THE INFLUENCE OF DOWNSCALING ON CLIMATE PROJECTIONS

A Summary of Impacts in Several Western U.S Basins

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GLOBAL CLIMATE PROJECTIONS ARE OFTEN DOWNSCALED TO EVALUATE LOCAL HYDROLOGY, AND THAT PROCESS CAN SIGNIFICANTLY CHANGE THE CLIMATE SIGNAL BEING EVALUATED. DYNAMICAL DOWNSCALING METHODS BETTER REFLECT PHYSICAL PROCESSES, AND SPATIAL/TEMPORAL CLIMATOLOGY EXPECTED IN THE WESTERN U.S.

INTRODUCTION

Global climate model projections form the basis of our understanding of future changes in climate. However, these climate models have significant biases and fail to resolve features necessary to make informed decisions in specific basins. When compared to observational datasets (Figure 1) global models do not resolve orographic precipitation, have large biases across the domain, and have too coarse a spatial resolution. As a result, most applications rely on statistical or dynamical downscaling methods to represent the characteristics of climate that are important for specific basins.

There are a wide variety of downscaling methods in use, and while most reproduce the historical climate accurately, there can be significant differences in the climate change (e.g. precipitation and temperature change) projected by different methods. This document aims to highlight some differences between three downscaling methods: the Intermediate Complexity Atmospheric Research model (ICAR: Gutmann et al., 2016), the LOcally Constructed Analog method (LOCA: Pierce et al., 2014), and the Bias Corrected Spatial Disaggregation method (BCSD: Wood et al., 2002).

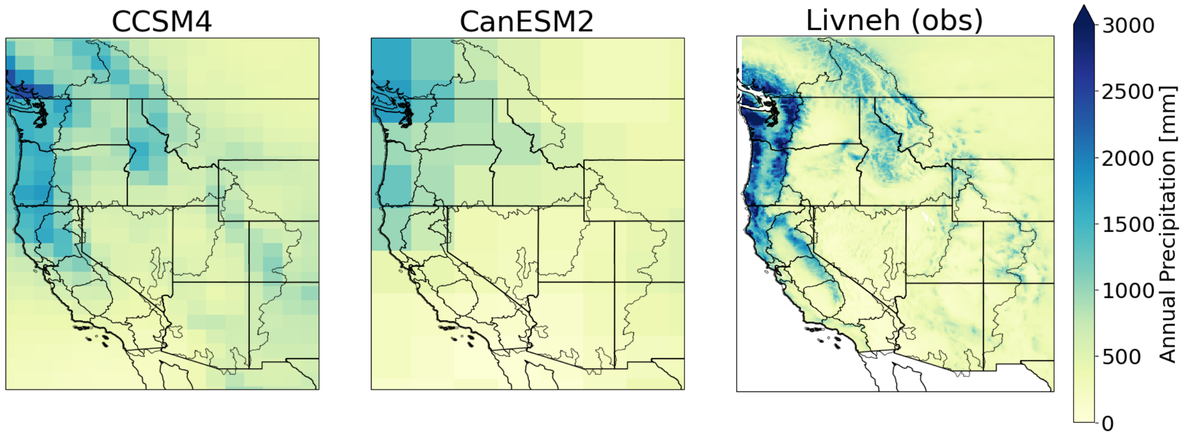


Figure 1. Precipitation across the Western US as represented in two typical global climate models (left, center) and in an observation-based dataset (right).

DOWNSCALING METHODS

The downscaling methods shown here include two widely used statistical downscaling methods and a quasi-dynamical downscaling method. The two statistical downscaling methods include the first widely used downscaling method for water resource applications, BCSD, and the method used in the most recent National Climate Assessment (NCA5), LOCA. The quasi-dynamical method reviewed here is the ICAR model. All three methods have been applied to eight global climate models (GCMs) from the Coupled Model Intercomparison Project phase 5 (CMIP5): CanESM2, CCSM4, CNRM-CM5,CMCC-CM, GFDL-CM3, HadGEM2-ES, MRI-CGCM3, and MIROC5. Climate change maps shown here were computed between the periods 2070-2100 and 1975-2005 using the Representative Concentration Pathway (RCP) 8.5 emissions scenario. For comparison, we also show results from a sensitivity experiment performed with one of the most physically complete atmospheric models, the Weather Research and Forecasting model (WRF: Skamarock and Klemp, 2008). The WRF model is too computationally expensive to perform the same direct downscaling, but it was used in an idealized experiment to represent the average climate change signal across 19 GCMs from CMIP5 for the same emissions scenario and time periods (Liu et al., 2017).

