managers had the ability to access and visualize the integration of climate change datasets and current protected areas network, better planning and management decisions could be made regarding protected areas at both landscape and site-level scales. To that effect, CBI staff worked closely with LCC representatives and designed the Landscape Climate Dashboard. This application allows users to explore, for all federally and tribally held protected areas, historic and projected climate as well as vegetation change, with an estimation of where soils are most vulnerable to erosion due to climate change. The design of the user interface was built with iterative feedback from regional managers to assure the tool provides useful insights that allow for the planning of short, medium, and long-term adaptation strategies.

3. Overview of CBI's climate consoles and dashboard

The first climate console was created for BLM managers in Utah (https://tinyurl.com/jb6tm5j). It provides climate projections until 2100 but also information on current human impacts on land and streams, soil characteristics, and climate exposure in the form of GIS (Geographic Information System) layers accessible through Data Basin where they reside. These non-climate data were generated by using a decision support model created at CBI (Sheehan and Gough, 2016) (see Methods section for details).

The second console was designed for the Desert Renewable Energy Conservation Plan in southern California (climateconsole.org/drecp). To address a common stakeholder request (Brown and Bachelet, 2017), it includes short term forecast straight from the National Oceanographic and Atmospheric Administration (NOAA)'s climate prediction center (http://www.cpc.ncep.noaa.gov/) as well as climate projections to 2075. Levels of human impacts on the landscape, soil characteristics (pH, erodibility, salinity), and potential climate exposure are generated, like in the Utah console, by using a decision support model created at CBI (Sheehan and Gough, 2016). In this case and in all the consoles that were developed later, based on users' requests (emails and informal phone conversations), each spatial layer is provided through an interactive transparent logic model that allows each GIS layer to be visualized on the screen.

With funding from the California Energy Commission (CEC) the *California Climate Console* (http://climateconsole.org) was designed to also include results from a vegetation model (MC2) that was used to simulate broad vegetation categories such as evergreen forests or grasslands and evaluate their sustainability in the future. It associates values to the carbon stocks and fluxes with the vegetation types that may change with various climate and land use projections as well as in response to simulated wildfires. The vegetation model results can be animated showing changes by decades. Like the other consoles, it also provides 5th Climate Model Intercomparison Program (CMIP5) climate projections and short-term NOAA forecasts, soil sensitivity and climate exposure, for a suite of reporting units (counties, ecoregions, Hydrological Unit Code 5 or HUC5 (Seaber et al., 1987), National Forests) for the entire state of California.

