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CLIVAR PPAL Panel Discussion

THE UNIVERSITY OF ARIZONA.

ATMOSPHERIC SCIENCES

UASCIENCE

1100 high specific humidity High Peaks 1500 LT breeze 1906= LT 0100 LT MCS in distance stratus/foo MCS to SW over ocean ∠at ~21°N

Diurnal Cycle of Convection Basis for generation of precipitation

Convective clouds form over the mountains in the morning.

By afternoon and everning storms propagate to the west towards the Gulf of California where they can organize into mesoscale convective systems if there is sufficient moisture and instability.

It's likely that a resolution less than 5 km, or alternatively superparmeterization, is necessary to represent this process correctly in regional models. Global models pretty much fail.

Nesbitt et al. (2008, J. Hydrometeor.)

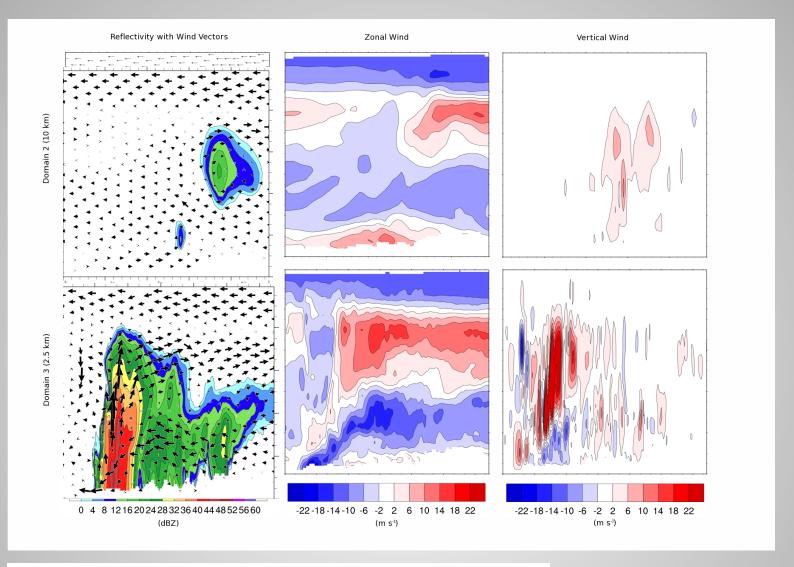
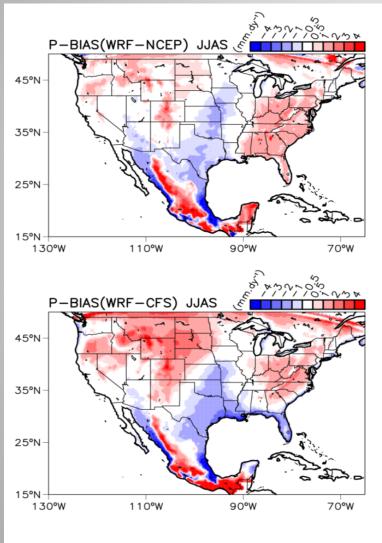


Figure 10: Cross sections of WRF model simulated radar reflectivity (dBZ) (left panels) on domains 2 and 3 with corresponding zonal and vertical wind velocities (m s⁻¹ and m s⁻¹, respectively) (center and right panels) at 0300 UTC 14 July. Wind vectors on radar reflectivity panel are scaled such that the horizontal wind is ten times larger than the vertical wind. The vertical planes to construct the cross section are defined intersecting a point at 29.69° N and 111.4° W and extending along constant latitude from 112.5° W to 107.5° W, and the frames have a height of about 20 km. They are averages of parallel planes north and south of the center and extend through the depth of the model.

