Using hybrid downscaling to make credible climate change projections in California's Sierra Nevada

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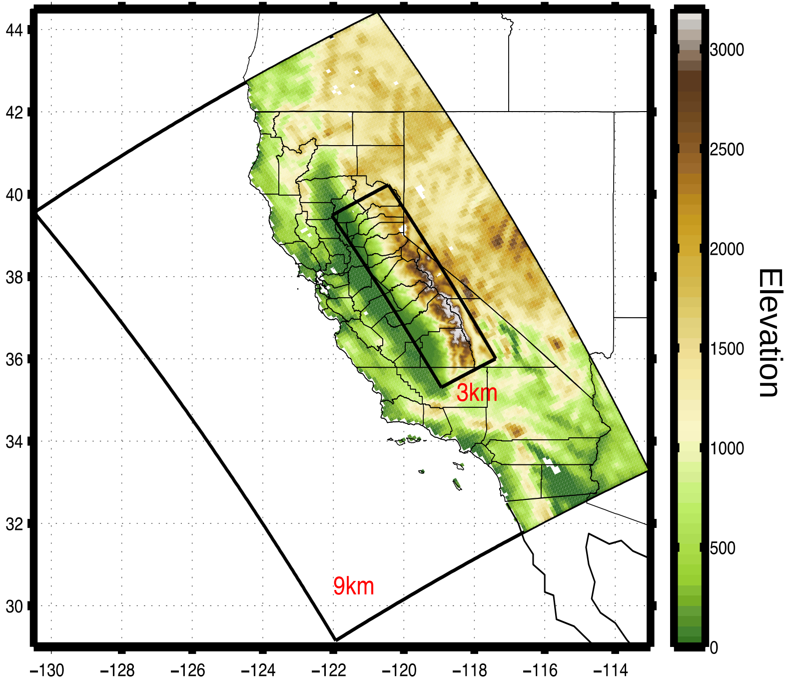
Hybrid downscaling – a brief overview

- The essence of hybrid downscaling is to do limited **dynamical** downscaling for a region, and then develop simple **statistical** models to mimic dynamical model behavior, i.e. do **hybrid** dynamical-statistical downscaling.
- The statistical models can then be used to produce regional data corresponding to any GCM, for any time slice or forcing scenario.
- Hybrid downscaling forces the researcher to diagnose climate change patterns produced by dynamical downscaling.
- It avoids the stationary assumption common to conventional statistical downscaling techniques.
- It allows for uncertainty characterization associated with GCM spread and forcing scenario.

Data Production



”Baseline” simulation of 1981–2015 climate. Weather Research and Forecasting (WRF) model forced by data from North American Regional Reanalysis (NARR).

5 future WRF simulations of Oct 2091–Sept 2101 climate, representing climate change signal from CNRM-CM5, GFDL-CM3, inmcm4, IPSL-CM5A-LR, MPI-ESM-LR GCMs under RCP8.5.

Hybrid downscaling projections of *mean changes* in temperature, snow cover, SWE, runoff, and 0-10 cm soil moisture at 2040–2060 and 2081–2100 under RCP8.5 and RCP4.5, representing full CMIP5 GCM ensemble.

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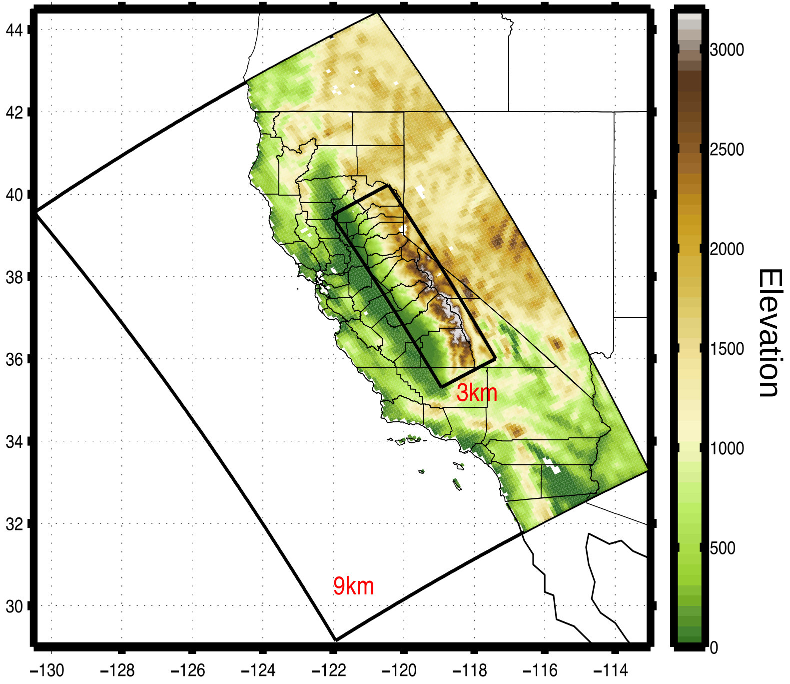

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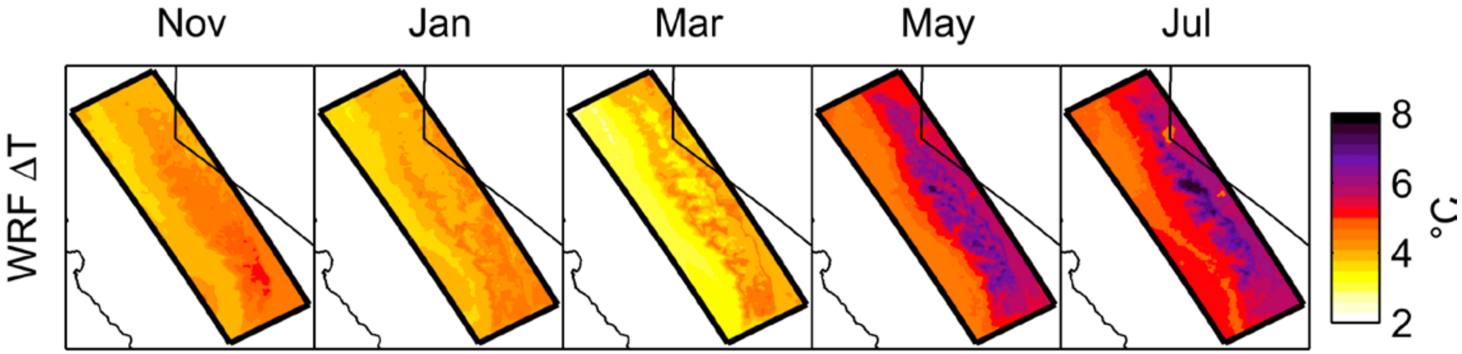
Dynamically downscaled warming



These are example warming patterns for 5 selected months, which span the most important phase of the annual cycle for Sierra water resources.

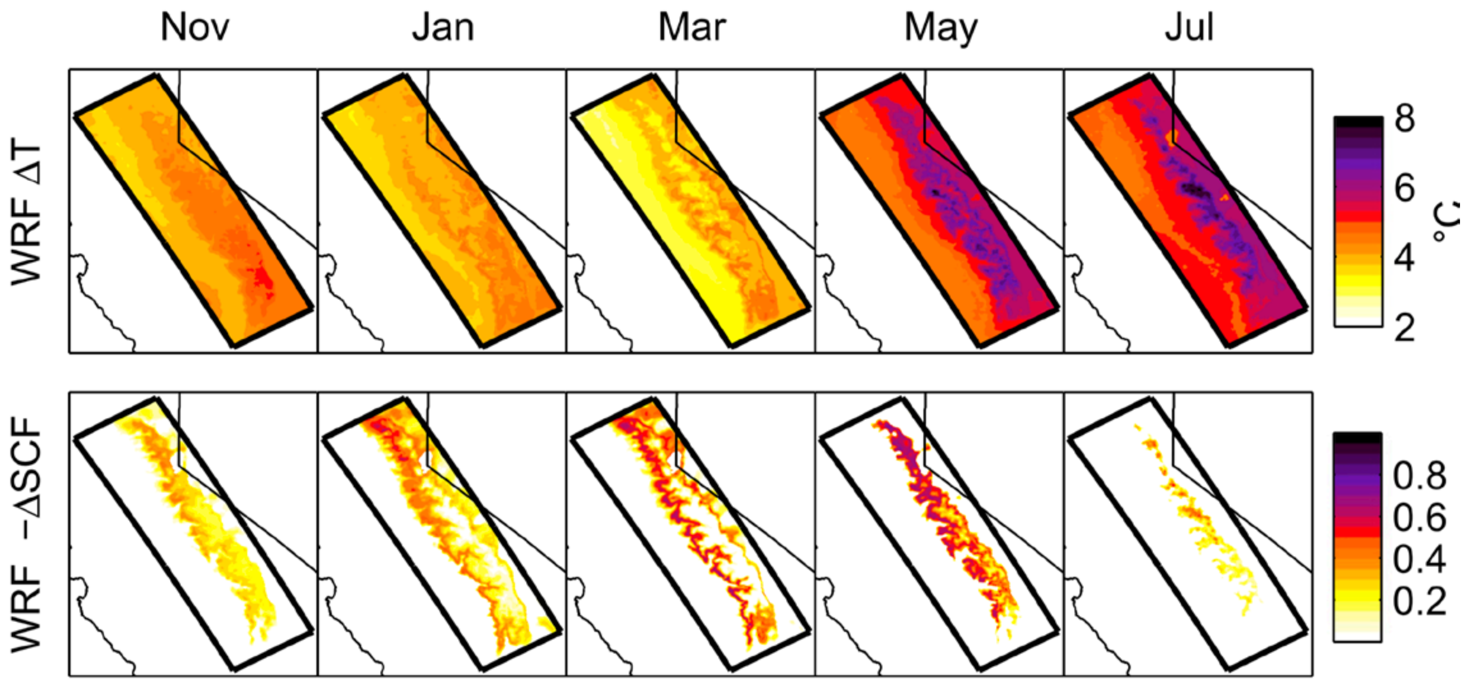
This is the average over all five dynamically downscaled futures. (Warming patterns are very similar for individual simulations, even if the magnitudes vary.)

Two features are evident:

1. Warming is greater on the continental side of the Sierra Nevada.
2. The imprint of snow albedo feedback is clear in every month.

Walton et al. 2017

Dynamically downscaled warming

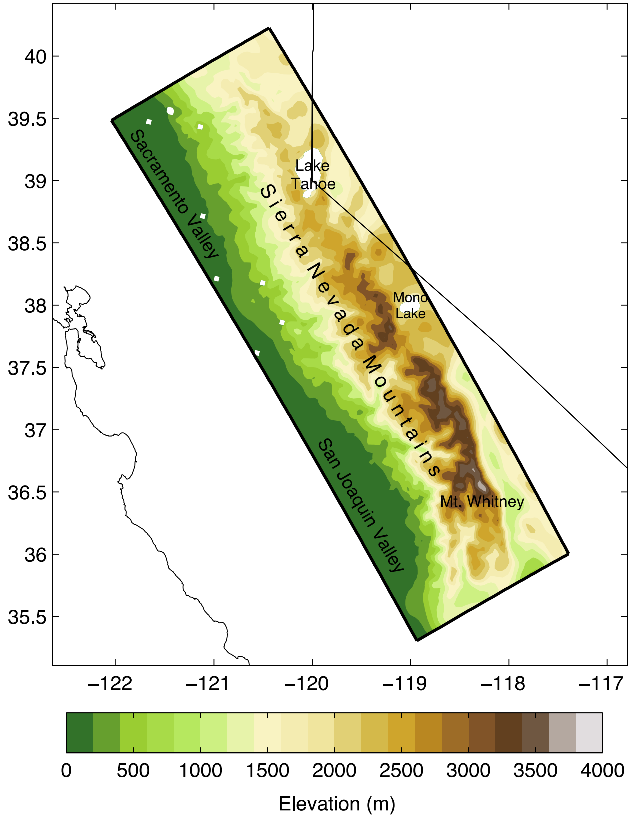


The impact of snow albedo feedback is especially evident if one compares the warming patterns to the change in fractional area covered by snow.

