AMERICAN
METEOROLOGICAL
SOCIETY

Bulletin of the American Meteorological Society

The DOI for this manuscript is doi: 10.1175/BAMS-D-14-00090.1

The final published version of this manuscript will replace the preliminary version at the above DOI once it is available.

If you would like to cite this EOR in a separate work, please use the following full citation:

Mote, P., M. Allen, R. Jones, S. Li, R. Mera, D. Rupp, A. Salahuddin, and D. Vickers, 2015: Superensemble regional climate modeling for the western US. Bull. Amer. Meteor. Soc. doi:10.1175/BAMS-D-14-00090.1, in press.

Superensemble regional climate modeling for the western US

Philip W. Mote[1], Myles R. Allen[2], Richard G. Jones[3], Sihan Li[1], Roberto Mera[1,4], David E. Rupp[1], Ahmed Salahuddin[5], Dean Vickers[5]

Corresponding author:

Philip Mote

Oregon Climate Change Research Institute

College of Earth, Ocean, and Atmospheric Sciences

CEOAS Admin Building 104

Oregon State University

Corvallis, OR 97330

tel. 541-913-2274

email pmote@coas.oregonstate.edu

[1] Oregon Climate Change Research Institute (OCCRI), Oregon State University, Corvallis OR
[2] School of Geography and the Environment, Oxford University
[3] Met Office Hadley Centre, Exeter, UK
[4] Now at Union of Concerned Scientists
[5] formerly with OCCRI, now unaffiliated

revised 2/20/2015

Abstract. Computing resources donated by volunteers have generated the first superensemble of regional climate model results, in which the Hadley regional model HadRM3P and atmospheric global model HadAM3P were implemented for the western US at 25km resolution. Over 136,000 valid and complete one-year runs have been generated to date: about 126,000 for 1960-2009 using observed sea surface temperatures (SSTs) and 10,000 for 2030-2049 using projected SSTs from a global model simulation. Ensemble members differ in initial conditions, model physics, and (potentially, for future runs) SSTs. This unprecedented confluence of high spatial resolution and large ensemble size allows high signal-to-noise ratio and more robust estimates of uncertainty. This paper describes the experiment, compares model output with observations, shows select results for climate change simulations, and gives examples of the strength of the large ensemble size.

Capsule. Volunteers contributing idle computing time are helping to create an unprecedented combination of high spatial and high statistical resolution in simulations of climate in the western US for 1960-2009 and 2030-2049.

1. Introduction

Climate system modeling has made tremendous advancements in recent decades. Rapidly expanding computational capabilities and scientific research on fundamental processes have allowed simultaneous progress on a variety of fronts, such as expansion of the processes represented in climate models including interactive carbon cycles represented by biogeochemical models (e.g., Flato 2011), increases in spatial resolution (global models now providing century-long runs at grid spacing as low as ~50km), and the number of simulations possible with a given model.

One area of research currently at the crossroads of basic research and applications is the description of present and future climate at spatial scales that are meaningful both scientifically and for management applications (e.g., Means et al. 2010). Regional climate models (RCMs, e.g. Giorgi 1990) have been implemented over specific areas of interest with resolutions as high as 500m (Wang et al. 2013) compared to 50-300 km for a GCM. Typically, such studies run the RCM one or at most a handful of times. The problem with having a very small number of simulations is that differences between past and future simulations can stem from several sources, not just the change in greenhouse gases: uncertainty is not well quantified. As O'Brien et al. (2011) note, some studies tacitly assume "that differences between model simulations are entirely due to a physical forcing" and show that internal variability can be larger than the signal in some instances; they also show that an ensemble of even 4 members can sometimes isolate physical responses from random internal variability. A variety of lines of evidence suggests that, depending on the quantity of interest, a minimum of 8-10 simulations may be needed just to achieve a robust estimate of the mean value of some global and regional quantities (see Mote et al. 2011), and far more if the desired quantity is an accurate measure of the uncertainty, e.g., the standard error of the mean. From large numbers of simulations, we may also better represent the probability distribution of the underlying population, which, for example, allows for direct calculation of the N-year return period. The return period (RP), used frequently with precipitation or streamflow data in risk analysis and design, is the average number of years N between those years in which an event x (e.g., the heaviest one-day rainfall of the year) of some magnitude is exceeded, and is calculated as $RP(x) = 1 / [1 - F(x)]$, where $F(x)$ is the cumulative distribution function of x.

Usually, estimates of uncertainty are derived by sampling available model results, without directly addressing the contributions from natural variability and model formulation; by contrast, Hawkins and Sutton (2011) explicitly quantified these different sources of uncertainty for global models, and Northrop and Chandler (2014) further investigated distributions for which the number of model runs is variable. Disentangling the contributions of natural variability, model formulation, and emissions scenario remains an important challenge requiring large numbers of simulations with a careful research design.

Figure 1 illustrates the tradeoff between spatial resolution and number of simulations in currently available climate modeling runs. Numerous global simulations are available through the Coupled Model Intercomparison Project 5 (CMIP5; Taylor et al. 2012): some modeling groups have provided, through the CMIP5 data portal, as many as 40 simulations of the 21st century, using 4 scenarios of future greenhouse gas concentrations known as Representative Concentration Pathways or RCPs. This large ensemble allows a rigorous quantification of uncertainty resulting from internal variability, anthropogenic forcing, and model formulation: In aggregate, CMIP5 provides several hundred simulations of future climate, each with up to 4 RCPs and up to 17 ensemble members constructed using different initial conditions. There is also an ensemble of 40 runs with the NCAR CCSM3 (Branstator and Tang 2010). However, the spatial resolution of the global models is inadequate for most impacts studies; statistical downscaling cannot properly represent important processes like snow-albedo feedback, so the downscaled changes may be inaccurate.

Over the past several years, more concerted efforts to generate ensembles of regional modeling have emerged. In some, the multiple GCMs drive a single RCM (4 in Duffy et at., 2007; 2 in Salathé et al., 2010; 3 in Deque et al, 2012; 3 in Hostetler et al. 2012). In addition, several coordinated ensemble modeling projects have been conducted with regional models. “Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects” (PRUDENCE; Christiansen et al, 2007), ran between 1 and 5 simulations using 8 RCMs at 50km over Europe, for 1961-90 and 2071-2100. The North American Regional Climate Change Analysis Project (NARCCAP; Mearns et al. 2009) had 12 simulations using 6 RCMs over the United States and Canada, also at 50km resolution, for 1971-2000 and 2041-2070. Other examples include ENSEMBLES (van der Linden and Mitchell 2009) involving 14 RCMs run over Europe and CLARIS (Boulanger et al., 2010) involving 7 RCMs run over South

America.

Recognizing that these efforts are limited to specific regions and do not follow a common experimental design allowing for cross-region comparison, the World Climate Research Programme initiated the Coordinated Regional Downscaling Experment (CORDEX) programme (Giorgi et al, 2009). CORDEX has defined standard RCM domains covering all land areas and some elements of an experimental protocol including a comprehensive diagnostic list and data/ meta-data format specifications. Importantly, in liaison with the global modeling community it was agreed that the data archiving protocol for CMIP5 would include 6-hourly 3-D data suitable for conversion to boundary conditions for RCMs. Initial results from CORDEX have included assessment of multi-RCM simulations driven by the new European Centre for Medium Range Weather Forecasts Reanalyses (ERA) dataset, ERA-Interim (Dee et al., 2011), over Africa (Nikulin et al. 2012) and Europe (Vautard et al., 2013) and an initial climate projection experiment driven by a sub-set of the CMIP5 GCMs over Europe (Jacob et al., 2013).

Though these coordinated ensemble downscaling simulation and projection experiments are a significant advance on earlier work, they still only involve relatively short simulations (20-30 years) of the climate of the recent past or single realizations of future climate change. These are sufficient to assess the ability of the models to represent mean climate and some aspects of climate variability and its drivers (e.g. Endris et al, 2013 and Kalognomou et al., 2013 for Southern and Eastern Africa respectively) or changes in these quantities (e.g. Laprise et al., 2013 for Africa).