Cassell et al. (in revision)

Model precipitation biases in WRF: downscaled NCEP reanalysis and CFSv1

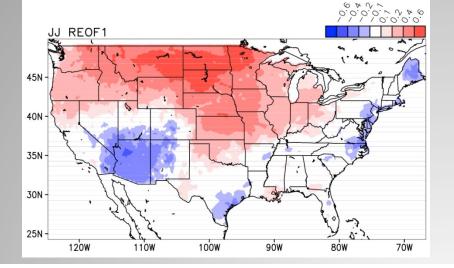


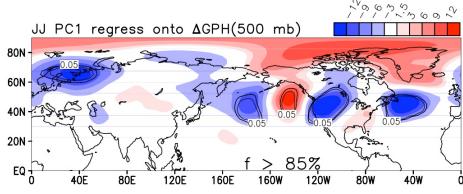
Castro et al. (2012, J. Climate)

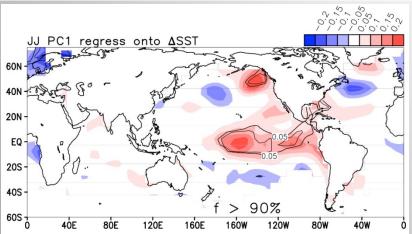
Systematic problems in the climatological representation of rainfall that are clearly terraindependent. Similar problems in other RCMs.

Reflects the fact that the RCM is challenged to represent organized, propagating convection, irrespective of the driving GCM.

This type of convection varies on an intraseasonal timescale and accounts for more precipitation away from the mountains.







Dominant mode of early summer precipitation (1950-2000)
PRISM-based JJ SPI

Antiphase relationship in early summer rainfall between Southwest U.S. and central U.S.



Relationship to atmospheric circulation anomalies
Teleconnection response
Quasi-stationary Rossby wave train



Relationship to sea surface temperature anomalies ENSO, Pacific decadal variability drive variation in tropical convection

Ciancarelli et al. (2013, Int. J. Climatol.)

Boreal warm season atmospheric teleconnections

Per classifications of Ding et al. (2011, J. Climate)

Western Pacific North
America Pattern (WPNA)

Circumglobal Teleconnection (CGT)

ENSO/PDV Forced: Early summer (JJ) (a) Probably most seasonally predictable (b) Indian monsoon forced: Late summer (JAS)

Figure 14. (a) Idealized atmospheric teleconnection pattern associated with JJ REOF 1 (ENSO/PDV forcing dominant). (b) Idealized atmospheric teleconnection pattern associated with AS REOF1 (likely dependent on Asian monsoon convection). Wet/dry areas over the United States indicated by blue/red.

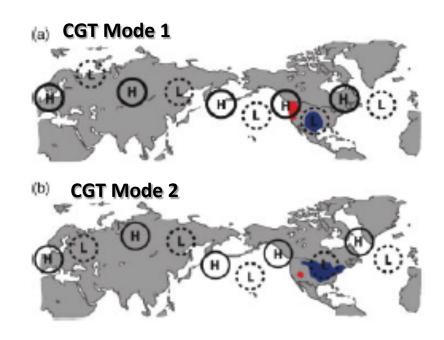
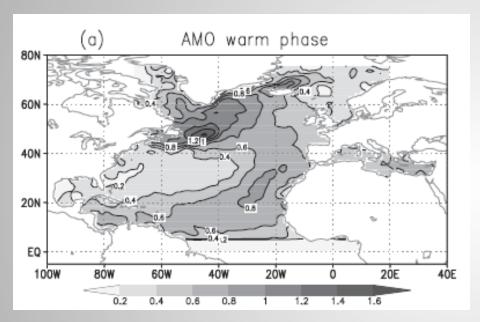


Figure 15. (a) Cartoon illustrating the CGT atmospheric teleconnection pattern associated with JJ REOF 2 (likely associated with the CGT). (b) Cartoon illustrating the CGT atmospheric teleconnection pattern associated with JJ REOF 5 (likely associated with the CGT). Wet/dry areas over the United States indicated by blue/red.

Ciancarelli et al. (2013, Int. J. Climatol.)

