Toward physically confident climate change projections in the Southwest United States and beyond

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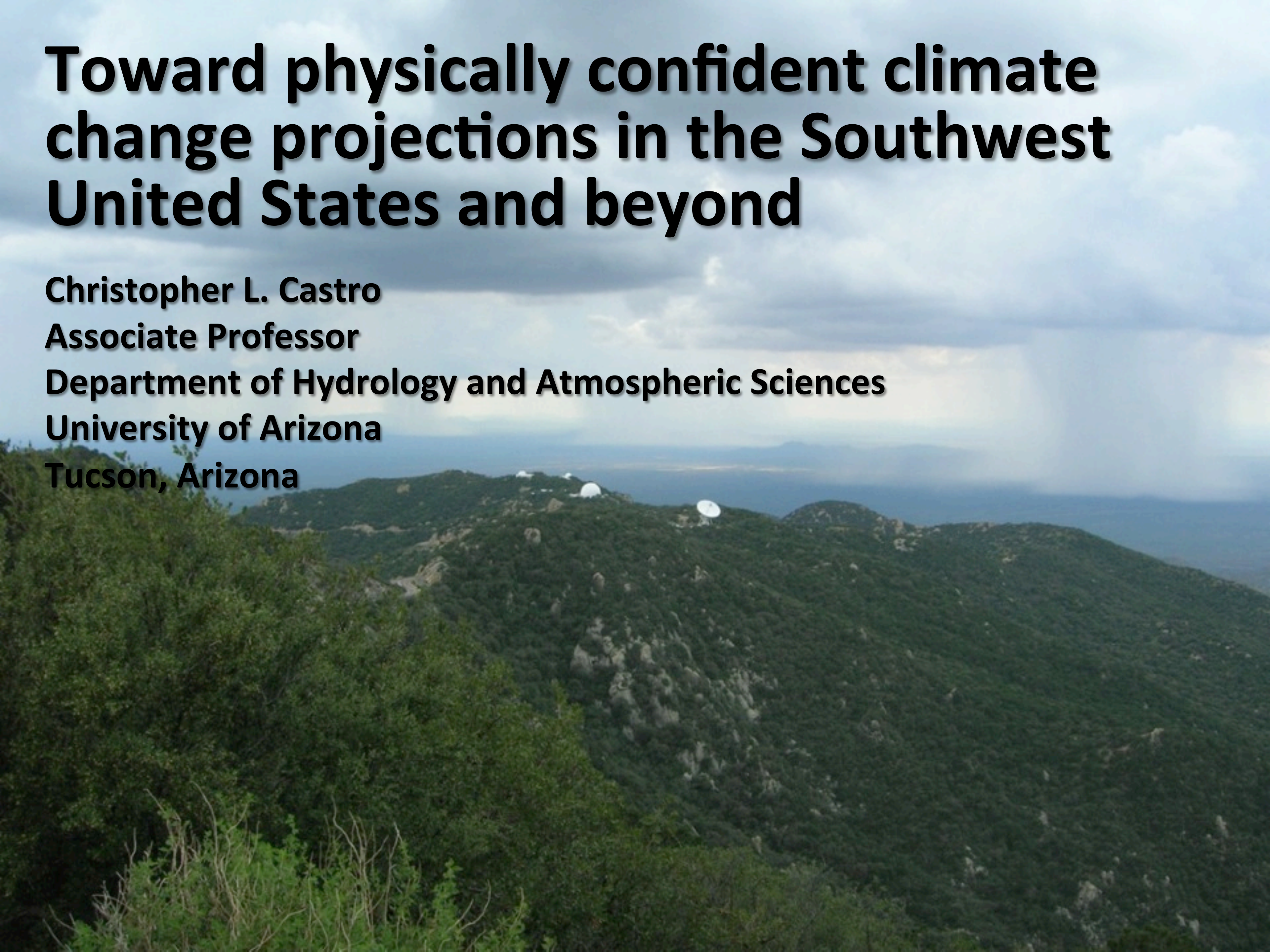


Presentation outline

Philosophical motivation: Statistical vs. physical confidence in downscaled climate projections for impacts assessment purposes

Dynamically downscaled steamflow projections in the Colorado River basin

The changing nature of the North American monsoon, as revealed by convective-permitting modeling

A roadmap forward for improving operational seasonal forecasts

Vision of a potential future at University of Washington

Funding support: National Science Foundation,(NSF), Strategic Environmental Research and Development Program (SERDP), Department of Interior (U.S. Bureau of Reclamation, USGS), Salt River Project, Central Arizona Project

Acknowledgements: Research group at UA and collaborators, as referenced in presentation.

The need for downscaling

Idea of downscaling: Data from global climate models are typically inadequate for regional and local impacts assessment. Must create higher spatial and temporal resolution information that better represents the meteorology and climatology, that is more suitable for impacts assessment purposes (e.g. water resources, ecosystems, natural hazard management, agriculture, etc.)

Two possible downscaling routes

Statistical: Develop an empirical relationship between large-scale climate and regional climate metrics based on historical data, and then apply to future global model projection

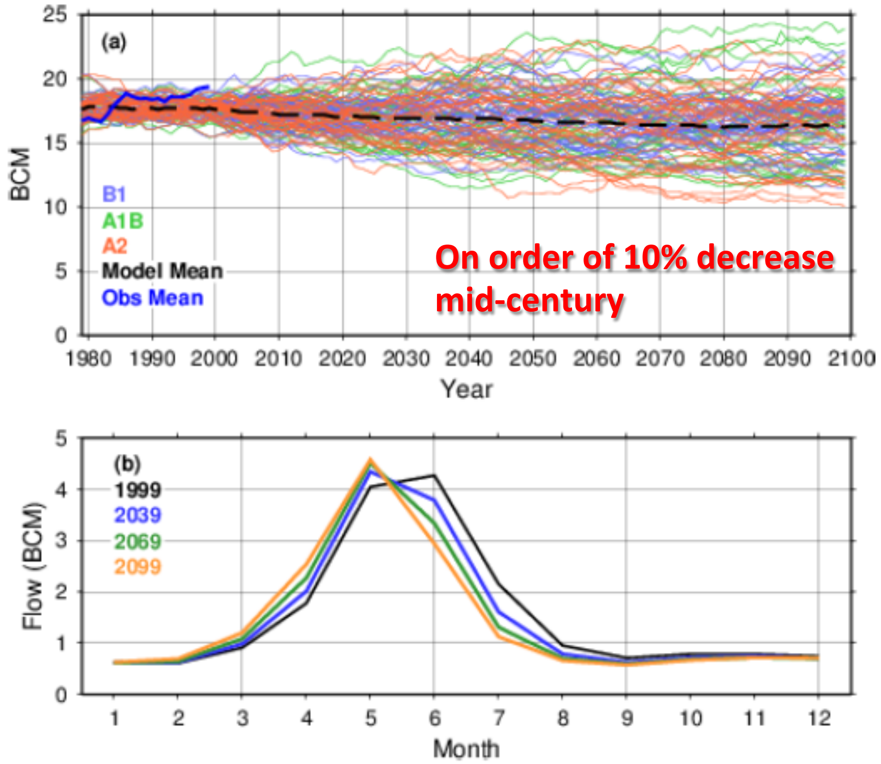
Dynamical: Apply a full-physics (typically limited area) regional climate model over a specific domain of interest to generate a higher resolution simulation.

Statistical or Dynamical Downscaling
Which is “right’’ way to go?

	Statistical	**Dynamical**
Pros	Simple and inexpensive Many realizations Relatively easy to apply	Represents physical processes Lots of variables available Characterize extremes Accounts for non-stationarity?
Cons	Stationarity problem Underestimates extremes No physical process basis	Relatively few realizations Computationally expensive Requires training, experience
	EMPHASIZES REDUCTION OF STATISTICAL UNCERTAINTY	**EMPHASIZES REDUCTION OF PHYSICAL PROCESS UNCERTAINTY**

The seductive paradigm of the "cloud of points"'

Full 112-Member BCSD CMIP 3 Ensemble Projection: Lees Ferry gauge for Upper Colorado



On order of 10% decrease mid-century

Fig. 6. **(a)** Simulated 30-yr average streamflows of the Colorado River at Lees Ferry AZ, 1979 through 2099. **(b)** The mean monthly average streamflows for the three future projection periods, compared with the historical 30-yr period flow ending in 1999.

Harding et al. (2012, HESSD)

Assumptions

Greater reduction in uncertainty with more ensemble members, or the "bigger cloud"

Mean of the multi-model ensemble is our most confident metric because of cancellation of model error

But what should Bureau of Reclamation do if dynamical downscaling would yield a substantially different result than BCSD, but with far fewer members??

REPORT TYPE (ALL CAPS)

USE OF CLIMATE INFORMATION FOR DECISION-MAKING AND IMPACTS RESEARCH: STATE OF OUR UNDERSTANDING

SERDP Project RC-2242

MARCH 2016

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Citation: Kotamarthi, R., L. Mearns, K. Hayhoe, C.L. Castro, and D. Wuebbles, 2016, Use of Climate Information for Decision-Making and Impacts Research: State of Our Understanding, prepared for the prepared for the Department of Defense, Strategic Environmental Research and Development Program, March.

SERDP
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One of the most debated tables by the authors in writing of this report….

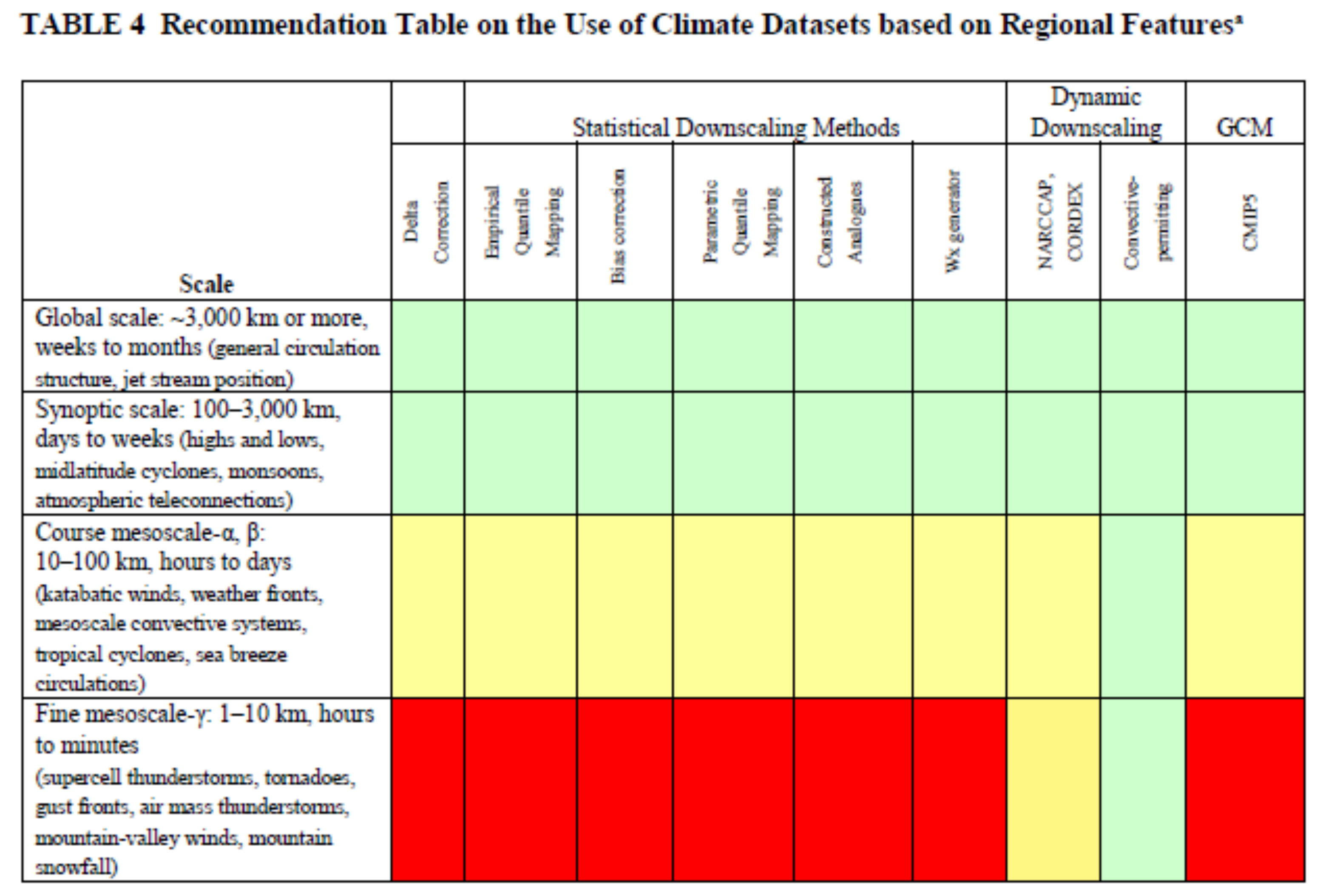
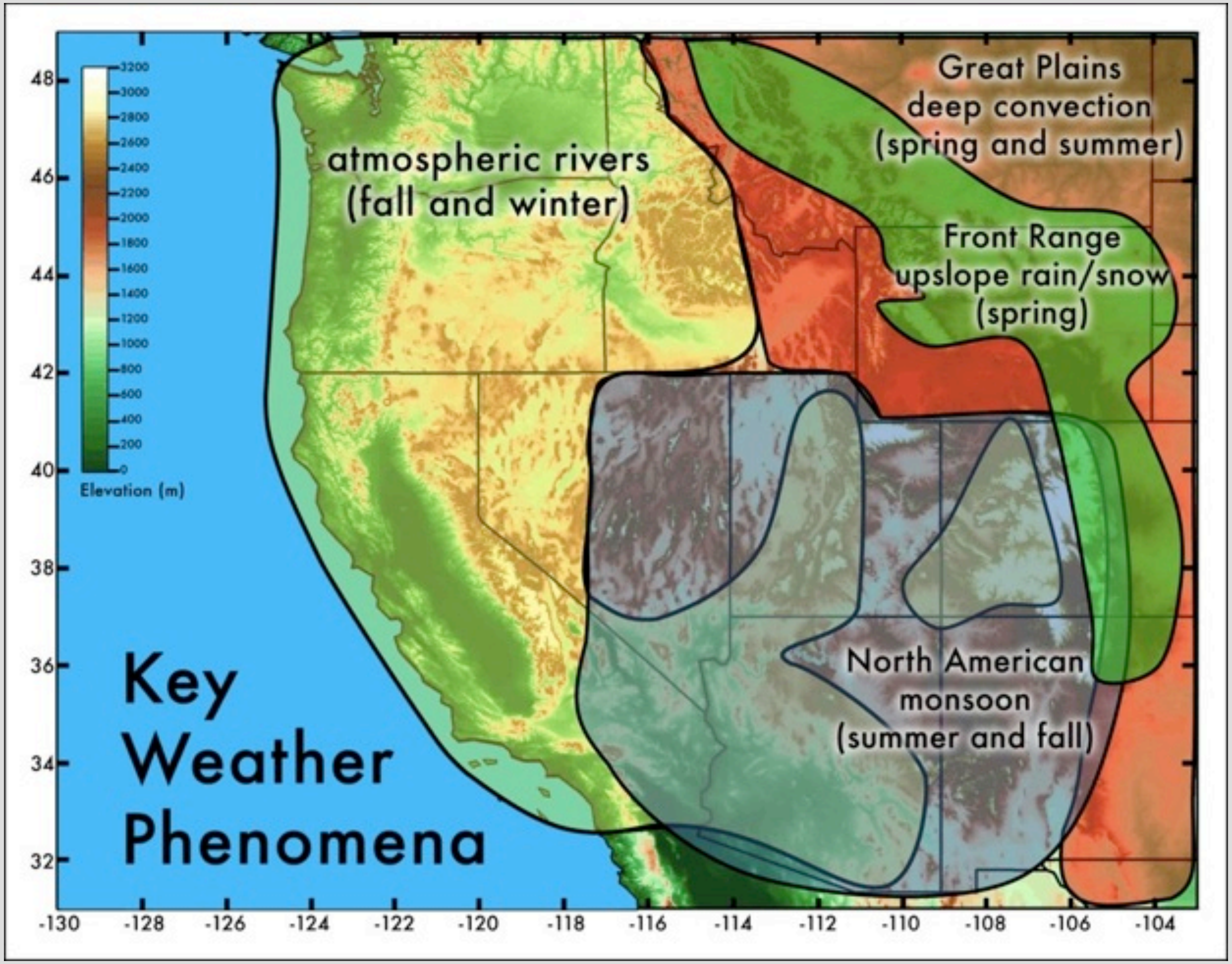


TABLE 4 Recommendation Table on the Use of Climate Datasets based on Regional Features[a]

Scale		Statistical Downscaling Methods					Dynamic Downscaling		GCM
	Delta Correction	Empirical Quantile Mapping	Bias correction	Parametric Quantile Mapping	Constructed Analogues	Wx generator	NARCCAP, CORDEX	Convective-permitting	CMIP5
Global scale: ~3,000 km or more, weeks to months (general circulation structure, jet stream position)	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
Synoptic scale: 100–3,000 km, days to weeks (highs and lows, midlatitude cyclones, monsoons, atmospheric teleconnections)	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
Course mesoscale-α, β: 10–100 km, hours to days (katabatic winds, weather fronts, mesoscale convective systems, tropical cyclones, sea breeze circulations)	🟨	🟨	🟨	🟨	🟨	🟨	🟨	🟩	🟨
Fine mesoscale-γ: 1–10 km, hours to minutes (supercell thunderstorms, tornadoes, gust fronts, air mass thunderstorms, mountain-valley winds, mountain snowfall)	🟥	🟥	🟥	🟥	🟥	🟥	🟨	🟩	🟥

What causes extreme precipitation in the West?