Walton et al. 2017

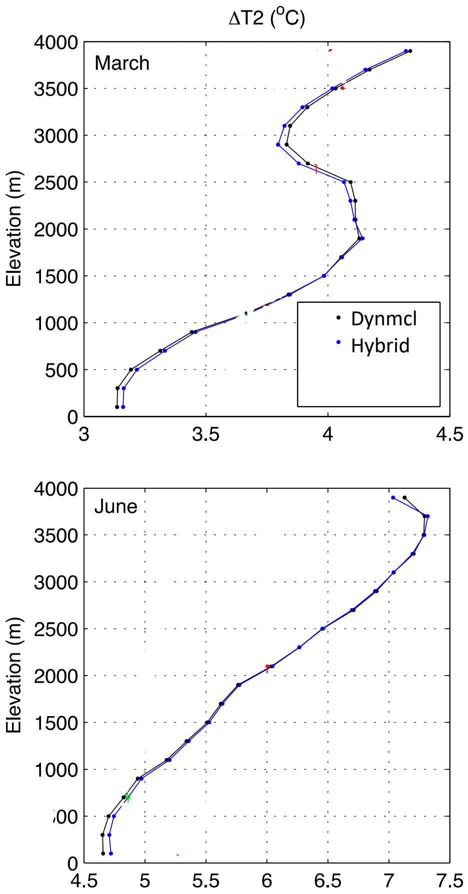
Development of Statistical Model

- Based on these results, we construct a simple mathematical model that takes as inputs the main drivers of regional warming.
- Through careful diagnostics, we have determined that those drivers are:
    1. Overall GCM warming in this region
    2. GCM warming contrast between N America and the adjacent Pacific Ocean
    3. Snow albedo feedback
- With these inputs, the statistical model then produces warming patterns that mimic those of WRF.



Walton et al. 2017

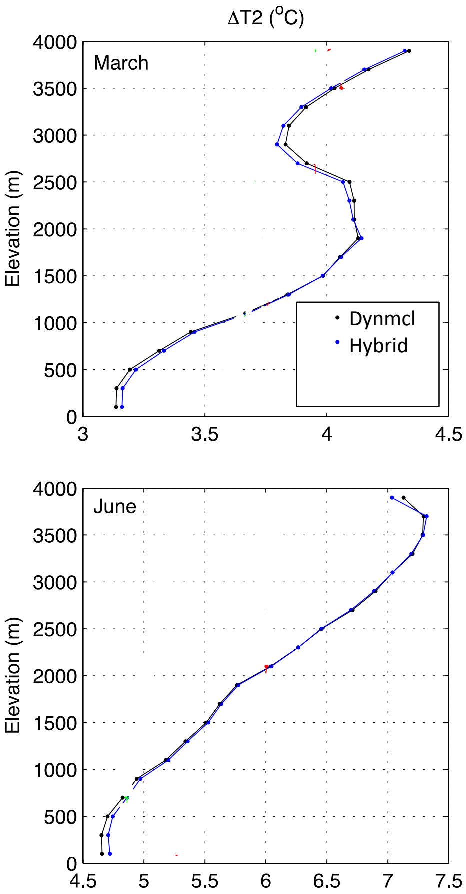
Test of Statistical Model



- This is the RCP8.5 end-century warming as a function of elevation, for March and June.
- Both the dynamical results from the 5-member ensemble and corresponding results from the statistical model are shown.
- The agreement is nearly perfect, indicating we can model WRF's warming patterns if we know:
    1) how much warming a GCM gives
    2) how much land-sea contrast that GCM has
    3) how much snow albedo feedback WRF produces

Walton et al. 2017

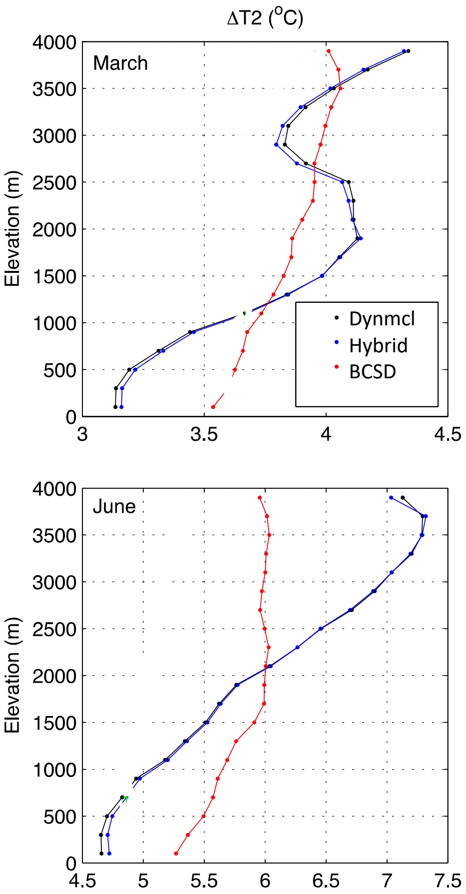
Other downscaling techniques



- How do these projections stack up against other downscaled data products?
- Here again is the warming produced by the hybrid approach as a function of elevation, for March and June.
- Let's now overlay the warming produced by two commonly used downscaling techniques.

Walton et al. 2017

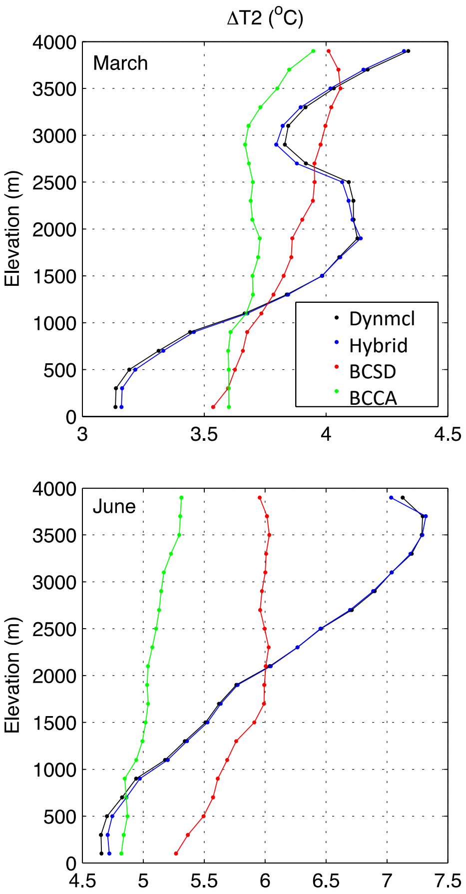
Other downscaling techniques



- Here's the warming given by BCSD, which may be one of the most commonly applied downscaling techniques.

Walton et al. 2017

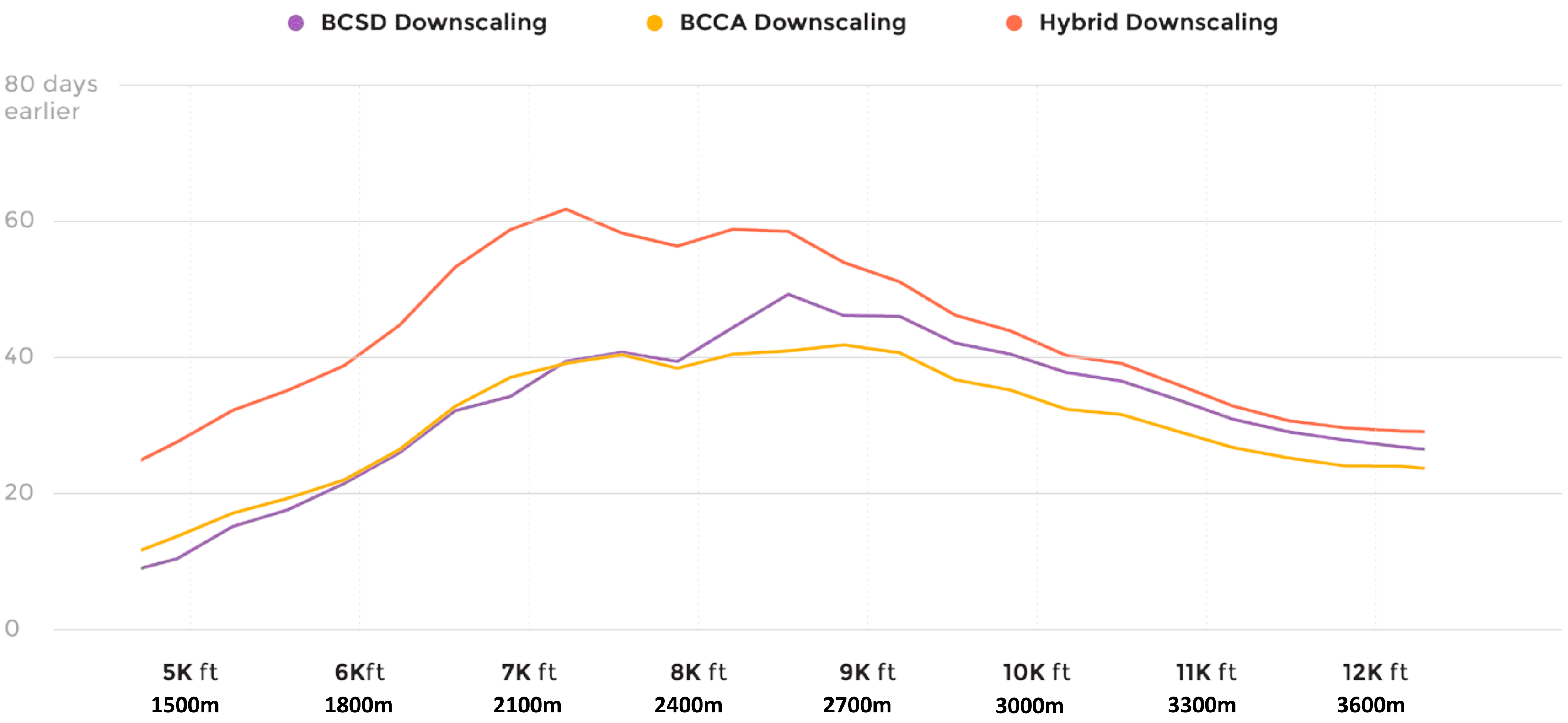
Other downscaling techniques



- And here's the warming given by BCCA, another common technique.
- Neither BCSD nor BCCA captures the large variations in warming with elevation.
- In fact, both BCSD and BCCA produce "flat" warming projections in the Sierra Nevada, with little spatial structure.

Walton et al. 2017

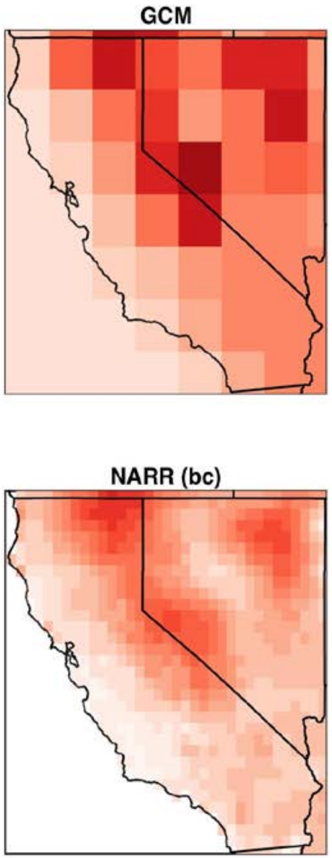
How Snow Albedo Feedback Affects Runoff Timing



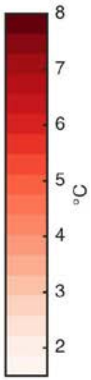
Schwartz et al. 2017

Why do downscaling techniques differ?

Apr ΔTmax (1991-2000 Fut–Hist)



- Here is the warming from a single GCM (CNRM-CM5) over the region of interest, and the warming from that GCM interpolated to the native grid of the North American Regional Reanalysis.
- The maximum warming is located in a zone where snow retreats in the GCM.
- Since topography is in the wrong place, the snow margin is in the wrong place, and so the warming has features we know are unphysical.



Walton et al. (in prep)

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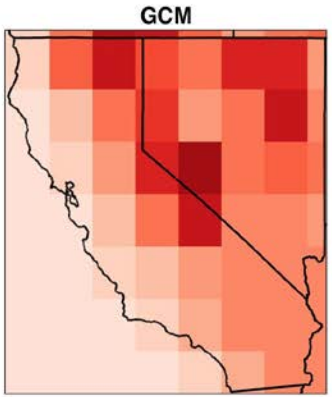
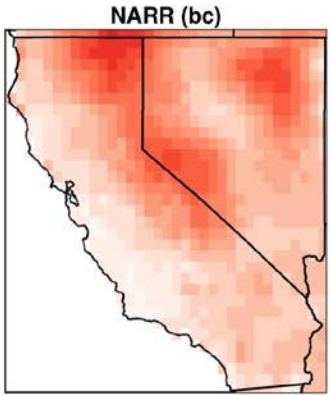
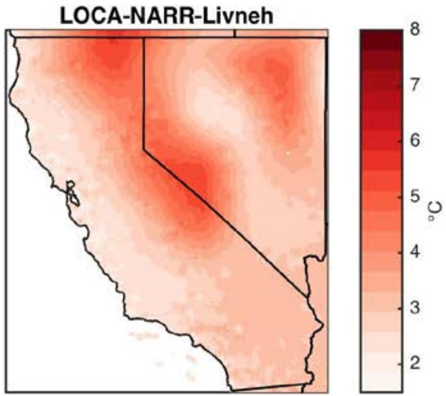


- Below is the high-resolution warming predicted by LOCA, an emerging statistical downscaling technique.
- In this case LOCA is trained on NARR data (coarse resolution dataset) and Livneh (fine resolution observationally-based gridded product).
- Its warming pattern matches that of the interpolated GCM.





