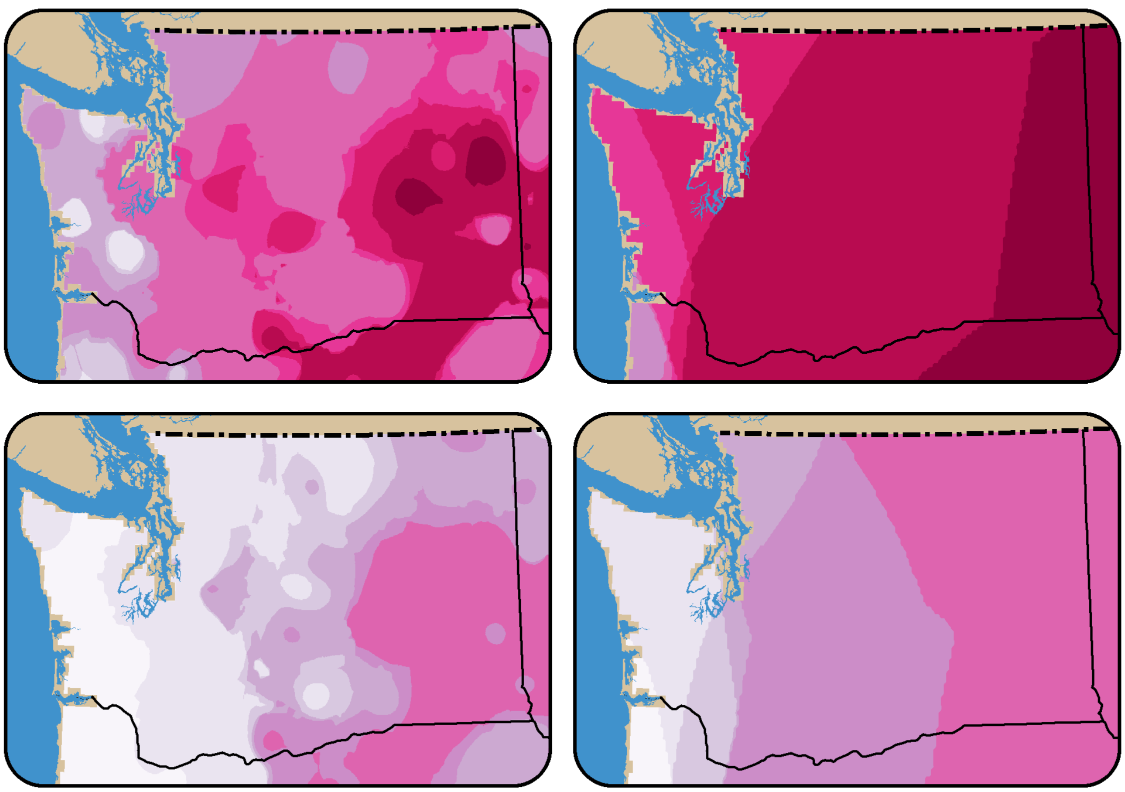
Washington Connected Landscapes Project:

An Evaluation of the Utility of Fine-Scale, Downscaled Climate Projections for Connectivity Conservation Planning in Washington State



WASHINGTON WILDLIFE HABITAT CONNECTIVITY WORKING GROUP

June 2013

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Acknowledgements

In addition to the generous contributions of Washington Wildlife Habitat Connectivity Working Group organizations, we wish to extend appreciation to the following entities that have provided funding critical to the accomplishment of this effort:

- Bureau of Land Management
- Great Northern Landscape Conservation Cooperative
- US Fish and Wildlife Service (Washington State Recovery Funds)
- Wilburforce Foundation

Full Document Citation

Washington Wildlife Habitat Connectivity Working Group (WHCWG). 2013. An evaluation of the utility of fine-scale, downscaled climate projections for connectivity conservation planning in Washington State. Washington Departments of Fish and Wildlife, and Transportation, Olympia, WA.

Document Availability

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Introduction

There is widespread disagreement on the appropriate application of climate change projections to resource management (e.g., Snover et al. 2013). Indeed, planners frequently disagree on whether to use climate projections at all, citing concerns about the "compounding uncertainties" inherent in using climate models to predict and respond to the biological impacts of climate change (Beier & Brost, 2009; Anderson & Ferree, 2010). In addition, climate models are typically available at much coarser scales (e.g., 100 km resolution) than are required for management, leading many to believe that climate models must be downscaled to fine scales (i.e., adjusted to a finer resolution using statistical or physical models; see Appendix C) to guide local to regional scale management decisions. Yet despite these reservations, it is also well accepted that climate models represent our best means of estimating future climate, and therefore may offer powerful tools for climate change adaptation.

The goal of this report is to evaluate whether fine-scale temperature and precipitation projections may be useful for informing connectivity conservation planning. Specifically, we ask whether fine-scale climate projections could be used to identify the most resilient areas within connectivity networks, i.e., those core habitat areas and corridors projected to see relatively little climatic change, thereby presenting good long-term connectivity conservation investments. To address this, we developed a fine-scale climate change dataset, and evaluated its utility in assessing the vulnerability of connectivity networks identified by the Washington Wildlife Habitat Connectivity Working Group (WHCWG 2010, 2011, 2012, 2013).

In this report we briefly describe the methods used to develop our fine-scale climate change projections, summarize projected future climatic conditions for the region, and then evaluate the utility of the downscaled data for connectivity conservation planning. Our evaluation centers on three criteria: (1) the magnitude of projected change, (2) degree of uncertainty, and (3) added value relative to alternative approaches. Specifically, we discuss the added value of the statistically downscaled dataset for connectivity conservation planning relative to Global Climate Model (GCM) projections and dynamically downscaled climate projections (i.e., physical, as opposed to statistical, downscaling). Finally, we discuss the potential utility of projections obtained from "downstream" impacts models (models that translate climate changes to changes in other variables, e.g., fire severity). Appendices provide additional detail on the methods, as well as background regarding GCM projections and downscaling approaches.

