EVALUATION OF INFLUENCE OF SPATIAL RESOLUTION ON EXTREME PRECIPITATION PROJECTIONS

PACIFIC CLIMATE IMPACTS CONSORTIUM

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Motivation

Changes in temperature and precipitation extremes are occurring (Figure 1 inset) and future climate projections are needed for planning. Projected changes in extremes from Global Climate Models (GCMs) are useful for understanding future evolution of climate but have spatial resolution that is too coarse for local decision-making.

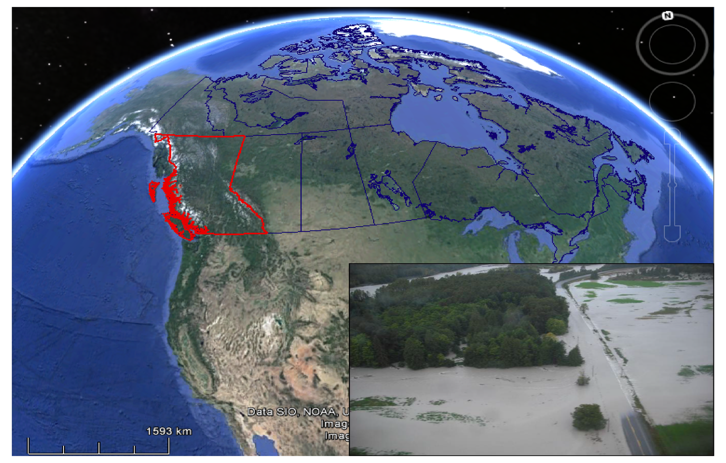


Figure 1: Study area. Inset: damage during a 200-year rainfall event in Bella Coola September 2010. Photo credit: BC Ministry of Transportation and Infrastructure.

Higher resolution is achieved via statistical and/or dynamical downscaling. We investigate the effect of downscaling on projected changes in extremes. Our study area is British Columbia, the westernmost Canadian province, just North of the United States Pacific Northwest (Figure 1).

Objective: to determine if projected changes in extreme precipitation from climate models are preserved after downscaling.

Experimental Design and Methods

We consider heavy precipitation, (R95ptot: total annual precipitation on days wetter than the 95th percentile on days with at least 1 mm precipitation in the past) and extreme precipitation (RP10: the daily event with a 10-year expected waiting time). To eliminate differences between model grids, simulations were re-gridded to 1.5° (GCMs) or 0.5° (RCMs) before analysis.