Ralph et al. (2011)

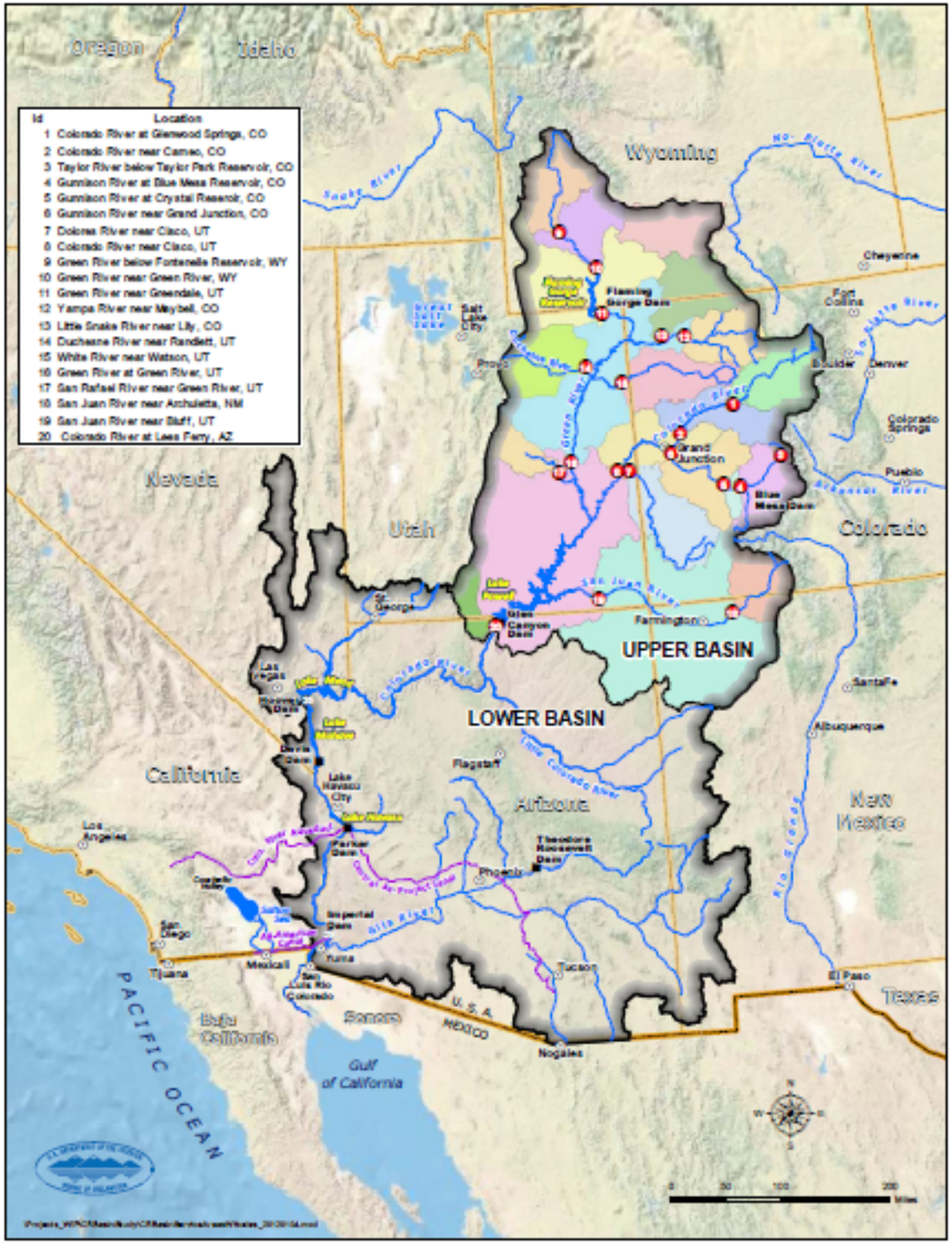
Projecting Water Resources in the Colorado Basin Using Dynamical Downscaling

U.S. DEPARTMENT OF THE INTERIOR
BUREAU OF RECLAMATION

CAP
CENTRAL ARIZONA PROJECT

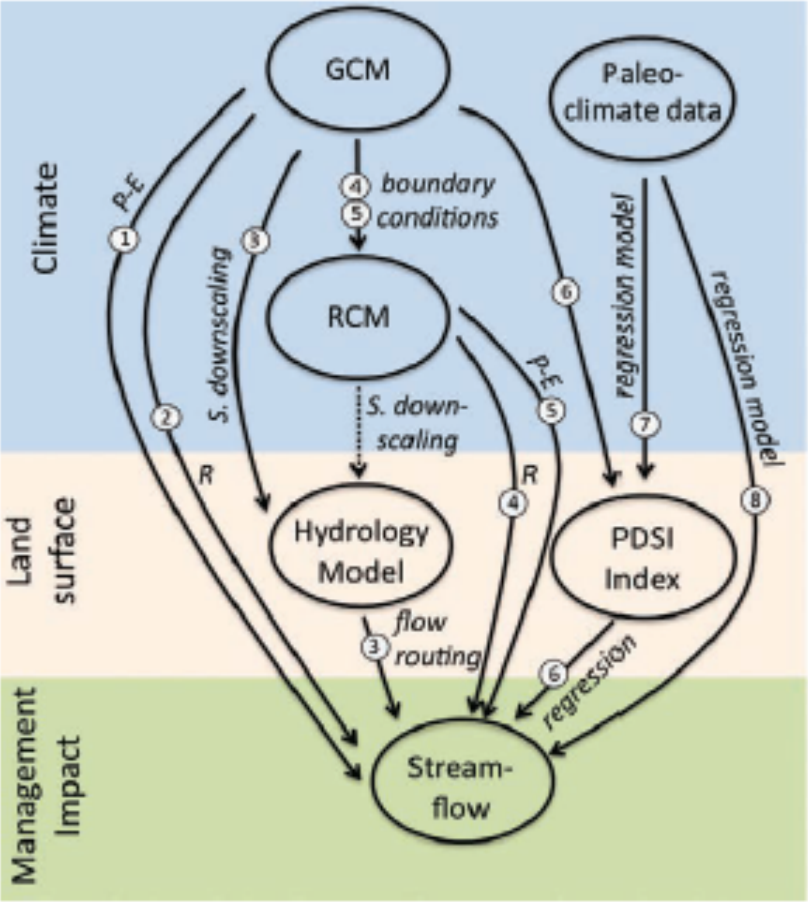
U.S. DEPARTMENT OF THE INTERIOR
MARCH 3, 1849

SRP
SALT RIVER PROJECT



Id	Location
1	Colorado River at Glenwood Springs, CO
2	Colorado River near Cameo, CO
3	Taylor River below Taylor Park Reservoir, CO
4	Gunnison River at Blue Mesa Reservoir, CO
5	Gunnison River at Crystal Reservoir, CO
6	Gunnison River near Grand Junction, CO
7	Dolores River near Cisco, UT
8	Colorado River near Cisco, UT
9	Green River below Fontenelle Reservoir, WY
10	Green River near Green River, WY
11	Green River near Greendale, UT
12	Yampa River near Maybell, CO
13	Little Snake River near Lily, CO
14	Duchesne River near Randlett, UT
15	White River near Watson, UT
16	Green River at Green River, UT
17	San Rafael River near Green River, UT
18	San Juan River near Archuletta, NM
19	San Juan River near Bluff, UT
20	Colorado River at Lees Ferry, AZ

Harding et al. (HESSD, 2012)



Studies using various approaches:

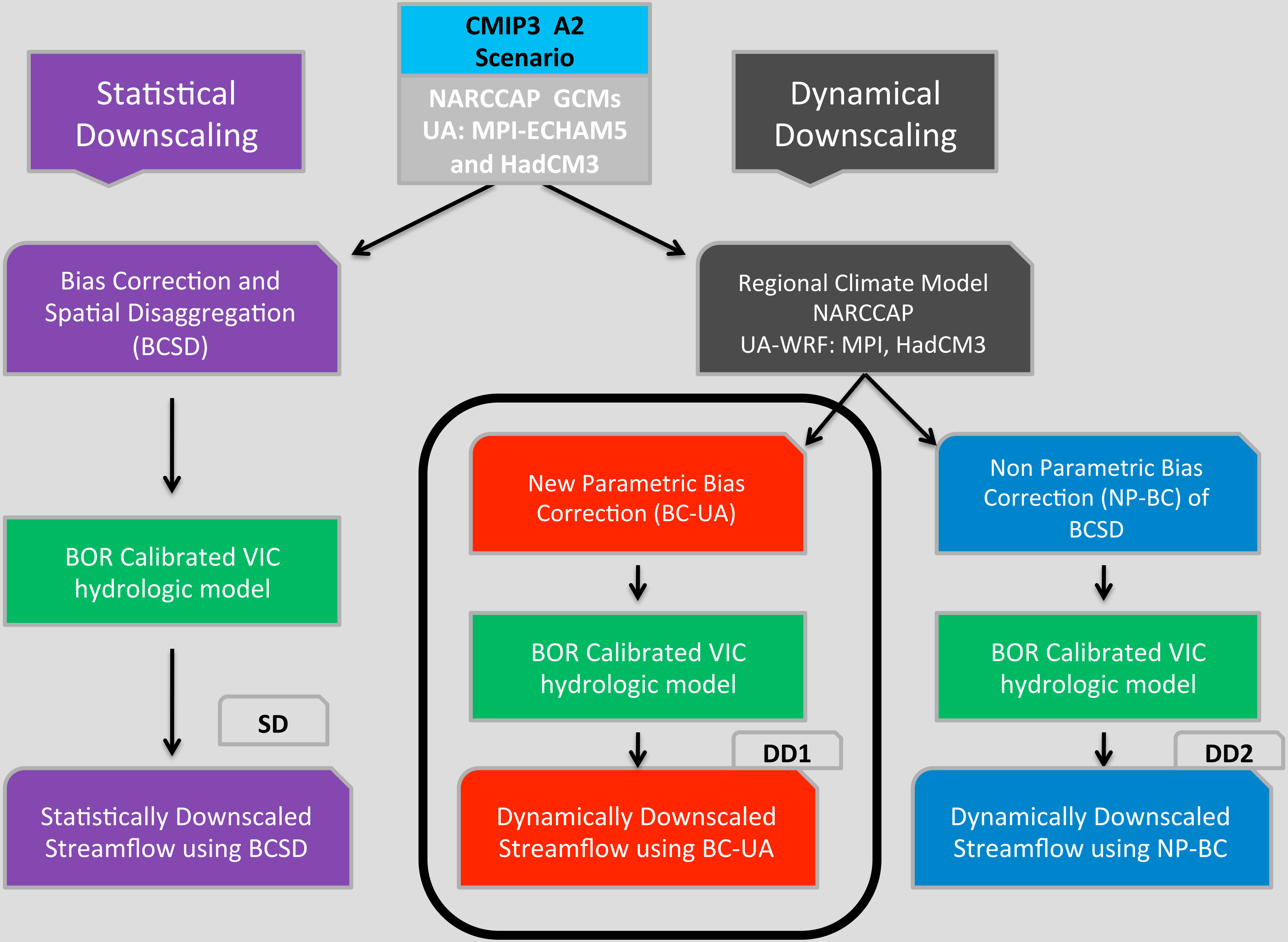
1. Seager et al. 2007; Seager et al. 2013
2. Milly et al. 2005
3. Christensen et al. 2004; Christensen and Lettenmaier, 2007; Cayan et al. 2010; USBR 2011a
4. Gao et al. 2011; Rasmussen et al. 2011
5. Gao et al. 2012
6. Hoerling and Eischeid 2007
7. Cook et al. 2004
8. Woodhouse et al. 2006; McCabe and Wolock 2007; Meko et al. 2007; USBR 2011a

Abbreviations:

GCM – Global Climate Model
RCM – Regional Climate Model
PDSI – Palmer Drought Severity Index
P – Precipitation
T – Temperature
R – Runoff
E – Evaporation
S. downscaling – statistical downscaling

FIG. 1. Approaches to generating future projections. Dotted lines indicate possible future studies. Land surface models (LSMs) are often incorporated into GCMs and RCMs, or they can be run (usually after downscaling) offline, in which case they use output from climate models (e.g., precipitation, temperature, wind speed) and essentially serve as macroscale hydrology models. Paleoclimate data can also be used to evaluate and improve how GCMs simulate historical climate.

Vano et al. (2014, BAMS)



CMIP3 A2 Scenario

NARCCAP GCMs
UA: MPI-ECHAM5
and HadCM3

Statistical Downscaling

Bias Correction and Spatial Disaggregation (BCSD)

BOR Calibrated VIC hydrologic model

SD

Statistically Downscaled Streamflow using BCSD

Dynamical Downscaling

Regional Climate Model
NARCCAP
UA-WRF: MPI, HadCM3

New Parametric Bias Correction (BC-UA)