Methods

We developed a set of fine-scale, monthly climate change projections by combining high-resolution mean climate grids (Daly et al. 1994, 2002) with a set of medium-scale, statistically downscaled climate projections (Hamlet et al. 2010, 2013). Specifically, climate model projections were adjusted to higher resolution (i.e., statistically downscaled) using information from gridded historical datasets. These gridded datasets were produced by using a sophisticated approach to interpolate surface observations of daily climate onto a high-resolution grid while accounting for the influence of terrain on climate (Daly et al. 1994, 2002; Hamlet et al. 2010, 2013). The result is a new dataset, produced at a resolution of 30 arc-seconds (~800 m). A detailed description of the dataset and its development is included in Appendix A.

For comparison, we also gathered raw global climate models and a dynamically downscaled projection produced using a regional climate model. The source of these data, as well as details about global models and downscaling approaches are all described in detail in the appendices.

Although climate models can be used to project decade-to-decade evolution of 21st century climate, for simplicity we did not consider time-evolving projections of climate change. Rather, we investigated the mean changes projected for the middle of the century (2040s). The 2040s were chosen in order to focus on near-term decisions in conservation planning. To further simplify the presentation, we only include results for the A1b emissions scenario. This emissions scenario was chosen because it is a middle-of-the-road scenario for 21st century greenhouse gas emissions, and global emissions since 2000 suggest that it will be representative of emissions going forward (Peters et al. 2012).

Summary of Downscaled Model Results

The downscaled climate projections can be used to examine the average change in temperature and precipitation across an area, as well as the range among models. Key results from the downscaled projections for Washington include:

1. ***A tendency towards greater warming in the interior, and less warming along the coasts.*** Projected changes in temperature and precipitation are shown in Figure 1 (2040s, A1b emissions scenario). The left-hand panels show the mean projected change for each variable. Temperature changes show a tendency for greater warming east of the Cascade range, particularly in the southeastern corner of the state.
2. ***Model uncertainty is relatively small for temperature, but large for precipitation.*** The right-hand panels in Figure 1 show the range among model projections (i.e., the difference between the model showing the greatest warming and the model showing the least warming by mid-century). This gives a crude estimate of the uncertainty in the projections (see Appendix B for further discussion of model uncertainty). Projected temperature changes (top-left panel) are much larger than the "noise" (i.e., uncertainty; top-right panel) associated with different models, while the magnitude of projected changes in precipitation is much smaller than the range among models. Uncertainties in precipitation projections stem primarily from the large year-to-year variability in precipitation and from limitations in our ability to simulate the processes associated with precipitation. Based on this observation, we focus the remainder of our discussion on projected changes in temperature, as projected changes in precipitation are small compared to uncertainty among model projections for the coming century.
3. ***Small but noticeable errors are present as a result of imperfections in the gridded historical dataset.*** Some of the features in the downscaled data – sharp lines and blotchiness that do not correspond to changes in topography – are likely a result of imperfections in the gridded