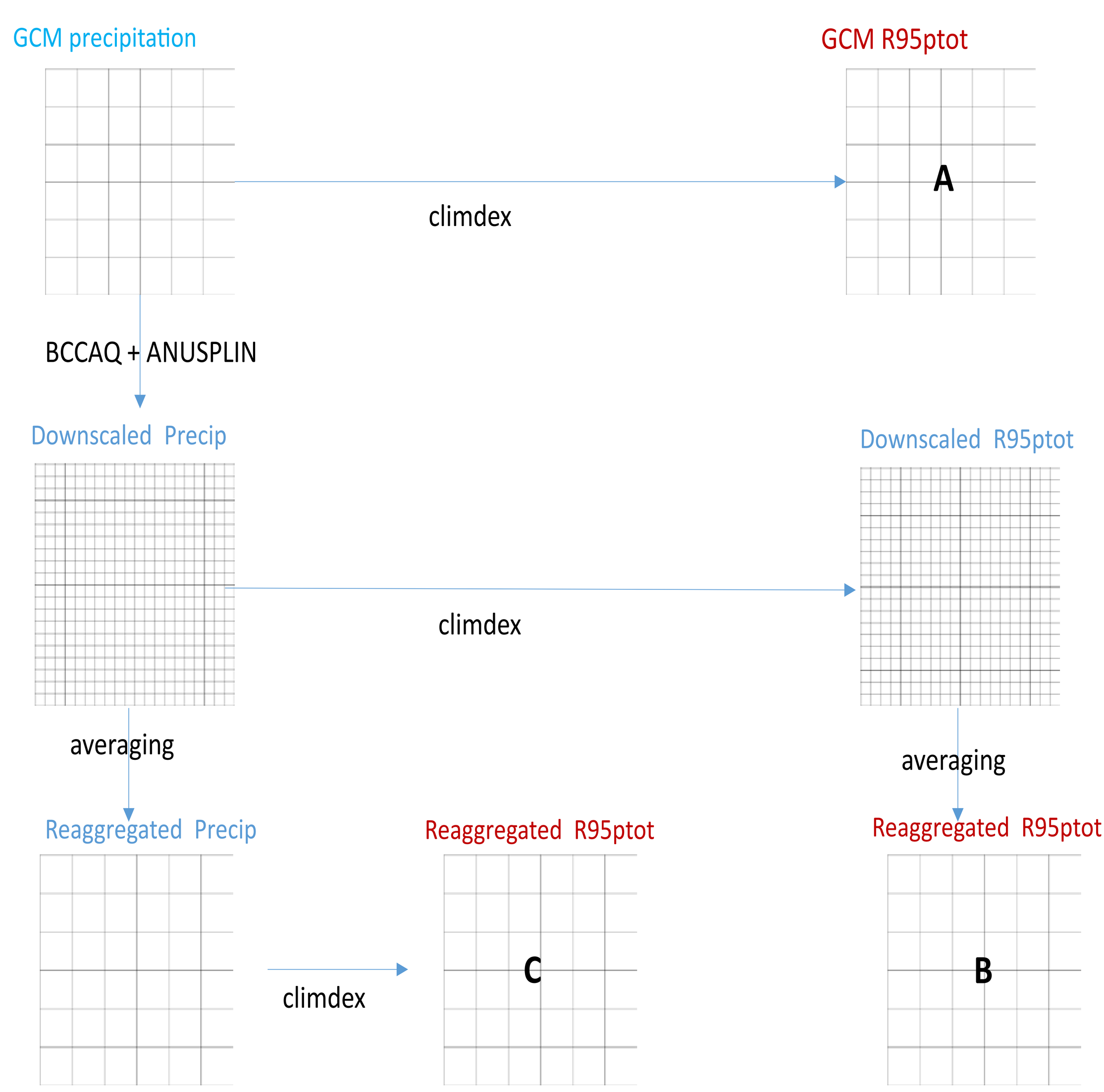


Figure 2: Experimental design for downscaling R95ptot index from coarse Global Climate Model (GCM) resolution using the BCCAQ statistical downscaling method and ANUSPLIN target dataset.

Downscaled GCM output (middle left) is re-aggregated to the original resolution in two ways: before (bottom row) or after (middle row) computing the R95ptot index.

Each result (B and C) is compared to the other and to R95ptot computed from the GCM directly (A; top row).

The approach is repeated using statistical downscaling of RCM simulations and for the 10-year return period extreme daily precipitation event.

We use Bias Correction Constructed Analogues Quantile mapping (BCCAQ), a field-based model output statistic method with high skill (Cannon et al. in prep) to statistically downscale 12 GCM simulations with RCP4.5 emissions from CMIP5 and the 11 NARCCAP RCM simulations. A gridded daily dataset (ANUSPLIN; McKenney et al. 2011) based on station data interpolated to 300 arc-seconds (~10 km) resolution with thin-plate splines was the downscaling target.

There and back again: GCMs

The historical 1971-2000 baseline R95ptot (Figure 3) shows that the west coast has considerably more precipitation during very wet days than the rest of the province.