However, for establishing robust estimates of higher moments of variability and extremes, and changes therein, requires the relevant climate states to be much better sampled. (The fact that studies are increasingly using multiple RCMs is potentially of use in this context, but the influence of differences in formulation on the results from such an ensemble make it difficult to argue that results from these simulations can be pooled to represent a common climate or changed climate). This is particularly relevant when assessing changes in the risk of extremes under transient climate where defining the "climate" of a particular decade or 30-year period can only be done by constructing multiple samples of the climate of the period in question. As demonstrated by Kendon et al. (2008), obtaining reasonable estimates of changes in moderately high intensity precipitation events (e.g. 95th or 99th percentiles of daily precipitation) in relatively high resolution RCM projections for a 30-year period requires multiple realizations of the projected changes.

To these other modeling efforts, each of which has strengths and weaknesses, can now be added the work presented here. It represents a significant advancement in simultaneously solving the problems of spatial resolution and large number of simulations (Fig. 1). By running a nested global-regional model on volunteers' computers, we have compiled over 136,000 simulated years (a "superensemble") at 25 km resolution - and the archive of simulations will continue to grow. This paper briefly describes the approach, compares the simulated results with observations, and provides a few examples of the advantages of the high resolution superensemble. Shortcomings of this approach, discussed in section 4, include the use of only one GCM, and the difficulty of generating long continuous runs. No regional modeling approach, including this one, simultaneously solves the challenges of high spatial resolution, complete process representation (including carbon cycle), and complete exploration of uncertainties.

2. ClimatePrediction.Net applied to the western US

Allen (1999) proposed using volunteers' computers to run large numbers of simulations with a global climate model; in 2003, climateprediction.net (CPDN) was publicly launched. CPDN uses various versions of the Hadley Centre's global climate model, configured to run on a personal computer. Using the "Berkeley Open Infrastructure for Network Computing" (BOINC, Anderson 2004), CPDN has leveraged the resources of tens of thousands of volunteers around the world to produce superensembles of climate simulations with many thousands of members and totaling over 126 million model-years and counting (Massey et al. 2014).

The chief strength of the CPDN approach (shortcomings are covered in the Discussion section) is that with this vast computing resource, large numbers of simulations can be performed to quantify various sources of uncertainty, including those associated with model formulation through the use of perturbed physics ensembles (Murphy et al., 2004). Perturbed physics ensembles are a way to explore the effects on simulated climate of specific parameter choices for a set of parameters. Using a parameter sampling approach described by Rowland (2011), each parameter is varied across its range in combinations of parameters that are selected to span multidimensional parameter space. Parameter combinations are evaluated both to determine the realism of the simulated climate compared with observed (20th century) climate, and to determine the climate sensitivity (Stainforth et al. 2005).

While large ensembles of global models (like CMIP5 and climateprediction.net) are valuable for quantifying uncertainty, they cannot by themselves solve another challenge of climate modeling: to quantify the likely changes at spatial scales that may be useful for applications, especially in regions of sharp spatial variations. The climate of the western United States varies greatly over short distances because of the effect of mountains and, near the coast, the ocean. Processes involving interaction between airflow and mountains, coastal fog and stratus, sea breezes, snow-albedo feedbacks, thin coastal clouds, and drainage of cold air in valleys, all conspire to produce vegetation ranging from wet temperate coastal rain forests to ice-covered mountain ranges to arid scrublands, all of which exist within 100 kilometers of each other in some places. These processes are likely as well to shape the regional response to the changing large-scale climate (see, for example, Leung et al. 2004 and Salathé et al. 2008).

The objective of the regional CPDN project (known as Weather@Home) is, to put it simply, to occupy the useful upper left corner of Figure 1: to simulate past and future regional climate with a novel combination of fine spatial resolution and very high number of simulations. Weather@Home nests the Hadley Regional Model HadRM3P (Jones et al. 2004) at 25 km spatial resolution over the western US (see Figure 2a) in the global atmospheric model HadAM3P, which runs at a spatial resolution of 1.25°×1.875° and 19 vertical levels; Weather@Home is also running in Europe, Africa, South Asia, and Australasia. The HadAM3P/HadRM3P model formulation is based on the atmospheric component of the HadCM3 climate model (Gordon et al., 2000). It consists of a coupled atmospheric and land surface model representing processes related to dynamical flow, atmospheric sulphur cycle, clouds, precipitation, radiation, land surface, and deep soil. The atmospheric component is a hydrostatic version of the full primitive equations with 19 vertical levels. The land-surface component comprises MOSES 2.2 (Met Office Surface Exchange Scheme version 2.2), which is a tiled land surface scheme (Essery et al., 2001) with soil moisture and temperature simulated over 4 soil levels. For a more complete description of the model configuration see Massey et al. (2014).

HadRM3P over this domain was initially configured and tested using reanalysis datasets for the period 2003-2007 and was also nested in the HadCM3 model and run for 100 years (Zhang et al 2009). To evaluate the regional simulation, they compared HadRM3P, WRF36 (Weather Research and Forecasting regional model at 36 km resolution), WRF12 (12km), and station observations for both means and extreme events (Zhang et al 2009; Dulière et al. 2011). Simulations for surface temperature were about as skillful for HadRM3P as for WRF-12, while for precipitation the HadRM3P simulation showed slightly less skill.

The process of building this superensemble begins when a volunteer registers with BOINC and obtains a task from the BOINC server at Oxford University, and the task runs on his/ her computer while it is idle. A display allows the user to check on the progress of the simulation, providing a visible reward and sense of engagement. A volunteer can also track, either as an individual or as team of volunteers, the total number of simulations completed and compare them to other volunteers. Our simulations are designed to last for one model year, though for a variety of technical reasons not all are completed (see Massey et al. 2014 for details). After the simulation finishes (typically after about 1 week in real time), the task post-processes the results and uploads them to the master database, hosted at Oregon State University (Fig. 2b).

The first set of simulations, which has now been completed, started between 2000 and 3740 work units on December 1 of certain years between 1959 and 2009 (Fig. 2c). These simulations included both standard physics, started every 5th year (1959, 1964,...) and perturbed physics (where the physical parameters were perturbed in the global model, and runs were started in every year). Initial conditions for the global model were also perturbed in both sets of runs by adding 3-D perturbations to the potential temperature field. These perturbations are calculated by first taking 348 next day differences from a 1-year integration of the global model, scaling the differences in the vertical, and then multiplying the perturbation fields globally by 1.1, 1.2, 1.3, 1.4 and 1.6 to generate a set of 1740 initial condition perturbations (for details see Massey et al. 2014). Although these initial condition perturbations are only applied in the global model, they immediately affect the regional simulations. A restart file containing information on the state of system at the end of the simulation period is uploaded to the server at Oxford and sent out with the same model binary file as a new task: the totals shown in each year (Fig 2c) include such runs, which explains why there is a declining (but still large) number of runs for the standard physics runs, in years following the first year of each set (1959 etc.). A file management error removed some of the first-year runs which is why there are more second year runs. For lower boundary conditions, these simulations use the HadISST v1.1 data set (Rayner et al. 2003) to specify the sea surface temperature and sea ice concentration for each month. Land surface (i.e. soil temperature and moisture) initial conditions were prescribed from a model climatology.

During simulation, GCM fields are fed to the RCM each day. HadAM3P runs for one day, a subset of global fields are saved for averaging and diagnosis, and 19 prognostic fields are saved in the sponge layer (several grid points bounding the domain) every 6 model hours. Then HadRM3P runs for one day, using the saved GCM data applied in the sponge layer as boundary conditions (as described in Jones et al., 1995). RCM outputs are not fed back to the GCM. This process is repeated until the end of the month when monthly diagnostics are performed, including the identification of extreme daily values of precipitation, wind speed, and maximum and minimum temperature. Small monthly "trickle" files consisting of regionally and globally averaged values of temperature are sent back to the BOINC server so that it can track progress of the work unit. As of January 2015, 136,124 complete and valid runs have been returned to the OSU server and retained after quality control: 52,150 historical standard physics, 73,961 historical perturbed physics, and 10,013 future runs.

For the simulations of future conditions, SST values consist of HadISST data to which have been added temporally smoothed fields of SST changes derived from long

CMIP5 simulations from HadGEM2-ES, using the forcings given by the Representative Concentration Pathway (RCP) 4.5 (van Vuuren et al. 2011; Taylor et al. 2012), a moderate greenhouse gas concentration scenario.