PRECIPITATION DIFFERENCES

Precipitation is the biggest driver of water supply in the west and is one the most uncertain elements in future climate projections. While all downscaling methods project increases in precipitation across most of the domain, the spatial patterns are markedly different between dynamical approaches (ICAR and WRF) and statistical approaches (BCSD and LOCA). BCSD and LOCA project roughly the same percentage increase on mountain tops as in valleys. In contrast, ICAR and the WRF sensitivity test project small percent increases on mountain tops, and even decreases near the crest and in the lee of mountains (Figure 2). This spatial distribution can be explained by the following physical processes, 1) changes from snow to rain result in less efficient extraction of moisture over mountains due to the time it takes rain to form relative to snow (Eidhammer et al., 2018), 2) less precipitation immediately downwind of the mountain crest due to the faster fall speed of rain vs snow, and 3) more precipitation further downwind of the mountains as more moisture makes it past the mountain range (Siler et al., 2016, Mass et al., 2022).

Key Finding: Dynamical downscaling approaches (ICAR and WRF) project less of an increase in precipitation on mountain tops than statistical methods (LOCA and BCSD)

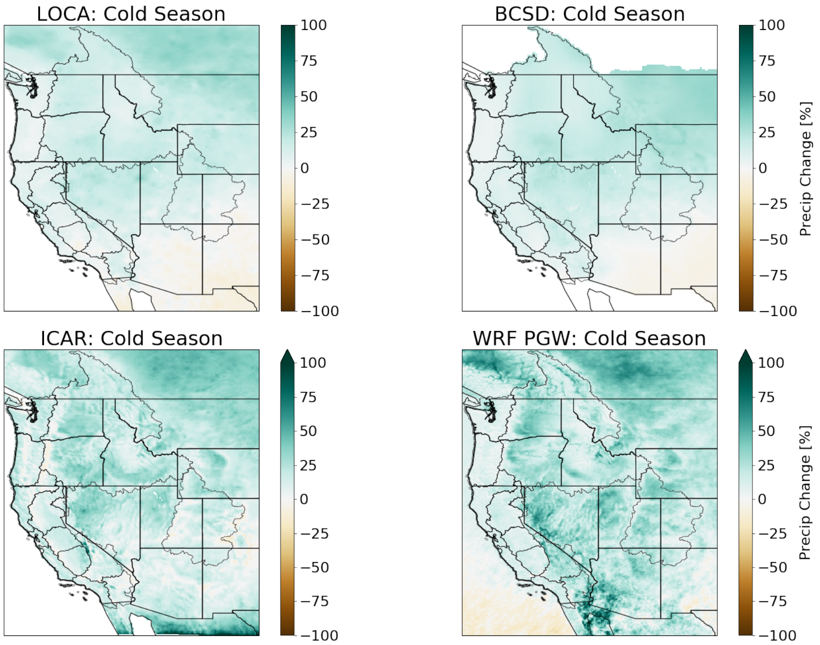
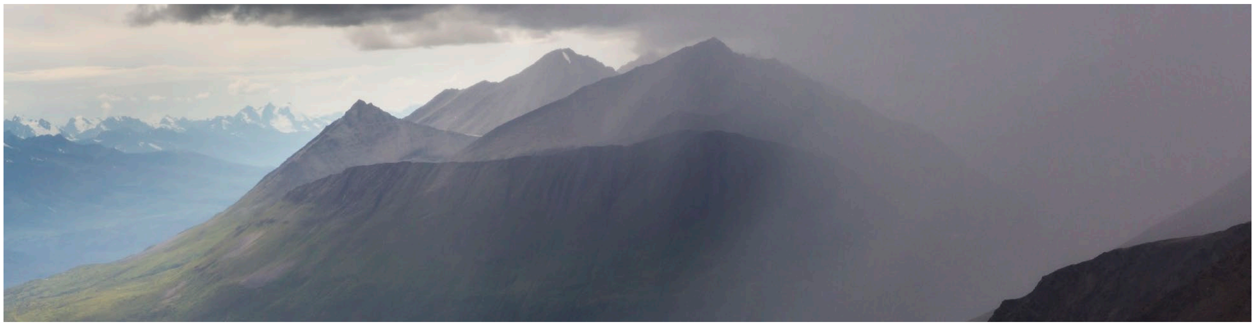