BOR Calibrated VIC hydrologic model

DD1

Dynamically Downscaled Streamflow using BC-UA

Non Parametric Bias Correction (NP-BC) of BCSD

BOR Calibrated VIC hydrologic model

DD2

Dynamically Downscaled Streamflow using NP-BC

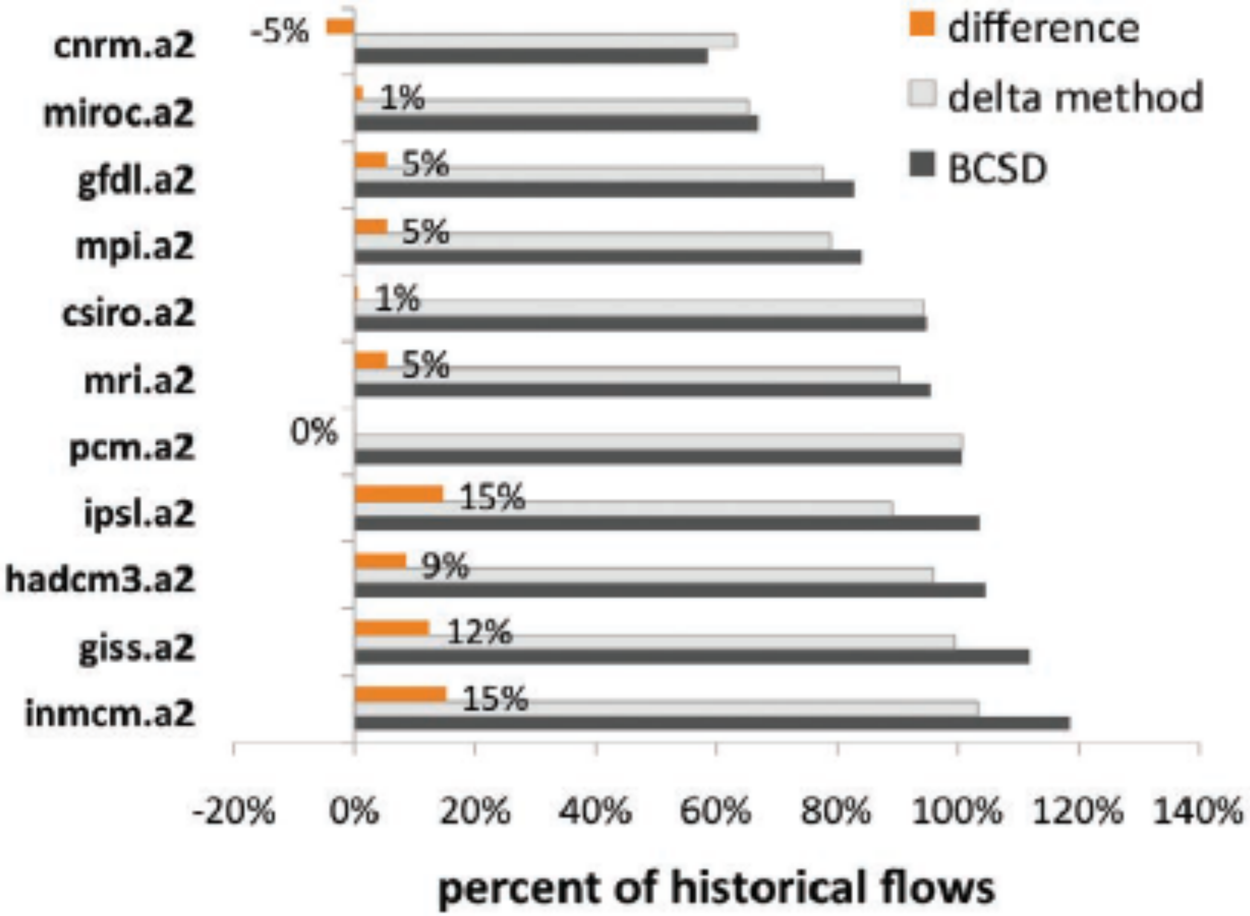
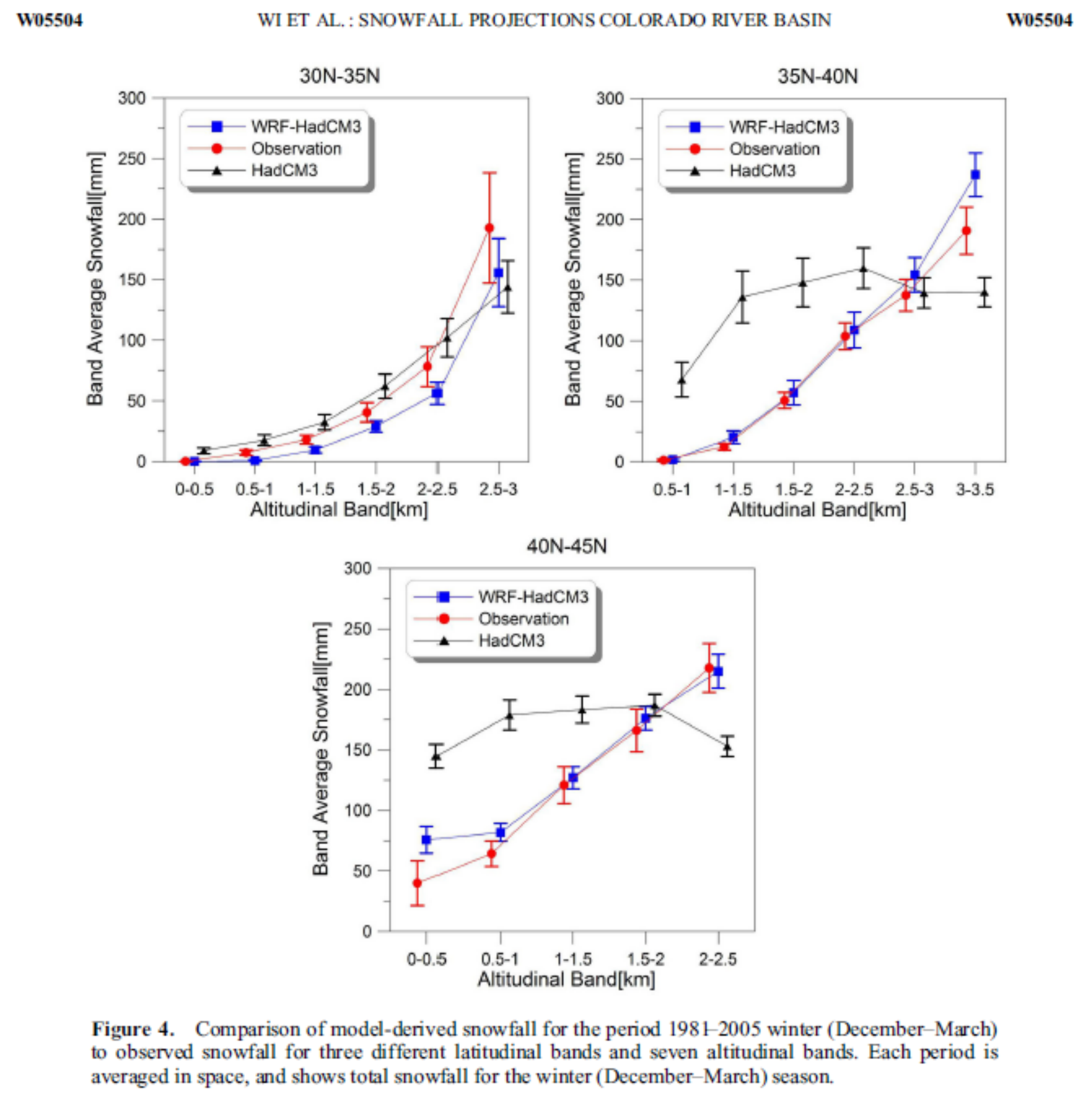


FIG. 6. Comparison of BCSD downscaling from C&L with a delta-method downscaling approach for Lees Ferry in the 2040–69 future period for A2 emission scenarios. On average, the BCSD approach has a decline in streamflow of 7% (average values of 93%), whereas with the delta method, declines are 13% (average values of 87%). Differences are the BCSD approach minus the delta-method approach.

Vano et al. (2014, BAMS)

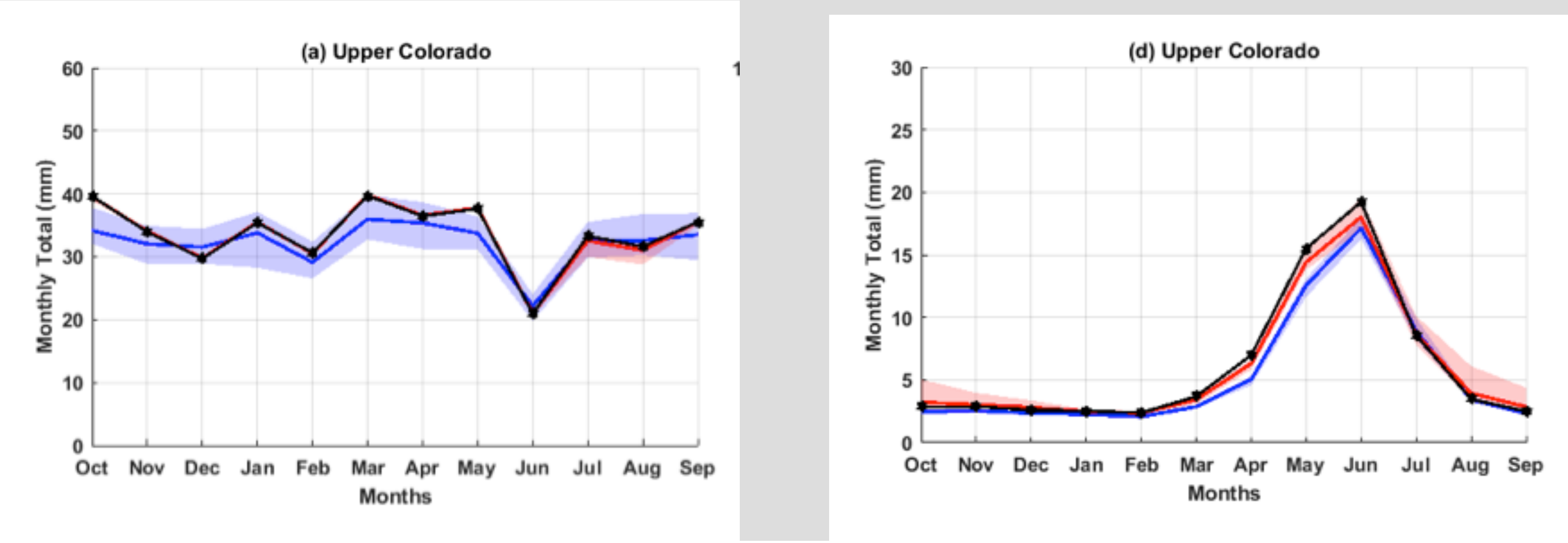


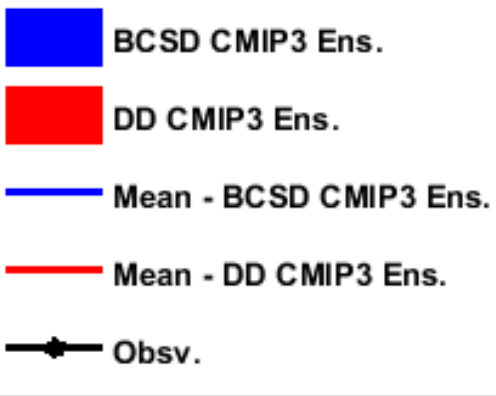
W05504 WI ET AL.: SNOWFALL PROJECTIONS COLORADO RIVER BASIN W05504

Figure 4. Comparison of model-derived snowfall for the period 1981–2005 winter (December–March) to observed snowfall for three different latitudinal bands and seven altitudinal bands. Each period is averaged in space, and shows total snowfall for the winter (December–March) season.

Wi et al. (2012, JGR-Atmos.)

Simulated vs. observed precipitation and streamflow at Lees Ferry: 1971-2000 historical period

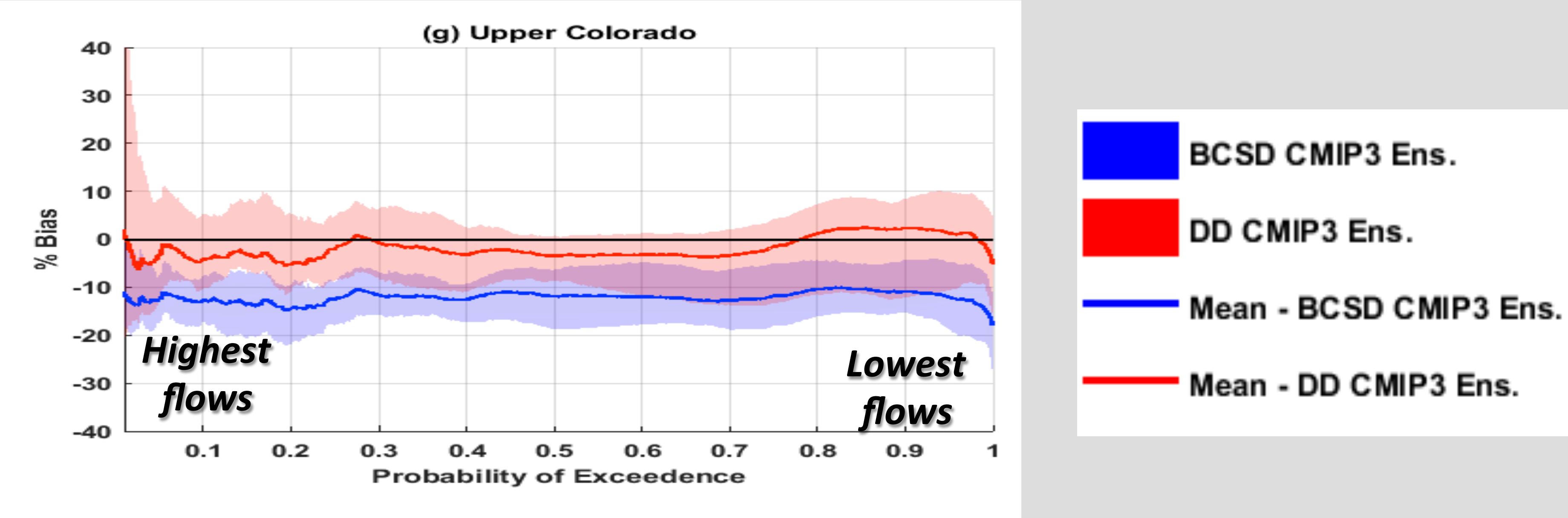




Mukharjee et al. (in preparation)

Bias in Downscaled Simulated to Observed Upper Colorado streamflow at Lees Ferry: 1971-2000 historical period

BCSD vs. NARCCAP + UA WRF RCMs



Highest flows

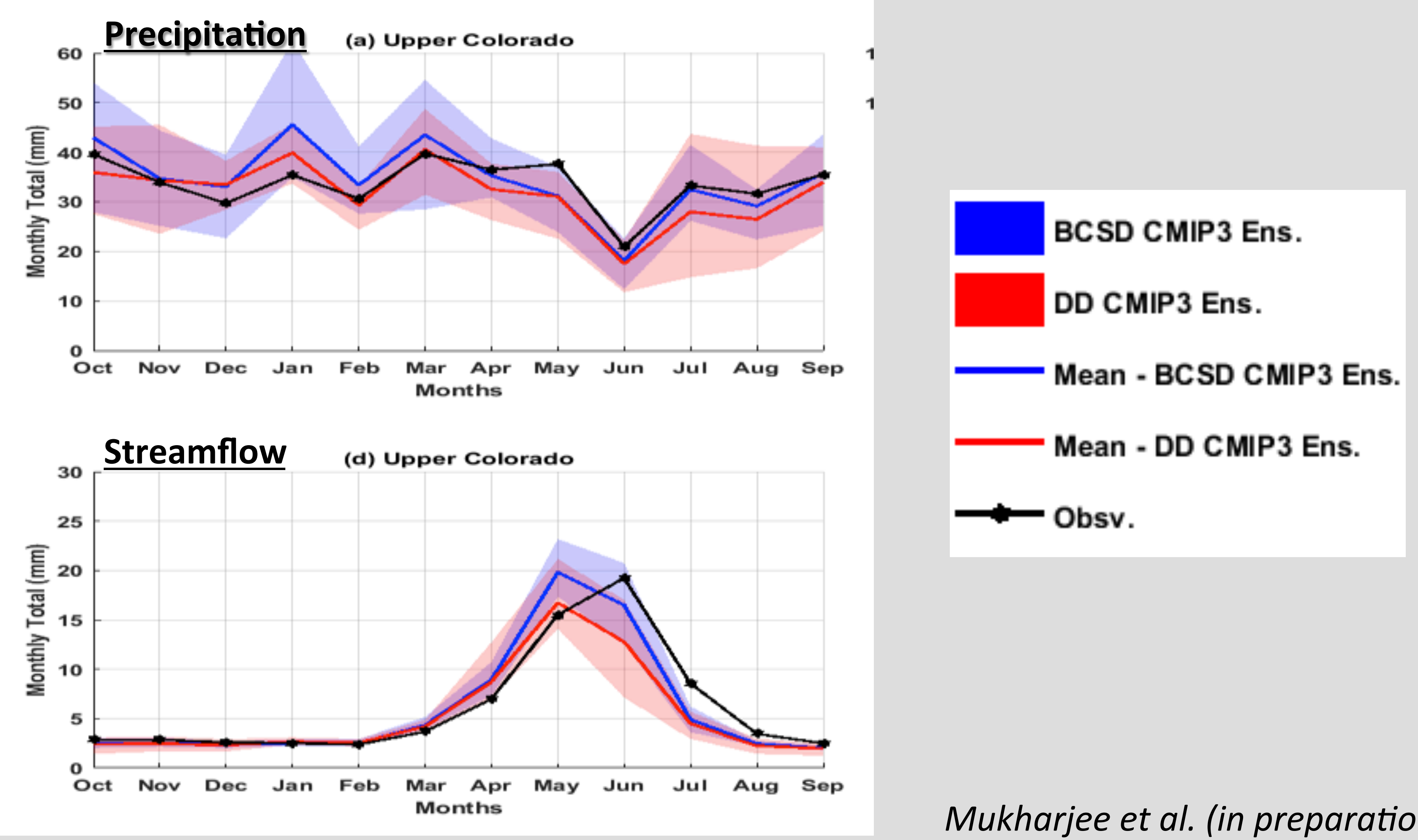
Lowest flows

Dynamical downscaling leads to <u>reduced bias</u> in representation of historical streamflow, generally independent of high and low flows. <u>The regional modeling component is main reason why</u>, not choice of bias correction technique.