3. Comparison with observations

A thorough comparison with observations, along with assessment of the suitability of different observational datasets, is beyond the scope of this paper. We provide some illustrative comparisons of both spatial and temporal patterns, and for simplicity, we focus on the standard physics simulations. For spatial patterns of temperature we use the North American Regional Reanalysis (NARR, Meisinger et al. 2006) which has a spatial resolution of 32 km. NARR and Weather@Home are interpolated onto a common 25-km grid and are adjusted for elevation using a standard lapse rate of 4.5°C/ km (Minder et al. 2011) for the Cascades and Sierras, and 6.5°C/ km elsewhere (the choice of lapse rate only affects correlations by at most 0.02).

In Weather@Home and NARR, the influences of terrain and coastal moderation are obvious in the temperature field, with mountain ranges typically at least 5°C cooler than surrounding low terrain (Figure 3): the spatial correlation between panels (a) and (b) is 0.98. The mean difference is -0.66°C, and the differences shown in Figure 3c are less than 2°C at a large majority of grid points and are not statistically significant ($p<0.05$, 2-sided t-test) except at a small fraction of grid points. Weather@Home tends to be too cool in a few mountain ranges and too warm in arid plains including the Snake River plain and Columbia plateau, especially in summer (not shown).

As an example of temporal variability, we compare the regionally averaged temperature from Weather@Home and NCDC's regionally averaged temperatures based on US Historical Climate Network data (Figure 4). The 50-year trends are nearly identical: 0.011°C/ yr for Weather@Home and 0.015°C/ yr for observations. Moreover, the correlation between the two time series is statistically significant with r=0.67. Because the only source of interannual variability common to both the instrumental record and the Weather@Home simulations is the global pattern of sea surface temperatures, this high correlation indicates the importance of sea surface temperatures. The observed variability is larger because the model curve (black) is an average of a large number of runs in each year - in a sense, the observations only sample the space of physically plausible climate states at the rate of one state per year whereas Weather@Home provides a more thorough sampling. Not only is there general agreement between Weather@Home and NARR on the trend and on individual warm and cool years, the shapes of the curves are similar, including a slight reduction in temperatures after the late 1990s consistent with the known combination of forcings (Abatzoglou et al. 2014).

Most studies of climate change focus on monthly mean changes in temperature and precipitation, but impacts of climate change on ecosystems and society involve other variables and shorter time periods. As implemented in the western US, the Weather@Home framework produces a total of over 40 output variables (Table 1). These output variables were designed with societal and environmental applications in mind and in consultation with end users, the better to inform a wide range of decisions. Figure 5 shows the rate of change in snow water equivalent (the depth to which water would cover the surface if melted), calculated by linear regression of April 1 observed values and monthly mean April values from the ensemble means (500 per year) 1960-2009. Nearly all mountain areas in the West show a reduction, and the correspondence between the model and observations is striking (see also Mote et al. 2005, Pierce et al. 2009). The biggest differences are in the southern Sierra Nevada mountains at moderate to high elevations, where as Mote (2006) showed, increases in temperature more than offset increases in precipitation to produce increases in observed Snow Water Equivalent over this period.

4. Results

We present a representative sample of interesting results, providing illustrations of the high statistical resolution, high spatial resolution in representing patterns of change, and the value of the superensemble in improving estimations of the mean and of statistical distributions.

With this superensemble we can study extremes with more statistical robustness. Our model outputs (Table 1) include the first, second, and third highest daily precipitation totals in each month, as well as the 3 highest high temperatures and the 3 lowest low temperatures (this approach uses less output disk space and I/O than saving daily values for the entire month). Figure 6 compares the return period curves (see section 1 for definition) for June-July-August maximum one-day temperature, for 4500 simulations each in the 1960s and the 2000s over California and Nevada. Results show an increase of, on average, 0.6°C at each return period. Or to put it another way, the return period of a given threshold drops by roughly a factor of 2-5 from the 1960s to the 2000s. Robust estimation of return periods using just a single decade is possible because each year contains hundreds of simulations representing different conditions that are physically consistent with the boundary forcing in that year. The error bars are acquired as follows. We sample the 4500 simulations 2000 times, with replacement, generating a return period curve for each sample. From these, the mean and 2.5 and 97.5 percentiles are extracted for each temperature, and also for each return period.

A chief benefit of a regional model is to understand the patterns of regional climate change, but as O'Brien et al. (2011) pointed out, differencing two regional model runs may conflate real physical changes with statistical noise because of small sample size. Our superensemble improves the likelihood that differences are physically meaningful. Figure 7 compares the simulated warming from the past (linear fits at each grid point for 1960-2009) with differences between the future runs and past runs, converted to °C/ yr for comparison. Average warming is greater in panel (b), consistent with global model simulations that show an acceleration in warming for early 21st century compared with late 20th century for the Northwest (Mote et al. 2013) as well as globally (IPCC, 2013). For the simulated past, warming rates are least in coastal gridpoints (especially around the San Francisco and Monterey Bay areas), and most in mountainous areas and in the inland states. Future warming has similar patterns but larger magnitudes. The enhanced warming in the Cascades and Sierras is dominated by enhanced springtime warming (not shown) associated with depletion of spring snowpack (Fig 5).

With such large ensembles, we can investigate other statistical properties of climate that are difficult to deduce from observations alone or from small numbers of simulations. Figure 8 shows the range in estimates of regional mean precipitation for ensembles of increasing size, averaged over the whole domain, for a single year. Although the mean is roughly the same, if only a single simulation is selected, it could differ from the ensemble mean by as much as 50%, whereas the spread decreases rapidly with ensemble size, illustrating the point made in the introduction and by O'Brien et al. (2011) that larger ensembles reduce the signal to noise ratio especially for sub-regional features.

5. Discussion

A series of previous studies (Deser et al. 2012, 2014; Wettstein and Deser 2014; Kay et al. 2015) have examined the impact of superposition of internally generated variability and anthropogenic climate change on projected climate trends over the next half century, using a 40-member ensemble of climate change simulations conducted with the National Center for Atmospheric Research (NCAR) community Climate System Model, version 3 (CCSM3). These studies looked at different aspects of uncertainty resulting from internally generated variability: signal to noise ratio, minimum number of ensemble members needed to detect a forced signal, which depends on climate variable, spatial and temporal scale, and geographical location of interest. They found substantial internal climate variability even on the global scale; the role of internal variability is considerably larger on the regional scale (e.g. Hawkins and Sutton 2011).

A new generation of coordinated regional modeling experiments will improve the quantification of uncertainty on the regional scale. Perhaps the most ambitious of these is CORDEX, which as Massey et al. (2014) note,

> ...[CORDEX] aims to understand some of the uncertainties in regional modelling by comparing many RCMs driven by both observations and output from multiple GCMs. Although weather@home is not part of CORDEX, it is aligning itself with the methodologies of CORDEX as closely as possible. For example, the European domain presented in this article has the same rotated pole as the CORDEX domain and contains the agreed common interior.

Our superensemble of regional model results can augment studies like those, by characterizing more completely the natural variability of climate on a regional scale and quantifying uncertainty in future projections more carefully. We provided here a few illustrations to show the value and capability of this superensemble.

As discussed by Massey et al. (2014), this regional project is one of six in the Weather@Home family of projects, and it is the first to present results for future climate change, joining NARCCAP (Mearns et al., 2009) and regCLIM (Hostetler et al. 2012) in presenting an ensemble of results for western North America.

The model formulation and experimental design used here do have drawbacks. Owing to the limitations in the memory footprint of most volunteers' computers, we run an atmosphere-only model, and SSTs are specified rather than being drawn from a free-running ocean-atmosphere model. Land surface data (e.g., vegetation roughness and type) are not perturbed, though they could be, and these can certainly influence regional climate including the albedo response of snowpack to warming. Also, unlike the CMIP5, NARCCAP, ENSEMBLES, and PRUDENCE experiments, we are using only a single atmospheric model, and even with the parameter perturbations it may not span the range of climate behaviors that are physically plausible and that would be represented by a collection of different models. Some regional modeling studies have been run with higher spatial resolution, which in some cases improves the representation of important processes (Zhang et al. 2009, Pavelsky et al. 2012). Finally, this experimental approach focuses on high numbers of short runs (1-5 years), but does not allow long continuous runs, which certainly have some advantages. In short, not all kinds of uncertainties can be better quantified with this approach than with other approaches.