With support mostly from BLM but also the Great Basin LCC, CBI

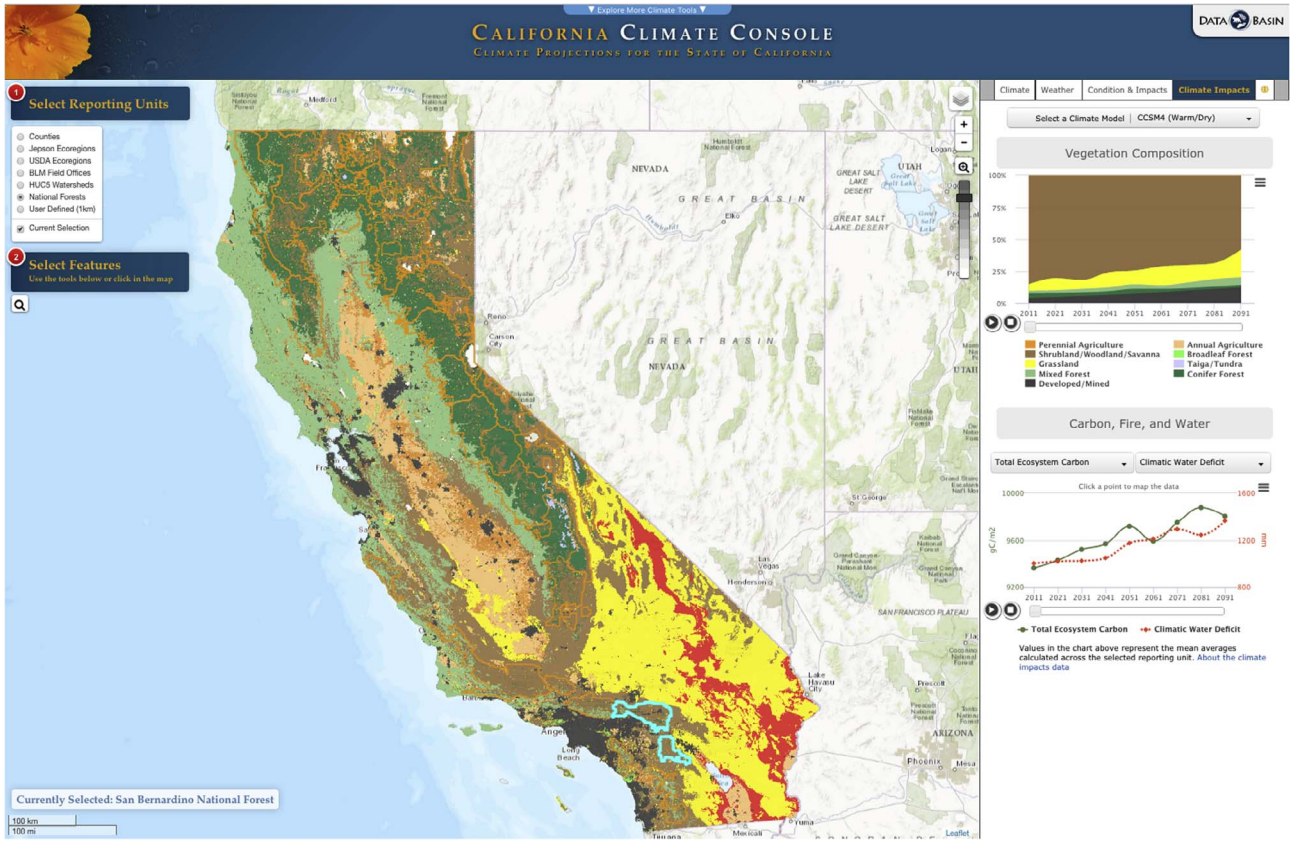

Fig. 1. Example of the California Climate Console showing modal vegetation for every decade of the 21st century as well as a time series of total ecosystem carbon and climatic water deficit (the difference between potential evapotranspiration and actual evapotranspiration or PET-AET) simulated by the MC2 model (Baker et al., 2017). The application also provides the annual or seasonal average or percent change in maximum or minimum temperatures, precipitation, PET, or aridity (the ratio of annual precipitation over PET) for current, mid- and end of the 21st century under the representative concentration pathway 8.5 as well as the short-term forecast from NOAA.

designed the *Sagebrush Climate Console* (http://climateconsole.org/sagebrush) to provide natural resource managers a site where CMIP5 climate projections, landscape intactness (varying from relatively undeveloped areas to highly fragmented human dominated areas), and soil sensitivity are available for a series of reporting units relevant specifically to sagebrush extent and grouse range. Addressing the feedback from surveyed users, the application also allows users to display short-term NOAA forecasts (http://www.cpc.ncep.noaa.gov/) as well as a set of relevant reference layers including the resilience-resistance map widely used for rapid assessment across rangelands (Maestas et al., 2016).

With funding from a group of western LCCs (Great Northern, Great Basin, California, and North Pacific) CBI staff designed the *Landscape Climate Dashboard* (http://climatedashboard.org) providing CMIP5 climate projections as well as soil sensitivity (the result of a decision support model) and vegetation change projections (from the vegetation model MC2) specifically for federally and tribally protected lands in the western USA.

4. Data sources

4.1. Historical climate data sources

In the consoles, we used climate data for the historical period (1971–2000) corresponding to the LT71m PRISM (Parameter-elevation Relationships on Independent Slopes Model) 30 arc-second spatial climate dataset for the Conterminous United States (Daly et al., 2008). It consists of a gridded time series of monthly-modeled values for precipitation (rain + melted snow), maximum, minimum, and mean temperatures. It uses data from station networks that have at least some stations with ≥20 years of observed data. To create a grid, Daly et al. (2008) use the climatologically-aided interpolation (CAI) method with 1971–2000 monthly climatologies.

4.2. Future climate projections

The applications only display future projections under Representative Concentration Pathway 8.5 (RCP 8.5) (Moss et al., 2010; Riahi et al., 2011), which is a highly energy-intensive scenario that results from high population growth and a moderate rate of technology development without establishment of climate change policies.

We chose to include only RCP 8.5 projections because most of the managers told us they were interested in extremes. Managers in eastern Montana told us that some of the mild climate futures available did not show anything different than what they already have been exposed to due to natural climate variability so they would not change their management actions for those. We did not create consoles for policy makers trying to enforce emissions reductions but for managers who want to prepare for the worst-case scenarios.