Mukharjee et al. (in preparation)

Downscaled CMIP3 Projected Absolute Changes in Upper Colorado River Precipitation and Streamflow: 2041-2070 minus 1971-2000

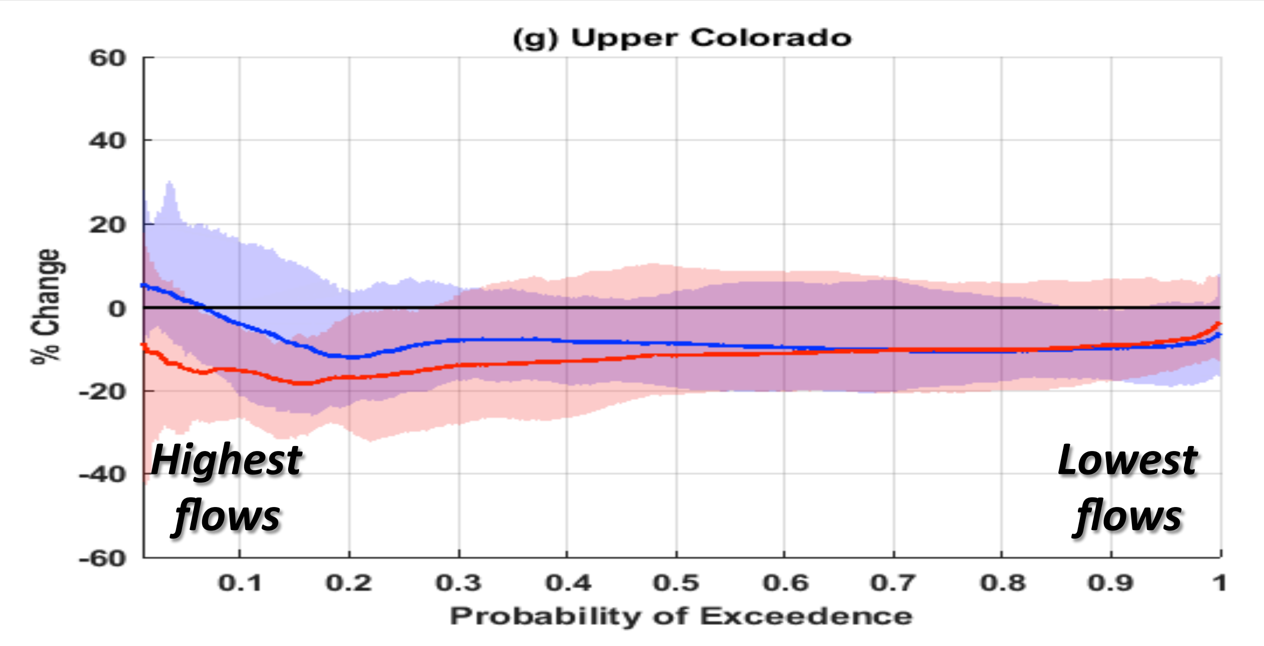
BCSD vs. NARCCAP + UA WRF RCMs



Mukharjee et al. (in preparation)

Downscaled CMIP3 Projected % Changes in Upper Colorado River Flow: 2041-2070 minus 1971-2000

BCSD vs. NARCCAP + UA WRF RCMs



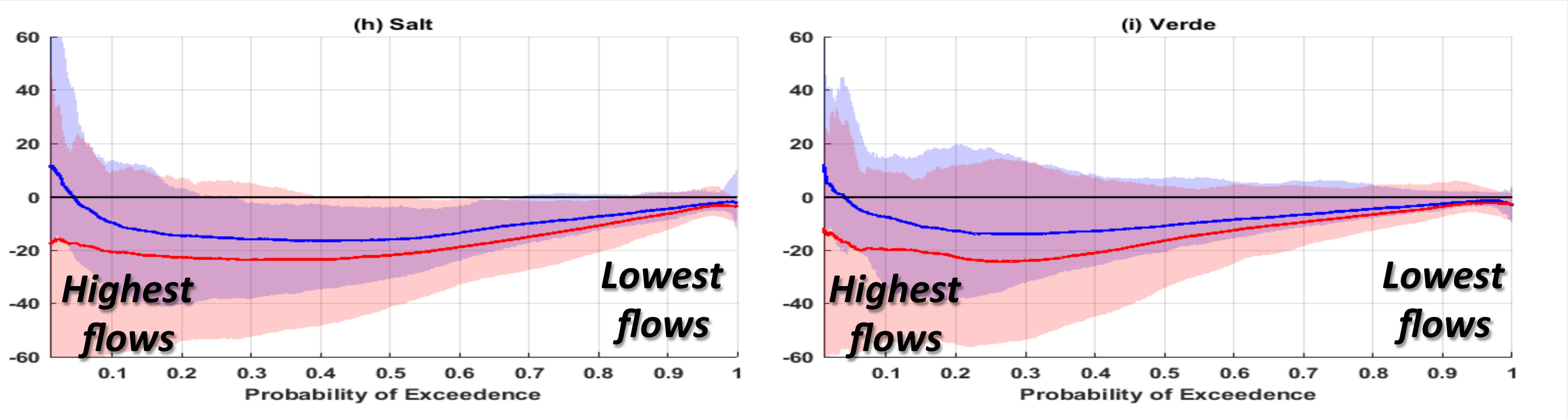
- 🟦 BCSD CMIP3 Ens.
- 🟥 DD CMIP3 Ens.
- — Mean - BCSD CMIP3 Ens.
- — Mean - DD CMIP3 Ens.

Greatest difference between a statistically vs. dynamically downscaled stream flow projection occurs for highest flows.

On order of 10-20% <u>lower</u> streamflow during peak flows with dynamical downscaling!

Mukharjee et al. (in preparation)

Downscaled CMIP3 Projected % Changes in Salt and Verde Streamflow (Lower Colorado Basin within Arizona): 2041-2070 minus 1971-2000
BCSD vs. NARCCAP + UA WRF RCMs



🟦 BCSD CMIP3 Ens.

🟥 DD CMIP3 Ens.

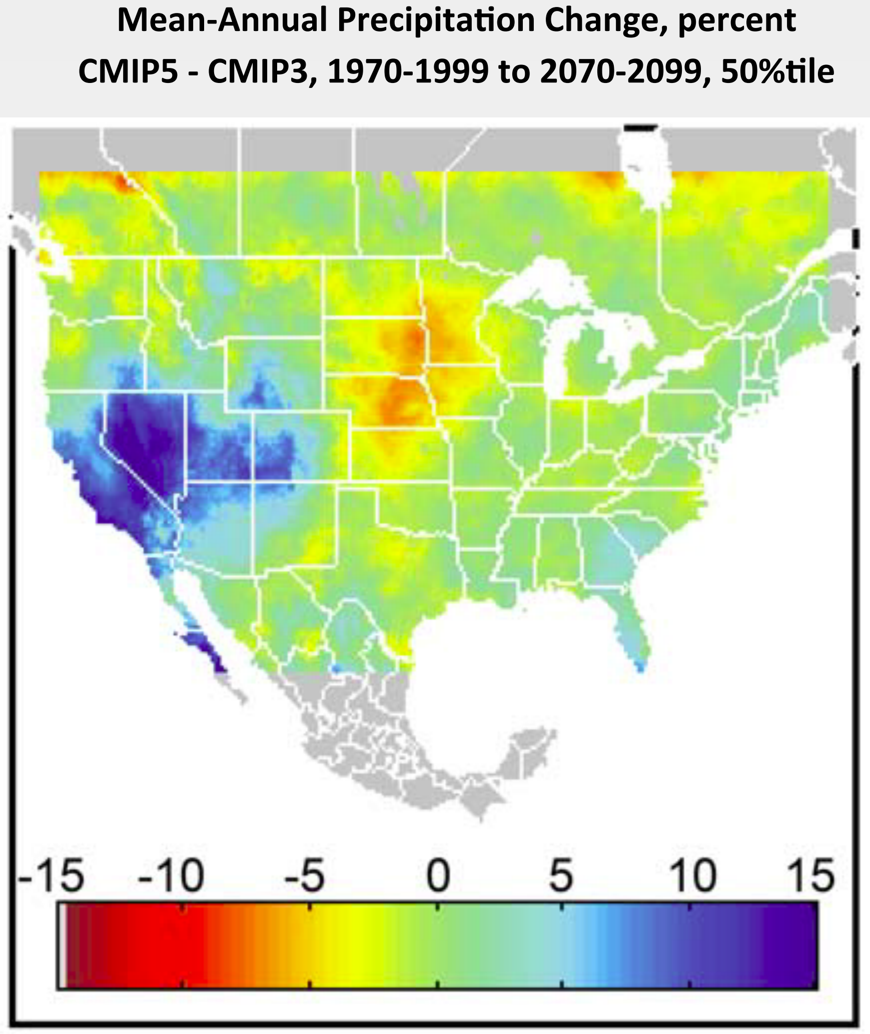
— Mean - BCSD CMIP3 Ens.

— Mean - DD CMIP3 Ens.

The potential decreases on the smaller rivers that are the lifeblood of the SRP system may be even more dramatic than for the Upper Basin!

Mukharjee et al. (in preparation)

CMIP5 minus CMIP3 BCSD climate projections From Bureau of Reclamation



Projected Southwest drying trend is not as dire in AR5

Projecting changes in monsoon severe weather events using convective resolving modeling

SERDP
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THE HUNTER'S EDGE
25th OPERATIONAL WEATHER SQ

NATIONAL WEATHER SERVICE

14TH WEATHER SQUADRON

Predominant monsoon severe weather hazards in the Southwest U.S.

Will these hazards potentially worsen with climate change?

Monsoon Thunderstorms in Arizona

Monsoon thunderstorms at Kitt Peak at mature stage with gust fronts.

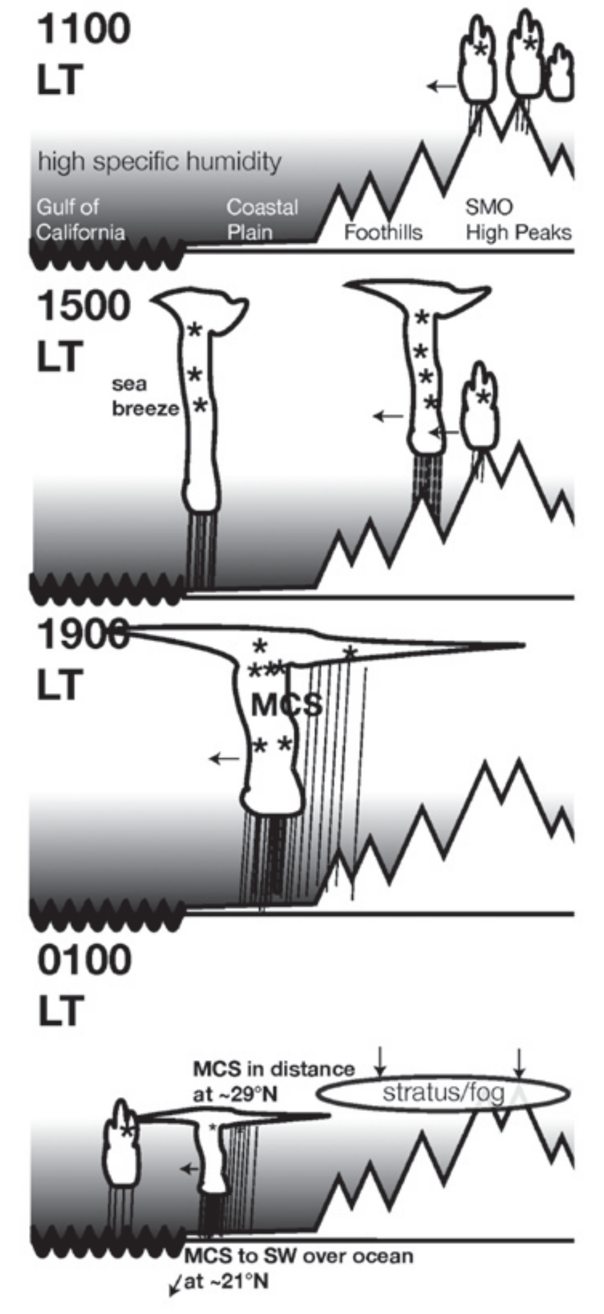
Forced by the diurnal mountain valley circulation

Form over the mountains during late morning to early afternoon

Reach mature stage by about mid-afternoon.

(*Photo taken around 3pm)*

Convective organization and propagation



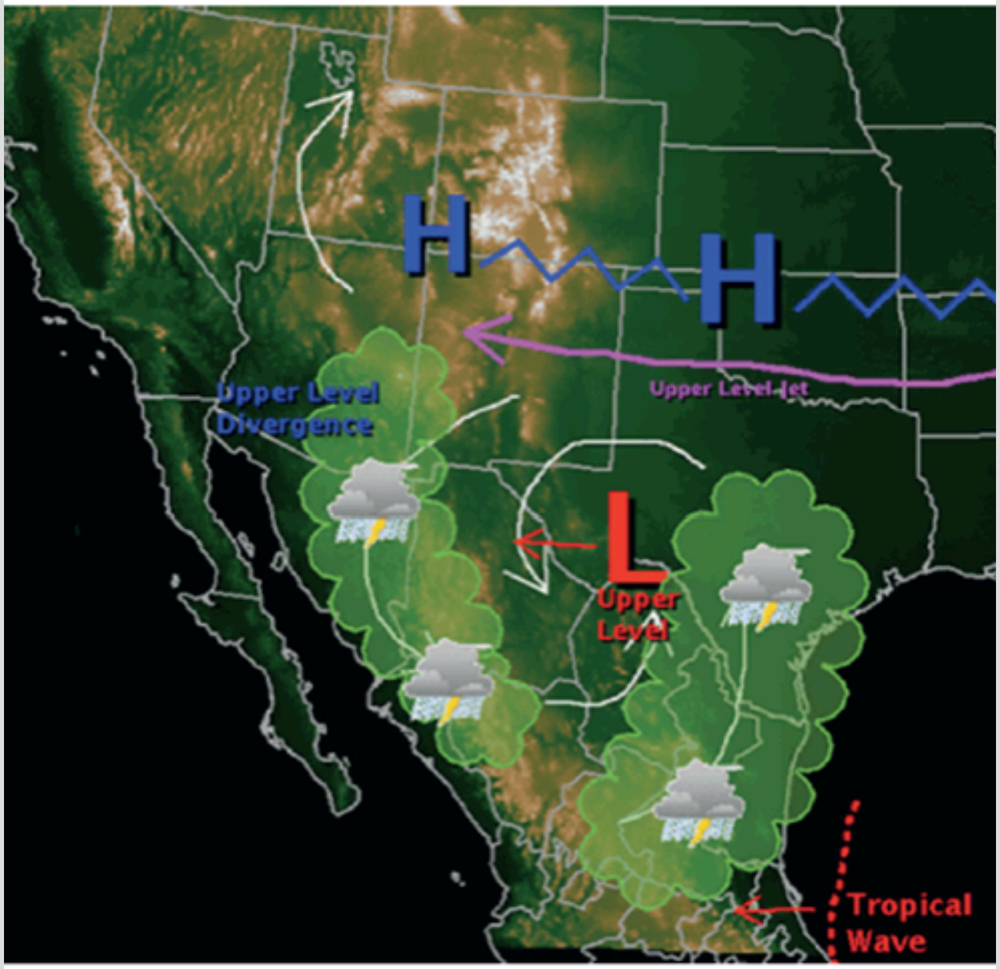
Nesbitt et al. (2008)

Convective clouds form over the mountains in the morning.

By afternoon and evening 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.

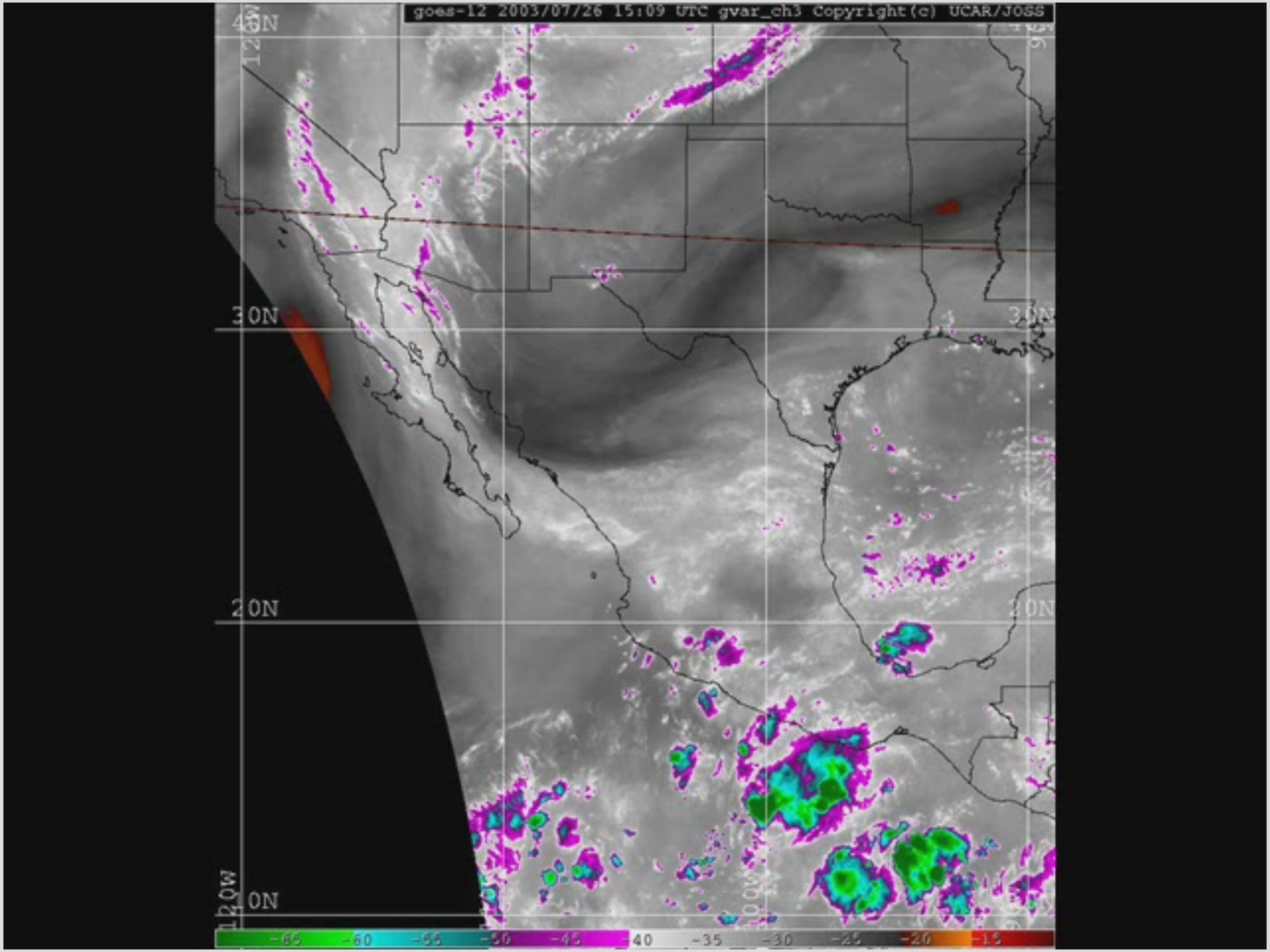
It's likely that a convective-permitting resolution (less than 5 km) is necessary to represent this process correctly in regional models. Global models pretty much fail.