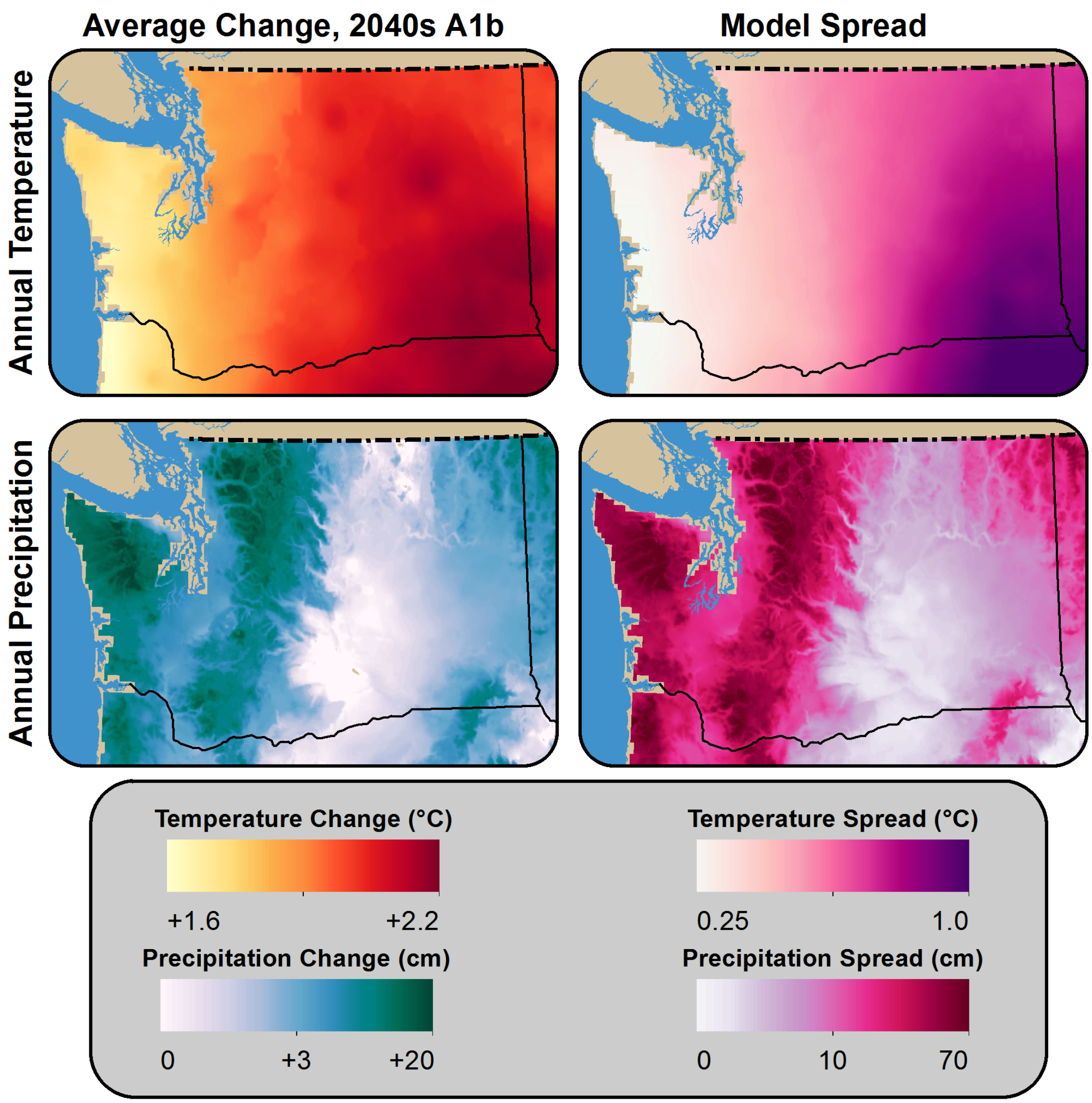

Figure 1. Projected changes in mean annual temperature (top row) and precipitation (bottom row) for the 2040s (A1b emissions scenario). The left-hand panels show the mean change projected by all 10 Global Climate Models (GCMs), while the right-hand panels show the range among all models, as defined by the difference between the model showing the greatest warming by mid-century (MIROC 3.2; Hasumi & Emori 2004), and the model showing the least warming (PCM1; Meehl et al. 2006). This gives a crude estimate of the uncertainty in the projections. Note that the range is much smaller than the projected change for temperature and much greater than the projected change for precipitation.

historical dataset that is the basis for the downscaling. These likely result from the interpolation method, in which point observations from surface stations are used to generate a gridded historical dataset (see Appendix A for details). Ultimately, these differences are small, showing distinctions on the order of 0.1°C.

These results suggest that downscaled projections of temperature changes are robust at the ecoregional level, but that the data should not be used to estimate relative changes at finer

scales. Thus, while downscaling climate models may be useful for increasing overall model accuracy, it provides little added value for on-the-ground connectivity conservation management (e.g., for identifying individual core areas and corridors that may be relatively resilient to climatic change).

One important caveat should be noted: the changes presented here are for annual average conditions. Although the picture is similar for seasonal variations, there is a weak tendency (i.e., not statistically significant) towards decreases in precipitation in summer and increases for other seasons. On shorter time scales (e.g., daily, weekly), much debate remains regarding the potential for extremes in temperature and precipitation to change more rapidly than the average: current research on climatic extremes – both past observations and modeling – is not yet clear on the trends that we can anticipate going forward.

Relative Benefits and Limitations of Alternative Climate Models

Global Climate Model (GCM) projections

Comparing the downscaled data to GCM projections reveals both the added value of the downscaled data as well as the limited scales to which it can be applied. Specifically:

1. ***The downscaled data show a general pattern of warming that is similar to but more detailed than that of the raw GCMs***.
   Figure 2 shows the degree of agreement among climate models for a given threshold amount of warming – i.e., how many of the ten global models project greater than 1.0°C, 1.5°C, or 2.0°C change in temperature for the 2040s given the A1b emissions scenario. Results for the downscaled data are shown in the left, while those from the raw GCMs are shown on the right. Although the latter generally show the east/west contrast in warming, the downscaled data show some additional detail, in particular related to the relatively lower rate of warming in northeast Washington, and higher rate in the southeastern portion of the state.
2. ***Although the downscaled data offer more detailed projections than GCMs, they are likely most reliable at the scale of ecoregions and broader***.
   As discussed above, the downscaled data are likely not reliable at fine spatial scales, as highlighted by the "blotchy" patterns discussed above regarding Figures 1 and 2. This is a consequence of two limitations in the statistically downscaled data: (1) the historical dataset, which forms the basis for the downscaling, is limited by the scarcity of surface meteorological observations, and (2) the fact that the global model projections are too coarse to resolve small-scale differences in sensitivity to warming.
3. ***Raw GCM projections show greater disagreement among models than the downscaled data, and show a slightly higher rate of warming overall.***
   When, as is done in statistical downscaling, biases are removed through comparison with the observationally-based historical dataset, the warming rate is slightly diminished, and there is a greater agreement among model projections. The downscaled data appear to be particularly more consistent in predicting areas with the greatest increase (>2.0°C) in average temperature.