Influence of Atlantic Multidecadal Oscillation

e.g. Hu and Feng (2011, J. Climate)



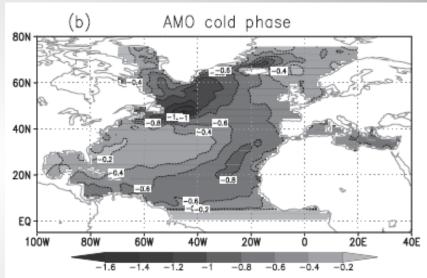
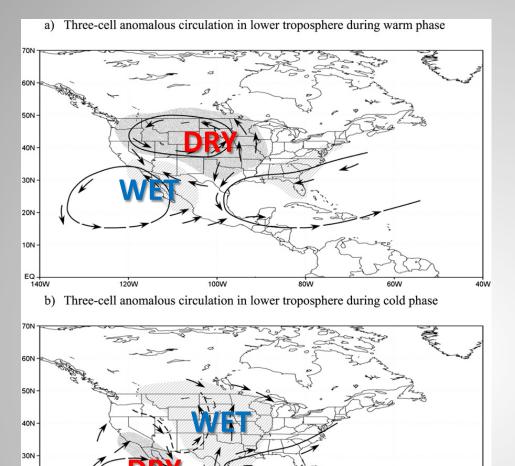


FIG. 1. (a) North Atlantic Ocean surface temperature anomalies in the warm phase of the AMO, and (b) as in (a), but for cold phase (unit: C). The SST anomalies are inflated by 2 times to amplify the signal to noise ratio and allow for clear dissection of causal mechanisms.



Warm phase: Weaker North Atlantic subtropical high, weaker Great Plains low-level jet.

Dry in central U.S., wet in Southwest U.S.

Cold phase: Stronger North Atlantic subtropical high, stronger Great Plains low-level jet.

Wet in central U.S., dry in Southwest U.S.

Probably synergistically interacts with ENSO-PDV forced variability.

FIG. 7. Schematic summary of pressure and flow anomalies (the three-cell anomalous circulation) in the lower troposphere during the (a) warm and (b) cold phase of the AMO and in the upper troposphere during the (c) warm and (d) cold phase of the AMO. The hatched areas have above average summer (JJA) precipitation and the dotted areas have below-average summer precipitation. The double line in (c),(d) indicates the upper-troposphere front.

100W

Hu and Feng (2011, J. Climate)

120W

20N

10N

EQ.

140W

Antecedent Land Surface Conditions

e.g. Zhu et al. (2007, J. Climate)

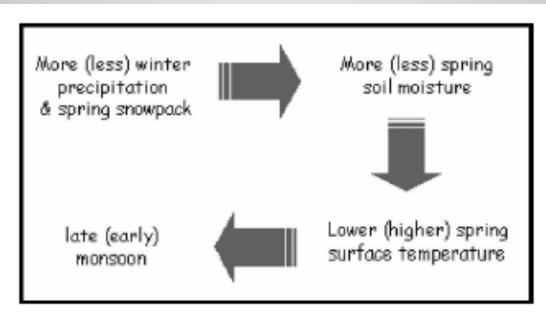


Fig. 1. Proposed winter-summer land surface-atmosphere feedback hypothesis for the North American monsoon.

Most of these types of studies explore this hypothesis in a statistical framework only.

The alternative hypothesis of atmospheric teleconnection mechanisms previously presented is also supported by idealized dynamical modeling.

Antecedent Precipitation (JFM) Anomalies associated with early and late monsoons in northwest Mexico

Zhu et al. (2007, J. Climate)

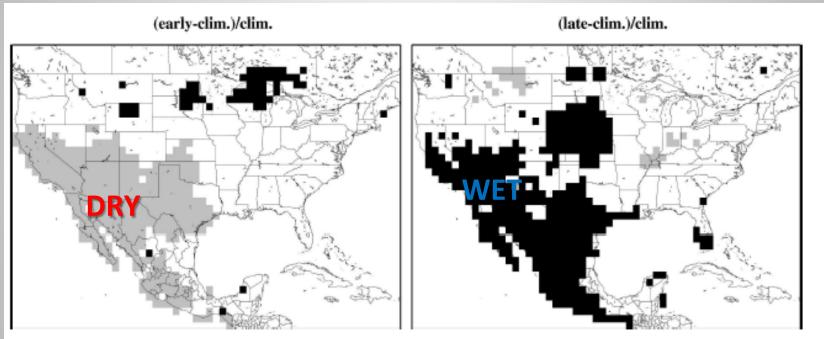


Fig. 9. JFM relative P anomaly composite for early and late monsoon years for MSa for 1950–99. Shaded area is $\geq 25\%$ (dark) or $\leq -25\%$ (gray).