The NEX US-DCP30 future climate dataset includes climate projections from 34 GCMs that have been statistically downscaled to 30 arc-second spatial resolution using the Bias-Correction Spatial Disaggregation (BCSD) method (Wood et al., 2004; Maurer and Hidalgo, 2008). First the bias in temperature and precipitation projections is corrected by comparing GCM results with "observations" from the PRISM dataset. The projections are then downscaled to the finer 30 arc-second rectangular grid using the complex spatial interpolation method during the "spatial-disaggregation" step (Thrasher et al., 2013).

For the California Climate Console, we selected 10 climate models (Access1.0, CanESM2, CCSM4, CESM1-BGC, CMCC-CM, CNRM.CM5,

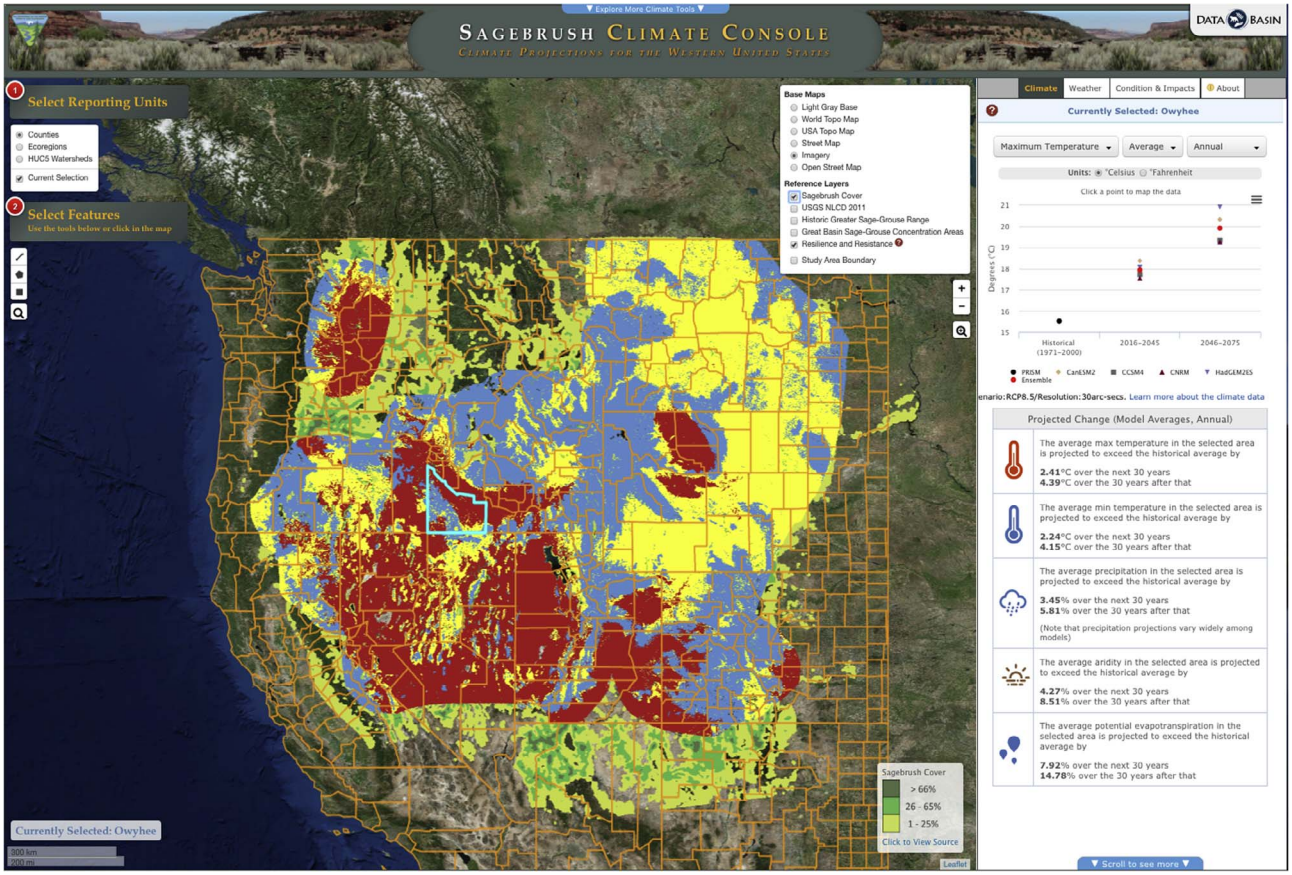

Fig. 2. Example of the Sagebrush Climate Console displaying two "reference" layers on the map, the sagebrush landscape cover (Knick et al., 2013) and the index of relative ecosystem resilience to fire and resistance to invasives (Maestas et al., 2016); the site also provides (to the right of the screen), in a text and a graphic form, the average as well as the % change in either maximum or minimum temperatures, precipitation, potential evapotranspiration (PET), or aridity (the ratio of annual precipitation over PET) for current, mid and end of the 21st century under the representative concentration pathway 8.5. Projections from four General Circulation Models (GCMs) illustrate the actual changes simulated at the four corners of the climate space for change in temperature and precipitation in the region.

GFDL-CM3, HadGEM2-CC, HadGEM2-ES, MIROC5), either General Circulation Models (GCMs) or Earth System Models (ESMs) from CMIP5 (Taylor et al., 2012). These 10 models were chosen based on evaluations of their ability to simulate historical climate conditions globally and over the southwestern United States, for the specific needs of California water resource planning (O'Daly et al., 2015). Ensemble values correspond to the average of these 10 models. Unfortunately, one of the modeling teams did not provide us with vapor pressure data and we could not run our vegetation model MC2 with these drivers. Consequently, the console only shows 9 scenarios for the climate change impacts.