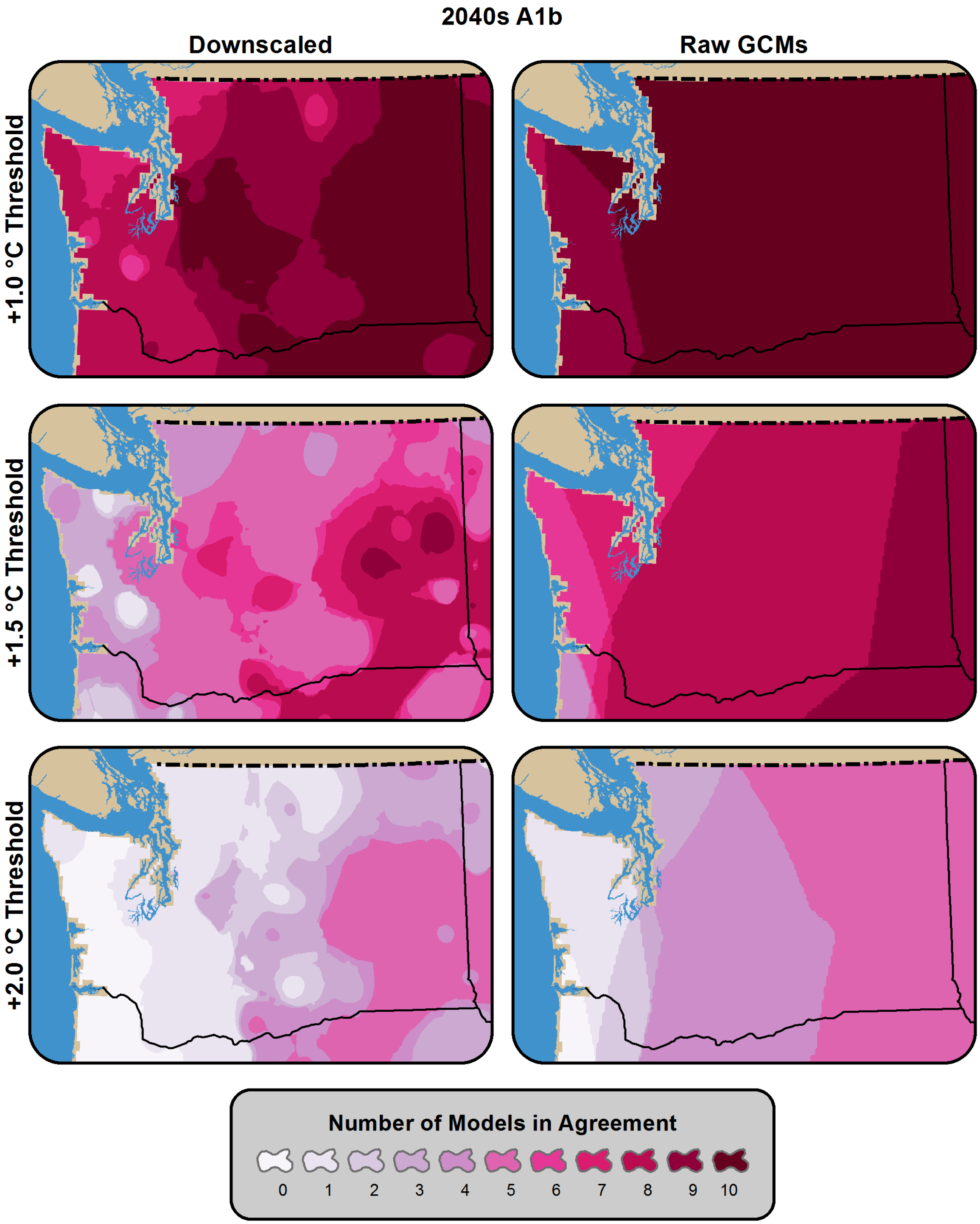

Figure 2. Extent of model agreement for three different thresholds of warming for the 2040s (A1b emissions scenario). The number of models showing greater than 1.0°C of warming are shown in the top row, 1.5°C in the middle row, and 2.0°C in the bottom row. The left-hand panels show results from the downscaled data, while the right-hand panels show results from the raw GCMs. Note that the downscaling primarily adds detail at the regional scale, and that the raw GCM projections are less consistent and are biased towards a slightly greater rate of warming. The greater consistency of the downscaled projections implies that they provide added value relative to the raw GCM projections.

- **These comparisons suggest that the statistically downscaled data offer some improvements over raw GCM projections, but should be interpreted at a coarser scale than their native ~800 m resolution.** Resolution is limited by both the coarse scale of global models and the scarcity of the surface observations upon which the statistical downscaling is based.

Dynamically downscaled projections

Dynamical downscaling, via a regional climate model, is able to provide more fine-scale detail in terms of projected changes across the landscape. Comparisons with the statistically downscaled results reveal the following:

1. ***The primary advantage of the dynamical downscaling is that it incorporates the processes that result in differential warming across the landscape*.**
   Figure 3 compares statistically downscaled data to that obtained through dynamical downscaling via the Weather Research and Forecasting (WRF) regional climate model (see Appendix A for details). Dynamical downscaling is a physically-based approach, meaning that differential sensitivities are modeled based on representations of the processes that drive changes in climate. Statistical downscaling, which uses the statistics of historical climate variations to adjust GCM projections, is not able to capture differences in the sensitivity to warming across the landscape. For example, depletion of soil moisture associated with increases in evaporative demand would likely result in greater warming relative to nearby areas with greater water availability. Similarly, earlier snowmelt and retreat of glaciers would likely lead to increased absorption of sunlight and therefore greater warming. Regional climate models can capture important local-scale interactions such as these. GCMs, in contrast, do not resolve such fine-scale variations in terrain and land cover, and therefore cannot capture the resulting variations in warming.

   Figure 3 illustrates the consequence of this distinction: the statistical downscaling reflects the 100-200 km resolution of the global models on which it is based, while the WRF model shows substantial local-scale structure.

2. ***The principal disadvantage of dynamical downscaling is that it is computationally expensive, and it is therefore not generally feasible to obtain projections from a robust ensemble of global models*.**
   The dynamically downscaled data provide a much more enticing picture of projected changes than the statistically downscaled projections. However, the WRF results shown in Figure 3 and included in this dataset are based on just one global model (and only one regional model) and are therefore not a robust representation of projected climatic change and associated uncertainty. Since regional model simulations are computationally expensive, it is unlikely that these will be able to replace statistical downscaling, given the flexibility and ease with which the latter can be applied.