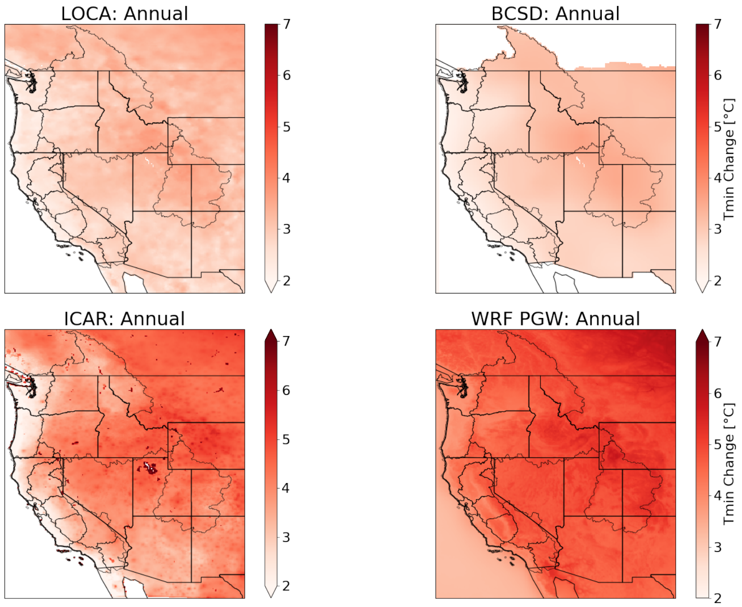
Figure 2. The mean end-of-century change in mean precipitation during the cool season (Sept-May) in four different downscaled datasets. Methods using a high-resolution atmospheric model (ICAR and WRF: bottom) predict less change on mountain tops and more in interior inter-mountain domains.



Source: Rain in the Wrangell Mountains, Alaska. Public domain photo by National Parks Service Neal Herbert

TEMPERATURE CHANGES

Temperature is critical for water resource estimates of evaporative losses, snow melt timing, and water quality thermal effects. All methods project increases in temperature, but there are differences in the spatial pattern and the change in minimum and maximum temperatures. The dynamical methods project larger changes in daily minimum temperatures (Figure 3) and smaller changes than the statistical methods in the daily maximum temperatures (Figure 4). Theory and historical observations agree that minimum temperatures should increase faster than maximum temperatures (Gil-Alana, 2018). This occurs because in a warmer world, there is little change in the solar radiation that drives mid-day maximum temperatures, but the longwave radiation that plays an important role in controlling minimum temperatures should increase because of increases in greenhouse gases and air temperatures.



Key finding: LOCA and BCSD project a smaller change in daily minimum temperatures than daily maximum temperatures, in contrast to ICAR, WRF, and recent historical trends

Figure 3. Projected changes in daily minimum temperature in statistically downscaled (top) and dynamically downscaled (bottom) data.

ICAR projects smaller changes in temperature along the west coast than other methods do, and both ICAR and WRF project larger increases in temperature in the interior mountain ranges, where the snow albedo feedback effect is expected to amplify warming.