Nonetheless, Weather@Home can provide unprecedented guidance to end users grappling with climate change. Society's awareness of the impacts of climate change has matured to the point that numerous public agencies, businesses, and investors are asking detailed questions about the future impacts of climate change. This is especially true in the western U.S., where many states, following the lead of California in 2005, have made formal commitments to incorporate climate adaptation into the long-range planning of their state agencies. Private businesses and federal agencies are also beginning proactively to adapt to climate change.

This awareness has led to a skyrocketing demand for detailed projections of future climate change, in a very wide range of practical applications. We have been asked to estimate the risk of future floods for determining how to manage and set policy in a flood plain; to project future wind speeds and evaluate the future energy production potential of wind farms; to project the probability of extremely intense rainfall for designing culverts, roads, bridges, and other infrastructure; to project future heat stress on humans; to project frequency of droughts for agricultural and water resources planning and policy; to project future sea level and height of storm surges for locating new infrastructure and protecting existing infrastructure; and much more. Indeed, the backers of this project (see acknowledgements) include management-oriented agencies.

Furthermore, the sophistication of requests has also increased: whereas a few years ago most users asked scientists for one best estimate of how a single climate variable would change, most users now want a range of that variable or even a probability distribution of that variable. The Weather@Home experiment outlined here and the data generated by the participation of tens of thousands of volunteers represents an important step in the quest for scientifically sound, societally relevant climate science.

Current and future work in this project includes a more complete evaluation of the 1960-2009 runs against observations. We are generating a new set of future simulations, in which we will save daily outputs of a few key variables. We will also use an expanded range for the parameter sets, because the physics perturbations used in the previous runs appear to have been too conservative.

Acknowledgments. We appreciate the efforts of the rest of the Weather@Home team over the years: Simon Wilson, Cameron Rye, Neil Massey, Andy Bowery, Friederike Otto, and Tolu Aina. Support for this work was provided by Microsoft Corp., the US Bureau of Land Management, the California Energy Commission, the US Geological Survey (award #G09AC00302, and a NW Climate Science Center fellowship), and through award #2011-68002-30191 from USDA National Institute for Food and Agriculture.

References

Abatzoglou, J., D.E. Rupp, and P.W. Mote, 2014: Understanding seasonal climate variability and change in the Pacific Northwest of the United States. J. Climate, 27, 2125–2142, doi:10.1175/JCLI-D-13-00218.1.

Allen, M.R., 1999: Do-it-yourself climate prediction. Nature, 401, 642, doi:10.1038/44266.

Anderson, D. P., 2004: BOINC: A system for public-resource computing and storage. Proceedings. Fifth IEEE/ACM International Workshop on Grid Computing. doi:10.1109/GRID.2004.14.

Bennett, J. C., F.L.N. Ling, D.A. Post, M.R. Grose, S.P. Corney, B. Graham, G.K. Holz, J.J. Katzfey, and N.L. Bindoff, 2012: High-resolution projections of surface water availability for Tasmania, Australia, Hydrol. Earth Syst. Sci., 16, 1287-1303, doi:10.5194/hess-16-1287-2012.

Boulanger, J.P. and Coauthors, 2010: A Europe-South America network for climate change assessment and impact studies. Clim. Change, 98, 307-329, doi:10.1007/s10584-009-9734-8.

Branstator, G. and H. Teng, 2010: Two limits of initial-value decadal predictability in a CGCM. J. Climate, 23, 6292-6311, doi:10.1175/2010JCLI3678.1.

Christensen, J.H., and O.B. Christensen, 2007: A summary of the PRUDENCE model projections of changes in European climate by the end of the century. Clim. Change, 81, 7–30, doi:10.1007/s10584-006-9210-7.

Claussen, M., L., and Coauthors, 2002: Earth system models of intermediate complexity: closing the gap in the spectrum of climate system models. Clim. Dyn., 18, 579-586, doi:10.1007/ s00382-001-0200-1.

Daly, C., M. Halbleib, J.I. Sith, W.P. Gibson, M.K. Doggett, G.H. Taylor, J. Curtis, and P.P. Pasteris, 2008: Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int. J. Climatol., 28, 2031–2064, doi:10.1002/ joc.1688.

Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Quart. J. Roy. Meteoro. Soc., 137: 553–597. doi:10.1002/ qj.828.

Déqué, M., P. Marquet, and R. Jones, 1998: Simulation of climate change over Europe using a global variable resolution general circulation model. Clim. Dyn., 14, 173-189, doi: 10.1007/ s003820050216.

Deser, C., A.S. Phillips, R.A. Tomas, Y.M. Okumura, M.A. Alexander, A. Capotondi, J.D. Scott, Y.-O. Kwon, and M. Ohba, 2012: ENSO and Pacific decadal variability in the Community Climate System Model version 4. J. Climate, 25, 2622–2651, doi:10.1175/ JCLI-D-11-00301.1.

Deser, C., A.S. Phillips, M.A. Alexander, and B.V. Smoliak, 2014: Projecting North American Climate over the Next 50 Years: Uncertainty due to Internal Variability. J. Climate, 27, 2271-2296, doi:10.1175/ JCLI-D-13-00451.1.

Duffy, P.B., and Coauthors, 2006: Simulations of present and future climates in the western United States with four nested regional climate models. J. Climate, 19, 873–895, doi: 10.1175/ JCLI3669.1.

Endris, H.S., and Coauthors, 2013: Assessment of the Performance of CORDEX Regional Climate Models in Simulating East African Rainfall. J. Climate, 26, 8453–8475, doi: 10.1175/ JCLI-D-12-00708.1.

Flato, G. M., 2011: Earth system models: an overview. WIREs Clim. Change, 2, 783–800. doi: 10.1002/ wcc.148.

Giorgi F., 1990: Simulation of regional climate using a limited area model nested in a general circulation model. J. Climate, 3, 941–963, doi:10.1175/ 1520-0442(1990)003<0941:SORCUA>2.0.CO;2.

Giorgi, F., C. Jones, and G. R. Asrar, 2009: Addressing climate information needs at the regional level: the CORDEX framework. WMO Bull. 58, 175-183.

Hawkins, E., and R. Sutton, 2011: The potential to narrow uncertainty in projections of regional precipitation change, Clim. Dyn., 37, 407–418, doi:10.1007/ s00382-010-0810-6.

Hegerl, G.C., F. W. Zwiers, P. Braconnot, N.P. Gillett, Y. Luo, J.A. Marengo Orsini, N. Nicholls, J.E. Penner and P.A. Stott, 2007: Understanding and Attributing Climate Change. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Susan Solomon et al., editors.]. Cambridge University Press, Cambridge, United

Kingdom and New York, NY, USA. http://www.ipcc.ch/publications_and_data/ar4/wg1/en/ch9.html.

Hostetler, S.W., J.R. Alder, and A.M. Allan, 2012: Dynamically Downscaled Climate Simulations over North America: Methods, Evaluation, and Supporting Documentation for Users. USGS Open File Report 2011-1238.

IPCC, 2013: Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. http://www.climatechange2013.org/images/report/WG1AR5_SPM_FINAL.pdf

Jacob, D., J. Petersen, B. Eggert, A. Alias, O.B. Christensen, L.M. Bouwer, A. Braun, A. Colette, M. Déqué, and G. Georgievski, 2013: EURO-CORDEX: new high-resolution climate change projections for European impact research. Reg. Environ. Change, 14, 563-578, doi:10.1007/s10113-013-0499-2.

Jones, R. G., J. M. Murphy, and M. Noguer, 1995: Simulation of climate change over Europe using a nested regional-climate model. I: Assessment of control climate, including sensitivity to location of lateral boundaries. Quart. J. Roy. Meteoro. Soc., 121, 1413-1449, doi:10.1002/qj.49712152610.

Jones, R. G., M. Noguer, D. Hassell, D. Hudson, S. Wilson, G. Jenkins, and J. Mitchell, 2004: Generating high resolution climate change scenarios using PRECIS. Report, Met Office Hadley Centre, Exeter, UK.