Resembles classic ENSO-type signature for winter precipitation variability in North America

Current warm season seasonal forecast skill in North American Multimodel Ensemble (NMME)

Kirtman et al. (2014, Bull. Amer. Meteor. Soc.)

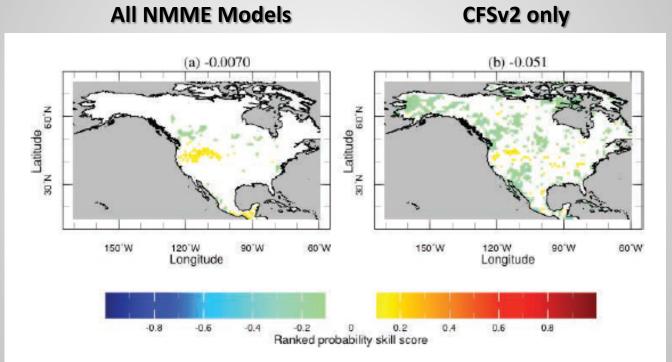


FIG. 9. Precipitation forecast RPSS for the (a) grand NMME multimodel ensemble and for (b) CFSv2. The skill is based on hindcasts initialized in Jan 1982–2009 and verified in the following JJA seasonal mean for tercile forecasts. Positive values indicate probabilistic skill that is better than climatology, and negative values indicate probabilistic skill that is worse than a climatological forecast. Global-averaged RPSS is noted in the figure.

Are skillful seasonal NAMS forecast possible?

Castro et al. (2012, J. Climate)

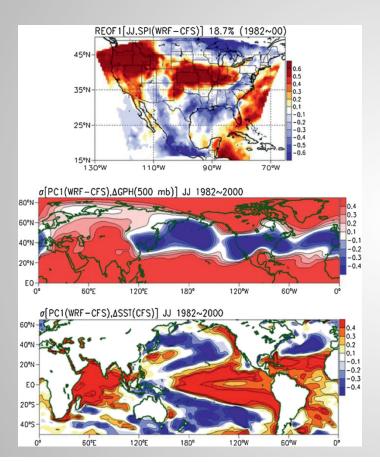


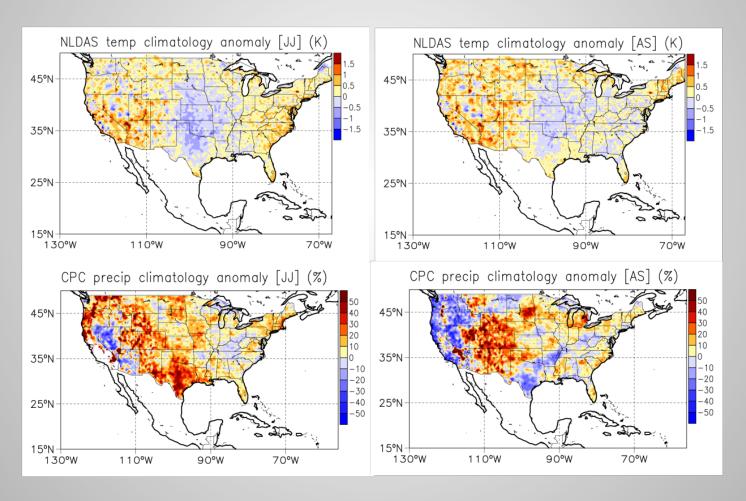
FIG. 18. (top) Most highly correlated mode of early warm season (JJ) SPI in WRF-CFS in comparison to first three REOF early warm season SPI modes from WRF-NCEP, shown as the regression on the principal component with variance explained. Specifically, this mode is most highly correlated with the second REOF from WRF-NCEP at a value of 0.44 with significance exceeding the 95% level. (middle) Corresponding PC correlation on normalized 500-mb geopotential height anomalies from CFS. (bottom) Corresponding PC correlation on CFS SSTA.