3. ***Dynamically-downscaled projections are subject to uncertainties in the GCM projections used to drive the regional model as well as uncertainties in the regional models themselves*.**

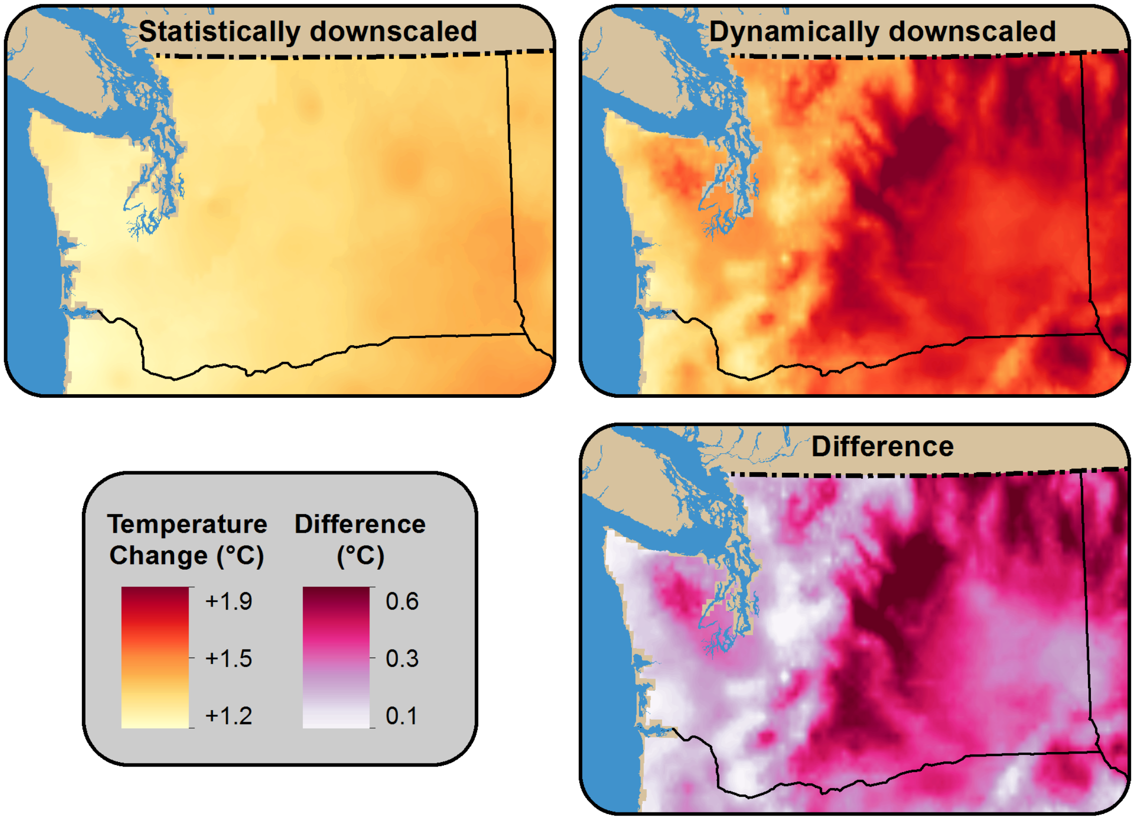

Figure 3. Maps comparing the statistically (top left) and dynamically (top right) downscaled temperature projections for the 2040s A1b scenario, along with the difference between the two (bottom right). In both cases the downscaling is based on the projections of one climate model: the ECHAM5 / MPI-OM global model (Roeckner et al. 1999; 2003). Since the projections are based on only one GCM, these cannot be viewed as a robust projection. However, the differences illustrate the potential for additional detail gained by using a mechanistic vs. statistical approach. Note that for this particular scenario, the dynamically downscaled simulation shows greater warming over the entire domain, with the additional warming most pronounced on the eastern slopes of the Cascades and foothills to the Rocky Mountains.

Since the regional models used in dynamical downscaling are driven by GCM projections, they are subject to the same biases that must be dealt with in statistical downscaling. Some biases may be amplified by the regional model. Second, the regional model is still a model, meaning that it is an incomplete representation of the climate and likely includes flawed representations of important processes. For example, at a resolution of 12 km many processes (e.g., thunderstorms, local-scale differences in evapotranspiration) are still not resolved and must therefore be represented statistically.

- **These comparisons suggest that dynamically downscaled climate projections provide the fine-scale detail needed to differentiate vulnerability among individual habitat core areas and corridors, but that substantial resources would be required to produce an ensemble that is robust to projection uncertainties.**

A Promising Fine-Scale Alternative: "Downstream" Climate Projections

Downscaled climate data can be used to drive additional models (herein referred to as "downstream" models) that translate changes in climate to changes in variables of direct relevance to connectivity conservation planning (e.g., snowpack, fire, pathogens). Specific features and benefits of such models include:

1. ***Changes in response variables (e.g., snow, fire) can have fine-scale structure even if temperature changes are broad in spatial scale.***
   Although the changes in temperature projected by GCMs are broad in scale, other variables may respond to warming in ways that highlight fine-scale distinctions in vulnerability. As an example, Figure 4 shows historical and projected changes in snowpack. These show very sharp spatial distinctions in the response to warming, primarily related to elevation and exposure to warm maritime air on the western slopes of the Cascades versus cooler continental air to the east.