Kalognomou, E-A., and Coauthors, 2013: A Diagnostic Evaluation of Precipitation in CORDEX Models over Southern Africa. J. Climate, 26, 9477–9506, doi:10.1175/ JCLI-D-12-00703.1.

Kay, J. E., and Coauthors, 2014: The Community Earth System Model (CESM) Large Ensemble Project: A Community Resource for Studying Climate Change in the Presence of Internal Climate Variability, Bull. Amer. Meteor. Soc., doi: 10.1175/ BAMS-D-13-00255.1.

Kendon, E. J., D. P. Rowell, R. G. Jones, and E. Buonomo, 2008: Robustness of future changes in local precipitation extremes. J. Climate, 21, 4280-4297, doi: 10.1175/ 2008JCLI2082.1.

Laprise, R., L. Hernández-Díaz, K. Tete, L. Sushama, L. Šeparović, A. Martynov, K. Winger, and M. Valin, 2013: Climate projections over CORDEX Africa domain using the fifth-generation Canadian Regional Climate Model (CRCM5). Clim. Dyn., 41, 3219-3246, doi:10.1007/ s00382-012-1651-2.

Lean, J. L., and D. H. Rind, 2009: How will Earth's surface temperature change in future decades? Geophys. Res. Lett., 36, L15708, doi:10.1029/ 2009GL038932.

Leung, L. R., Y. Qian, X. D. Bian, W. M. Washington, J. G. Han, and J. O. Roads, 2004: Mid-century ensemble regional climate change scenarios for the western United States. Clim. Change, 62, 75-113, doi: 10.1023/ B:CLIM.0000013692.50640.55.

Massey, N., R. Jones, F.E.L. Otto, T. Aina, S. Wilson, J.M. Murphy, D. Hassell, Y.H. Yamazaki, and M.R. Allen, 2014: Weather@home: development and validation of a very large ensemble modelling system for probabilistic event attribution. Quart. J. Roy. Meteoro. Soc., doi:10.1002/qj.2455.

Means, E., M. Laugier, J. Daw, L. Kaatz, and M. Waage, 2010: Decision support planning methods: Incorporating climate change uncertainties into water planning. Water Utility Climate Alliance. http://www.wucaonline.org.

Mearns, L. O., W. J. Gutowski, R. Jones, L.-Y. Leung, S. McGinnis, A. M. B. Nunes, and Y. Qian, 2009: A regional climate change assessment program for North America. EOS Trans. AGU, 90, 311-312, doi:10.1029/2009EO360002.

Mesinger, F., and CoAuthors, 2006: North American Regional Reanalysis. Bull. Amer. Meteor. Soc., 87, 343–360, doi:10.1175/BAMS-87-3-343.

Mote, P.W., 2006: Climate-Driven Variability and Trends in Mountain Snowpack in Western North America. J. Climate, 19, 6209–6220, doi: 10.1175/JCLI3971.1.

Mote, P.W., Alan F. Hamlet, Martyn P. Clark, and Dennis P. Lettenmaier, 2005: Declining mountain snowpack in western North America. Bull. Amer. Meteor. Soc., 86, 39–49, doi:10.1175/BAMS-86-1-39.

Mote, P., L. Brekke, P. B. Duffy, and E. Maurer, 2011: Guidelines for constructing climate scenarios, Eos Trans. AGU, 92, 257-258, doi:10.1029/2011EO310001.

Mote, P., J. Abatzoglou, and K. Kunkel, 2013: Climate change in the Northwest. Chapter 2 in Dalton, M., P.W. Mote, and A.K. Snover, eds., 2013: Climate Change in the Northwest: Implications for Our Landscapes, Waters, and Communities. Island Press, 224 pp.

Murphy, J.M. et al., 2004: Quantification of modelling uncertainties in a large ensemble of climate change simulations. Nature, 430, 768-772, doi:10.1038/ nature02771.

Nikulin, G., and Coauthors, 2012: Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. J. Climate, 25, 6057–6078, doi:10.1175/ JCLI-D-11-00375.1.

Northrop, P.J., and R.E. Chandler, 2014: Quantifying Sources of Uncertainty in Projections of Future Climate. J. Climate, 27, 8793–8808, doi:10.1175/ JCLI-D-14-00265.1.

O'Brien, T.A., L.C. Sloan, and M.A. Snyder, 2011: Can ensembles of regional climate model simulations improve results from sensitivity studies? Clim. Dyn., 37, 1111-1118, doi:10.1007/ s00382-010-0900-5.

Pall, P., T. Aina, D.A. Stone, P.A. Stott, T. Nozawa, A.G.J. Hilberts, D. Lohmann, and M.R. Allen, 2011: Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature, 470, 382–385, doi:10.1038/ nature09762.

Pavelsky, T. M., S. Kapnick, and A. Hall, 2011: Accumulation and melt dynamics of snowpack from a multiresolution regional climate model in the central Sierra Nevada, California, J. Geophys. Res., 116, D16115, doi:10.1029/ 2010JD015479.

Pierce, D. W., and Coauthors, 2008: Attribution of declining western US snowpack to human effects. J. Climate, 21, 6425–6444, doi:10.1175/ 2008JCLI2405.1.

Rayner, N. A., D.E. Parker, E.B. Horton, C.K. Folland, L.V. Alexander, D.P. Rowell, E.C. Kent, and A. Kaplan, 2003: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. J. Geophys. Res., 108, 4407, doi:10.1029/ 2002JD002670.

Rosenberg, E.A., P.W. Keys, D.B. Booth, D. Hartley, J. Burkey, A.C. Steinemann, and D.P. Lettenmaier, 2010: Precipitation extremes and the impacts of climate change on stormwater infrastructure in Washington State. Clim. Change, 102, 319-349, doi: 10.1007/ s10584-010-9847-0.

Rowland, D., 2011: Quantifying Uncertainty in Projections of Large Scale Climate Change. D. Phil thesis, Balliol College, Oxford.

Salathé, E.P., R. Steed, C.F. Mass, and P. Zahn, 2008: A high-resolution climate model for the United States Pacific Northwest: Mesoscale feedbacks and local responses to climate change. J. Climate, 21, 5708–5726.

Salathé, E.P., L.R. Leung, Y. Qian, and Y. Zhang, 2010: Regional climate model projections for the State of Washington. Clim. Change,102, 51-75, doi: 10.1007/ s10584-010-9849-y.

Stainforth, D.A., et al., 2005: Uncertainty in predictions of the climate response to rising levels of greenhouse gases. Nature, 433, 403-406, doi: 10.1038/ nature 03301.

Stroeve, J., M. Holland, W. Meier, T. Scambos, and M. Serreze, 2007: Arctic sea ice decline: faster than forecast. Geophys. Res. Lett., 34, L09501, doi:10.1029/ 2007GL029703.

Taylor, K., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. Bull. Amer. Meteor. Soc., 93, 1689–1696, doi: 10.1175/ BAMS-D-11-00094.1.

van der Linden, P. & Mitchell, J. F. B. eds., 2009: ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project. Met Office Hadley Centre, Exeter, UK.

van Vuuren, D. P., and Coauthors, 2011: The representative concentration pathways: an overview. Clim. Change, 109, 5-31, doi: 10.1007/ s10584-011-0148-z.

Vautard, R., and Coauthors 2013: The simulation of European heat waves from an ensemble of regional climate models within the EURO-CORDEX project. Clim. Dyn., 41, 2555-2575, doi:10.1007/ s00382-013-1714-z.

Wang, C., R. G. Jones, M. Perry and C. Johnson, 2012: Using an ultra-high resolution regional climate model to predict local climatology. Quart. J. Roy. Meteorol. Soc. 139: 1964–1976. doi: 10.1002/ qj.2081.

Wettstein, J. J., and Deser, C., 2014: Internal variability in projections of twenty-first-century Arctic sea ice loss: Role of the large-scale atmospheric circulation. J. Climate, 27, 527–550. doi:10.1175/ JCLI-D-12-00839.1.

Zhang, Y, V Dulière, P Mote, E.P. Salathé Jr., 2009: Evaluation of WRF and HadRM Mesoscale Climate Simulations over the United States Pacific Northwest. J. Climate, 22, 5511–5526, doi: 10.1175/ 2009JCLI2875.1.