Walton et al. (in prep)

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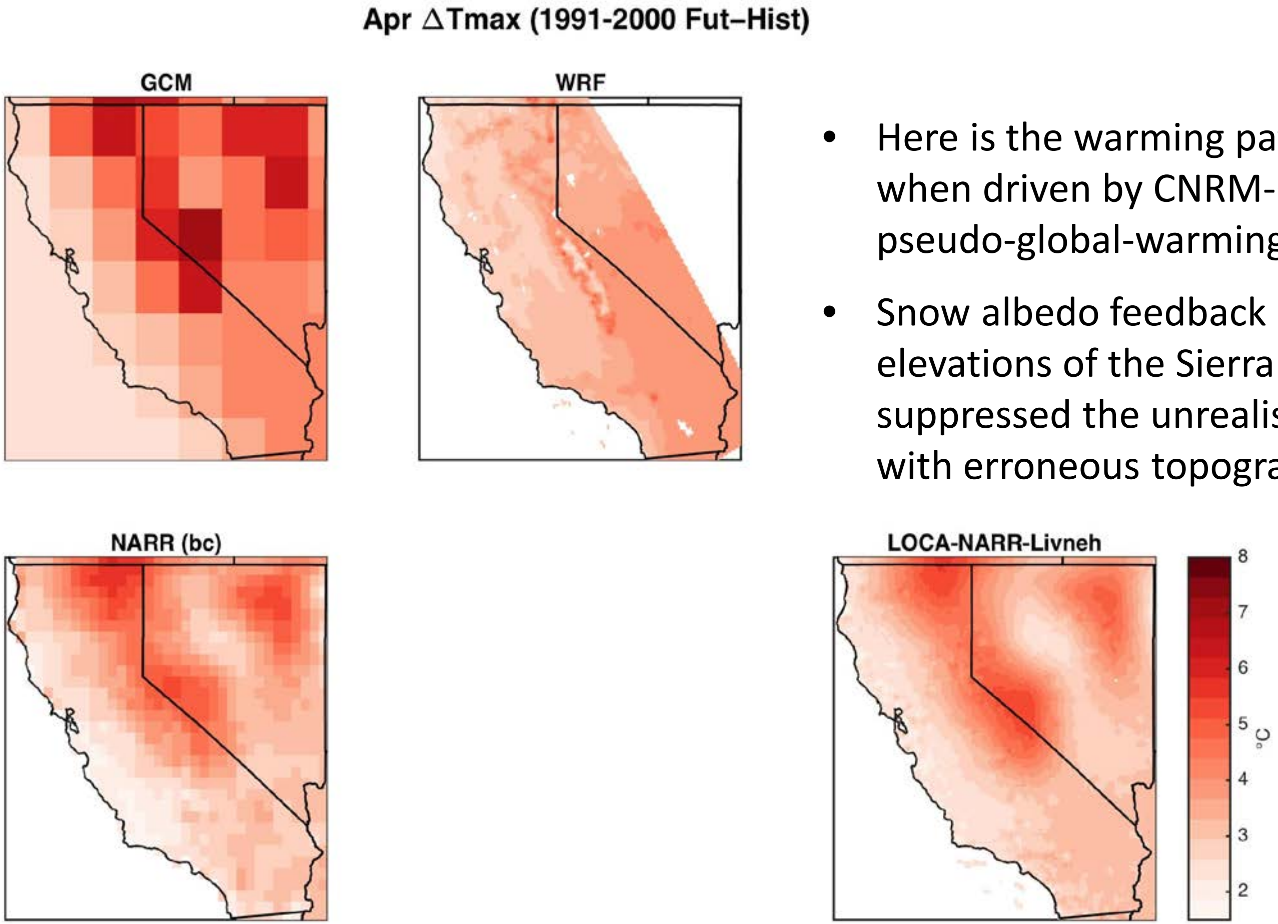
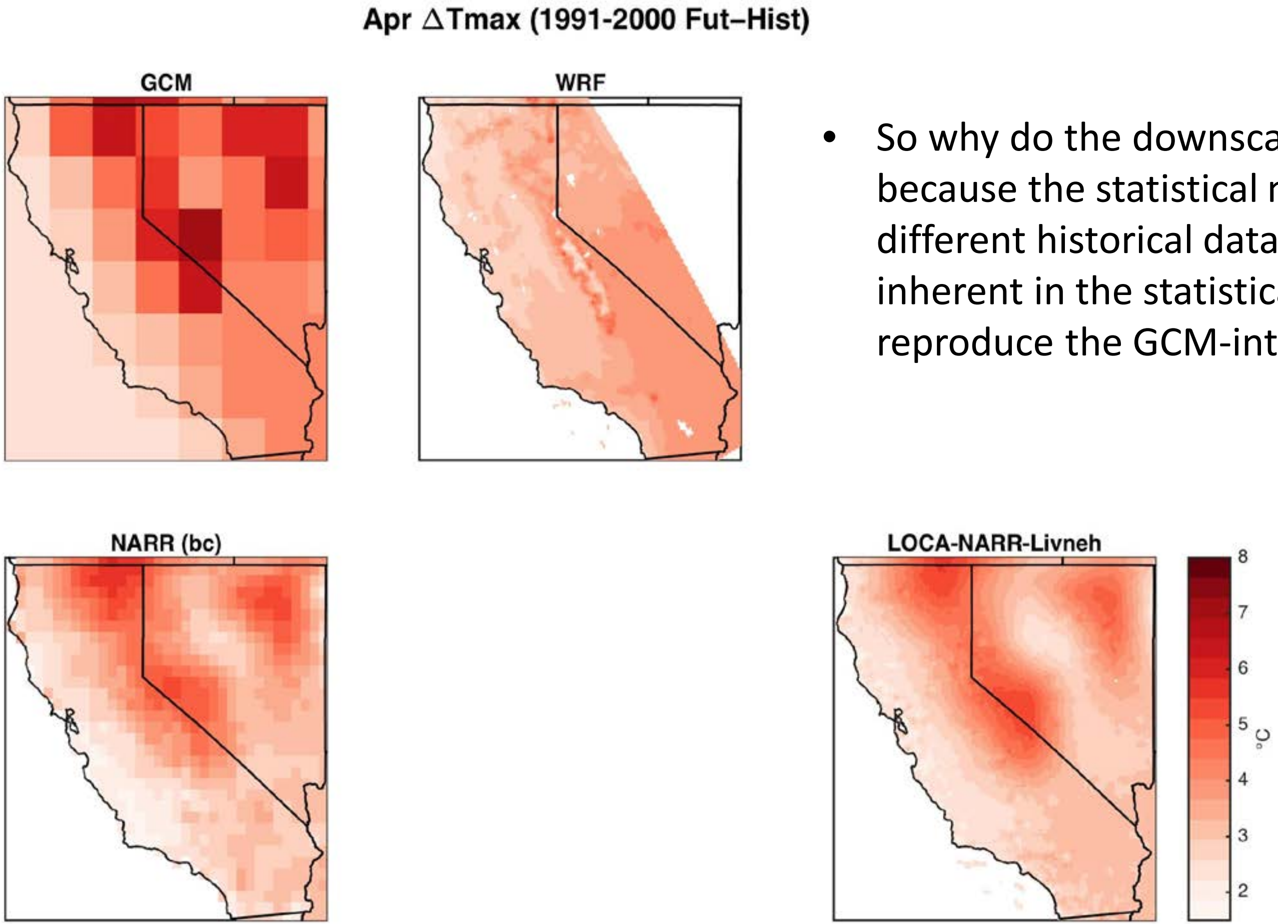


- Here is the warming pattern produced by WRF when driven by CNRM-CM5 data using the pseudo-global-warming method.
- Snow albedo feedback is visible in the mid-elevations of the Sierra Nevada, and WRF has suppressed the unrealistic warming associated with erroneous topography in the GCM.

Walton et al. (in prep)

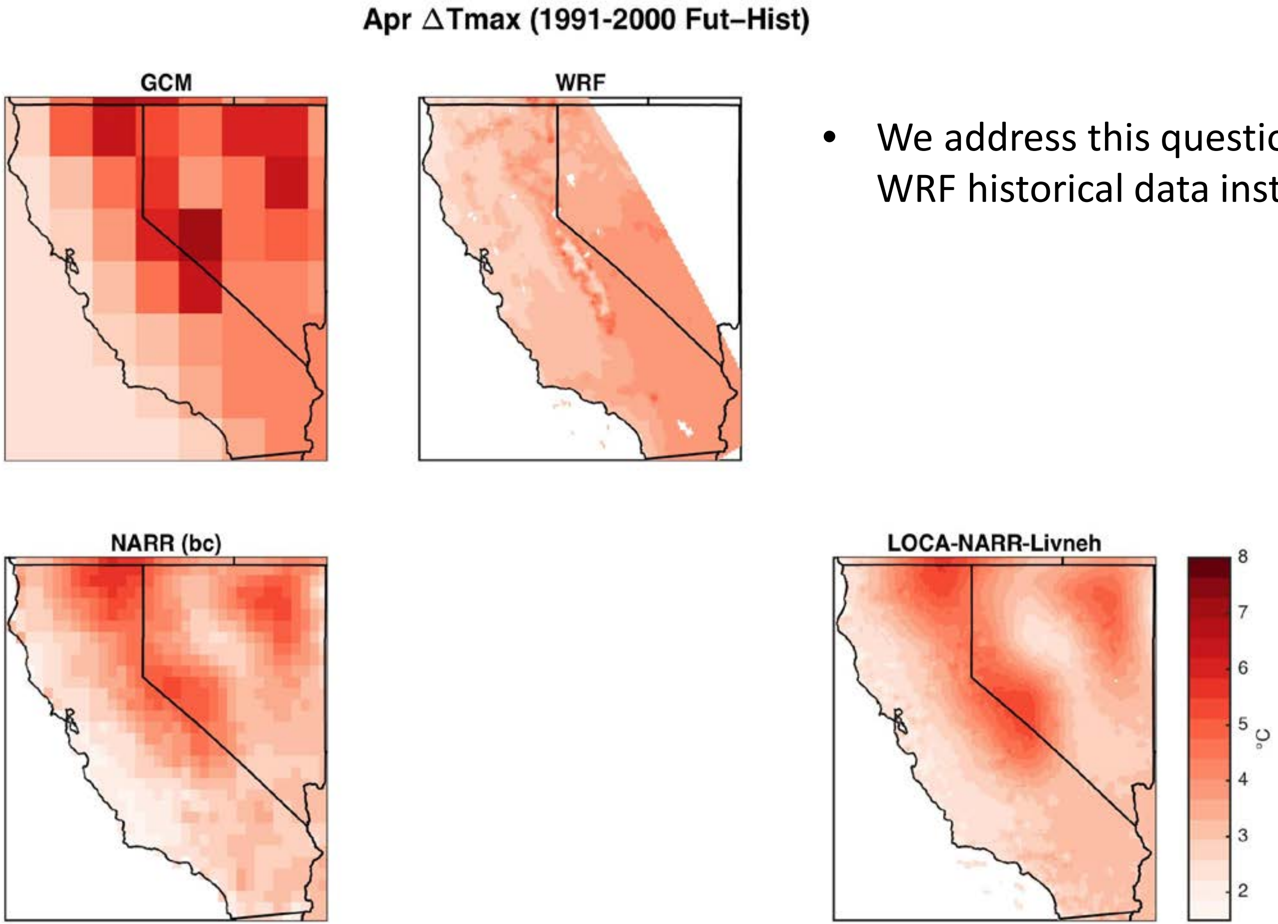
Why do downscaling techniques differ?



- So why do the downscaling methods differ? Is it because the statistical method is trained on a different historical data set, or is there something inherent in the statistical method that causes it to reproduce the GCM-interpolated pattern?