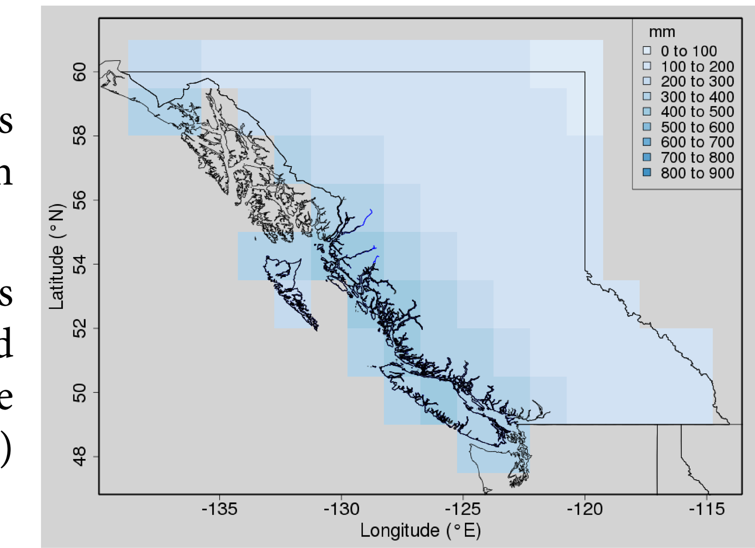


Figure 3: R95ptot 1971-2000: GCM (ensemble average).

As the statistical downscaling is a quantile-based bias correction method, the difference between downscaled re-aggregated and GCM simulated 1971-2000 baseline R95ptot (Figure 4) is virtually identical (but opposite in sign) to GCM bias..

The GCM simulated wet coast is more spread out than observations resulting in a dry bias in the wettest parts of the west coast and a wet bias in the interior to the east of the coast. The GCMs also do not resolve a relatively wet high mountain area in the southeast corner of the province.

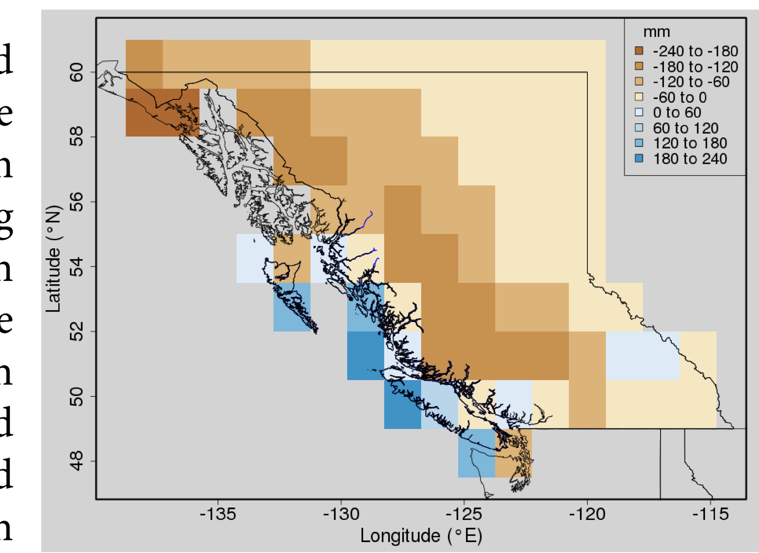


Figure 4: R95ptot difference between 1971-2000 downscaled re-aggregated and GCM (ensemble averages).

By the 2050s, the difference between downscaled re-aggregated and GCM exhibits a similar pattern to Figure 4 but increased by about 30% in magnitude (not shown). In other words, at most locations the net effect of downscaling and re-aggregating is to "remove" water in the past and even more water in future. On the outer coast where GCMs have a dry bias, downscaling "adds" water in the past and even more water in the future. Differences in projected percentage change in R95ptot between downscaled reaggregated and GCMs are dominated by the elimination of the GCMs' biases. The net effect is an apparent magnification of projected R95ptot percentage increases across the province (Figure 5).

This effect is larger for measures of precipitation that are more extreme, and vice versa. Annual total precipitation exhibits differences of less than a few percent across the majority of the province (not shown) while differences for the more extreme 1 in 10-year event RP10 (not shown) are roughly double those of R95ptot in Figure 5.