For the Sagebrush Console, ensemble climate values however correspond to the average of 10 models from CMIP5 (Taylor et al., 2012) that were chosen based on evaluations of their ability to simulate historical climate conditions globally and specifically over the western United States (Rupp et al., 2013). We only display the ensemble and four climate models (HadGEM-ES "hot & dry", CanESM2.1 "hot & wet", CCSM4 "warm & dry", and CNRM-CM5 "warm & wet"), either General Circulation Models (GCMs) or Earth System Models (ESMs) that are representative of the 4 quadrants of the climate space created by the 10 models chosen by Rupp et al. (2013).

For the Climate Dashboard, climate projections from 9 models (CanESM2, CCSM4, HadGEM2-CC, HadGEM2-ES, IPSL-CM5A-MR, NorESM1-M, BCC-CSM1-1-M, MIROC5, CSIRO-Mk3.6.0) are displayed. The nine models capture a wide range of projected change for both annual average temperature and annual precipitation under the highly energy-intensive scenario representative concentration pathway 8.5 (RCP 8.5; Meinshausen et al., 2011; van Vuuren et al., 2011). Models were chosen based on evaluations of their ability to simulate historical climate conditions globally and over the western United States (Rupp et al., 2013) and only 9 of the 10 models chosen by Rupp et al. provided enough information to run our vegetation model MC2.

4.3. Decision support models

4.3.1. Environmental evaluation modeling system (EEMS)

Sheehan and Gough (2016) created a decision support tool called the *Environmental Evaluation Modeling System (EEMS)*. It is an application that allows users to build and explore tree-based logic models using normalized spatial datasets. Spatial data are converted into fuzzy space (i.e. normalized between −1 "totally untrue" and +1 "totally true") and fuzzy logic operations are used to combine nodes hierarchically until a final value representing the answer to a particular question is produced. The user interface for EEMS has been designed as an interactive transparent web tool that shows each spatial layer as a box in the logic tree. It is possible to display every spatial layer used to arrive at the logical conclusion of the logic tree by clicking on every box. When the user clicks on one of the box, not only does the console display the map layer but the other layers that were used to create it are brought up (as other clickable boxes) to explain how the layer was created. At the very bottom of the logic tree, the original raw data are displayed in grey colored boxes.

4.3.2. Soil sensitivity and exposure

Soil sensitivity was developed using EEMS. In the consoles, we defined potential impact as a combination of "site sensitivity" defined