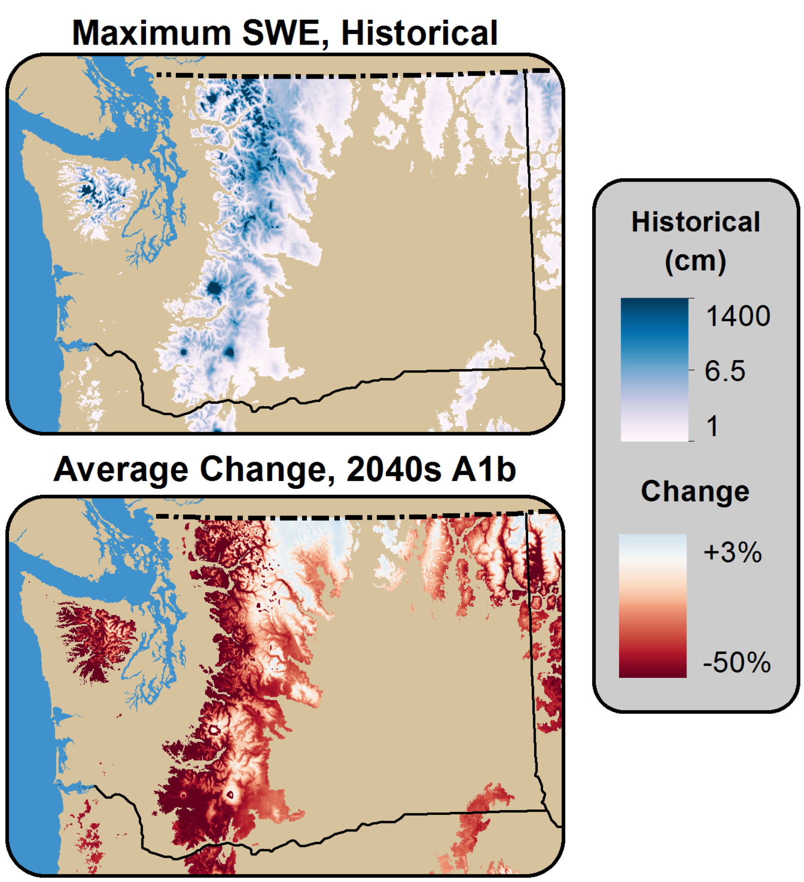

Figure 4. Example "downstream" products that can be obtained using downscaled temperature and precipitation data. These maps show estimates of April 1st snow water equivalent (SWE), obtained using the composite average statistically downscaled projection (Littell et al. 2011) and the Variable Infiltration Capacity (VIC) macroscale hydrologic model (Liang et al. 1994, Gao et al. 2010). Maps show the historical distribution of SWE (top) along with projected changes for the 2040s (bottom), using the average of the ten best climate models.

Figure 4 shows that it is possible to have fine-scale variations in a "downstream" variable resulting from coarse-scale changes in climate. To understand why, it is helpful to consider the source of the calculations. The snow model used to produce Figure 4 is driven by a downscaled dataset of daily temperature and precipitation. At any particular grid cell, the downscaled time series is a combination of the *relative changes* shown in Figures 1 and 2 and the *absolute* time series in temperature and precipitation obtained from the gridded historical dataset, which reflects the influence of terrain on local climate (see Appendix A). Although the projected *changes* (i.e., relative changes) may only be robust at scales coarser than the ecoregional level, changes in climate associated with differences in elevation and terrain features can be important at small scales (e.g., comparing a ridge to its adjacent valley; see Figure A.1). As a result, not only do the historical simulations reflect the terrain-based variations in climate (more snow in cold places, and less where it is warm), but the sensitivity will be affected as well: areas near the snowline show the greatest response to warming, while areas that are either very warm or very cold show very little change. In other words, the fact that snow melts at 0°C dictates a varied response to warming across the landscape; even if the entire state warmed by the exact same amount, areas that are near the freezing point would change more rapidly than areas that are warmer or cooler.

Generalizing from the above example, any variable that has a non-linear or threshold response to changes in climate (e.g., snow, soil moisture, fire risk, etc.) will exhibit a varied response across the landscape. If the relationship between such variables and climate is well-characterized – i.e., if the sensitivities are quantified – such variables could be used to provide information on differential sensitivity to climate change, thus identifying regions where exposure to climate change is greatest.

2. ***Uncertainty in climate projections does not preclude robust changes in response variables***.
   "Downstream" models are driven using downscaled climate data. A common concern is the compounding uncertainties associated with global models, downscaling, and the downstream models themselves. These uncertainties are of course propagated through to the final result of any calculation. However, large uncertainty in the inputs need not imply that nothing can be concluded from "downstream" model projections.

   As discussed above, non-linear and threshold responses can result in fine-scale variations in impacts. Uncertainties in GCMs, downscaling, and downstream models will contribute to the spread in such projections, but will not necessarily overwhelm the signal of change. The snowline will rise with warming, for instance, despite some uncertainty about how far it will shift uphill. Similarly, projection uncertainties may result in some uncertainty about the magnitude and location of impacts, but changes will nonetheless still be concentrated in areas near the snowline. As above, the same argument applies to any other variable that responds non-linearly to temperature.

- **These results suggest that "downstream" models – models that translate climate variables to variables of interest to connectivity planning – represent a promising approach to assessing differences in vulnerability across connectivity networks.** The primary challenge to their application lies in accurately quantifying the relationship between impacts of interest and climate variables.

Conclusions

Uncertainties in global model projections and downscaling methodology suggest that statistically downscaled climate change projections are best viewed at the regional scale (e.g., at the scale of the Columbia Plateau) and are not verifiably reliable at smaller spatial scales. This means that, if the only variables of interest are temperature and precipitation, very little is gained by using fine-scale instead of lower-resolution GCM projections.

However, there are two reasons that downscaled data may nonetheless prove useful for habitat connectivity planning:

1. **Statistical downscaling involves correcting GCMs for absolute biases – biases in the mean and distribution of temperature and precipitation.** Removing these biases is likely to make for more accurate GCM projections.
2. **"Downstream" model results (e.g., snow, water availability, fire risk) based on downscaled data can respond to warming in ways that vary at fine scales across the landscape.** For example, changes in snowpack are likely to be much greater near the 0°C isotherm than at nearby locations where temperatures are farther from the freezing point, even if the net warming is the same at each location. Such variables can introduce greater spatial detail by means of a non-linear response to warming, thus highlighting fine-scale variations in connectivity network vulnerability.

Finally, it is important to consider the sensitivity of connectivity-relevant impacts. Some processes are sensitive to large-scale changes in climate, while others require fine-scale projections. Since the latter requires more resources, it is worth critically evaluating if and how such information would impact decisions.

The WHCWG anticipates applying the lessons learned from this evaluation to its future assessments, particularly its upcoming analysis of climate-connectivity across the Washington-British Columbia transboundary region.