Inverted trough: Favors upward motion and vertical wind shear



Pytlak (2005)

An active monsoon day…



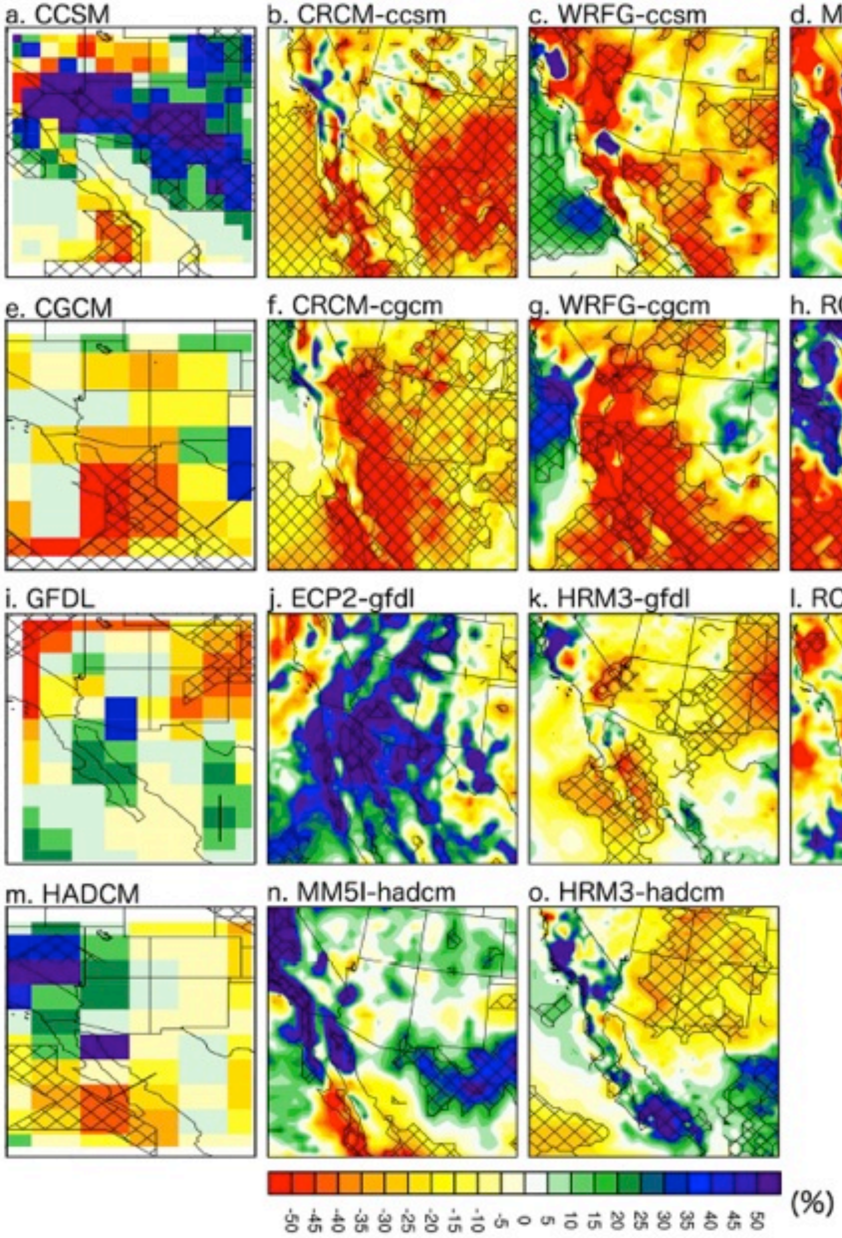


Figure 3: JA average precipitation change (%) from the baseline period. Hatching indicates where the change is statistically significant at the 0.1 level.

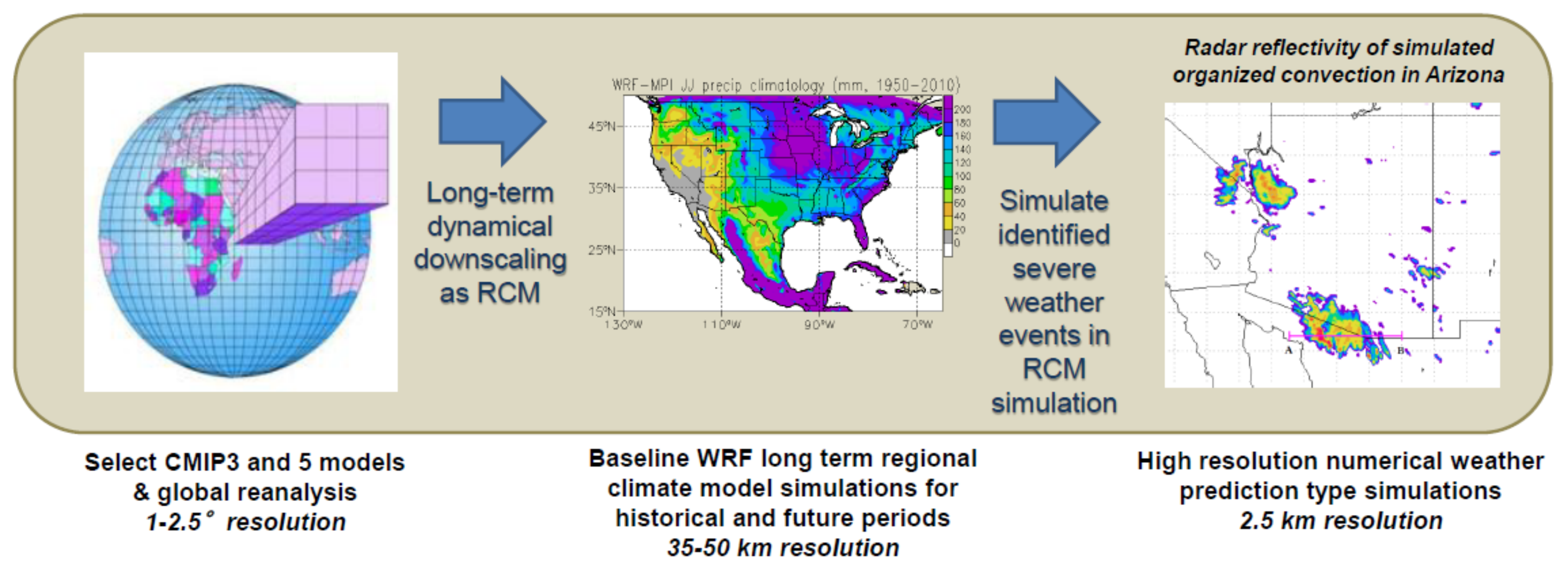
NARRCAP Ensemble Results

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)

Technical Approach

Dynamical downscaling to address severe weather question



Long-term dynamical downscaling as RCM

Simulate identified severe weather events in RCM simulation

Radar reflectivity of simulated organized convection in Arizona

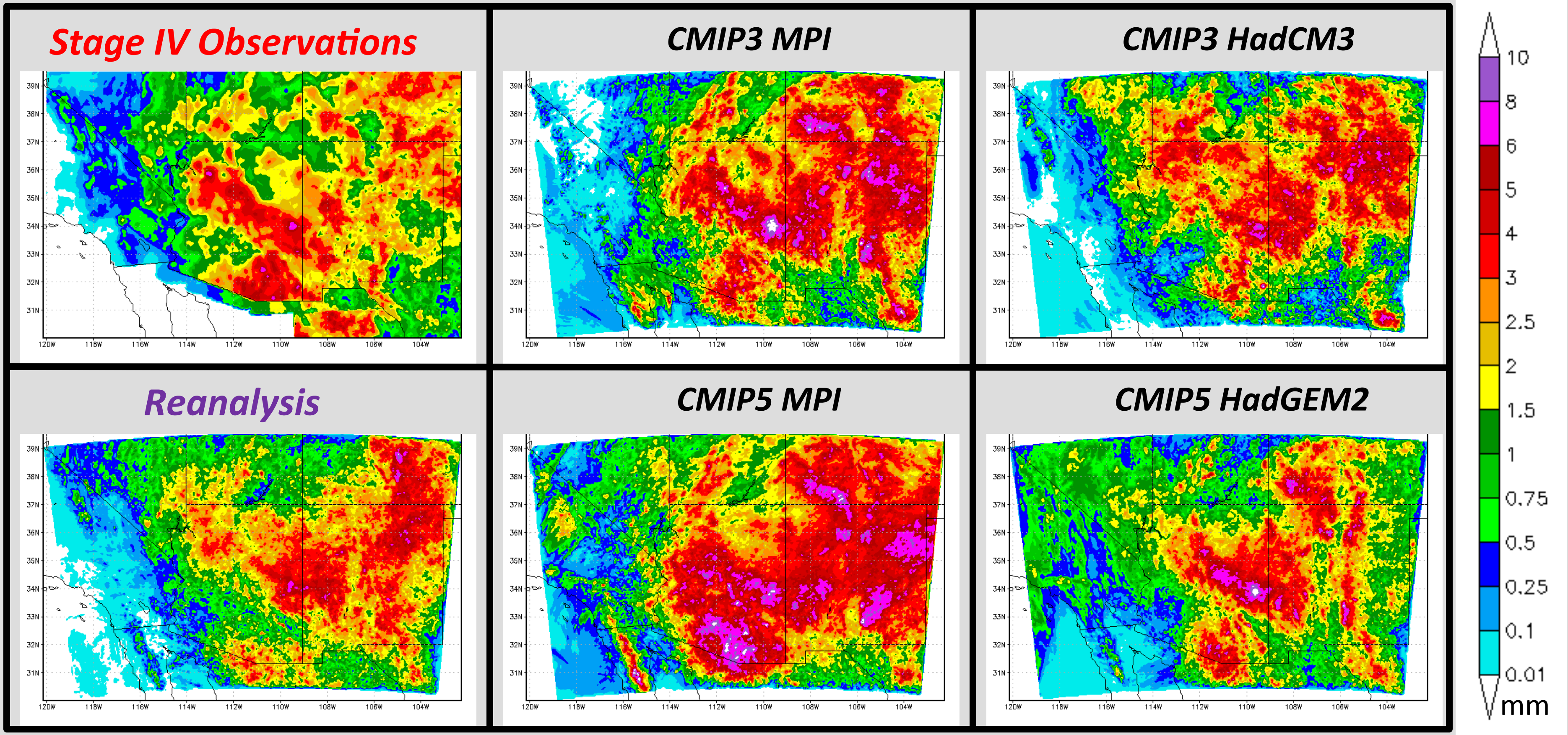
Select CMIP3 and 5 models & global reanalysis
1-2.5° resolution

Baseline WRF long term regional climate model simulations for historical and future periods
35-50 km resolution

High resolution numerical weather 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.

Daily average precipitation WRF hi-res modeled vs. observed for favorable severe weather events (2002-2010)



Stage IV Observations

CMIP3 MPI

CMIP3 HadCM3

Reanalysis

CMIP5 MPI

CMIP5 HadGEM2

Widespread precipitation in Southwest, with maxima on terrain
CMIP paradigms generally comparable to Stage IV

Luong et al. (in preparation)
Presented at 2015 AGU Fall meeting

Changes in the atmospheric environment for monsoon thunderstorms during the last thirty years in downscaled NCEP reanalysis

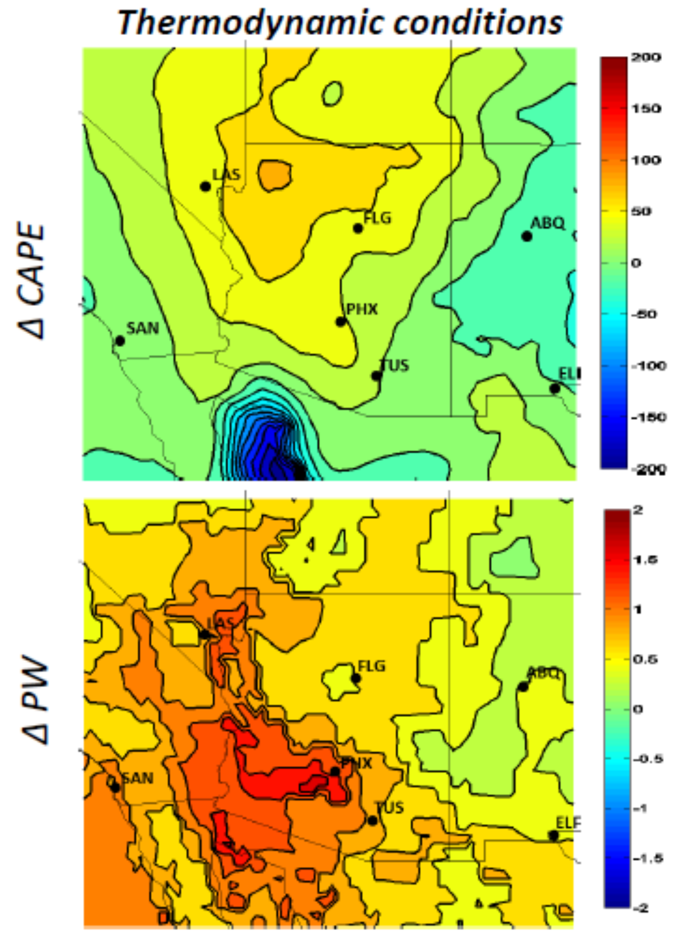


Figure 2: JA differences in downscaled reanalysis (1980-2010 minus 1950-1979) for convective available potential energy (CAPE, J kg^{-1}) and precipitable water (PW, mm). Operational radiosonde sites indicated. (Jares et al., in preparation)