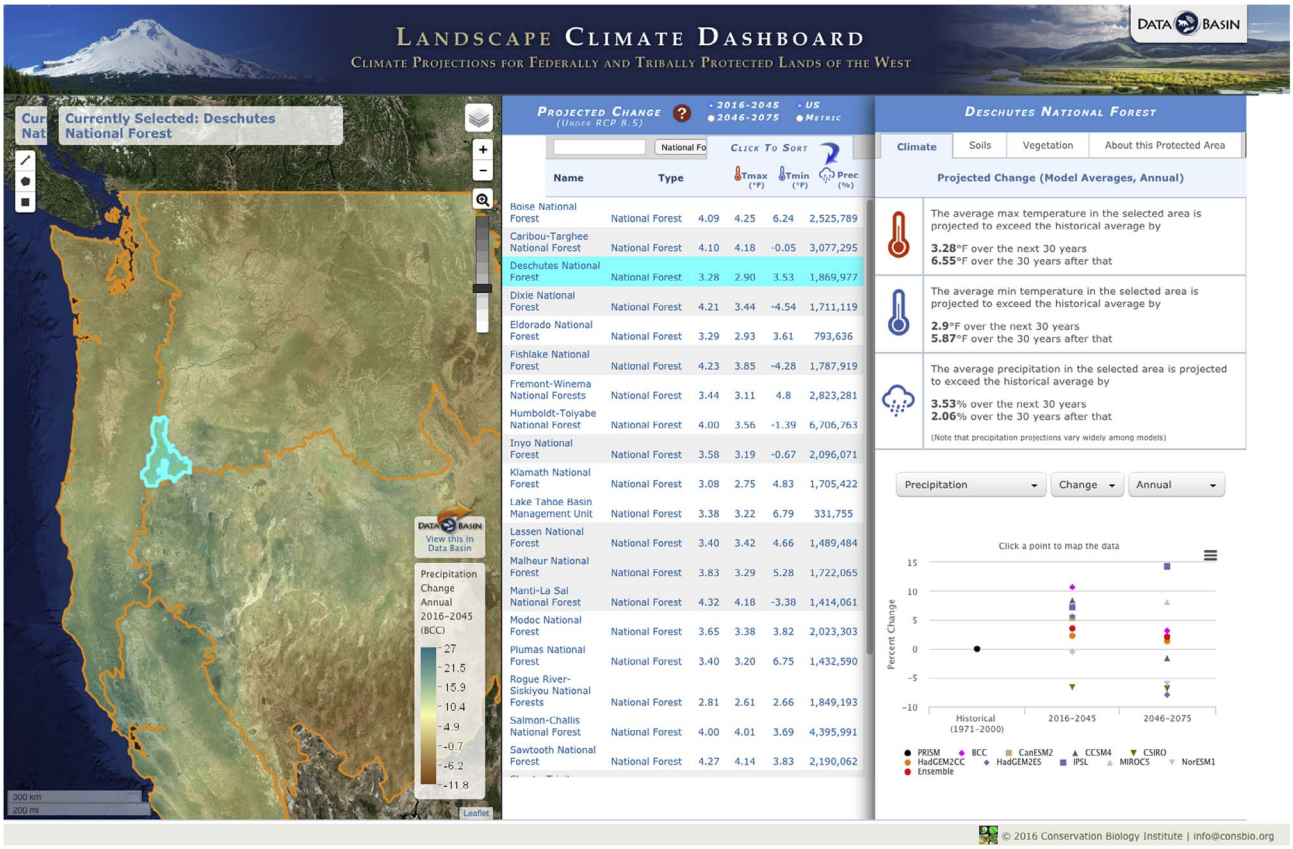

Fig. 3. Example of the Landscape Climate Dashboard displaying the list of national forests in the western US; the average change in maximum and minimum temperature as well as the % change in precipitation is displayed here specifically for the Deschutes National Forest (Oregon, USA) over the next 30 years under the representative concentration pathway 8.5. Climate variables have been averaged for 9 climate models.