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Appendix A: Development of the Fine-Scale, Downscaled Climate Projections

The climate projections described in this report were produced at a monthly time-step and a resolution of 30 arc-seconds (about 800 m). Time series information was obtained from the 1/16th degree (about 6 km) resolution Columbia Basin Climate Change Scenarios Project (CBCCSP; Hamlet et al. 2010; 2013). The CBCCSP dataset is a comprehensive set of statistically downscaled climate projections, using multiple downscaling approaches, greenhouse gas emissions scenarios, and time evolving projections of 21st century change. These projections were adjusted to 30 arc-second resolution using mean climate fields obtained from the Oregon State Parameter Regression on Independent Slopes Model (PRISM; Daly et al. 1994; 2002). Specifically, we computed mean climate fields using CBCCSP data for each calendar month, bi-linearly interpolated these to 30 arc-second resolution, then used the differences between these and PRISM to bias-correct the CBCCSP time series to 30 arc-second resolution. The result is a set of fine-scale projections that match the fine-scale climatology of PRISM, but the time evolution of the CBCCSP dataset. As an illustration, Figure A.1 shows the maps corresponding to mean temperature and precipitation for the months of January and July.

The CBCCSP dataset is based on a statistical downscaling of global model projections, implemented using a daily time-step, 1/16th degree gridded historical dataset (see Hamlet et al. 2010 for a detailed description). The gridded historical dataset is produced by combining surface meteorological observations with assumptions regarding the impact of terrain features (elevation, exposure, etc.) on temperature and precipitation in order to interpolate these onto the output grid. Note that this approach is superior to that of climateWNA (Wang et al. 2012), which uses a simple lapse rate adjustment for temperature, and applies no adjustment at all to precipitation. Nonetheless, in remote and topographically complex regions, the terrain-based assumptions can result in biases in the gridded product, and these biases can vary with meteorology and season. At larger scales – as defined by the density of surface observations from which the gridded product is produced – we can be confident that the gridded observations are a good approximation. Similarly, averages over longer time periods are likely to be more accurate. However, biases are likely to increase with decreasing spatial scale – this is an important limitation when considering the utility of the dataset for connectivity planning.

For comparison with the statistically downscaled CBCCSP data, we also included a dynamically downscaled projection using the Weather Research and Forecasting (WRF, http://www.wrf-model.org; see Appendix C for an overview of downscaling approaches) model, run at a resolution of 12 km and implemented following Salathé et al. (2013; see also Leung et al. 2006). Since regional model simulations are computationally expensive, only one global model was used to drive the simulations: the ECHAM5/MPI-OM global climate model (Roeckner et al. 1999; 2003). Results from the WRF simulations were first adjusted to the resolution of the CBCCSP dataset then, as above, adjusted to the final 30 arc-second grid.

Snow simulations were performed using the Variable Infiltration Capacity (VIC) macroscale hydrologic model (Liang et al. 1994; Gao et al. 2010), and applied using the simpler set of downscaled projections described by Littell et al. (2010).

Note that the PRISM data do not extend beyond the U.S. border with Canada. This is a key limitation of the current dataset, since the border cuts across some of the latitudinal and elevational gradients that species ranges are likely to follow as they track shifting areas of climatic suitability. This problem is exacerbated when major borders fragment large tracts of natural lands that would otherwise offer opportunities for range migration and persistence for a broad range of organisms. Both of these situations are true of the U.S./Canadian border.