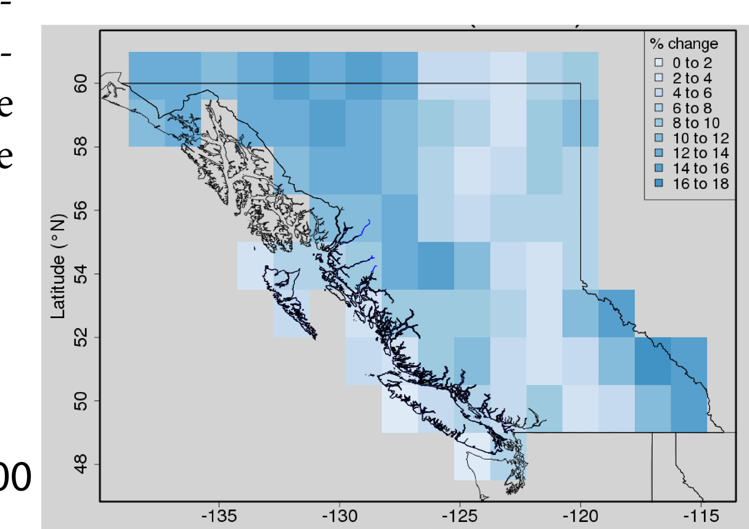
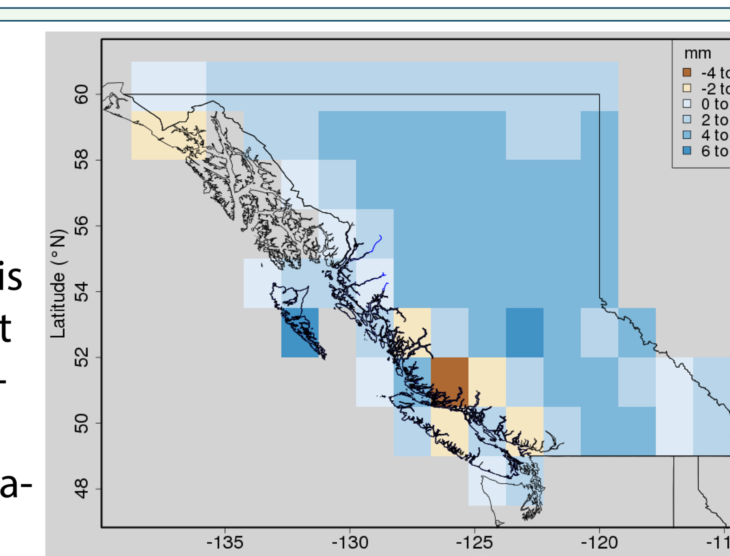


Figure 5: R95ptot difference between downscaled re-aggregated and GCM 2050s anomaly as percent of 1971-2000 baseline (ensemble averages).

Order of operations

Figure 6: Our default approach is to compute R95ptot at fine scale then re-aggregate (Figure 2: B). The alternative is to re-aggregate daily precipitation then compute R95ptot (Figure 2: C). The difference between approaches is small compared to the effect of bias correction (Figure 4) for R95ptot. As a percentage of historical values, these anomalies range from -2% to +10%.



RCMs

For the ensemble of RCM runs larger differences are present between downscaled re-aggregated and coarse scale at several locations (compare Figures 7 and 5).

The effect of statistical downscaling on the climate change signal can be stronger here despite the smaller scale difference from about 50 km to 10 km vs. 150 km to 10 km. The comparison is now being made on a "coarse scale" much finer than for the GCMs, however. Factors related to model bias discussed in the centre panel are also at work here.

In other words, despite overall smaller RCM than GCM bias (not shown), the finer scale enables resolving some locations with considerably higher biases.