Walton et al. (in prep)

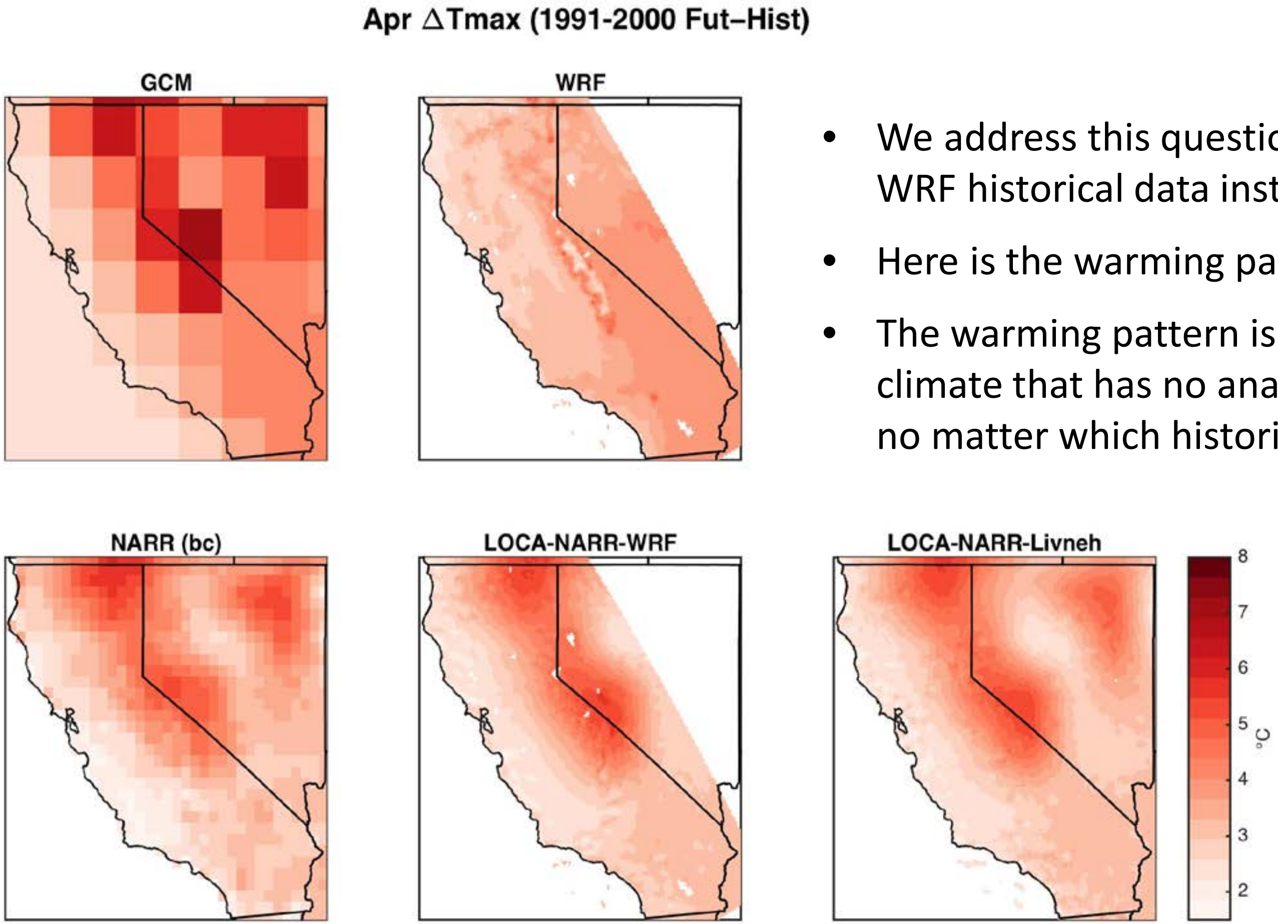
Why do downscaling techniques differ?



- We address this question by training LOCA on WRF historical data instead of Livneh.

Walton et al. (in prep)

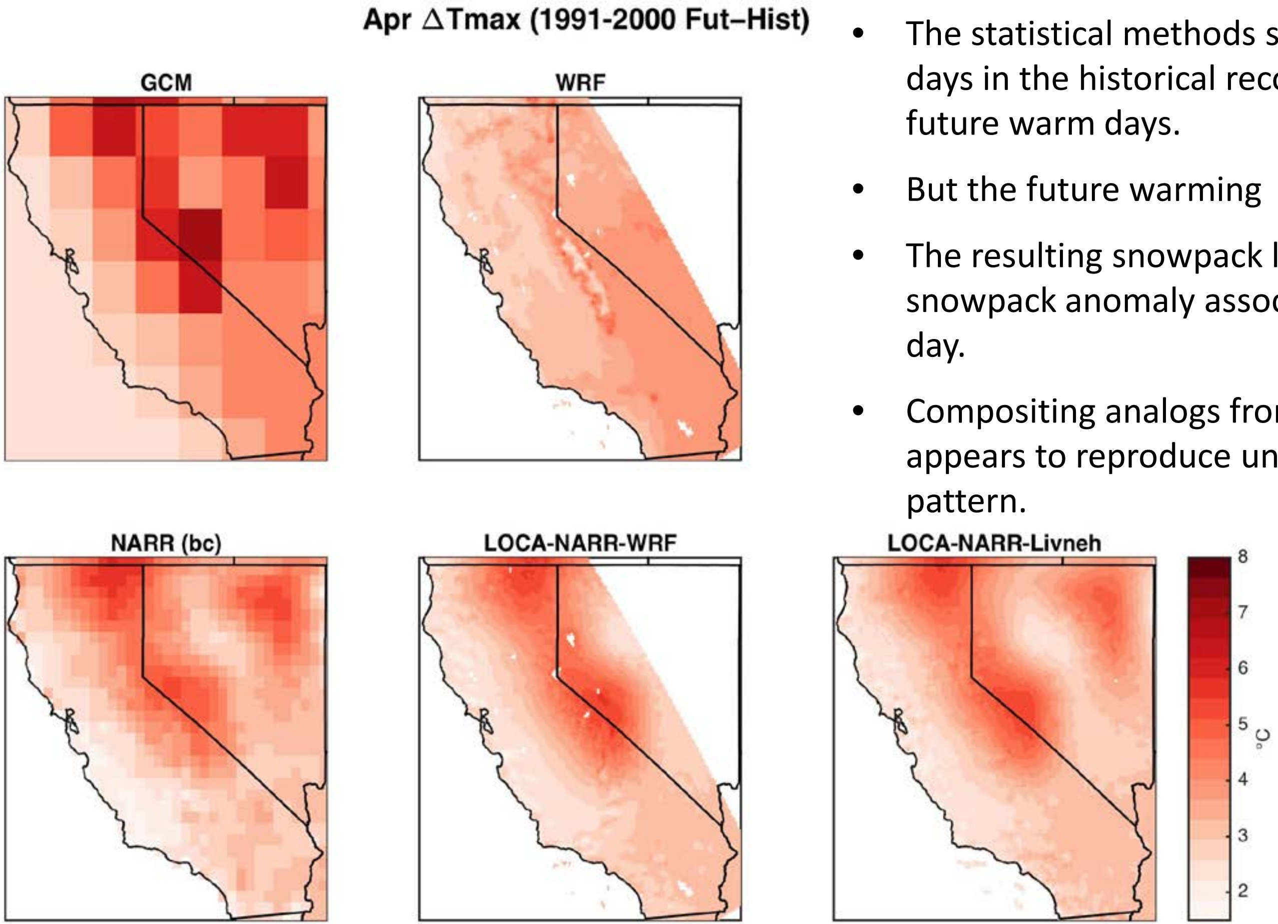
Why do downscaling techniques differ?



- We address this question by training LOCA on WRF historical data instead of Livneh.
- Here is the warming pattern that results.
- The warming pattern is a feature of the future climate that has no analog in the historical period, no matter which historical dataset is used.

Walton et al. (in prep)

Why do downscaling techniques differ?



- The statistical methods search for a warm day or warm days in the historical record and then create composite future warm days.
- But the future warming is sustained over many years.
- The resulting snowpack loss is very different from the snowpack anomaly associated with an unusually warm day.
- Compositing analogs from the historical record also appears to reproduce unphysical features of the GCM pattern.

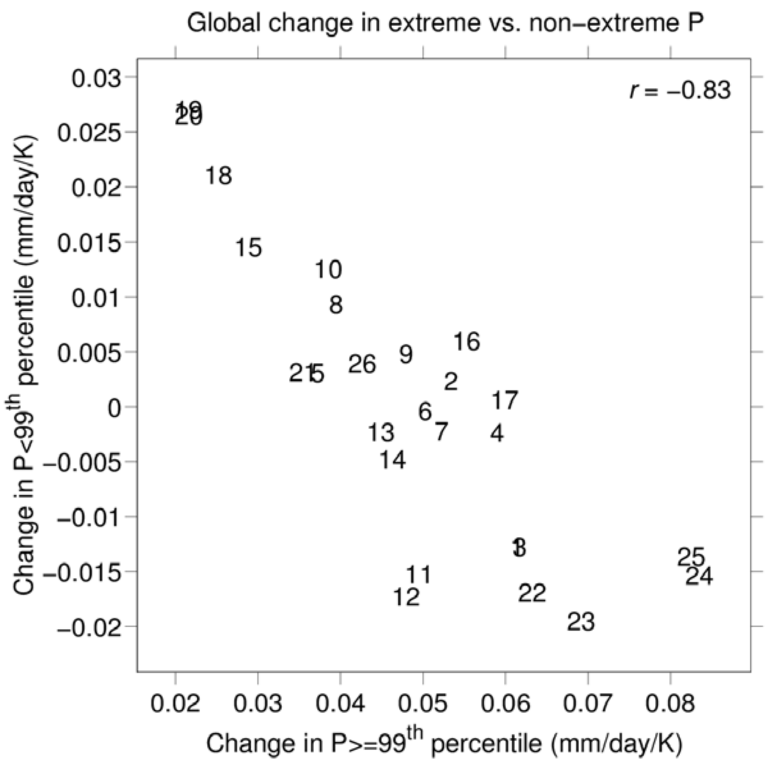
Walton et al. (in prep)

Conclusions

- To have confidence in high-resolution climate projections used for decision making, it is critical to evaluate the physical mechanisms that underpin regional change patterns.
- If one formalizes this evaluation process through hybrid downscaling, one also has the benefit of a statistical model that can downscale an arbitrarily large GCM ensemble, providing ensemble-mean and uncertainty estimates associated with GCM spread.
- In the case of California's Sierra Nevada, snow albedo feedback adds critical spatial structure to the warming patterns, with important follow-on effects, e.g. runoff timing.
- Purely statistical methods have trouble capturing the warming pattern associated with snow albedo feedback, because the process has no analog at the daily time scale in the historical record.


Shifting gears entirely…
…to extreme precipitation

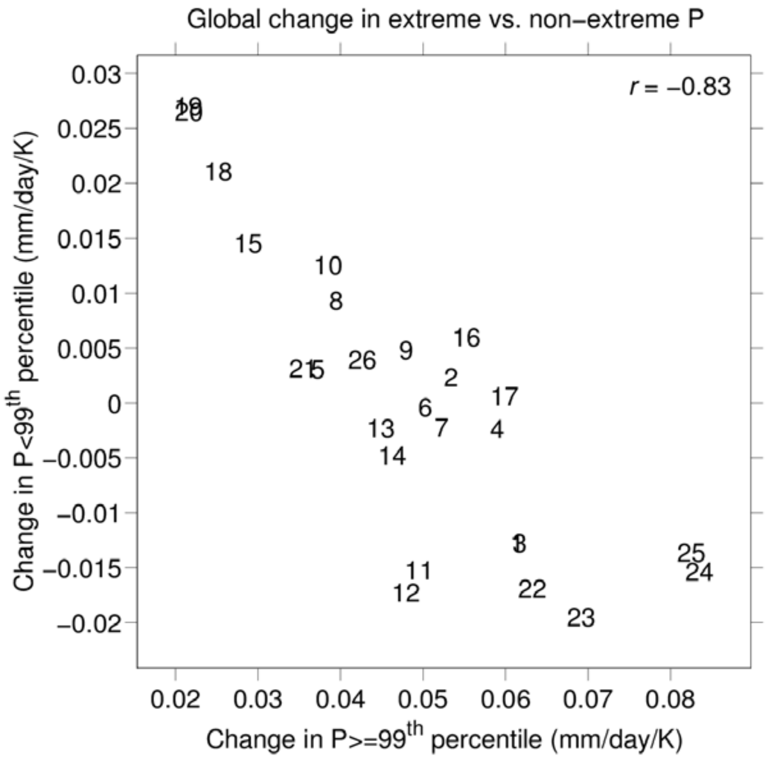
Compensation across the precipitation distribution in time



Thackeray et al. 2018, *submitted*

- For every CMIP5 GCM, we can calculate the change in daily extreme precipitation (>99th percentile) and average that change over the globe.
- Likewise for every model we can calculate the daily precipitation change during the non-extreme events (rest of the distribution).
- Shown here is the result when we scatter those two quantities against one another.
- If a particular model shows a large precipitation increase during very wet events, it will have a smaller increase or even a decrease during light-moderate events, and vice versa.
- So the models seem to be saying that changes in one part of the distribution have to be compensated for by changes in the rest of the distribution.