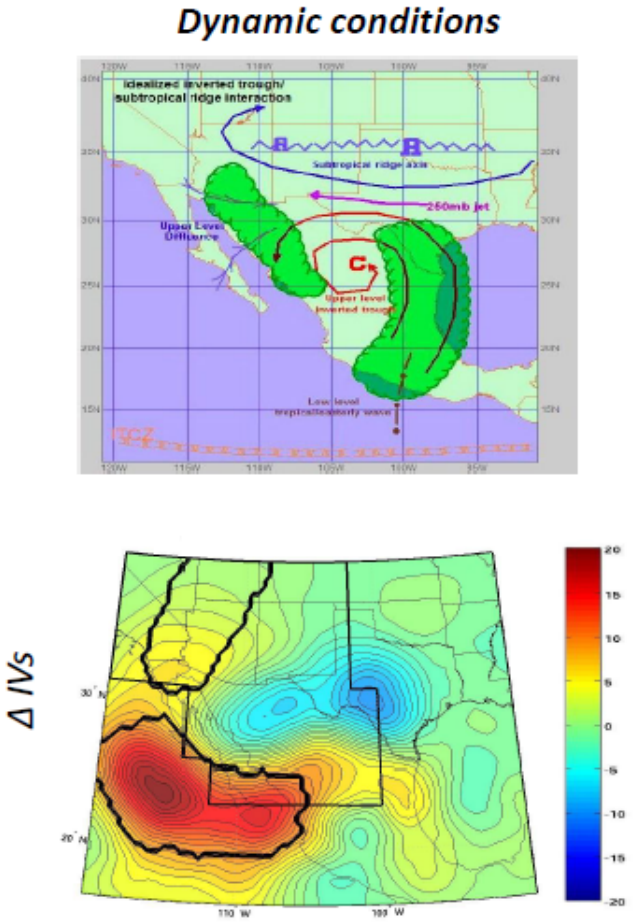
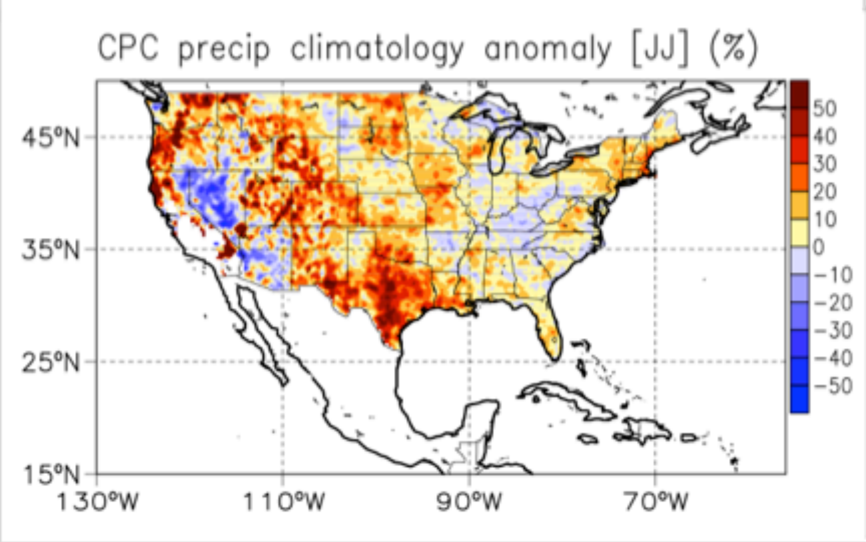
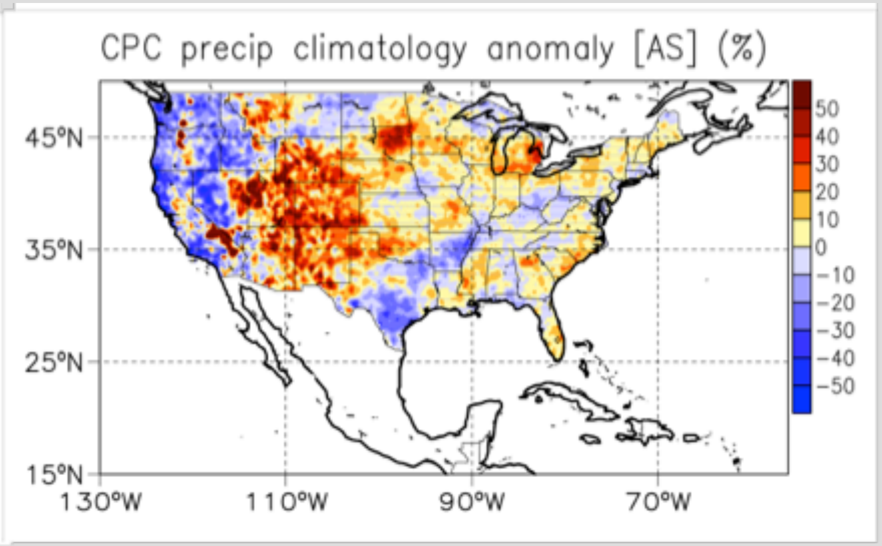


Figure 3: Top: conceptual model of inverted trough (IV) from Pytlak et al. (2005). Bottom: Difference in IV track density (1980-2010 minus 1950-1979) during peak of the monsoon (mid-July to mid-August). Differences field significant at 93% level. (Lahmers et al., submitted).

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

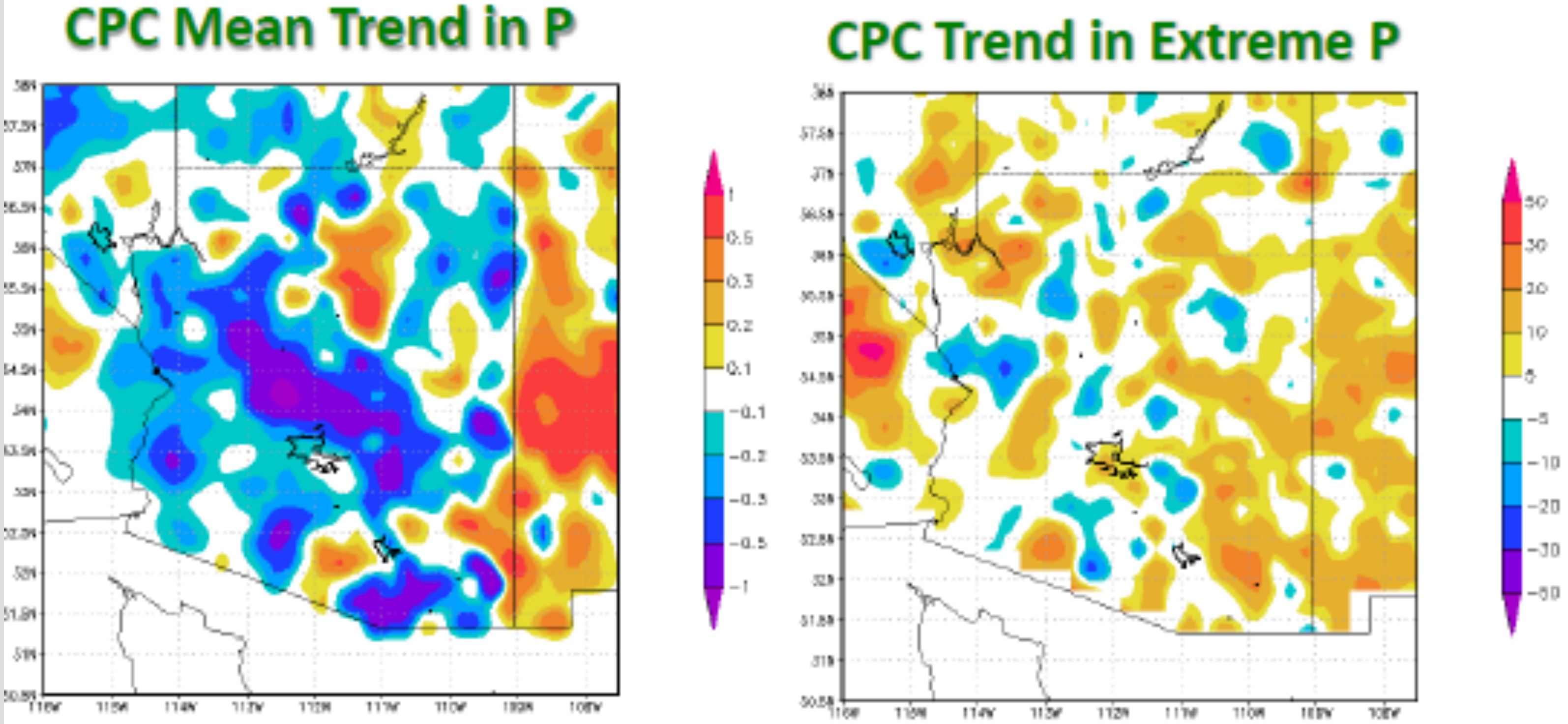




Recent observational record seems to comport with "wet gets wetter, dry gets drier idea"

More monsoon precipitation, but tending to occur mostly in mountainous areas. More thermodynamically favorable, but less dynamically favorable.

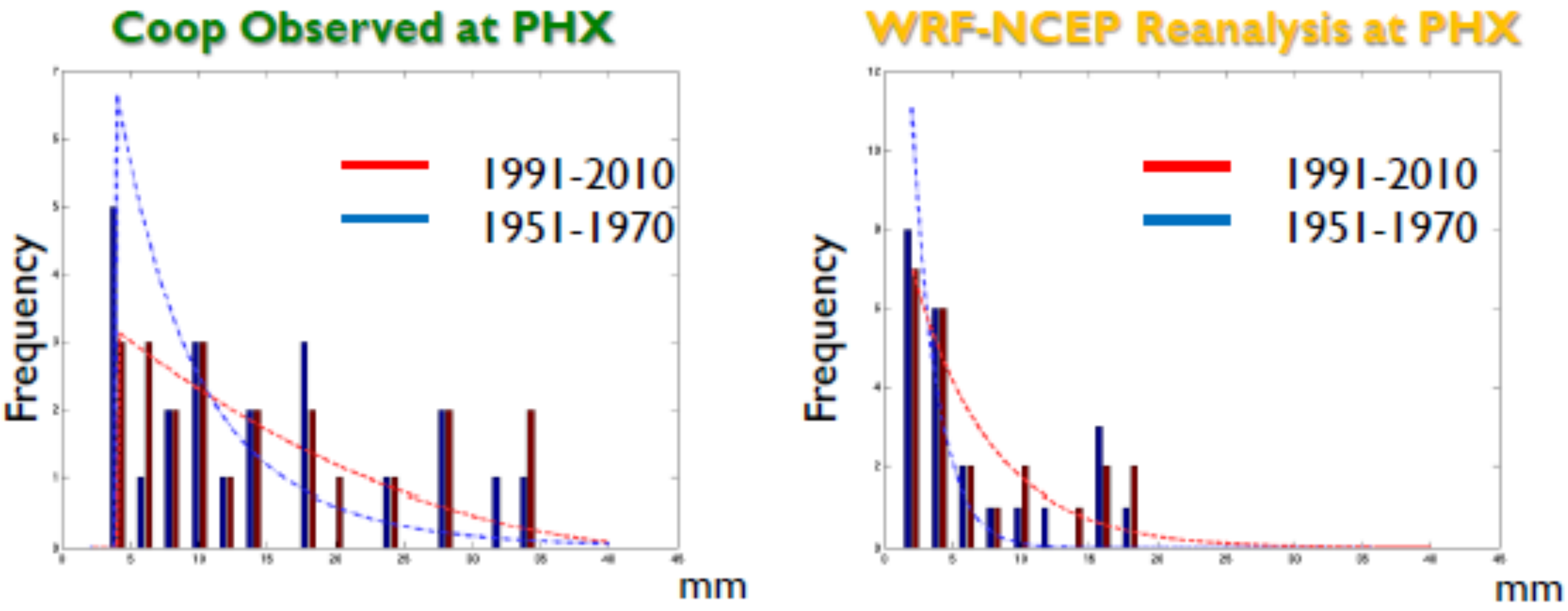
Chang et al. (2015, JGR Atmos.)


CPC Mean Trend in P

CPC Trend in Extreme P

Figure 5: CPC mean and extreme (top 5%) precipitation locally significant trends (1991-2010 minus 1951-1970) (mm day^{-1}) for the period JA using a peak-over-threshold method for extremes.

Luong et al. (in preparation)
Presented at 2015 AGU Fall meeting



Coop Observed at PHX

WRF-NCEP Reanalysis at PHX

Figure 6: Coop station comparison of probability distribution of daily precipitation extremes to downscaled reanalysis severe weather events for Phoenix using peak-over-threshold method (mm day^{-1}) for the period JA.

Luong et al. (in preparation)
Presented at 2015 AGU Fall meeting

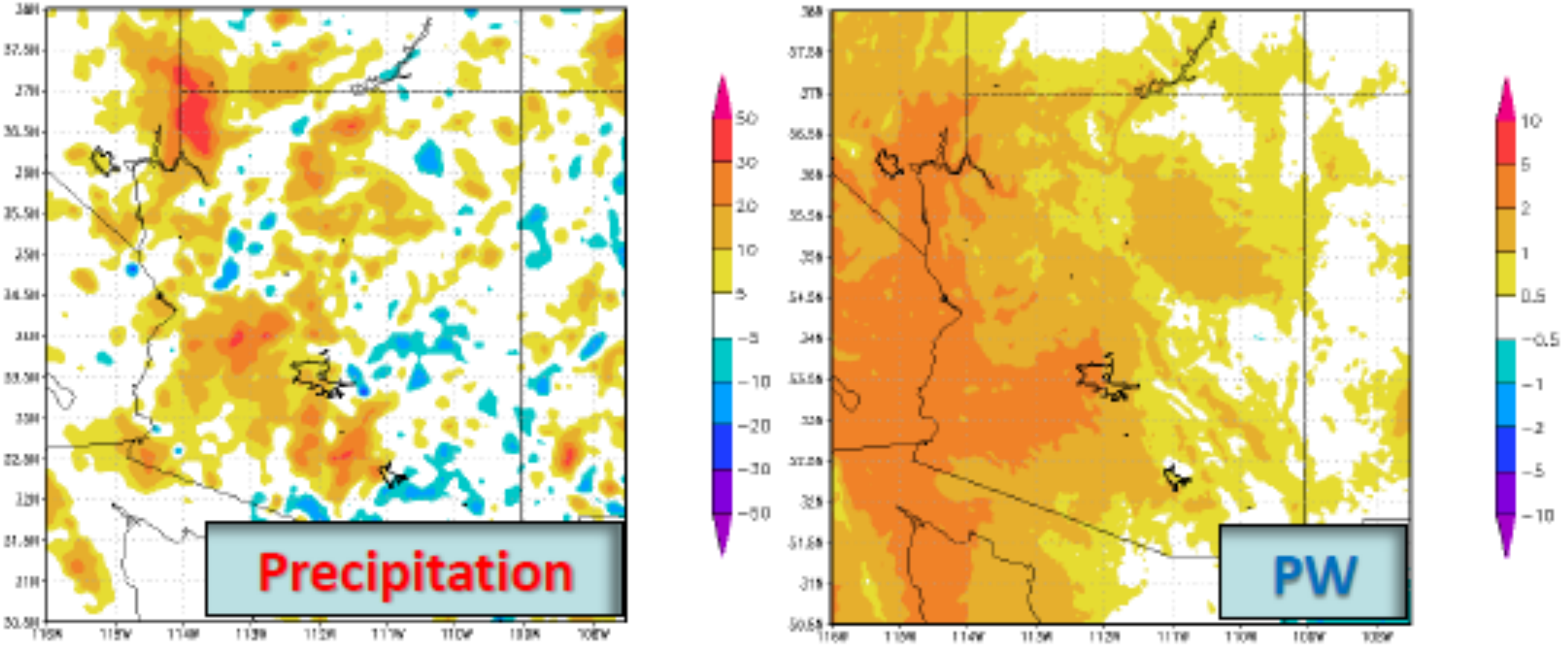
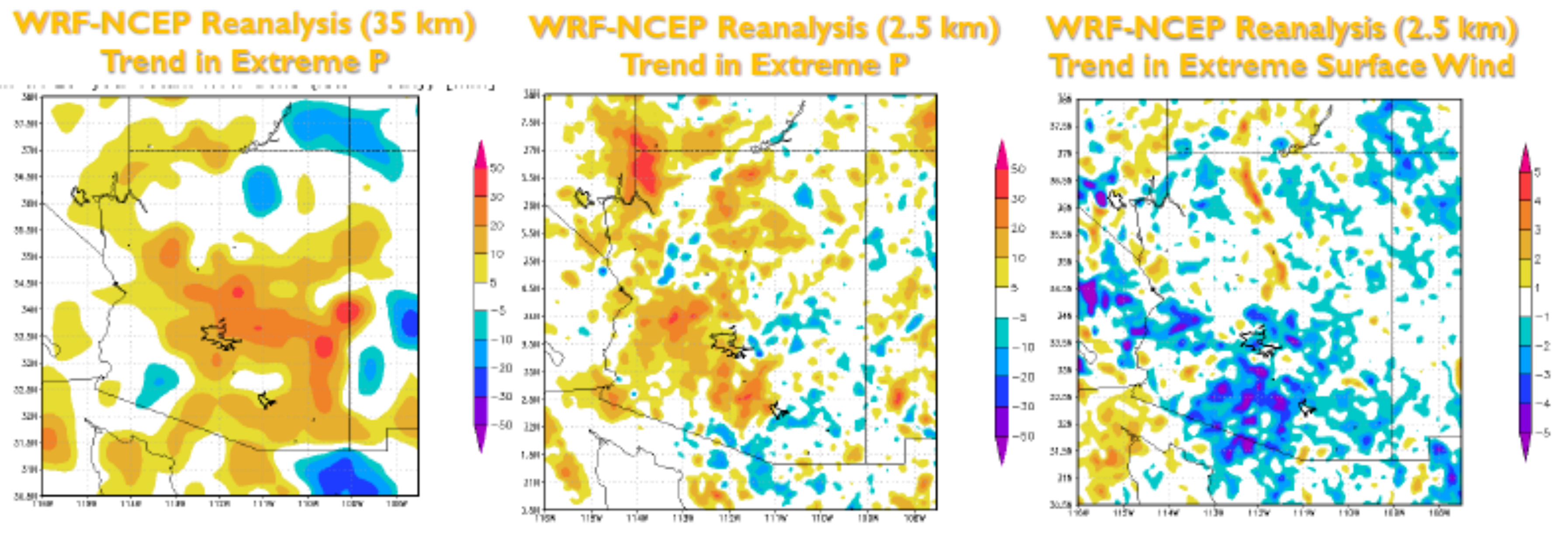


Figure 7: Downscaled reanalysis extreme (top 5%) precipitation and mean precipitable water trend (1991-2010 minus 1951-1970) [mm day^{-1}]

Luong et al. (in preparation)
Presented at 2015 AGU Fall meeting



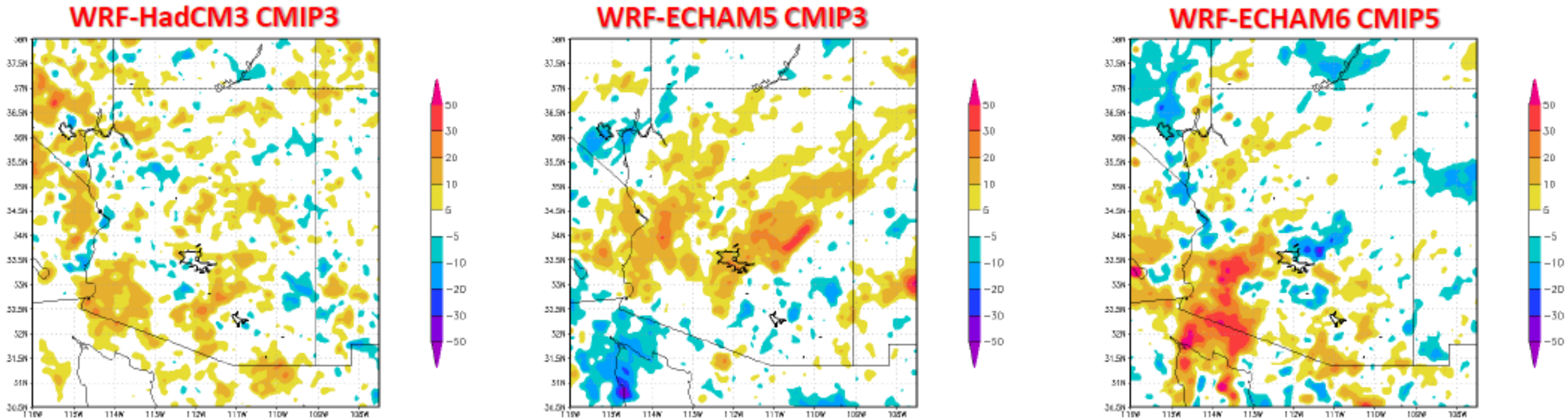
WRF-NCEP Reanalysis (35 km)
Trend in Extreme P

WRF-NCEP Reanalysis (2.5 km)
Trend in Extreme P

WRF-NCEP Reanalysis (2.5 km)
Trend in Extreme Surface Wind

Figure 7: Trend in downscaled reanalysis locally significant extreme (top 5%) precipitation (mm day^{-1}) and surface wind speed (m s^{-1}) (1991-2010 minus 1951-1970), for period JJAS using a peak-over threshold method.