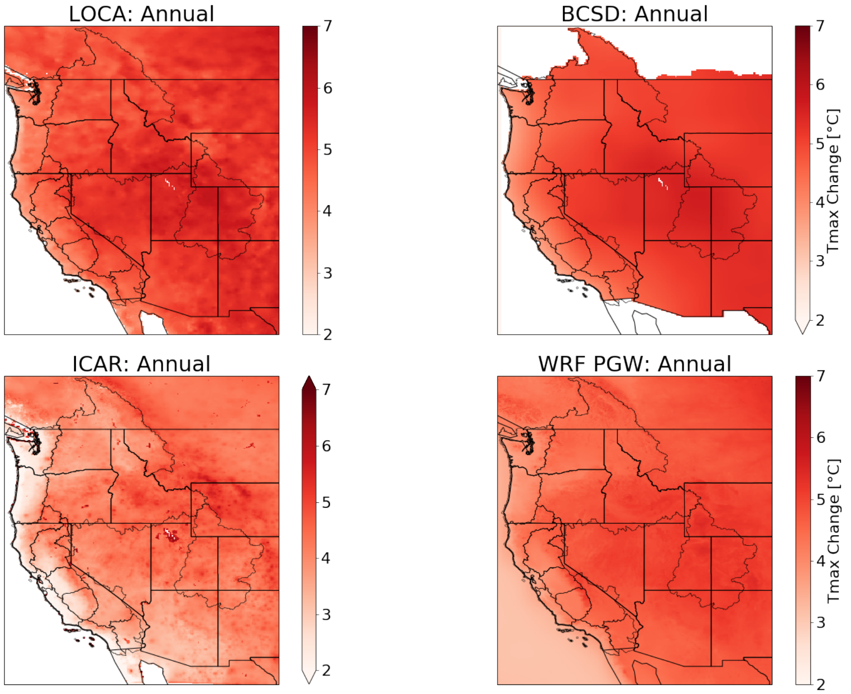


Figure 4. Projected changes in daily maximum temperature in statistically downscaled (top) and dynamically downscaled (bottom) data.

CONCLUSION

Dynamically based and statistically based downscaling methods project similar large-scale patterns of changes in precipitation and temperature; however, the smaller scale variability exhibits significant differences. WRF sensitivity experiments, ICAR direct downscaling, and theory agree that mountain tops should see less of a percent increase in precipitation, and that the lee side of mountain ranges may see decreases in precipitation, and that the region downwind from mountain ranges should have larger precent increases in precipitation. Statistical downscaling methods (LOCA and BCSD) both predict smoother spatial patterns of cool season precipitation changes, reflecting the GCMs' change signal. Similarly, dynamical methods and theory agree that daily minimum temperatures should increase faster than daily maximum temperatures, while statistical downscaling methods (BCSD and LOCA) predict the opposite.

Dynamically downscaled climate change projections better represent physical processes and agree with observed and theoretically expected patterns of change. Climate change projections are a useful tool for water managers to analyze and plan for future water supplies, yet it is vital to understand that different downscaling methods introduce unique changes to the climate signal and the hydrologic implications from these differences need to be considered.

REFERENCES

Eidhammer, T., Grubišić, V., Rasmussen, R., & Ikdea, K. (2018). Winter precipitation efficiency of mountain ranges in the Colorado Rockies under climate change. Journal of Geophysical Research: Atmospheres, 123, 2573–2590. https://doi.org/10.1002/2017JD027995

Gil-Alana LA. Maximum and minimum temperatures in the United States: Time trends and persistence. Atmos Sci Lett. 2018; 19: e810. https://doi.org/10.1002/asl.810

Gutmann, E., I. Barstad, M. Clark, J. Arnold, and R. Rasmussen, 2016: The Intermediate Complexity Atmospheric Research Model (ICAR). J. Hydrometeor., 17, 957–973, https://doi.org/10.1175/JHM-D-15-0155.1.

Liu, C., Ikeda, K., Rasmussen, R. et al. Continental-scale convection-permitting modeling of the current and future climate of North America. Clim Dyn 49, 71–95 (2017). https://doi.org/10.1007/s00382-016-3327-9

Mass, C. F., E. P. Salathé, R. Steed, and J. Baars, 2022: The Mesoscale Response to Global Warming over the Pacific Northwest Evaluated Using a Regional Climate Model Ensemble. J. Climate, 35, 2035–2053, https://doi.org/10.1175/JCLI-D-21-0061.1.

Pierce, D. W., D. R. Cayan, and B. L. Thrasher, 2014: Statistical Downscaling Using Localized Constructed Analogs (LOCA). J. Hydrometeor., 15, 2558–2585, https://doi.org/10.1175/JHM-D-14-0082.1.

Reclamation, 2014: Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Hydrology Projections, Comparison with preceding information, and summary of User Needs', prepared by the U.S. Department of the Interior, Bureau of Reclamation, Technical Services Center, Denver, Colorado. 110pp.

Skamarock, W. C. & Klemp, J. B. (2008) A time-split nonhydrostatic atmospheric model for weather research and forecasting applications. Journal of Computational Physics 227, 3465–3485.

Wood, A.W., Leung, L.R., Sridhar, V. et al. Hydrologic Implications of Dynamical and Statistical Approaches to Downscaling Climate Model Outputs. Climatic Change 62, 189–216 (2004). https://doi.org/10.1023/B:CLIM.0000013685.99609.9e