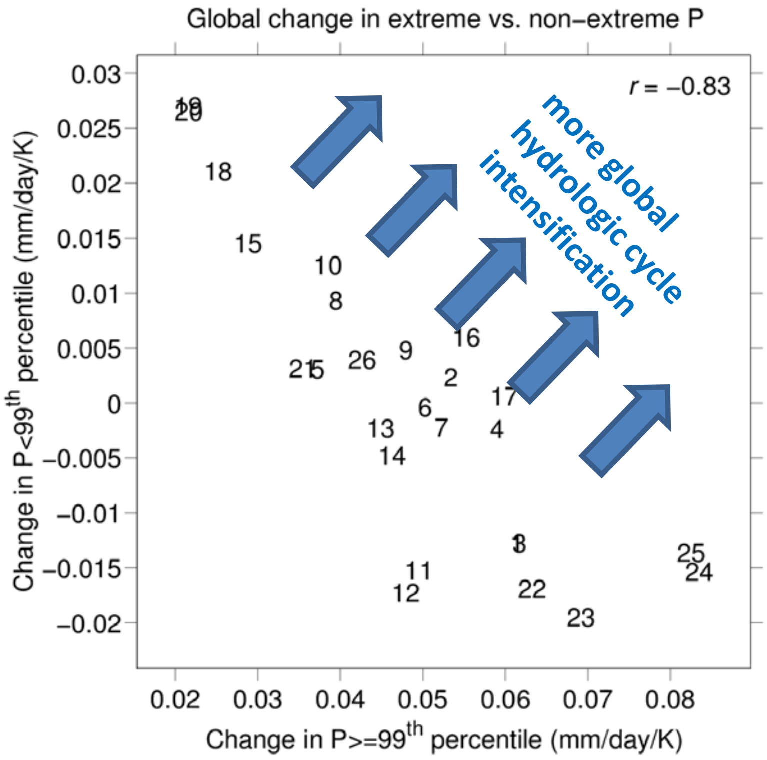
Compensation across the precipitation distribution in time



Thackeray et al. 2018, *submitted*

- This result is highly robust to how we define the extremely wet and not-so-extremely-wet parts of the distribution.
  - *r* (P≥99+,P<99) = -0.82
  - *r* (P≥95+,20≤P<95-) = -0.83
  - *r* (P≥90+,20≤P<90-) = -0.86
  - *r* (P≥95,P<95) = -0.88
  - *r* (P≥90,P<90) = -0.86
  - *r* (wetting,drying) = -0.85
- This compensation effect is clearly a big driver behind the very large spread in changes in extreme precipitation.

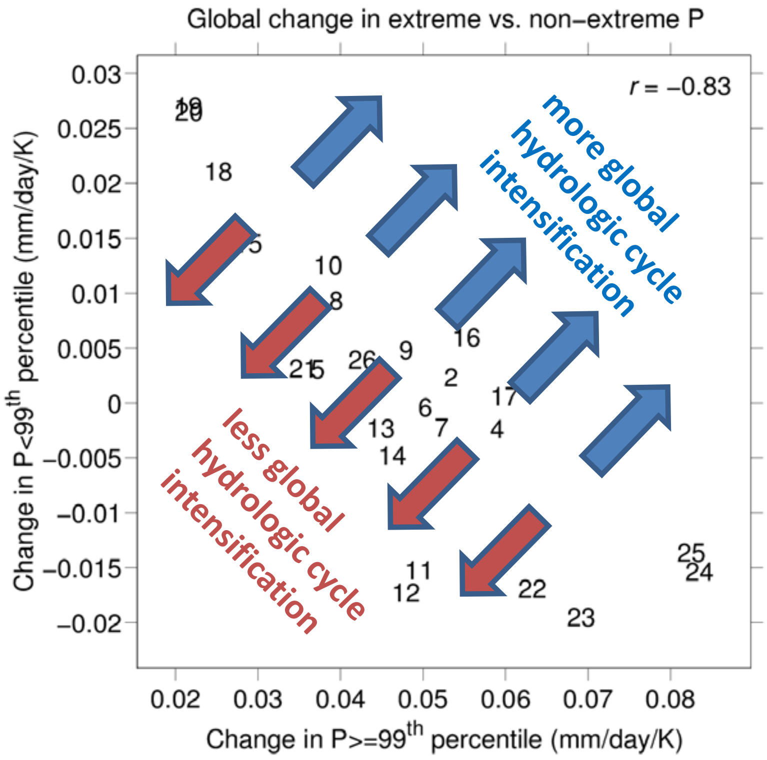
Connection to global hydrologic cycle intensification



Thackeray et al. 2018, *submitted*

- The atmosphere's energy budget is changing in such a way as to favor more precipitation (global hydrologic cycle intensification).
- The sum of the change in extreme and non-extreme precipitation has to equal the global precipitation increase.
- So the more global hydrologic cycle intensification seen in a particular model, the more it should be shifted toward the upper right of this plot.

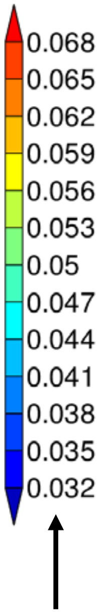
Connection to global hydrologic cycle intensification



Thackeray et al. 2018, *submitted*

- Likewise, the less global hydrologic cycle intensification seen in a particular model, the more it should be shifted toward the lower left.
- Let's see what happens when we color-code these numbers by the global precipitation increase.

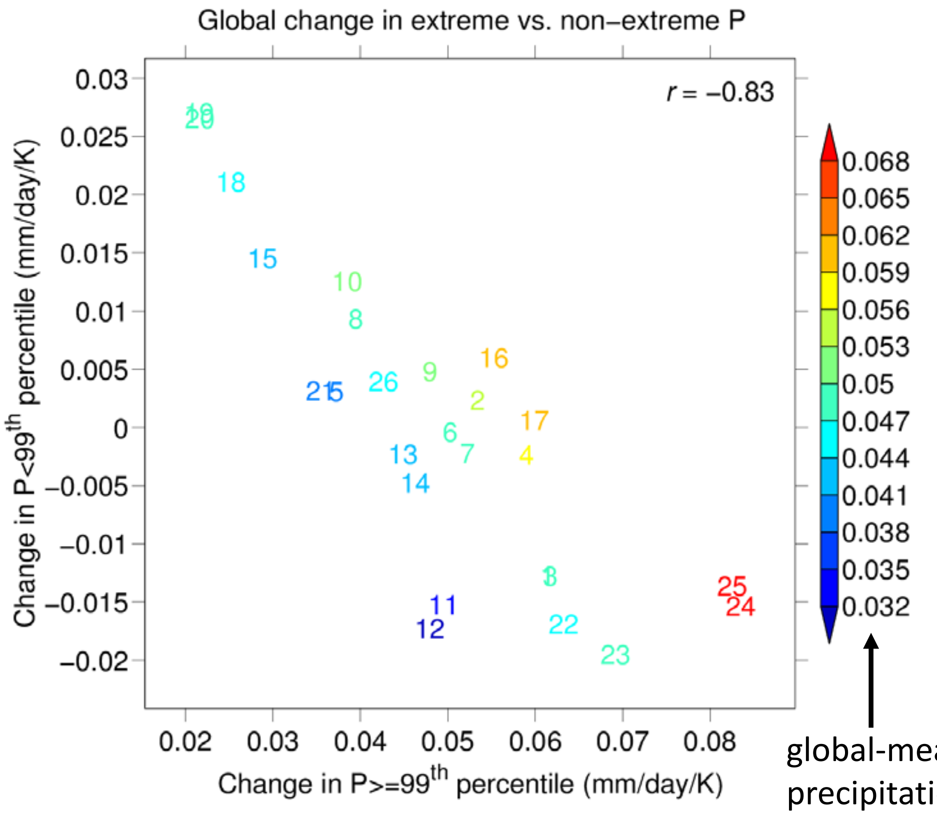
Connection to global hydrologic cycle intensification



global-mean total
precipitation
change (GT,
mm/day/K)

- Here's our colorbar corresponding to the global-mean precipitation increase. (Red colors indicate more increase, blue, indicate less.)

Connection to global hydrologic cycle intensification

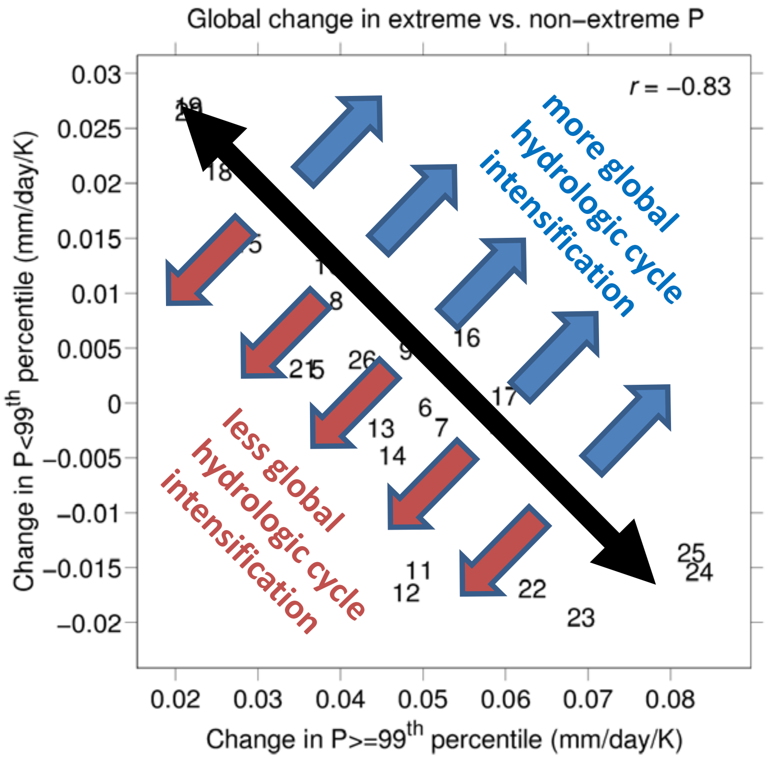


global-mean total precipitation change (GT, mm/day/K)

Thackeray et al. 2018, *submitted*

- And here's the plot from before, now color-coded by how much global hydrologic cycle intensification seen in each model.
- The models are organized in exactly the manner we predicted!

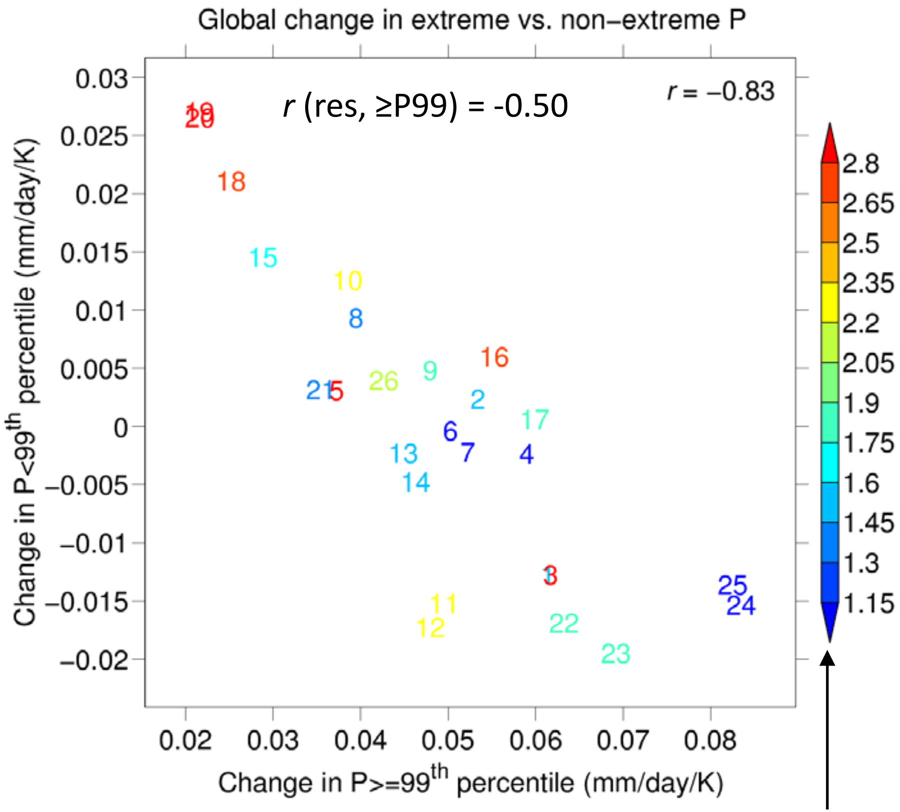
Connection to global hydrologic cycle intensification



Thackeray et al. 2018, *submitted*

- The spread in global hydrologic cycle intensification leads to spread in local precipitation extremes.
- But the main “axis” of spread in this plot is associated with the trade-off between changes in extreme and non-extreme precipitation, and large intermodel differences in extreme precipitation are seen even when those models have the same global precipitation increase.
- So what determines whether a model produces a big increase in extremely wet precipitation at the expense of the non-extreme precipitation, and vice versa?