Luong et al. (in preparation)
Presented at 2015 AGU Fall meeting



WRF-HadCM3 CMIP3

WRF-ECHAM5 CMIP3

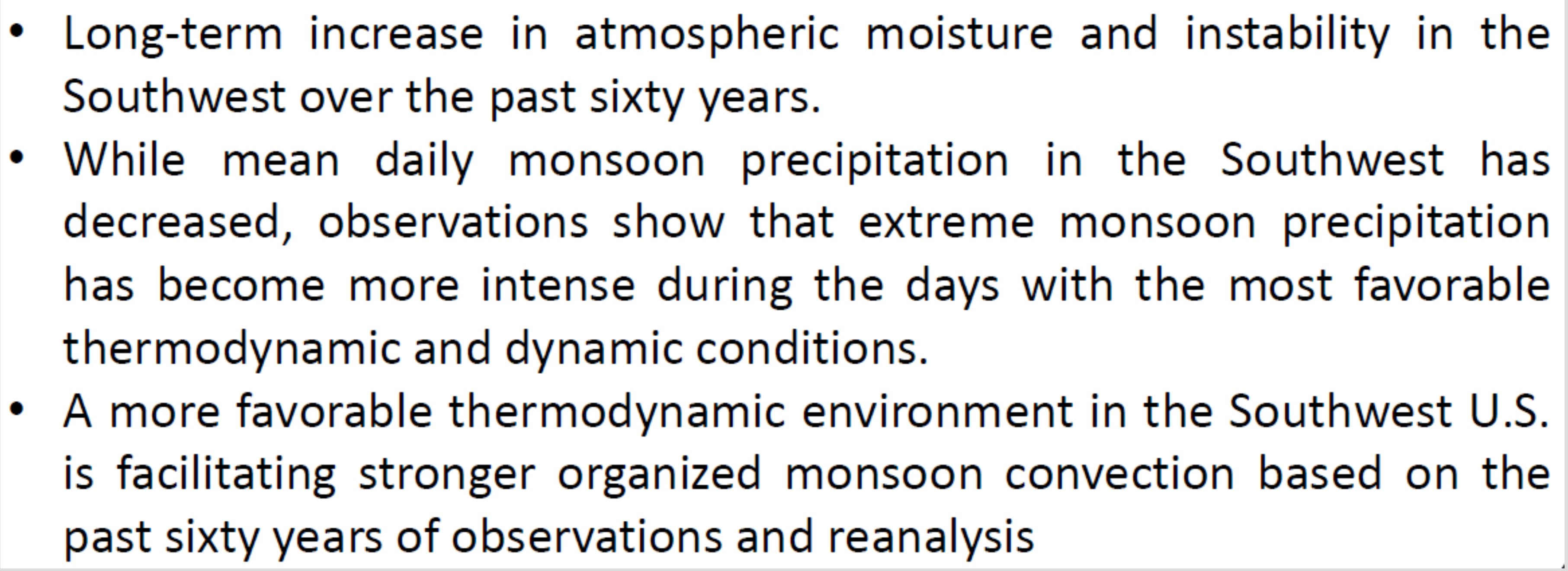
WRF-ECHAM6 CMIP5

Figure 9: Near future projected extreme (top 5%) precipitation trends (2021-2040 minus 1991-2010) [mm day^{-1}] from downscaled CMIP3 HadCM3 (left), CMIP3 ECHAM5 (middle), and CMIP5 ECHAM6 (right)

Luong et al. (in preparation)
Presented at 2015 AGU Fall meeting

How is monsoon precipitation changing in the Southwest?

From the perspective of convective-permitting climate modeling

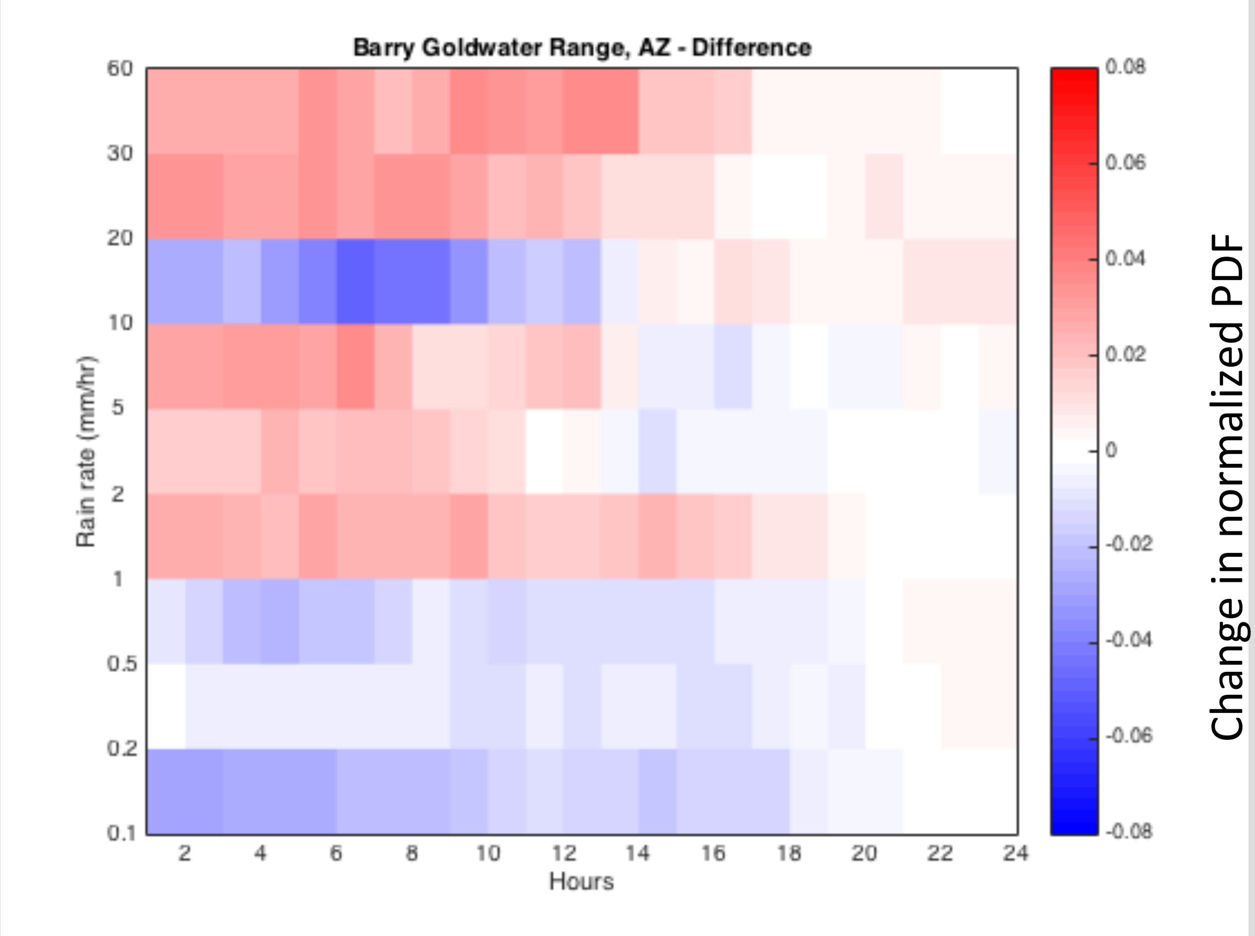


- Long-term increase in atmospheric moisture and instability in the Southwest over the past sixty years.
- While mean daily monsoon precipitation in the Southwest has decreased, observations show that extreme monsoon precipitation has become more intense during the days with the most favorable thermodynamic and dynamic conditions.
- A more favorable thermodynamic environment in the Southwest U.S. is facilitating stronger organized monsoon convection based on the past sixty years of observations and reanalysis

Consistency in results (so far) with dynamically downscaled CMIP3 and CMIP5 model paradigms for future projections suggest anthropogenic climate change is the likely driver…

Joint PDF Changes in Intensity, Duration
Downscaled reanalysis: 1990-2010 minus 1950-1970

Example of final translation of information to facility scale



Will consider future projections, multiple variables of interest for weather forecasting purposes per operational threshold criteria of 25th OWS.

Interannual variability: Teleconnections at monsoon onset (late June, early July)

e.g. Castro et al. (2001, *J. Climate*)

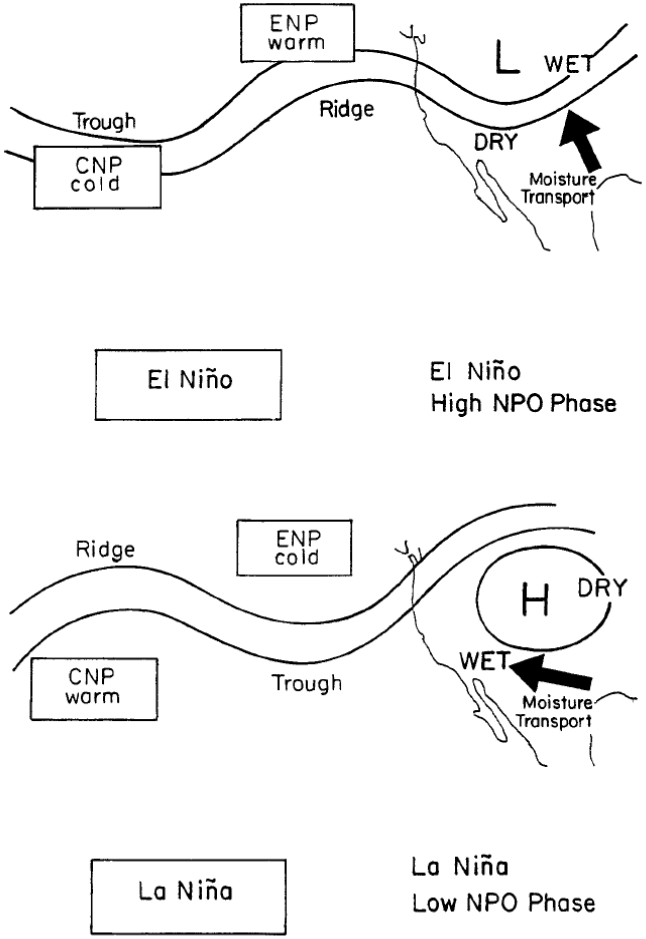
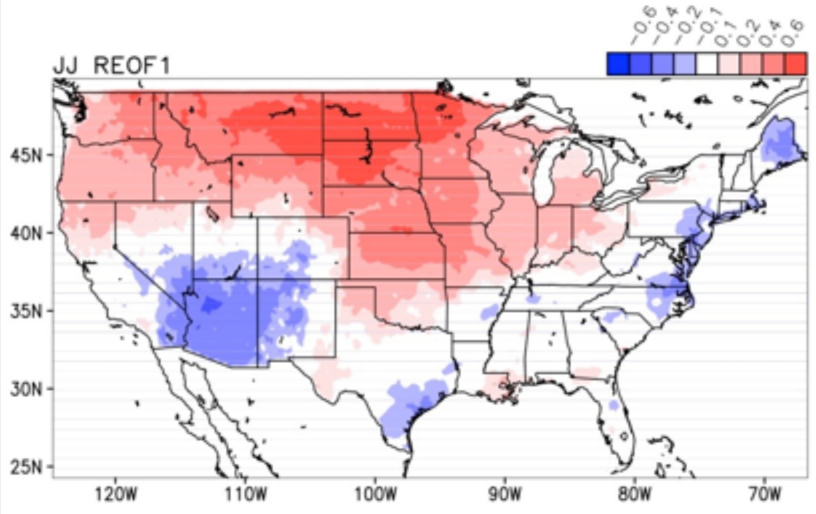


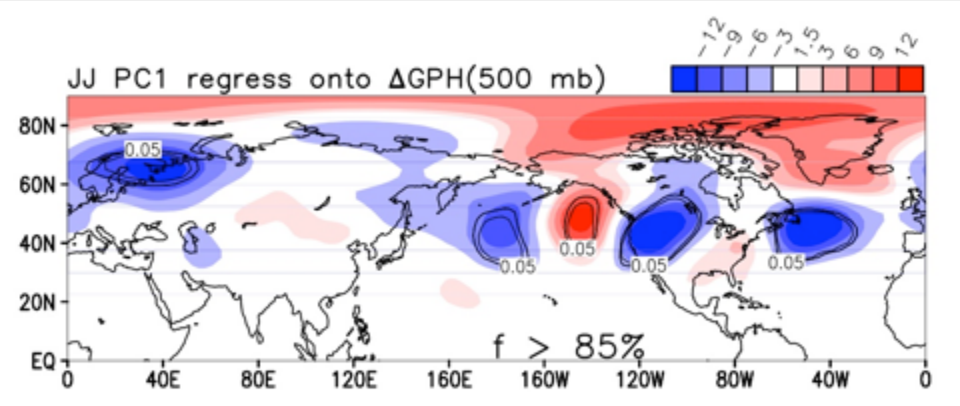
Fig. 14. Idealized relationship of monsoon ridge position and midlevel moisture transport to Pacific SSTs at monsoon onset.

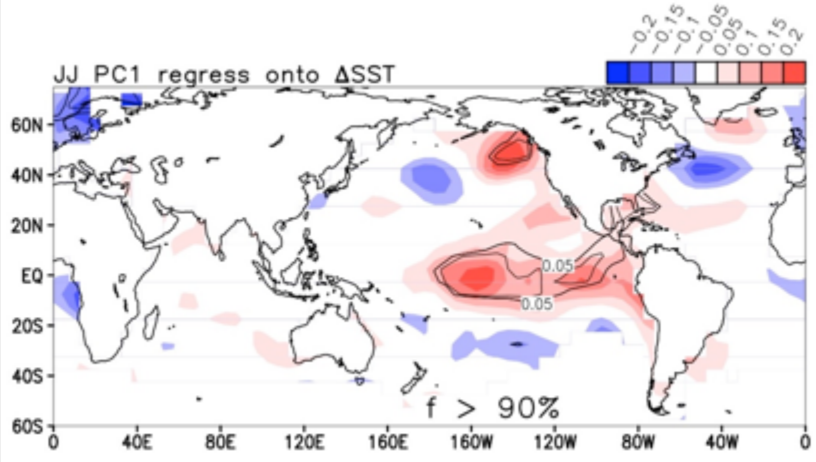
The onset and variability of North American Monsoon System (NAMS) is partly controlled by warm season atmospheric teleconnections

Teleconnections driven El Niño Southern Oscillation (ENSO) and Pacific Decadal Variability (PDV)

Influence monsoon ridge positioning in early summer.







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)

ENSO/PDV Forced: Early summer (JJ)
Probably most seasonally predictable

(a)

(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.

Circumglobal Teleconnection (CGT)

(a) **CGT Mode 1**

(b) **CGT Mode 2**

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.)