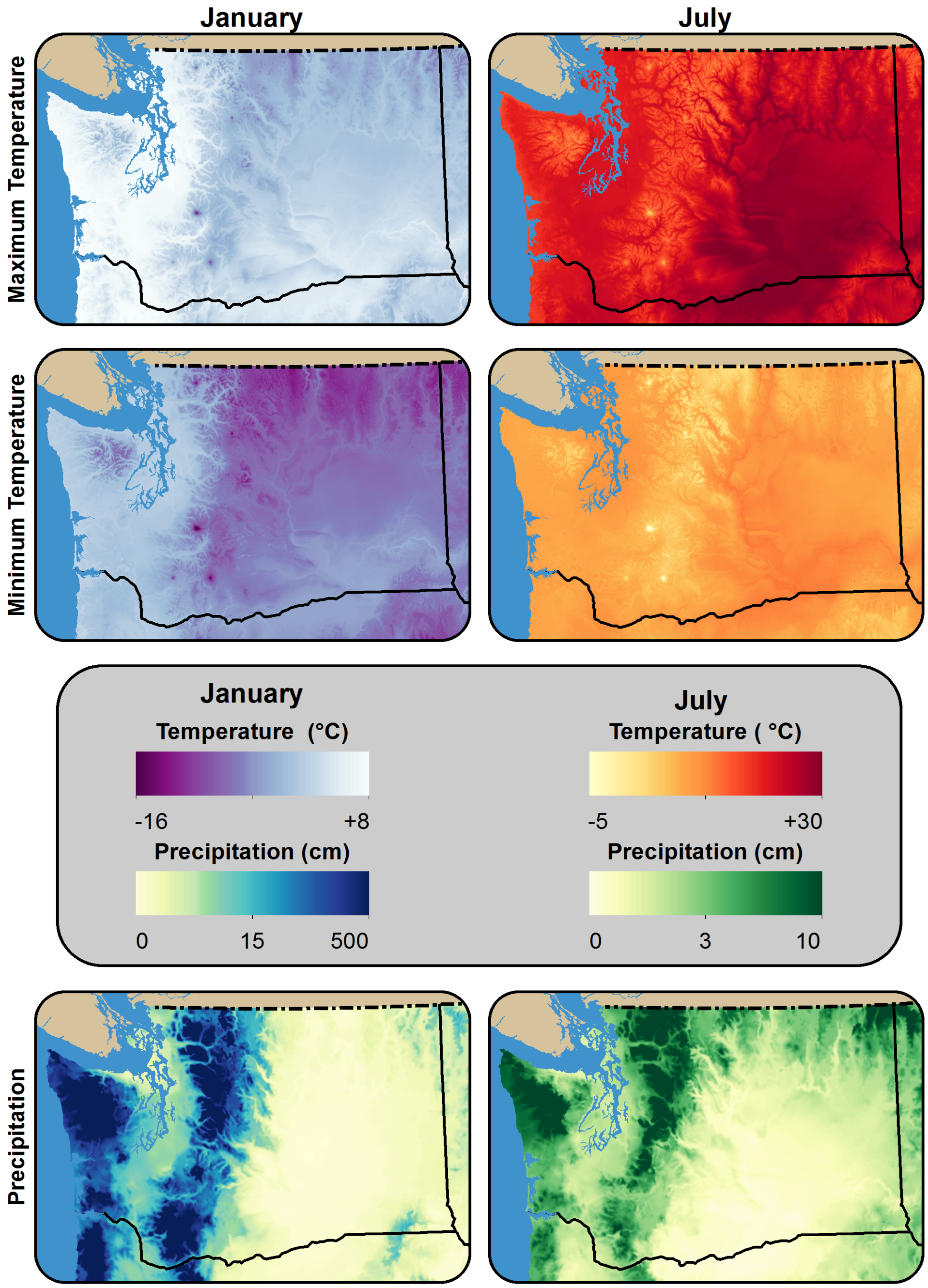

Figure A.1. Example maps of the 30 arc-second 1971-2000 climatology from PRISM (Parameter Regressions on Independent Slopes Model; Daly et al. 1994; 2002). These are the source of the fine-scale resolution in the downscaled dataset – the latter was adjusted to match these when averaged over the same time period. Maps are shown for the months of January (left) and July (right) for average daily maximum (top row), minimum (middle row) temperature (°C) and precipitation (bottom row; cm).

Appendix B: Global Climate Model (GCM) Projections

Global Climate Model simulations represent the state of the art in predicting future changes in climate, and span a wide range of possible futures. Models – and their associated uncertainties – have improved over time, but important uncertainties remain, some of which are irreducible.

GCMs are sophisticated numerical representations of the processes affecting the Earth's climate. Coupling atmosphere, ocean, and land models, GCMs simulate the interactions among these and the implications for changing temperature, precipitation, and other climate variables. GCMs perform well across a variety of metrics (e.g., Knutti et al. 2013), including good fidelity to 20th century variations in temperature, and newer model versions have improved measurably over time.

Despite clear model skill and general agreement among different models, GCMs are subject to a number of important uncertainties. These uncertainties fall into two categories:

1. *Reducible uncertainties:* These are associated with model scale and sophistication, and can be improved upon over time. For instance, computational limitations dictate that GCMs are run at a low spatial resolution. This means that many important processes (e.g., interactions between weather and topography) must be represented statistically rather than with physical models, and may therefore lack important sensitivities to climate change.
2. *Irreducible uncertainties:* These are associated with human emissions of greenhouse gases and natural climate fluctuations: processes that affect the climate but are inherently limited in their predictability (Snover et al. 2013). These uncertainties dictate an approach that considers the range of possible futures, since it is not possible to a priori define which scenario is most likely (e.g., we don't know which emissions path is more likely, but can bracket the range of possibilities).

In the conservation planning context, uncertainty is therefore a reality that must be dealt with. Research is ongoing into better quantification of GCM uncertainties, but typical approaches involve the following:

- *Ranking GCM performance* based on ability to capture the region / variables that are relevant to the project. For instance, all of the results presented in this report are based on the subset of 10 global models that best represented the climate and trends observed for the Pacific Northwest.
- *Considering projections from a range of emissions scenarios.* Greenhouse gas emissions scenarios – "what if" scenarios about future emissions – are used to bracket the range of emissions possibilities.
- *Considering projections from an "ensemble" of different GCMs.* Uncertainties associated with model scale and sophistication can be approximated by considering differences among results obtained from different global models. This is an approximation, since modeling groups collaborate with each other and the resulting GCMs are not fully independent – i.e., the range among models is unlikely to fully span the uncertainty in our understanding of the climate system.
- *Considering differences among like simulations from a single GCM.* Simulations

obtained by driving a single GCM with slight perturbations to initial conditions can be used to estimate the uncertainty associated with natural variability (e.g., Deser et al. 2012).

Appendix C: Downscaled Climate Projections

Downscaled climate projections translate low-resolution GCM projections to scales that are relevant to management and decision-making. However, this increased resolution comes with increased potential for error and uncertainty, which can stem from both input GCM data and downscaling methodology.

Since GCMs are low in spatial resolution (~100-200 km), they do not resolve many landscape-scale features that are important in resource management. This problem is addressed using the technique of "downscaling." Downscaling refers to methods that relate the large-scale changes projected by GCMs to smaller-scale changes on the landscape. Downscaling can be implemented in one of two ways (see Appendix A for the specific implementations used for this report):

1. ***Statistical downscaling:***
   Imposes the statistics of GCM variations on an observed historical time series.

Advantages	*Disadvantages*
• Inexpensive to implement, allowing numerous GCM projections and emissions scenarios to be downscaled in tandem. • Removes absolute biases in GCM simulations (by doing x).	• Assumes that past variability is representative of future variability. • Sensitive to errors in the observed historical dataset.

2. ***Dynamical downscaling:***
   Regional Climate Model (RCM) simulations use GCM outputs as a boundary condition.

Advantages	*Disadvantages*
• Physically-based model captures climate processes that are not resolved by GCMs. • Projections can exceed the range of historical variability.	• Computationally expensive; not feasible to produce a large ensemble or adequately assess RCM uncertainty. • Retains some biases from GCMs (e.g., location of storm track). • RCMs are subject to their own uncertainties.