Influence of model resolution

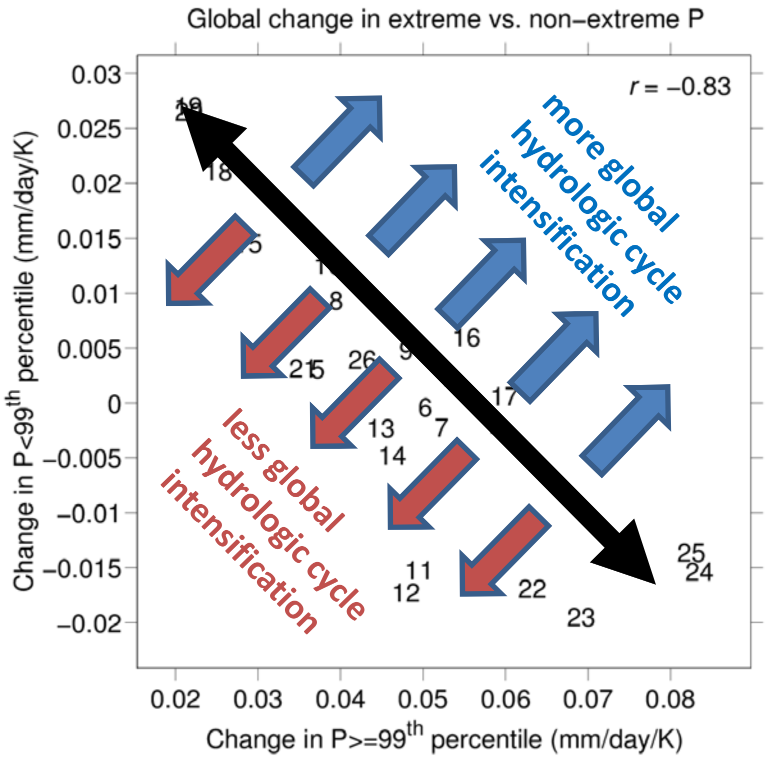


resolution length scale (deg, if all grid cells are squares)

- One important connection to the trade-off is with resolution.
- It's not a perfect relationship, but GCMs with higher resolution tend to produce larger increases in extreme precipitation, and modest decreases in non-extreme precipitation.
- The highest resolution GCM is so far from being convection-permitting that it'd be silly to extrapolate from this relationship to the convective scale.
- Still, the plot is powerful motivation for this group. Even the GCMs admit that the character of extremes really does change at higher resolution!

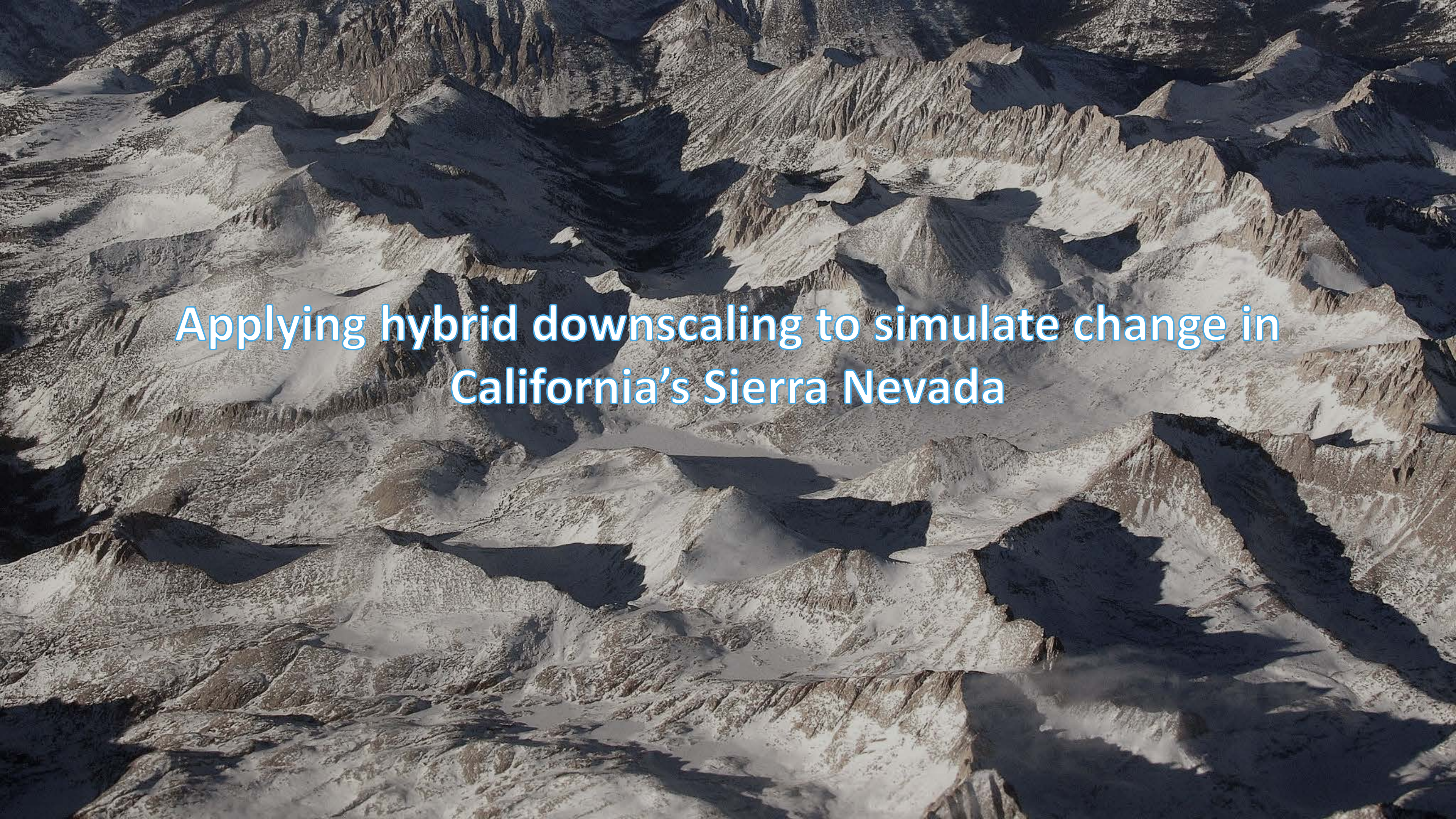

END

Connection to global hydrologic cycle intensification



Thackeray et al. 2018, *in prep.*

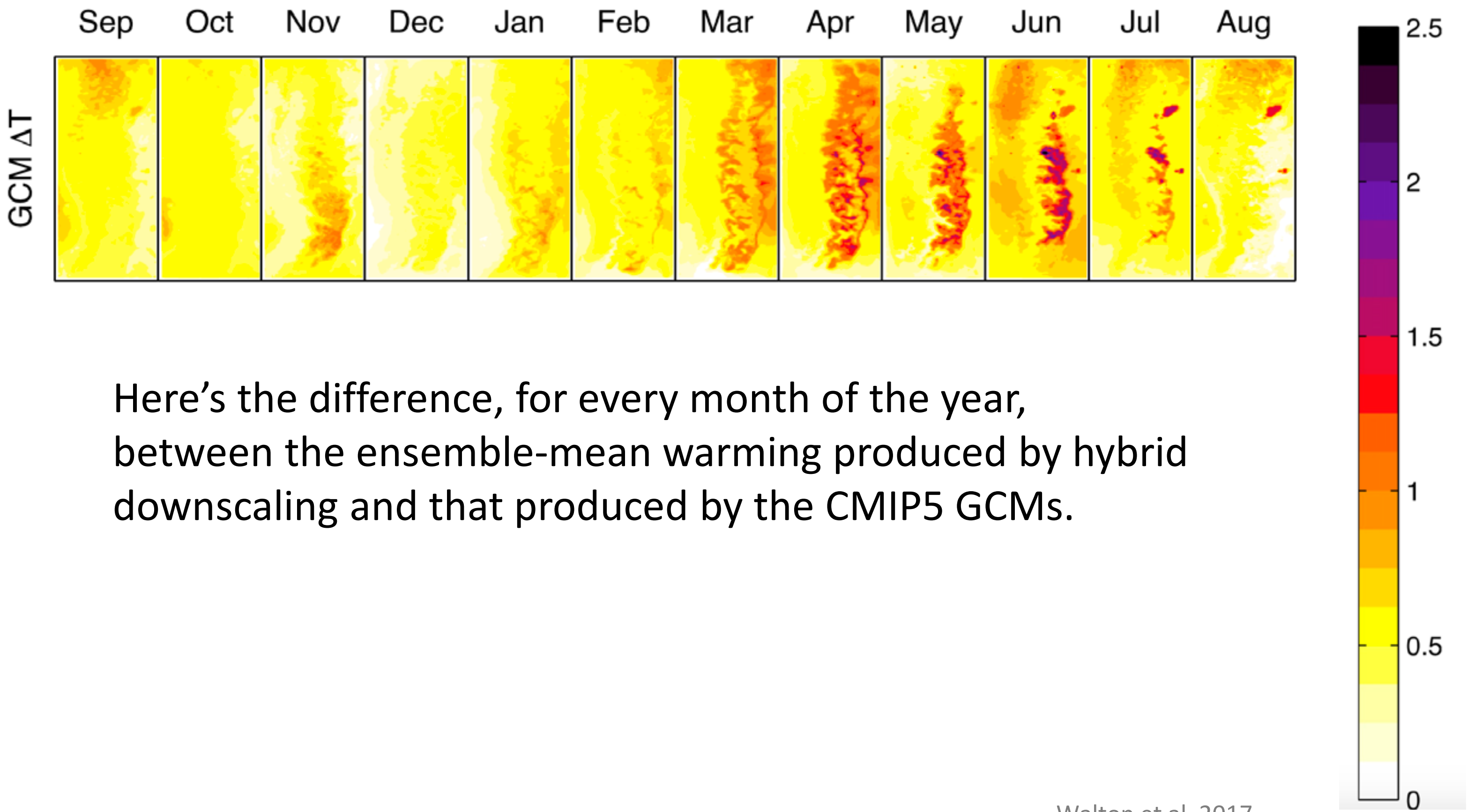
- We've seen that the spread in global hydrologic cycle intensification leads to the spread in precipitation extremes.
- But the main "axis" of spread in this plot is associated with the trade-off between changes in extreme and non-extreme precipitation.
- So what determines whether a model produces a big increase in extremely wet precipitation at the expense of the non-extreme precipitation, and vice versa?



Applying hybrid downscaling to simulate change in California's Sierra Nevada

Extra Slides

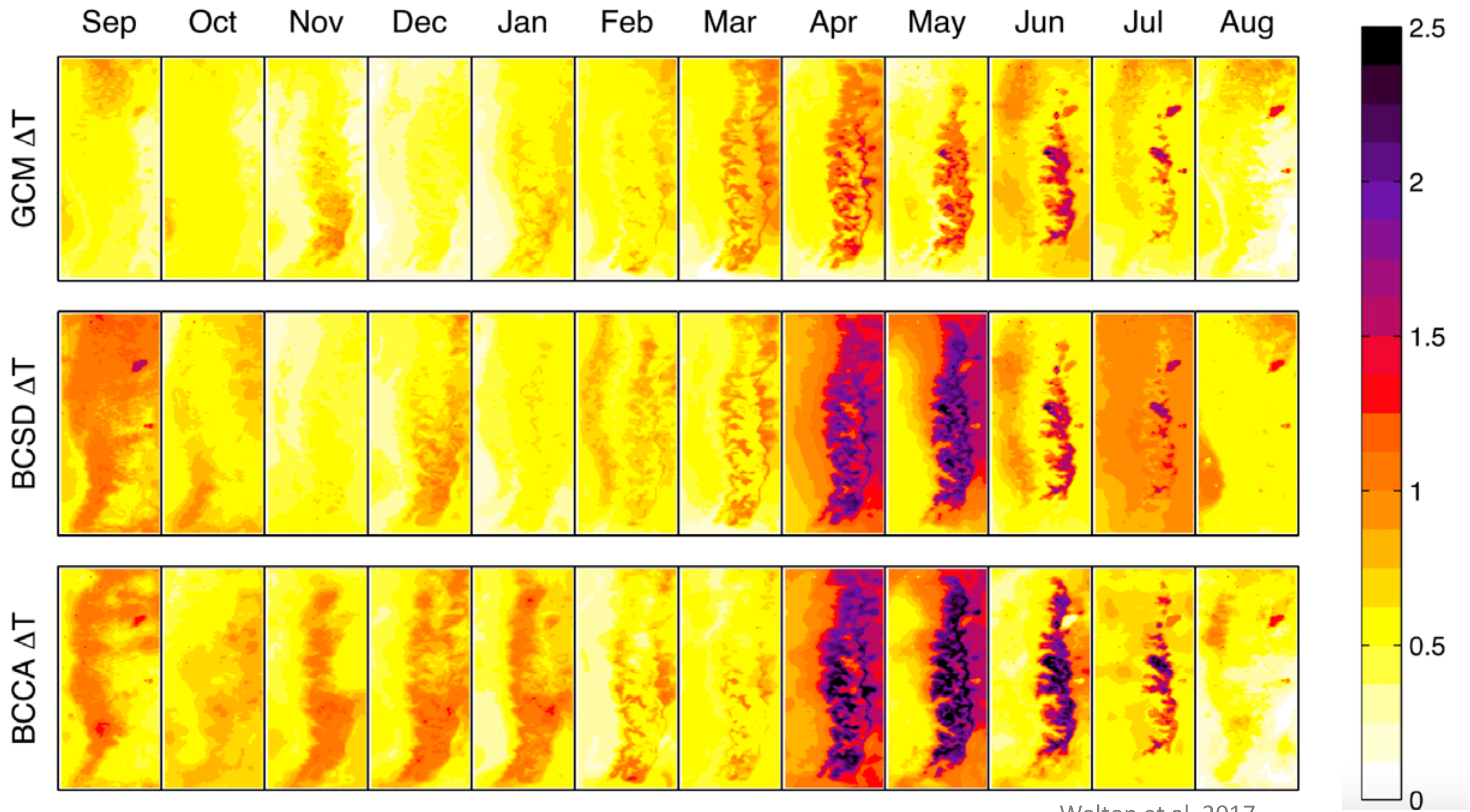
Differences in ensemble-mean warming patterns



Here's the difference, for every month of the year, between the ensemble-mean warming produced by hybrid downscaling and that produced by the CMIP5 GCMs.