Global seasonal forecast models, such as the Climate Forecast System model used by U.S. Climate Prediction Center do have an ability to statistically represent WPNA response and its impact on warm season precipitation.

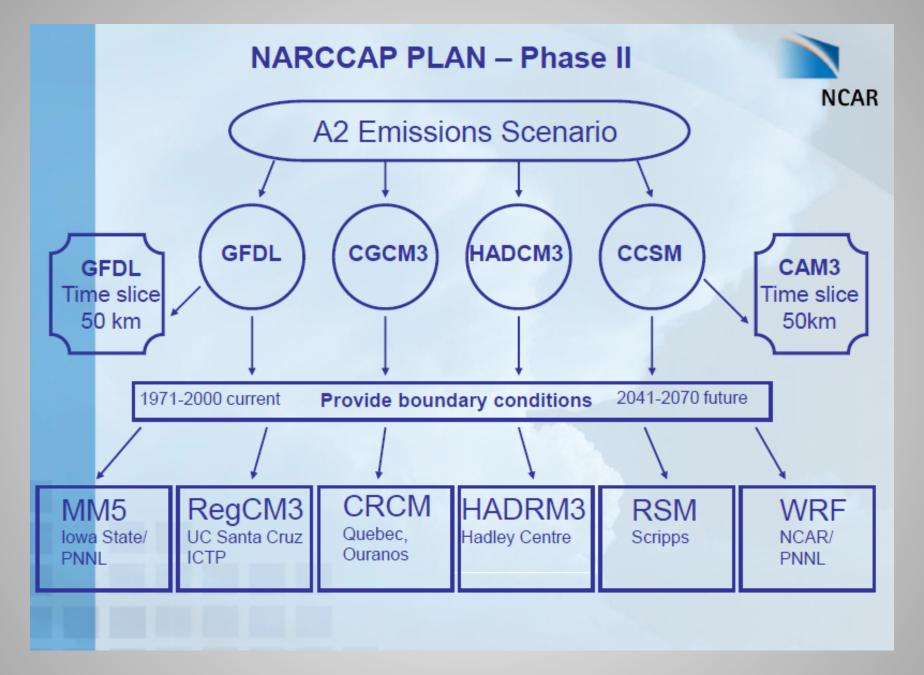
For skillful NAMS forecasts, a seasonal forecast GCMs must have an ability to deterministically represent warm season atmospheric teleconnections.

Observed Change in Early and Late Warm Season Climatology: 1980-2010 minus 1950-1980

Chang et al. (JGR, accepted)

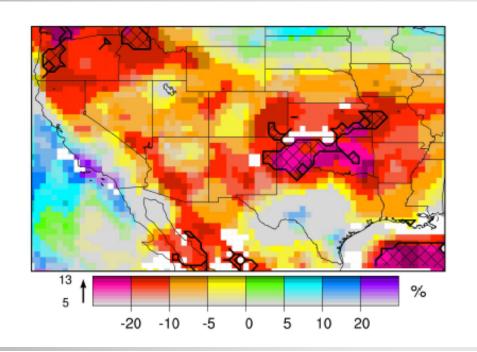


Recent observational record seems to comport with "wet gets wetter, dry gets drier idea"



Ensemble mean JA projected precipitation change (%) of NARCCAP models and degree of confidence

Bukovsky et al. (2015, J. Climate)



Considering the core NAMS region, the change in precipitation is slightly negative.

But this decrease is relatively small and there is little agreement among the NARCCAP models.