Table 1. Output variables from the global (HadAM3P, monthly) and regional (HadRM3P, 5-day averages)

Variable	global	regional
Geopotential height, temperature, & relative humidity at 500 hPa	x	
Soil moisture content	x	x
Temperature at 1.5m	x	x
Dew point at 1.5m	x	x
Surface temperature after timestep	x	
Surface boundary layer heat fluxes (W/m^2)	x	
Surface latent heat flux (W/m^2)	x	x
Surface sensible heat flux (W/m^2)	x	x
Net downward surface shortwave flux (W/m^2)	x	x
Net downward surface longwave radiation flux (W/m^2)	x	x
Outgoing shortwave radiation flux (top of atmosphere, W/m^2)	x	x
Outgoing longwave radiation flux (top of atmosphere, W/m^2)	x	x
Clear-sky upward shortwave flux (top of atmosphere, W/m^2)	x	x
Clear-sky upward longwave flux (top of atmosphere, W/m^2)	x	x
U, V components of wind at 10m	x	x
U, V components of wind on pressure levels (hPa)	200, 500, 850	200
Pressure at mean sea level	x	x
Relative humidity at 1.5m	x	x

Total precipitation rate (kg/ m^2/ s)	x	x
Total snowfall rate, large scale plus convective (kg/ m^2/ s)		x
Total rainfall rate, large scale plus convective (kg/ m^2/ s)		x
Surface runoff amount (kg/ m^2/ s)		x
Surface snow amount (kg/ m^2)		x
Total downward shortwave flux at the surface		x
Total downward longwave flux at the surface		x
Geopotential height: pressure levels (200, 500, 850 hPa)		x
Minimum temperature at 1.5m: monthly mean and 1st, 2nd, 3rd lowest		x
Maximum temperature at 1.5m: monthly mean and 1st, 2nd, 3rd lowest		x
Precipitation on the 3 wettest days of the month		x

Figure captions.

Figure 1. Depiction of the tradeoff between spatial resolution, represented by longitudinal grid spacing, and number of simulated years (note the log scale). Global modeling results available through CMIP5 are shown as blue circles, one for each model[6], with the total number of years including all ensemble members and all RCPs. The large red circle for NARCCAP represents 12 models, all with the same grid size and number of years. Regional simulations in PRUDENCE (purple circles) include between 1 and 5 simulations with a given model. A typical standalone regional model experiment is indicated by the thin red circle. The work described in this paper consists of almost 140,000 simulated years at 25km resolution.

Figure 2. (a) Domain and elevation of terrain (meters) used in these simulations. (b) flowchart indicating how "workunits" issued to volunteers turn into results on the OSU server. (c) Number of valid runs per year.

Figure 3. Dec-Jan-Feb average temperature in °C as simulated by Weather@Home (left) and by the North American Regional Reanalysis (middle), for 1979-2009, and the difference (right). The Weather@Home figures are formed by averaging up to 100 simulations per year.

[6] Details on model resolution are taken from IPCC 2013, Table 9.1; details on number of runs available are from the CMIP5 archive at LLNL.

Figure 4. Annual mean temperature, averaged over the Pacific Northwest, for weather@home (25-100 simulations per year) and observations from the National Climatic Data Center (red), along with linear fits.

Figure 5. Linear trends in snow water equivalent in cm from (top) observations (1960-2009), for April 1 (Mote 2006, updated) and (bottom) the weather@home simulations (1960-2009), averaged for the month of April. Red indicates declines and blue increases.

Figure 6. Return period curves of maximum one-day temperature in June-July-August, each curve representing 4500 standard physics weather@home simulations for the 1960s and 2000s over California and Nevada. Uncertainties are calculated both with respect to return period (horizontal bars) and temperature (vertical bars).

Figure 7. a. Linear trend in annual mean temperature, 1960-2009; b. Difference in annual mean temperature, future runs minus past runs, in °C/ year.

Figure 8. Convergence in annual mean precipitation for 2007-08, averaged over the weather@home domain (land grid points), as the ensemble size increases. Samples of 1, 4, 16, and 64, and 256 members were randomly selected from a set of 500 simulations. Box-and-whiskers show the median, inner quartiles, and extremes of the regional mean calculated from those samples.

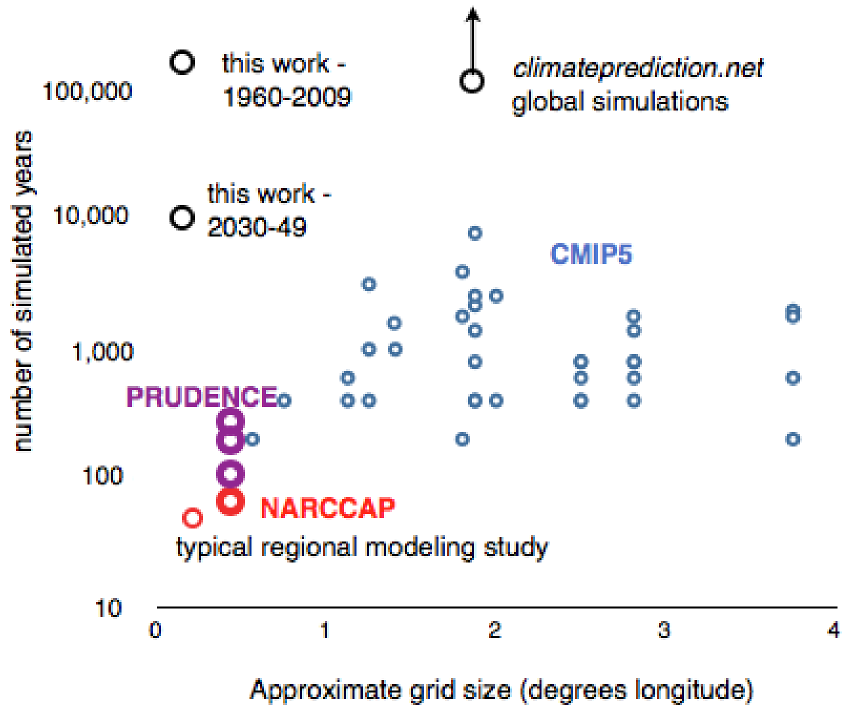
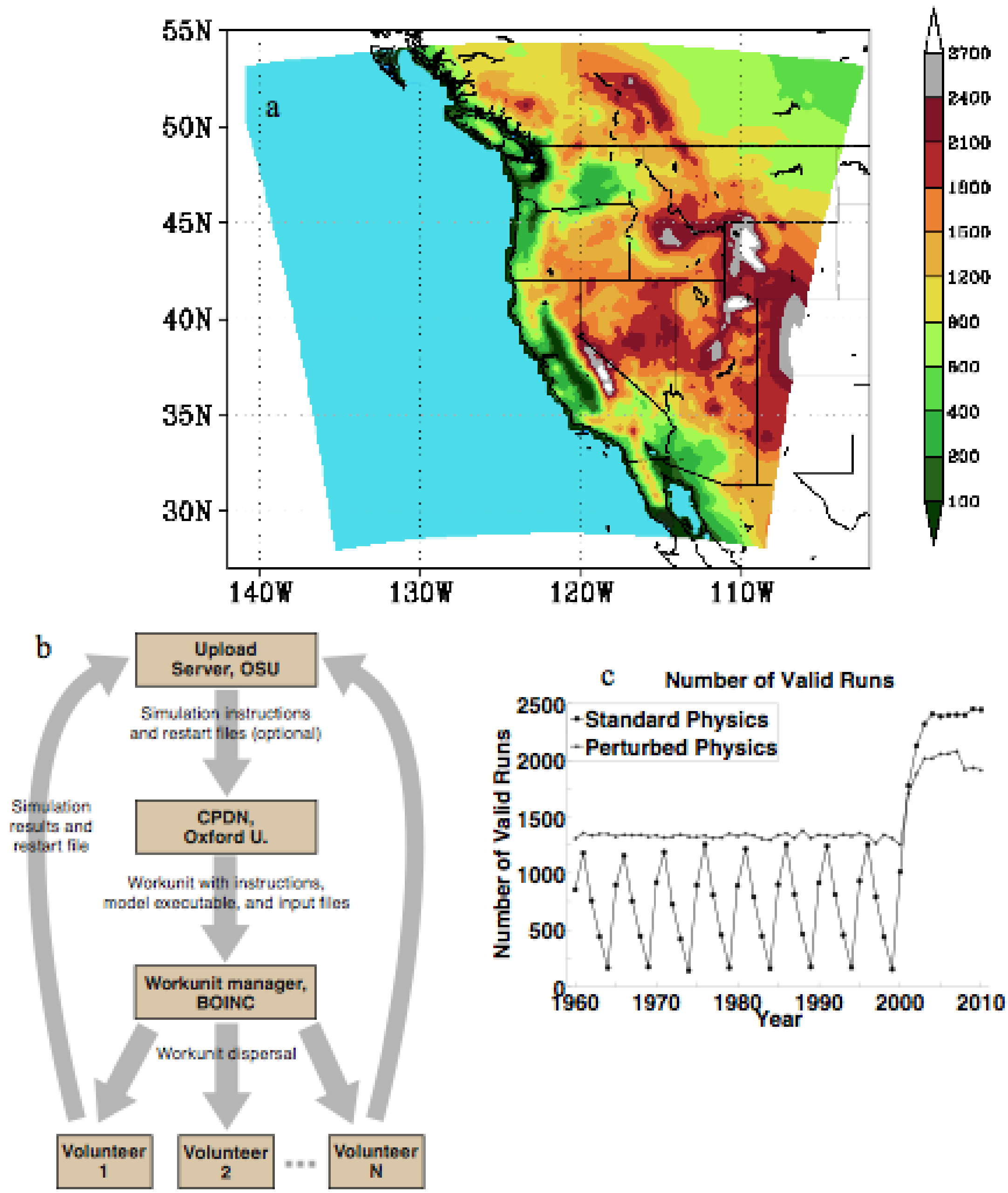