Walton et al. 2017

Differences in ensemble-mean warming patterns

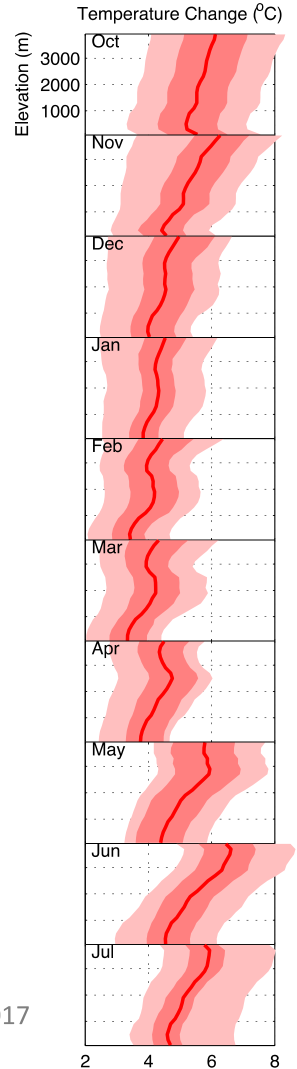


Walton et al. 2017

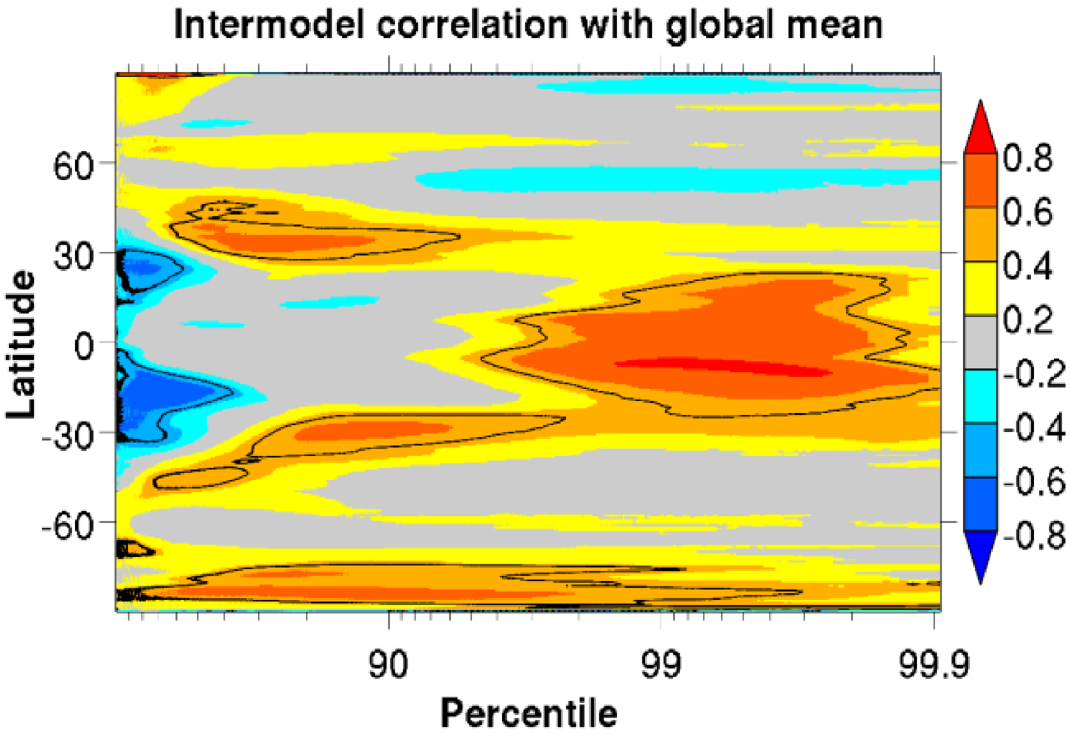
Warming Outcomes

- The simple model can now be used to produce warming patterns that we would have produced *had we downscaled all available GCMs dynamically*.
- This is the RCP 8.5 end-century warming as a function of elevation, from October through July.
- The solid red line is the ensemble-mean, and the red shading is an indication of uncertainty associated with GCM spread.
- Note the “warming bulge” associated with snow albedo feedback. It moves to higher elevations with the seasonal retreat of the snowline.

Walton et al. 2017



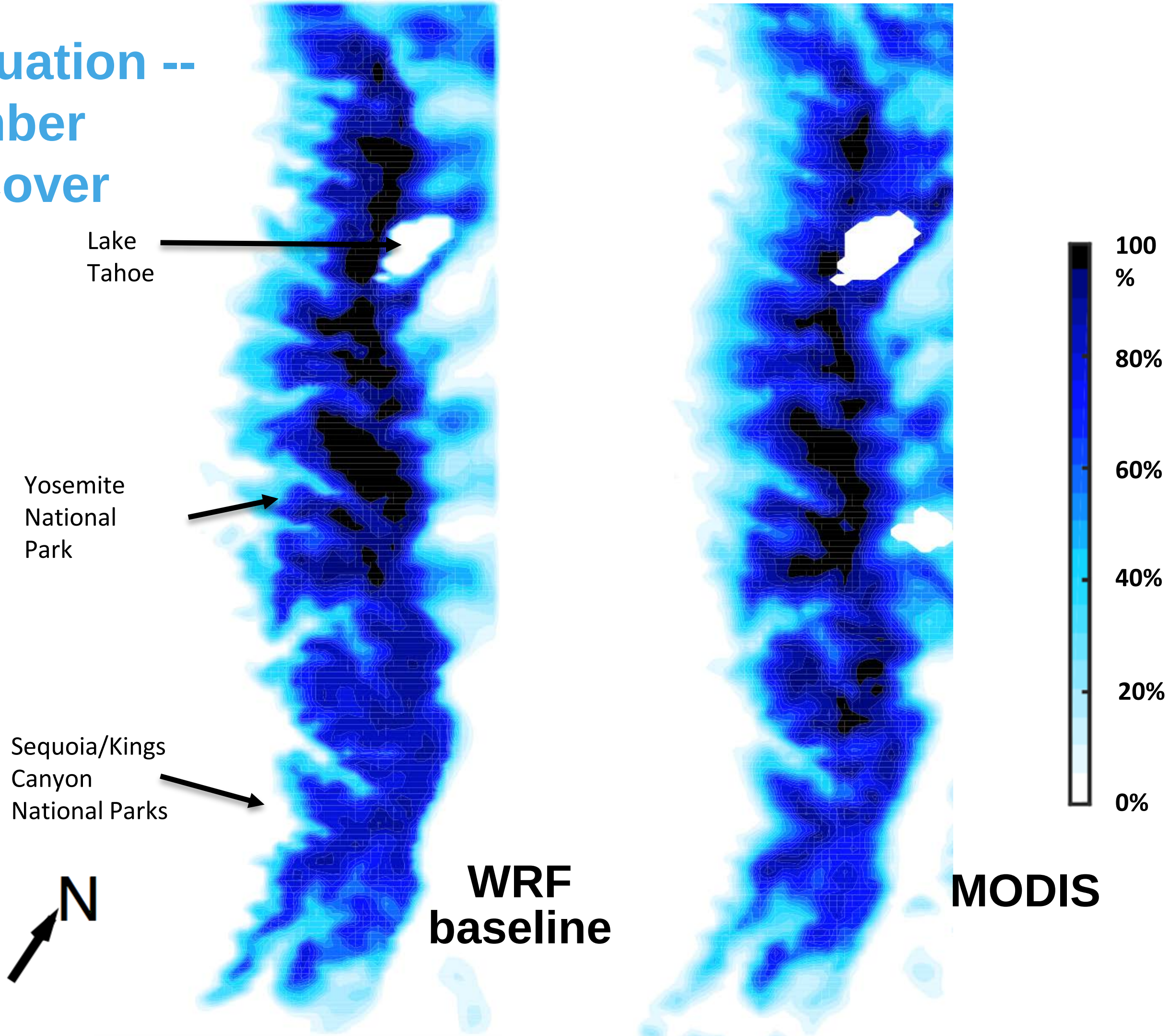
Regional footprints



Thackeray et al. 2018, *in prep.*

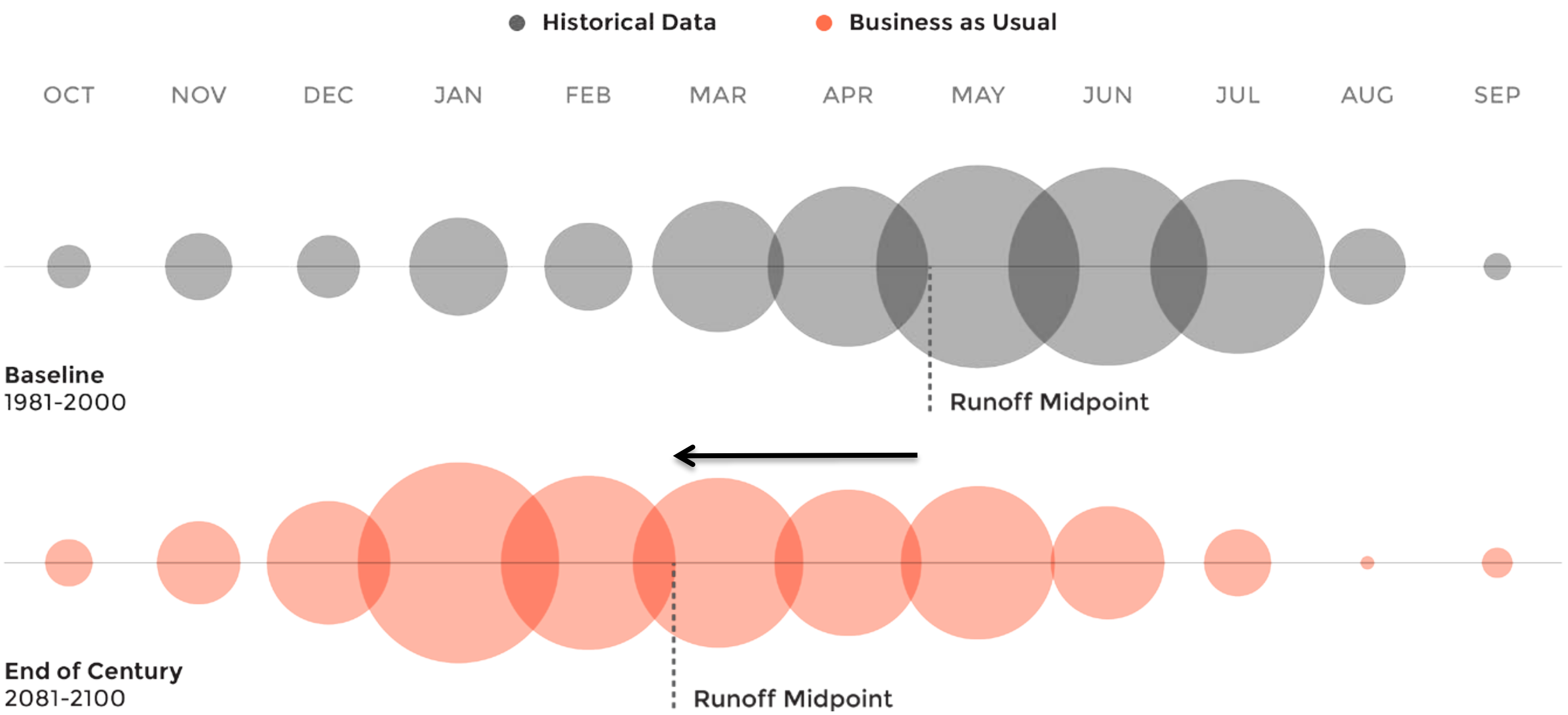
- Where does the global increase in precipitation have the strongest link with the local increase in extreme precipitation?
- Here's the inter-model correlation between the local increase in precipitation and the globally-averaged precipitation increases, as a function of latitude and position within the distribution.
- Clearly the increase in tropical extremes is strongly influenced by the global hydrologic cycle change.
- There are also subtropical signals in both hemispheres (atmospheric rivers).
- Another way to think of these results is that the increases in tropical extremes and large atmospheric river events account for much of the required latent heat increase when the global hydrologic cycle intensifies.