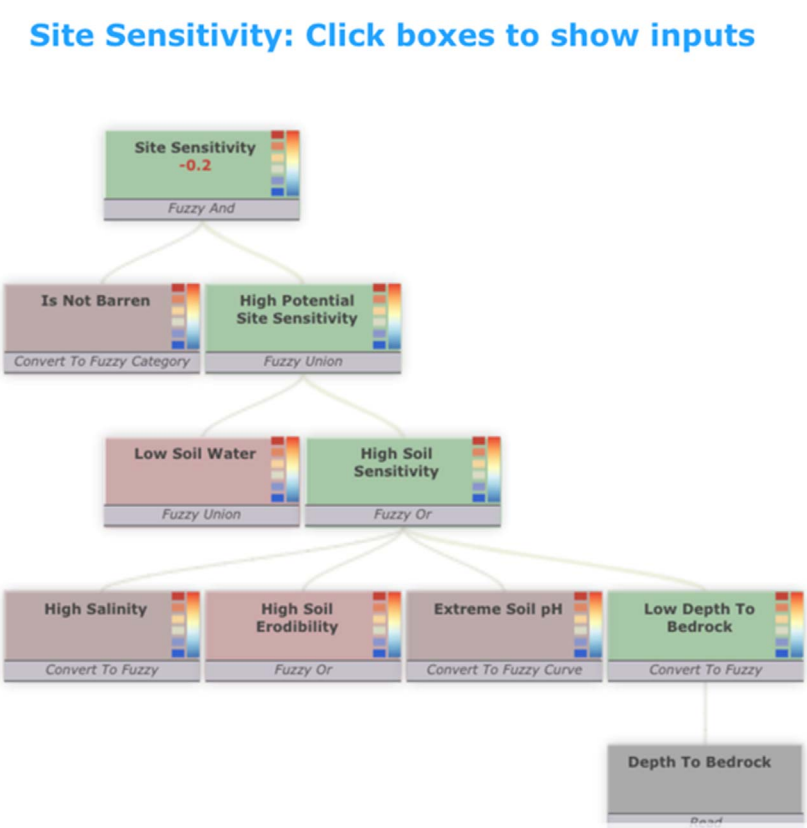

Fig. 4. Example an Environmental Evaluation Modeling System (EEMS) model displaying the site sensitivity logic model. The logic tree includes data on the depth to bedrock, soil pH, wind and water erodibility, salinity, available water capacity, PE, that are combined to quantify the site sensitivity to climate change currently entirely based on soil data. Clicking on each of the logic tree boxes allows the user to discover how each spatial layer has been generated.

only by soil characteristics and "climate exposure" describing the degree to which a site may experience climate change. The entire logic tree used to create the final soil sensitivity map can be explored in the console and with eemsonline.org. Soil data for this analysis were obtained from the conterminous United States Multi-Layer Soil Characteristics data (Miller and White, 1998) and the STATSGO soil database (Soil Survey Staff, 2015). Climate data sources are described above.

4.3.3. Climate impacts

The Dynamic Global Vegetation Model MC2 (Bachelet et al., 2015) was run from 1895 to 2100 for 9 future climates under RCP 8.5 for the state of California (Baker et al., 2017). The simulated vegetation types were aggregated into broad categories and displayed on the console. The model simulated the pools and fluxes of carbon such as net primary production, net biological production, aboveground dead biomass, biomass consumed by fire, as well as some hydrological fluxes such as surface runoff and actual evapotranspiration (AET) associated with the various land cover and included land use change.

5. Software implementation

5.1. Viewer software and GIS processing

All the applications described in this paper are developed in Django, an open-source python-based web framework. The consoles are built on a single generalized Django web application, the framework of which is developed and maintained by CBI staff, which typically involves general updates, bug fixes, and improvements. Note that you can switch between consoles by clicking the "Explore More Climate Tools" pull down menu at the top of the screen. The back-end (server side) code used to process users requests varies between consoles, as does the front-end templates, reporting units, etc., but they share much of the same code base (for example, a single JavaScript file is used to create the climate charts that you see on the main tab of each console).

Spatial data used in each console are stored in the same centralized PostgreSQL/PostGIS database and queried against using raw SQL and spatial queries generated through user actions on the front end (e.g., a map click or a selection made on one of the dropdown menus). Query results are packaged into JSON format and sent from the server to the front end for display in the charts. Front-end components were developed using JavaScript/JQuery, Ajax, HTML, and CSS. Several open-source JavaScript libraries were also employed (including Leaflet, Highcharts, JIT, Alertify, intro.js, and selectBoxIt) in addition to several custom libraries developed at CBI.

Post-processing of the climate and EEMS data for integration into the PostGIS database was conducted in ArcGIS 10.3 (ESRI, 2017) using a combination of python scripts, script tools, and Model Builder models. Each climate dataset was converted from NetCDF format to a file geodatabase raster, and subsequently projected to a coordinate reference system appropriate for the study area using a cubic convolution resampling method and an output spatial resolution of 1 km. The zonal means for each raster dataset was then calculated for each of the reporting units and iteratively joined back to the attribute table of the reporting units dataset. Each reporting units dataset was then projected to GCS WGS84 (EPSG 4326) (in shapefile format) and simplified using mapshaper (mapshaper.org) in order to reduce the complexity of the polygons and the number of vertices. Each reporting units dataset was then inserted into the PostGIS database using the PostGIS Shapefile Import/Export manager.