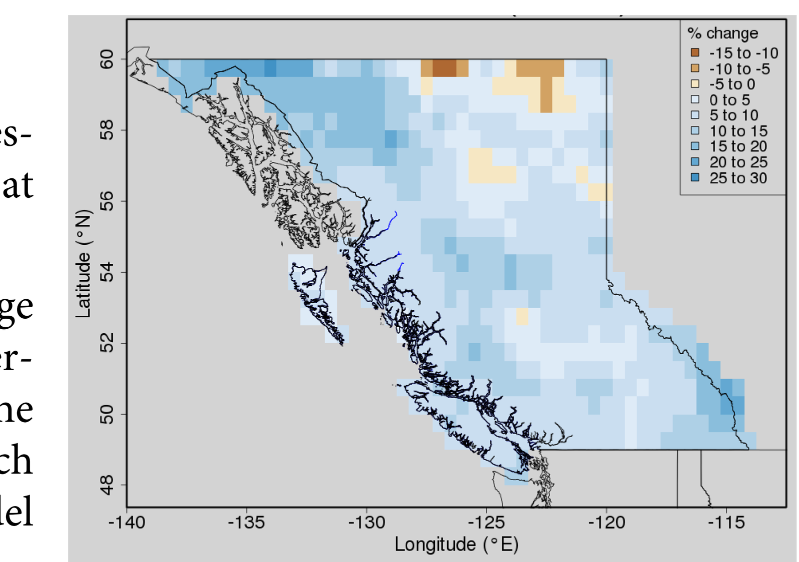


Figure 7: R95ptot difference between downscaled re-aggregated and RCM 2050s anomaly as percent of 1971-2000 baseline (ensemble averages).

Uncertainty

Downscaling roughly preserves projected large scale changes in annual precipitation, but not for extremes. R95ptot is modestly amplified while the change in RP10 is comparable to the uncertainty between runs (Figure 8).

The anomaly fields from the GCM and downscaled reaggregated output were compared using the spatial Kolmogorov-Smirnov test of similarity and the Walker field significance test. Both tests indicate that the downscaled reaggregated and GCM anomalies come from the same distribution for annual precipitation and R95ptot (10 and 9 of 12 runs, respectively). Both tests also indicate that for all 12 runs, projected changes in RP10 are from a different distribution than the GCM anomalies at the 10% significance level.

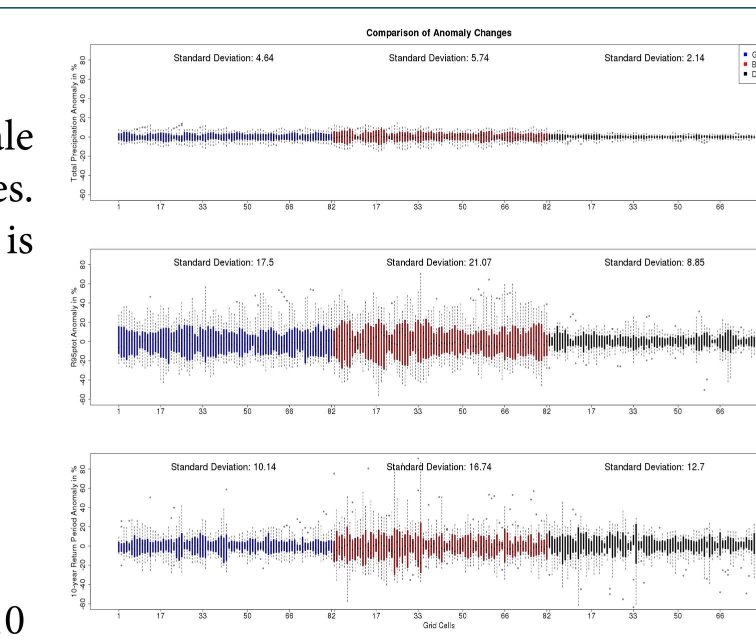


Figure 8: Boxplots of range of projected percent changes from each of 12 ensemble members for GCMs (blue), downscaled re-aggregated (red), and difference (black).

Conclusions

The main effect of statistical downscaling on projected change in extremes is due to correction of historical bias. This does not necessarily mean downscaling is adding value.

The coarse scale projected change in annual precipitation is retained but heavy precipitation (R95ptot) is somewhat amplified and extreme precipitation change (RP10) is considerably altered. Since it is these extremes that are needed for planning, further work is needed.

In next steps we will compare results at a coarser scale (e.g. 5°) to reduce the influence of bias correction on results and also separate into small and large scale explicitly as in Di Luca et al. (2013). Finally, we plan to compare projected changes from RCMs to that of their driving models in the same ways.

Statistical downscaling methods that are explicitly designed to preserve coarse scale projected changes including extremes would be a welcome development for regional decision-making.

Works cited

Cannon, A.J., S.R. Sobie, and T.Q. Murdock, in prep., Downscaling extremes - an intercomparison of multiple gridded methods.

Di Luca, A., R. de Elía, and R. Laprise, 2013: Potential for small scale added value of RCM's downscaled climate change signal. Clim. Dyn., 40, 601–618.

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