Model Evaluation -- December Snow Cover



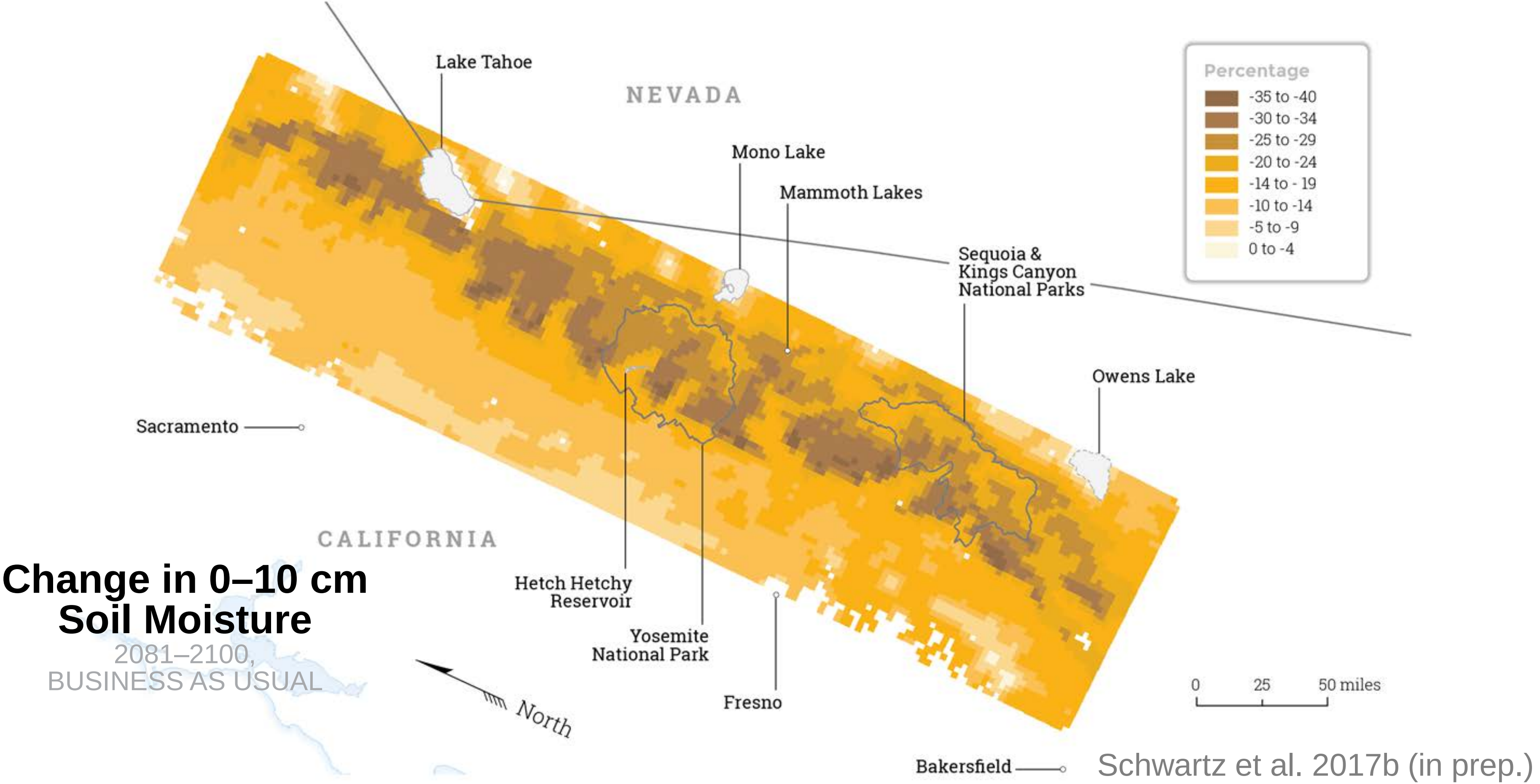
Earlier Shift in Runoff Timing

RCP 8.5, end-century, CMIP5 ensemble mean



Schwartz et al. 2017

Loss of Summertime Soil Moisture

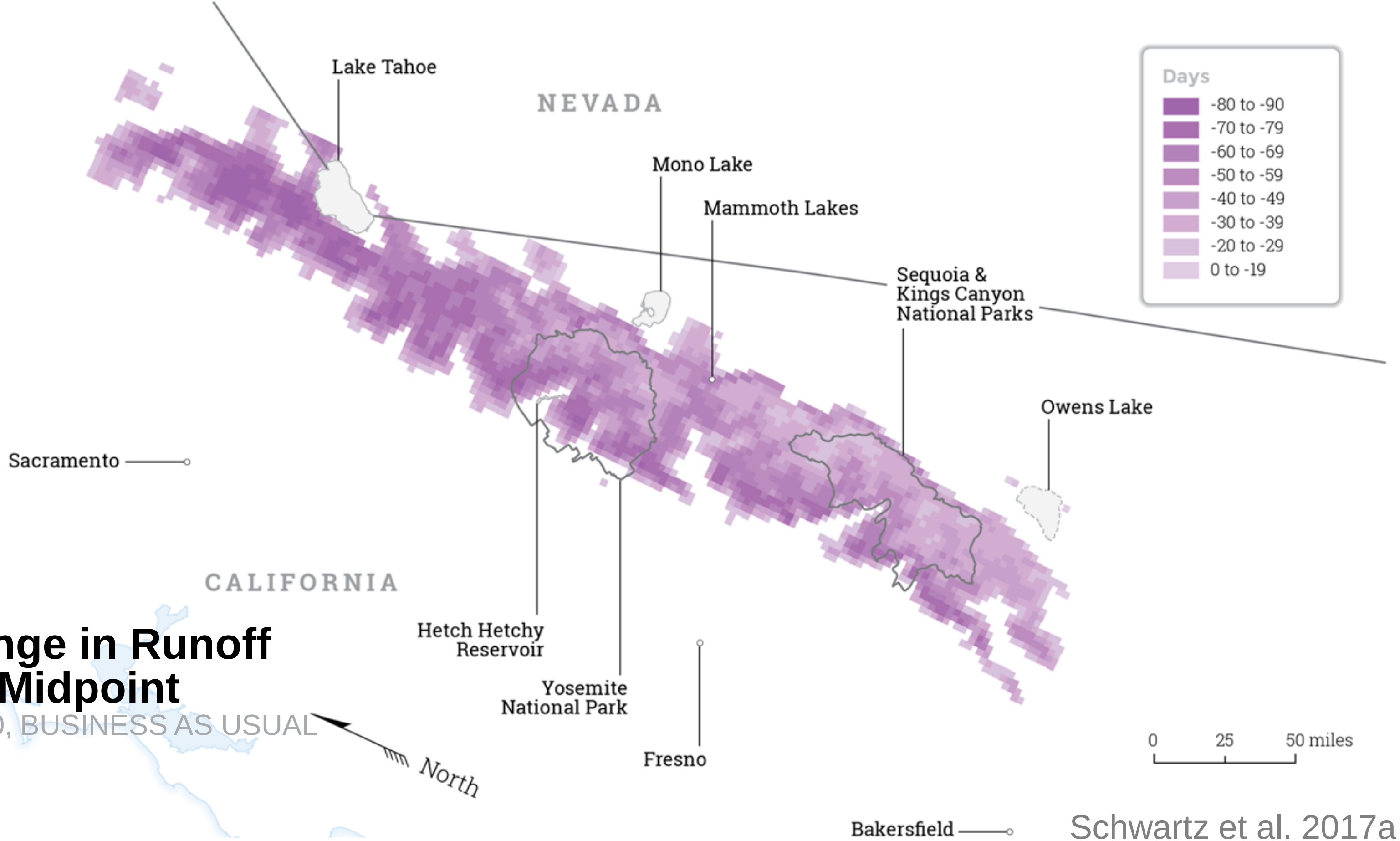


Change in 0–10 cm Soil Moisture

2081–2100, BUSINESS AS USUAL

Schwartz et al. 2017b (in prep.)

Earlier Shift in Runoff Timing

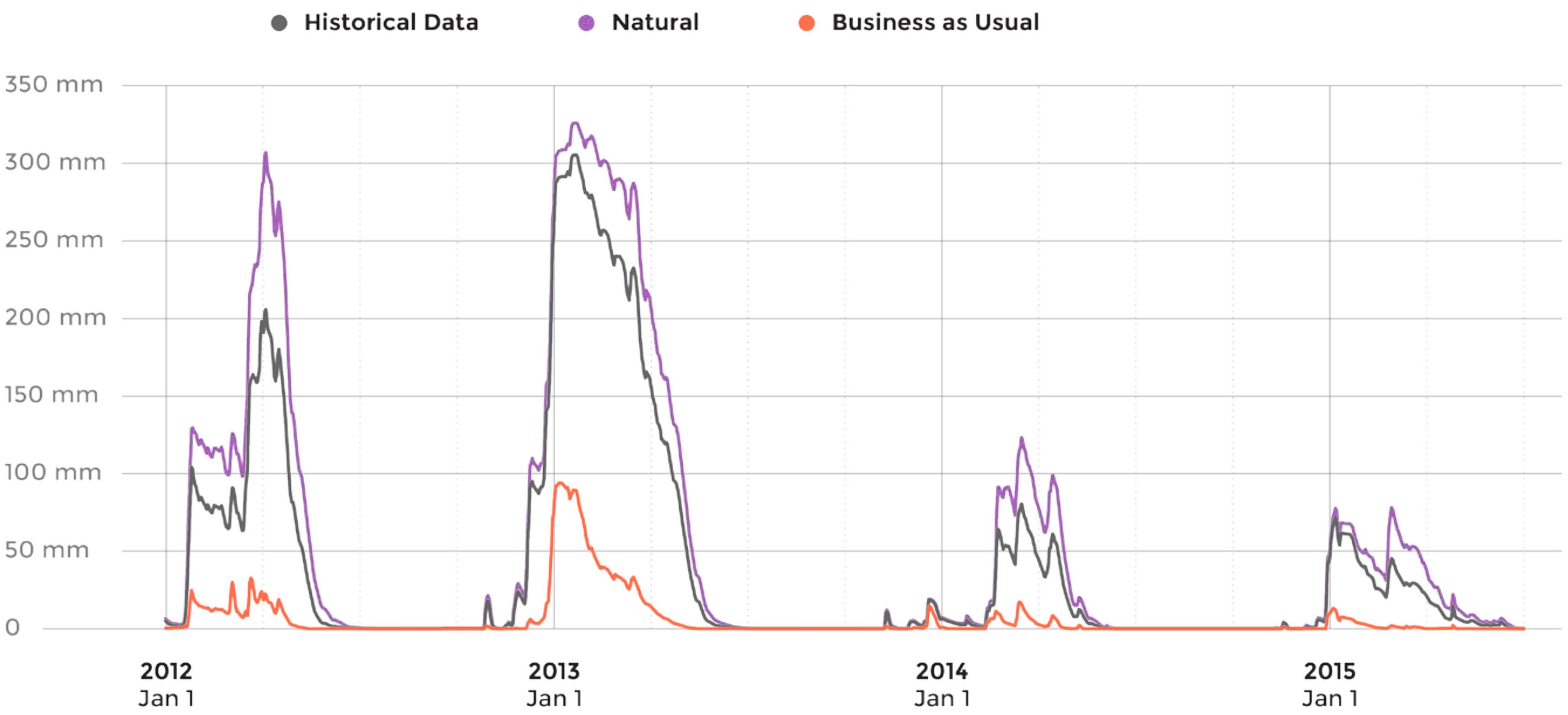


Change in Runoff Midpoint

2081–2100, BUSINESS AS USUAL

Schwartz et al. 2017a (in rev.)

Snowpack Severely Impacted During Drought



Berg and Hall 2017