Figure 1. Depiction of the tradeoff between spatial resolution, represented by longitud i-

nal grid spacing, and number of simulated years (note the log scale). Global modeling results available through CMIP5 are shown as blue circles, one for each model[7], with the total number of years including all ensemble members and all RCPs. The large red circle for NARCCAP represents 12 models, all with the same grid size and number of years. Regional simulations in PRUDENCE (purple circles) include between 1 and 5 simulations with a given model. A typical standalone regional model experiment is in-

[7] Details on model resolution are taken from IPCC 2013, Table 9.1; details on number of runs available are from the CMIP5 archive at LLNL.



dicated by the thin red circle. The work described in this paper consists of almost 140,000 simulated years at 25km resolution.

Figure 2. (a) Domain and elevation of terrain (meters) used in these simulations. (b) flowchart indicating how “workunits” issued to volunteers turn into results on the OSU server. (c) Number of valid runs per year.

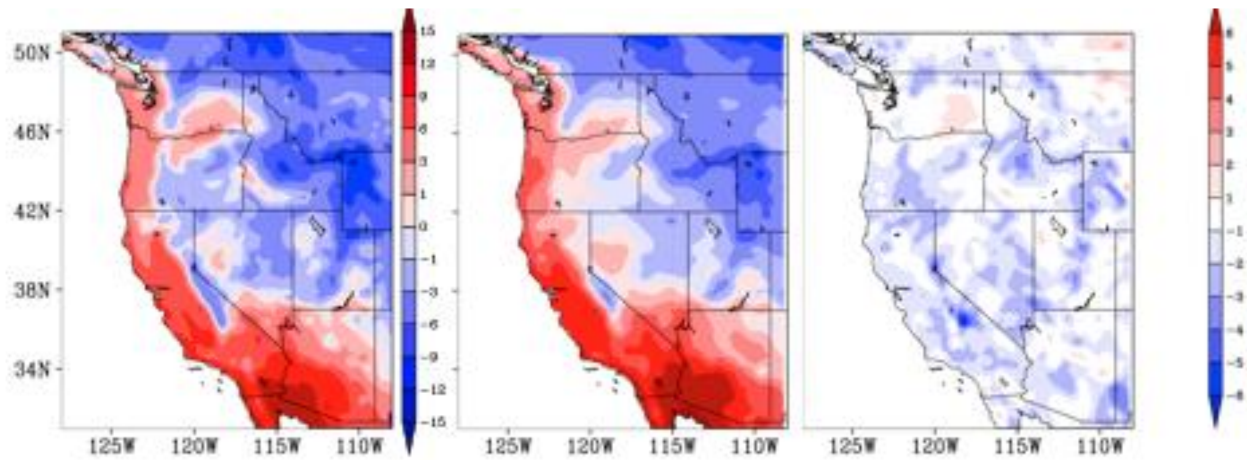


Figure 3. Dec-Jan-Feb average temperature in °C as simulated by Weather@Home (left) and by the North American Regional Reanalysis (middle), for 1979-2009, and the difference (right). The Weather@Home figures are formed by averaging up to 100 simulations per year.

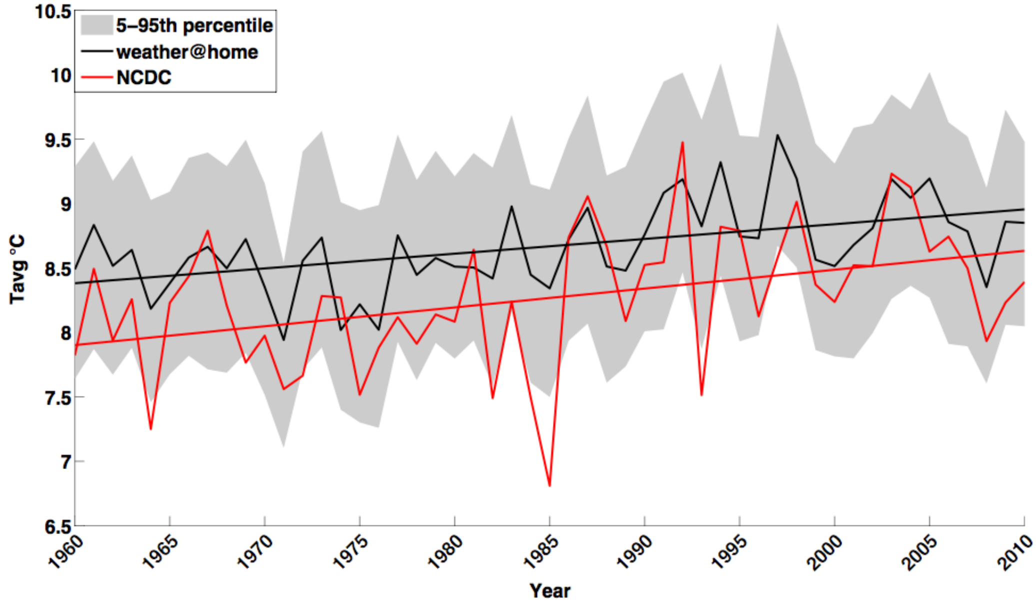


Figure 4. Annual mean temperature, averaged over the Pacific Northwest, for weather@home (25-100 simulations per year) and observations from the National Climatic Data Center (red), along with linear fits.