Figure 2: Average JA precipitation change (%) from the baseline period in the 11-model ensemble mean. Precipitation is presented following methodology proposed by Tebaldi et al. (2011), with slight modification: hatching indicates where more than 50% of the models show change that is significant at the 0.10 level (as determined by a t-test) and where more than 75% of the models agree on the sign of change (thus, where the majority of the models agree on significance and sign). White grid cells indicate where more than 50% of the models show change that is significant but also where 75% of the models or less agree on the sign of the change (thus indicating true disagreement and little information). Additionally, the number of models that agree on the sign of the change is indicated by the color saturation and value (the vertical axis on the color bar). To facilitate creating this ensemble average, all models were regridded to a common 0.5° × 0.5° latitude/longitude grid.

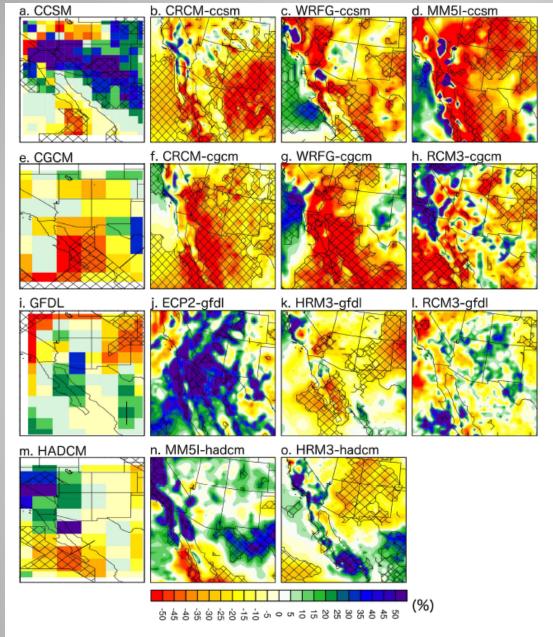


Figure 3: JA average precipitation change (%) from the baseline period. Hatching indicates where the change is statistically significant at the 0.1 level.

Note in some cases there can be differences in the sign of precipitation projections among RCMs even when forced by the same CMIP3 GCM.

Bukovsky et al. (2015, J. Climate)

Improved North American monsoon precipitation in CMIP5 models

Cook and Seager (2013, J. Geophys. Res.)

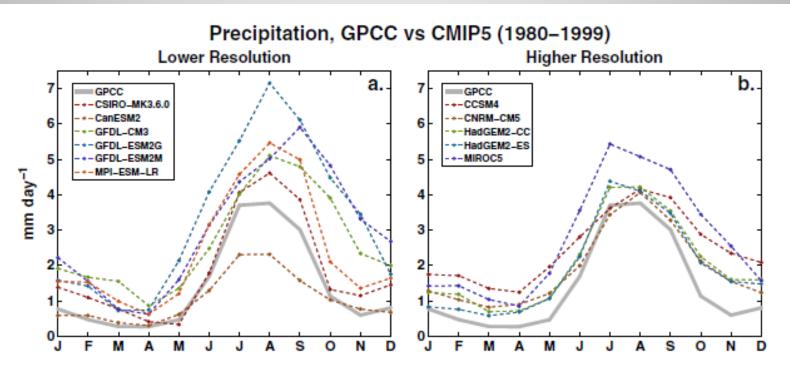


Figure 2. Comparison of precipitation climatologies (1980-1999) for the core NAM region in the CMIP5 historical simulations (dashed lines) and the GPCC precipitation data (grey line). Lowest resolution models are shown in (a), highest resolution models are displayed in (b). Where multiple ensemble members were available, the model climatologies represent ensemble averages.

Ensemble mean changes in North American Monsoon Precipitation in CMIP5 models

Cook and Seager (2013, J. Geophys. Res.)