5.2. Data processing

5.2.1. Climate data preparation

All PRISM data used for the historical period were converted from the ESRI ASCII raster format (ESRI, 2014) to the Network Common Data Form (NetCDF; Rew et al., 1997; UNIDATA, 2015). We then compared the PRISM NetCDf files to the NEX dataset. We discovered that, when the NEX data were processed by Thrasher et al. (2013), the left lower corners of the PRISM data were incorrectly used as the center coordinates in the downscaling process of the NEX NetCDF files. Therefore, the origin of the NEX US-DCP30 data had to be altered to conform to the PRISM files. The NEX grids were adjusted by one-half grid cell (0.004166666667 decimal degrees) so that the two datasets would be spatially aligned and consistent.

Once all of the data were in the NetCDF format and spatially aligned, the climate variables, maximum average monthly temperature, minimum average monthly temperature, and average monthly precipitation were extracted from the historical and future climate datasets. We calculated a multi-model ensemble for each of the variables by taking the un-weighted mean for all future projections. All NetCDF files and calculations of the five climate variables (minimum and maximum temperature, precipitation, aridity, and potential evapotranspiration) were processed in the NCAR Command Language (NCL) software program (NCL, 2014).

We created three thirty-year climatologies (1971–2000, 2016–2045, and 2046–2075) directly from the NetCDF files for each climate variable. The monthly data were averaged as annual mean maximum and minimum temperatures and summed as annual total precipitation and then averaged of each of the three thirty-year periods.

Two derived climate variables, *potential evapotranspiration* (PET) and aridity (ratio of annual precipitation over PET), were also generated. PET was calculated using the 1985 version of the Hargreaves potential evaporation equation (Hargreaves and Allen, 2003):

$$\mathrm{PET} = 0.0023 \times 0.408RA \times (\mathrm{Tavg} + 17.8) \times \mathrm{TD}^{0.5} \tag{1}$$

where RA is the extraterrestrial radiation ($\mathrm{MJ\,m^{-2}\,d^{-1}}$), Tavg (°C) is the average daily temperature, and TD (°C) is the temperature range. The constant 0.408 is the inverse of latent heat flux of vaporization at 20 °C. It is used to convert extraterrestrial radiation units from $\mathrm{MJ\,m^{-2}\,d^{-1}}$ to $\mathrm{mm\,d^{-1}}$. RA was calculated using the r.sun (Šúri and Hofierka, 2004) routine in the GRASS geographic information system (GRASS, 2015).

Aridity was defined as P/PET where P is annual precipitation. The percentage change in aridity was calculated by following Feng and Fu's method (2013):

$$\Delta(\mathrm{P/PET})/(\mathrm{P/PET}) \approx (\Delta P/P) - (\Delta \mathrm{PET/PET}) \tag{2}$$

where P is the annual total precipitation (mm) and Δ (delta or change value) is calculated by subtracting historical values from future values; for precipitation and aridity, change was calculated as a percent change from the historical (((future-historical)/historical) ∗ 100).

5.2.2. Decision model data preparation

Input data to EEMS models were normalized between −1.0 and +1.0. The inputs were then combined using logic operators to create a decision tree. Each grid cell in the study area was evaluated independently. Models were implemented using data in NetCDF format.

All soil variables were downloaded for the conterminous United States from the State Soil Geodatabase (SSURGO), or NATSGO when SSURGO was not available (https://soilseries.sc.egov.usda.gov/osdname.asp), and processed in ESRI ArcInfo workstation (ESRI, 2014). Polygon data were converted to a raster dataset with a cell size of 0.0083333333 decimal degrees. The data were then clipped to the western United States and exported in NetCDF format.

Susceptibility to water erosion was calculated from the Universal Soil Loss Equation (Wischmeier and Smith, 1978):

$$A = R*K*L*S*C*P \tag{3}$$

where A is predicted average annual soil loss, R is measured rainfall erosivity, K is soil erodibility, L is slope length factor, S is steepness of the slope, and C and P represent the respective erosion reduction effects

of management (C) and erosion control practices (P).

L and S can be combined to represent the role of topography in erosion (Hickey, 2000):

$$LS = (As/22.13)^{0.4} \times (\sin\theta/0.09)^{1.4} \times 1.4 \quad (4)$$

where As is the unit of contributing area (m), θ is the slope in radians. We then combined the K factor with LS to estimate the susceptibility of a soil to water erosion.