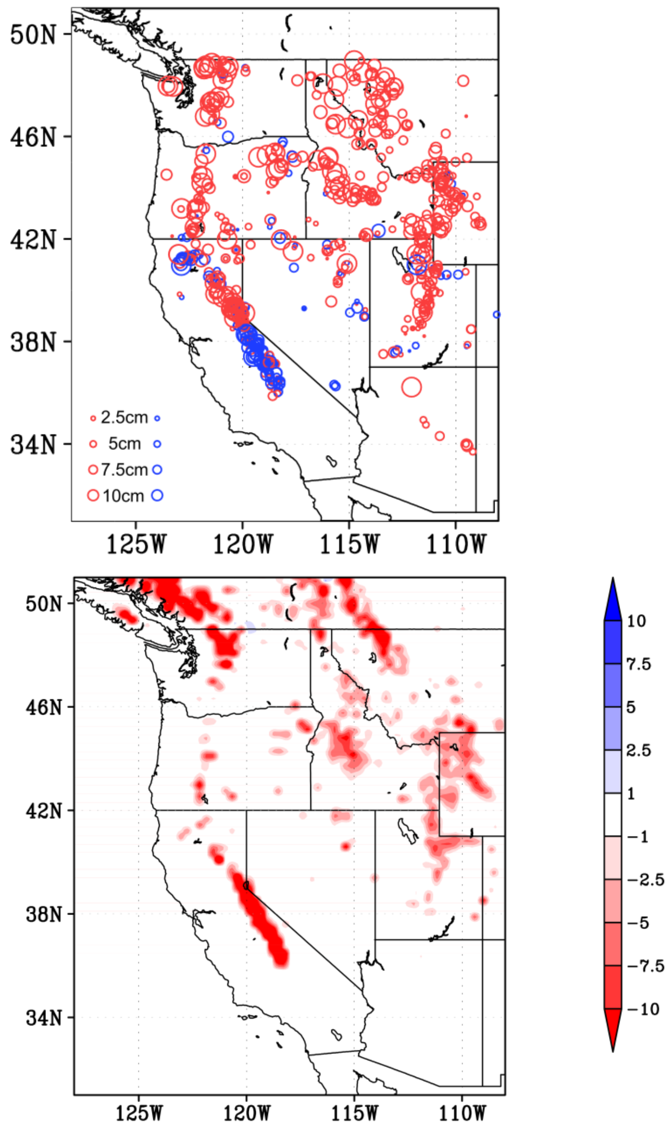


Figure 5. Linear trends in snow water equivalent in cm from (top) observations (1960-2009), for April 1 (Mote 2006, updated) and (bottom) the weather@home simulations (1960-2009), averaged for the month of April. Red indicates declines and blue increases.

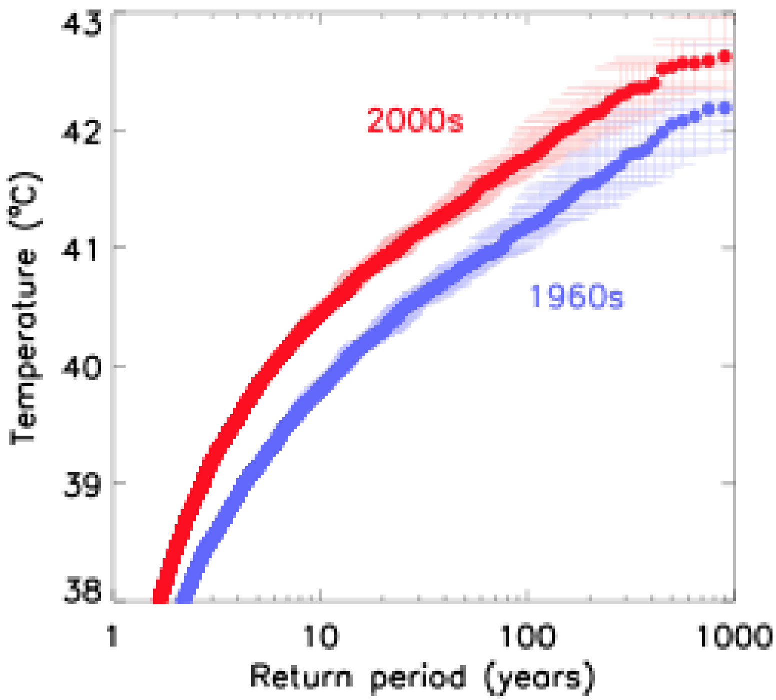
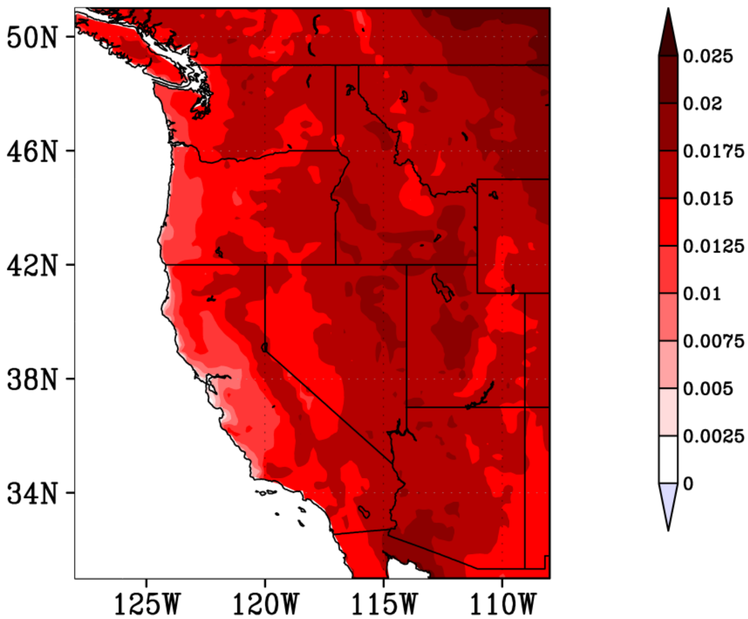
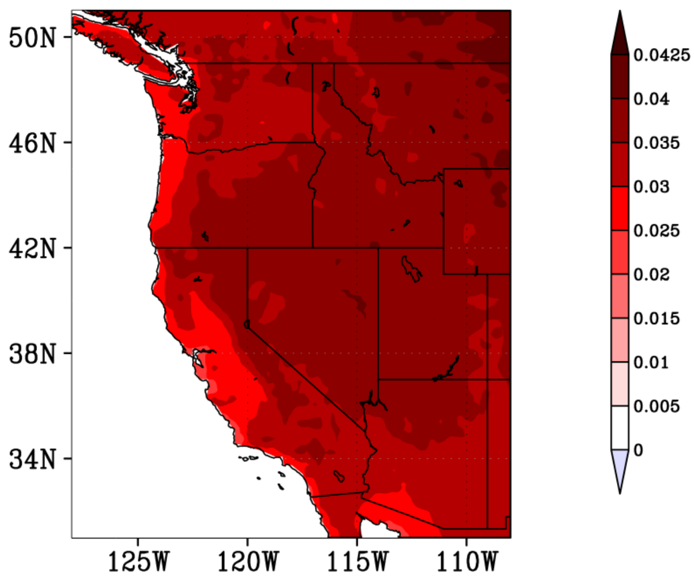

43
42
41
40
39
38
2000s
1960s
Temperature (°C)
1
10
100
1000
Return period (years)

Figure 6. Return period curves of maximum one-day temperature in June-July-August, each curve representing 4500 standard physics weather@home simulations for the 1960s



and 2000s over California and Nevada. Uncertainties are calculated both with respect to return period (horizontal bars) and temperature (vertical bars).

Figure 7. a. Linear trend in annual mean temperature, 1960-2009; b. Difference in annual mean temperature, future runs minus past runs, in °C/ year.



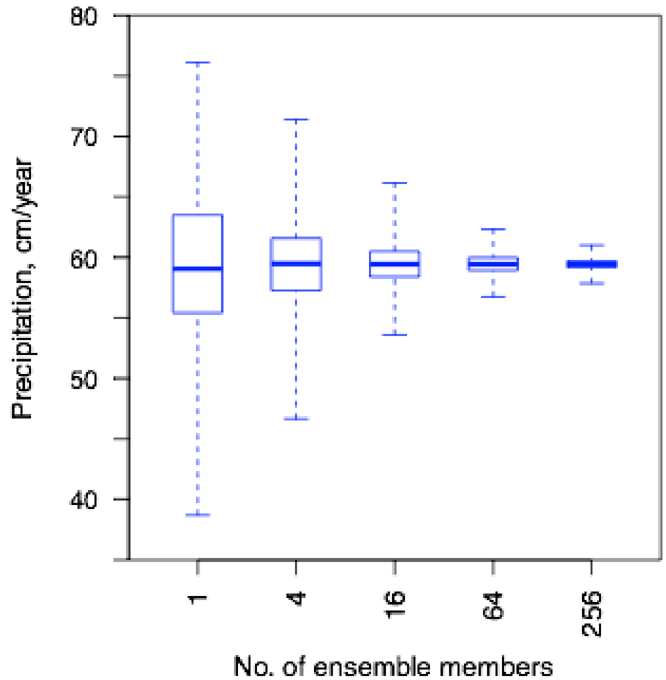


Figure 8. Convergence in annual mean precipitation for 2007-08, averaged over the weather@home domain (land grid points), as the ensemble size increases. Samples of 1, 4, 16, and 64, and 256 members were randomly selected from a set of 500 simulations. Box-and-whiskers show the median, inner quartiles, and extremes of the regional mean calculated from those samples.