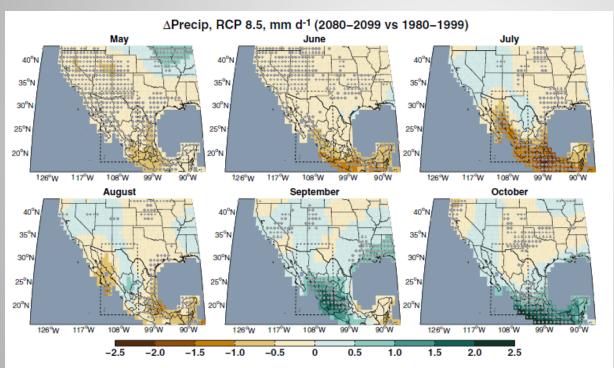
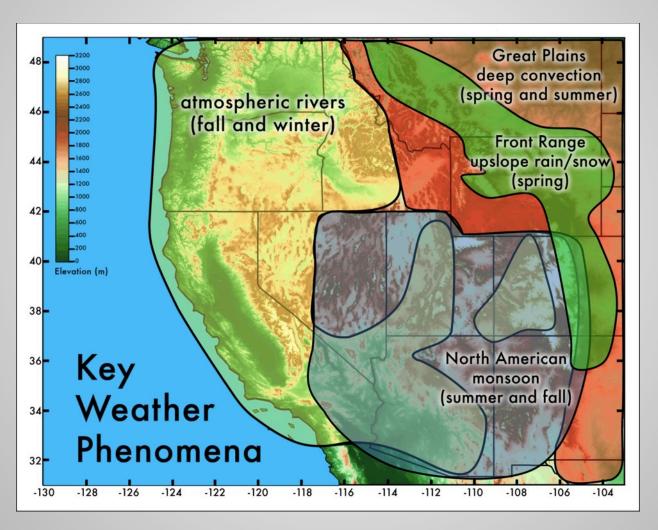


Figure 7. Multi-model mean precipitation differences (mm day⁻¹), calculated as mean precipitation for 2080-2099 (RCP 8.5 scenario) minus the mean precipitation for 1980-1999 (historical scenario) for the extended monsoon season (May-October). Core NAM region is outlined with the black dashed lines. Grey crosses indicate cells for which the sign of the change in at least 9 of the 11 models agrees with the sign of the change in the multi-model mean.

Decreases in precipitation during early summer due to enhanced atmospheric stability, under more intense monsoon ridge.

Increases in precipitation in late summer and early fall once stability barrier can be overcome.

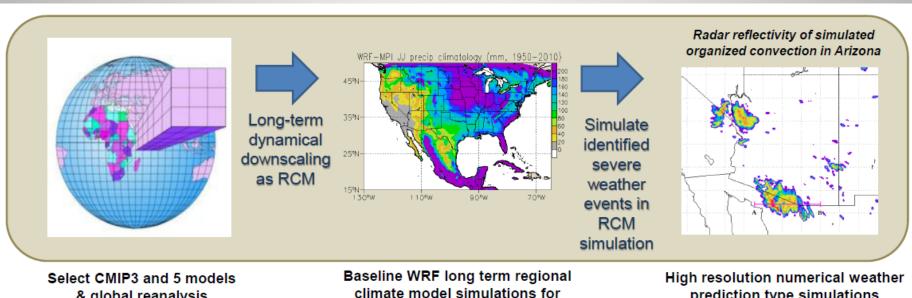
What causes extreme precipitation in the West?



Ralph et al. (2011)

Technical Approach

Dynamical downscaling to address severe weather question



& global reanalysis 1-2.5° resolution

climate model simulations for historical and future periods 35-50 km resolution

prediction type simulations 2.5 km resolution

Yields climate change projection results that simulate possible changes in extreme events in a physically-based way, using a well-established modeling paradigm for weather forecasting.

Panel issues

How should the NMME reforecast (and other similar) products be used to evaluate warm season skill? Should there be some distinction between the large-scale atmospheric circulation and surface temperature and precipitation?

What are physically based metrics that could be applied to climate prediction and projection models (e.g. NMME and CMIP) that could be used as differential weighting in creating ensemble averages?

It is well recognized in weather forecast community that convective resolving scale (or superparameterization) is essential for the warm season to reasonably simulate organized convective structures. How do we adapt this paradigm for climate forecasts/projections in a way that is computationally feasible?

Do we need a community MRED Phase II experiment to evaluate the value added of regional modeling with use of the NMME reforecast data? What kinds of procedures and metrics would be appropriate for an effort of this type?