Climate Exposure uses maximum temperature, minimum temperature, and precipitation on a seasonal basis and an annual basis. Change was calculated for two future time periods, 2016–2045 and 2046–2075, compared to the historical period, 1971–2000. Projections from each of the climate futures were used along with ensemble mean values from those models. Temperature and precipitation differences were normalized using the standard deviation over the historical period:

$$D = (Xf - Xh)/SIG_{Xh} \quad (5)$$

where D is the difference, Xf is the mean of the variable in the future period, Xh is the mean of the variable in the historical period, and SIG_{Xh} is standard deviation of the variable in the historical period.

Site Sensitivity and Climate Exposure models contribute equally to the Potential Climate Impact model. As with the Climate Exposure Model, the Climate Impacts Model was run for each climate future. Run results using ensemble climate data are displayed on the Console.

5.3. Real-time mapping

For map display purposes, each NetCDF file used in these applications was converted to a PNG using a custom python script and Clover (a python-based NetCDF utility developed at CBI). When a user clicks any data point in one of the charts, the corresponding PNG is retrieved from the server through an AJAX request and displayed in the map using Leaflet's image Overlay function.

6. Discussion and final remarks

Potential users of climate science research are often unable to access or interpret the vast array of available climate science research results (Kemp et al., 2015). They also do not have time to search for or read the volumes of reports and new papers published continuously on the subject (Berrang-Ford et al., 2011). Furthermore the media have focused not on the strengths of climate models but on the uncertainty of their simulations, creating a maelstrom of controversy that has deterred decision makers from using model results while climate research moves on and models continue to improve. The simple attitude of using models as tools to synthesize and explore gaps in current knowledge seems to have been forgotten. While a reasonable discussion of current scientific knowledge and limitations could actually enhance the dialogue between managers and decision makers to prepare for an uncertain future, it now behooves scientists and software developers to create an environment conducive to evaluating and sharing usable climate science results (Dilling and Lemos, 2011) with non-experts who might bring competing perspectives and values (Feldman and Ingram, 2009).

Visual analytics, "analytical reasoning facilitated by interactive visual interfaces" are used "to synthesize information and derive insight from massive, dynamic, ambiguous and often conflicting data /…/ [and to] provide timely, defensible, and understandable assessments" (Thomas and Cook, 2005). Visual interactive representations are thus an appropriate tool to allow natural resource managers and decision makers "to see, explore, and understand … at once" the large amount of information produced by climate change scientists.

Audiences also request significant uncertainty guidance with both quantitative and qualitative metrics of uncertainty for their climate risk assessments and adaptation strategies. To address this difficult challenge, CBI has created a series of climate consoles that not only offer the most recent climate projections for a suite of climate models and not just an ensemble mean but also allow for presentation and dissemination of this information to and by a range of audiences beyond stakeholders of the various projects that funded the tools. CBI staff have done surveys and held workshops to present the tools to colleagues and organizations that could use them and address adaptive management guidelines and legal requirements towards climate change adaptation. Since the tools can always be refined, feedback from users is invaluable and continuous dialogue between users, information producers and software developers is critical to the development of sites that will yield practical applications (Feldman and Ingram, 2009; Dilling and Lemos, 2011).

Stakeholders for the various climate consoles designed by CBI have been decision makers, natural resource managers, and practitioners. Uncertainty levels about future climate projections have been shown to be influenced by stakeholders' beliefs about climate change, their own experience with extreme events, concern about their community or their area of interest, and their access to relevant information (Morton et al., 2017). If most of stakeholders' uncertainty is caused by insufficient information, improved access to climate records, as well as decision support tools that simulate different climate scenarios and their impacts, can improve evaluation of future risks and willingness to consider adaptation strategies. However, more information may be insufficient to address claims of uncertainty when differing political and cultural norms contest the parameters of climate change (e.g. Adger et al., 2013; Funk and Kennedy, 2016). This suggests that ultimately scientific knowledge must be linked to social values and beliefs and trusted sources of information for widespread adaptive management to a changing climate to occur. (See Figs. 1–4)

Software availability

Software name: CBI Climate Consoles and Dashboard

Software URL: http://climateconsole.org and http://climatedashboard.org

Developer: Mike Gough, Conservation Biology Institute (CBI)

Contact information: bacheled@oregonstate.edu

Software required: Internet browser Firefox or Chrome

Hardware required: Any web-enabled device

Program languages: Python, Django, JavaScript/JQuery, Ajax, HTML, CSS

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