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

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

All NMME Models **CFSv2 only**

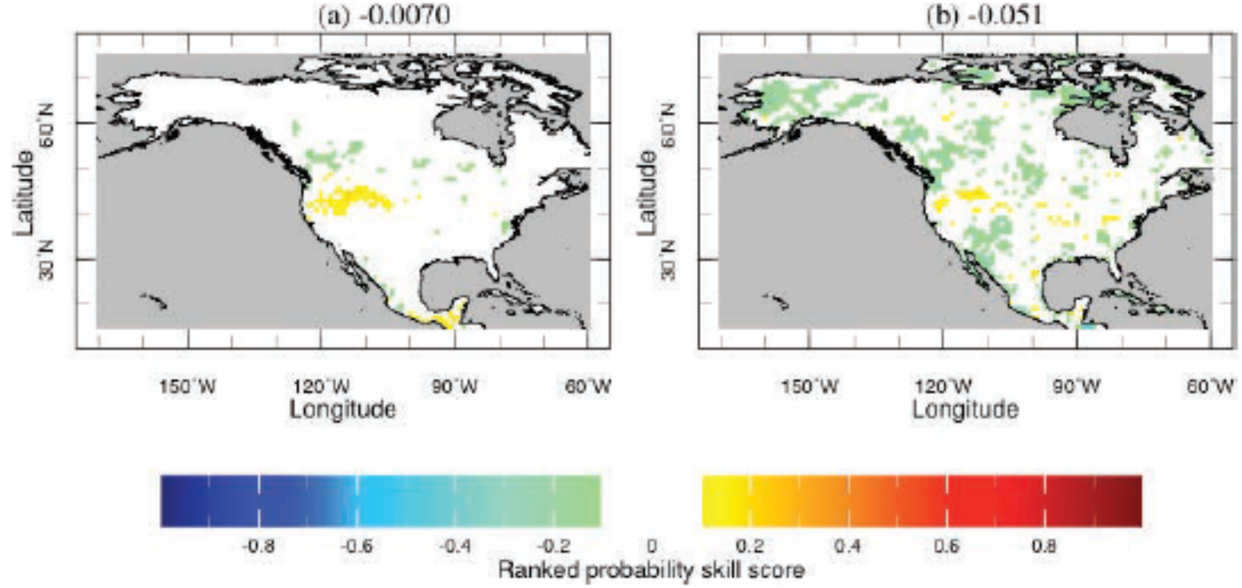


FIG. 9. Precipitation forecast RPSS for the (a) grand NMME multimodel ensemble and for (b) CFSv2. The skill is based on hindcasts initialized in Jan 1982–2009 and verified in the following JJA seasonal mean for tercile forecasts. Positive values indicate probabilistic skill that is better than climatology,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

Are skillful seasonal monsoon forecasts possible? Castro et al. (2012, *J. Climate*)

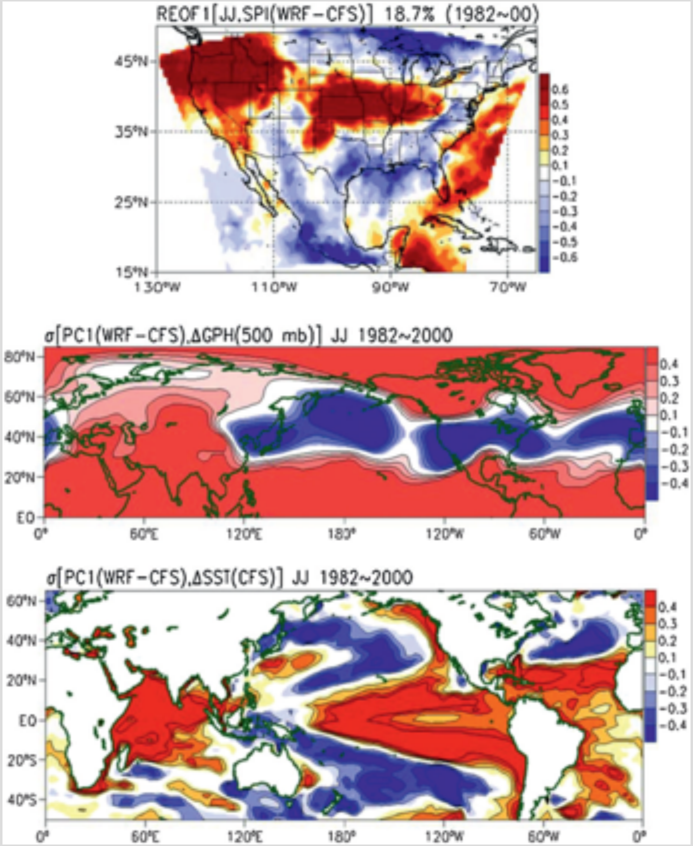


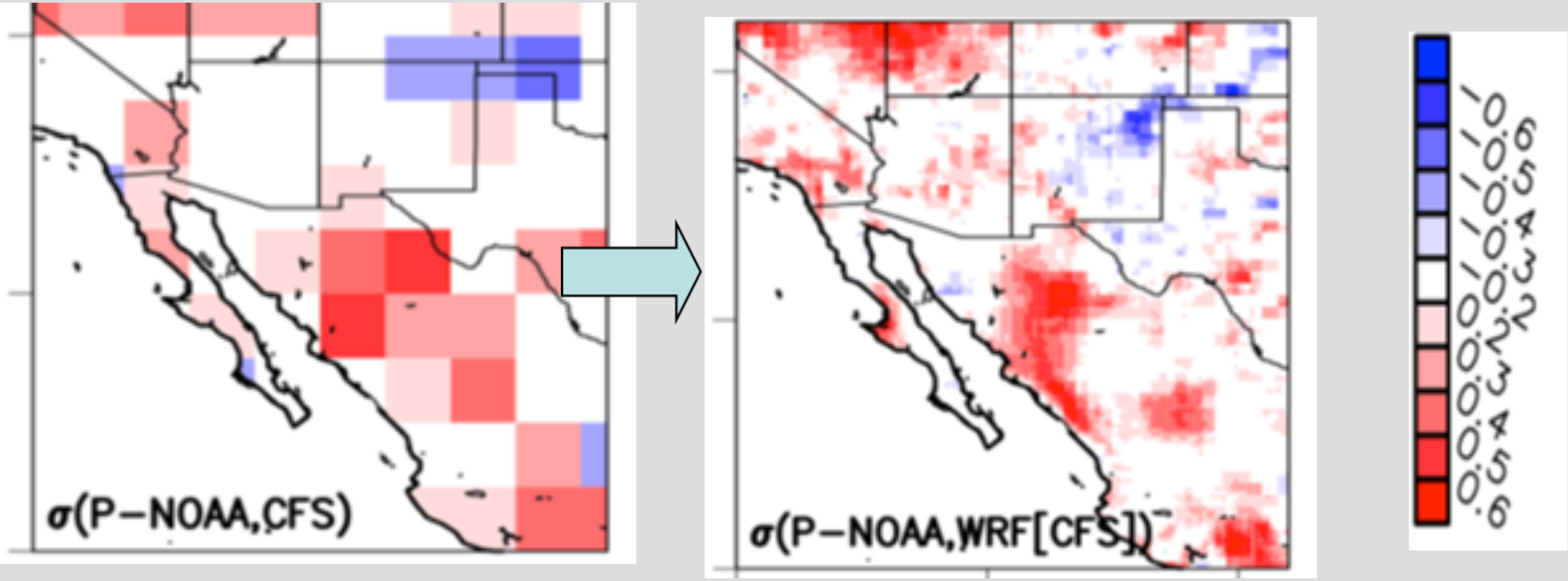
FIG. 18. (top) Most highly correlated mode of early warm season (JJ) SPI in WRF-CFS in comparison to first three REOF early warm season SPI modes from WRF-NCEP, shown as the regression on the principal component with variance explained. Specifically, this mode is most highly correlated with the second 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 CFS do have an ability to statistically represent WPNA response and its impact on warm season precipitation.

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

A high resolution (convective-permitting) RCM would probably then add value, given its ability to much better represent organized convection.

Early summer (JJ) precipitation anomaly correlation for NAME Tier 2 Region

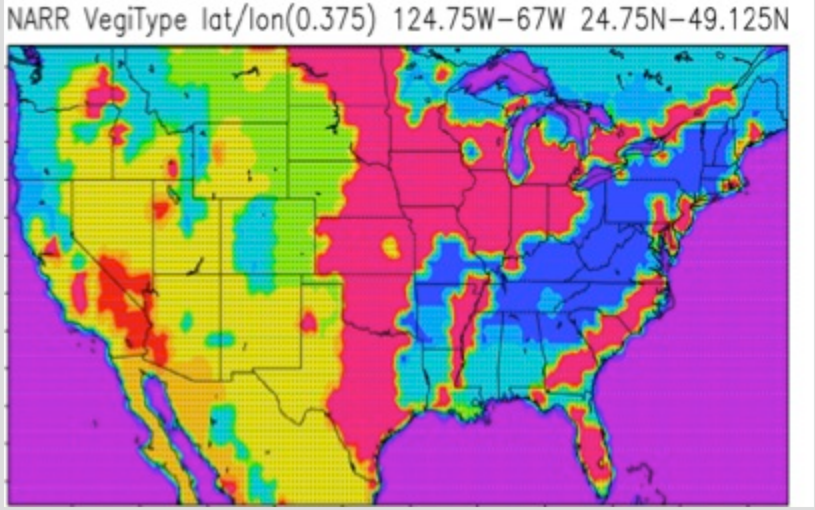

CFS model

WRF Downscaled CFS model

Castro et al. (2012, J. Climate)

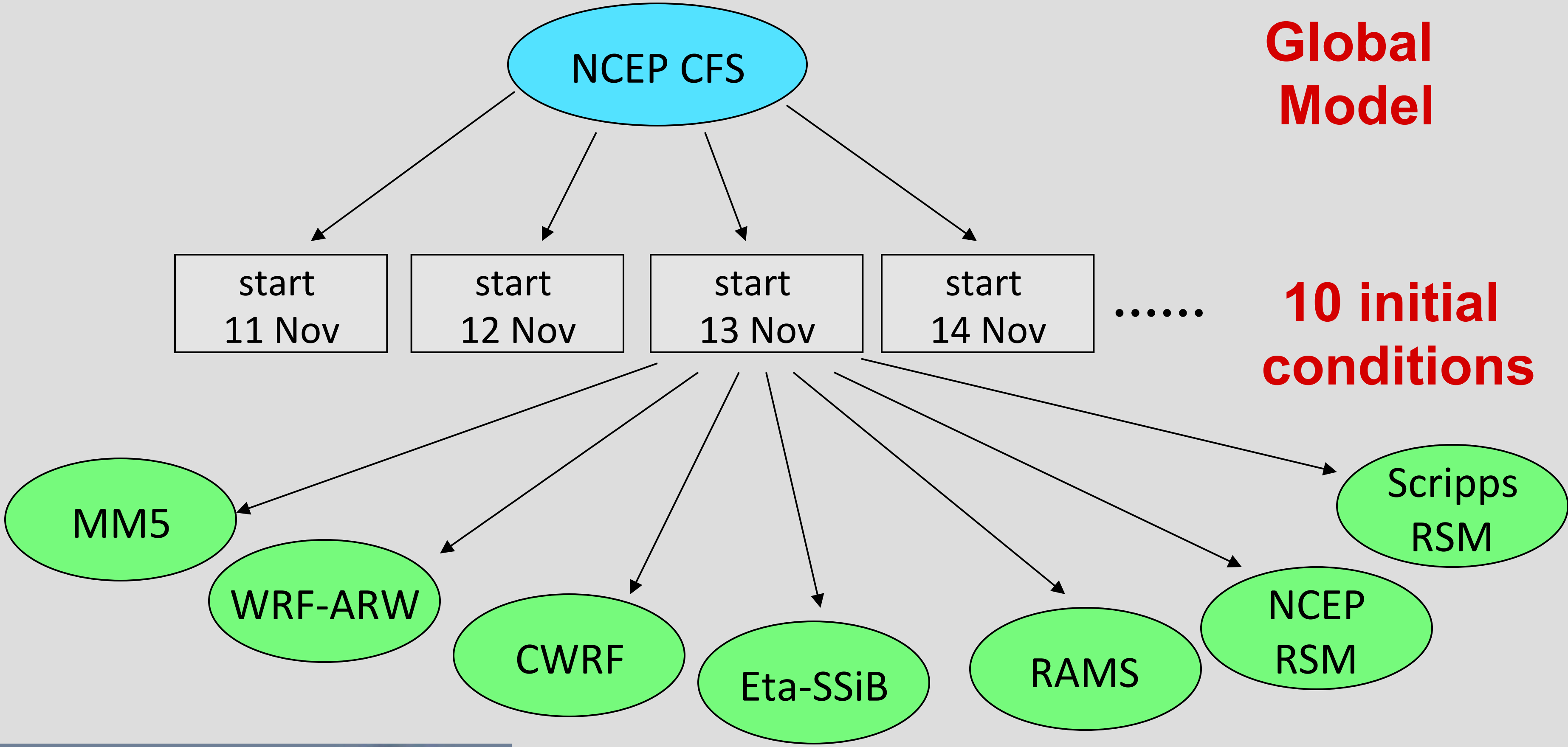
Multi-RCM Ensemble Downscaling of multi-GCM Seasonal Forecasts (MRED)

- Test usefulness of downscaling winter seasonal forecasts from global models by using an ensemble of regional models.
- Downscale 23 years of winter (December-April) reforecasts from the NOAA CFS global seasonal forecast model (T62L64, ~1.9° lat/lon).
- Domain is the coterminous U.S. at grid spacing 32 km.
- Downscaled each member of a 10 member CFS ensemble for each winter 1982-2004.



Courtesy Prof. Ray Arritt, Iowa State

MRED Ensemble



NCEP CFS

Global Model

start 11 Nov

start 12 Nov

start 13 Nov

start 14 Nov

……

10 initial conditions

MM5

WRF-ARW

CWRF

Eta-SSiB

RAMS

NCEP RSM

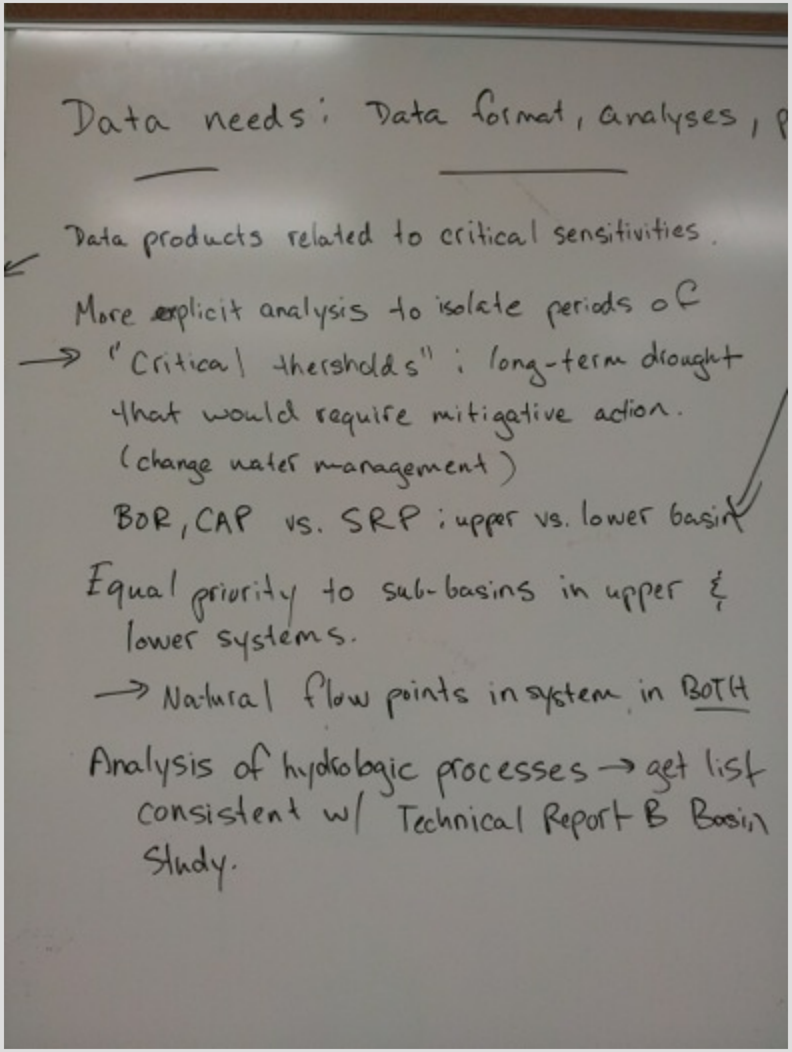
Scripps RSM

Regional Models

Courtesy Prof. Ray Arritt, Iowa State

These types of applications are informed by a process of co-production of knowledge with stakeholder users…

Discussion period at the end of workshops is <u>the</u> most important part!



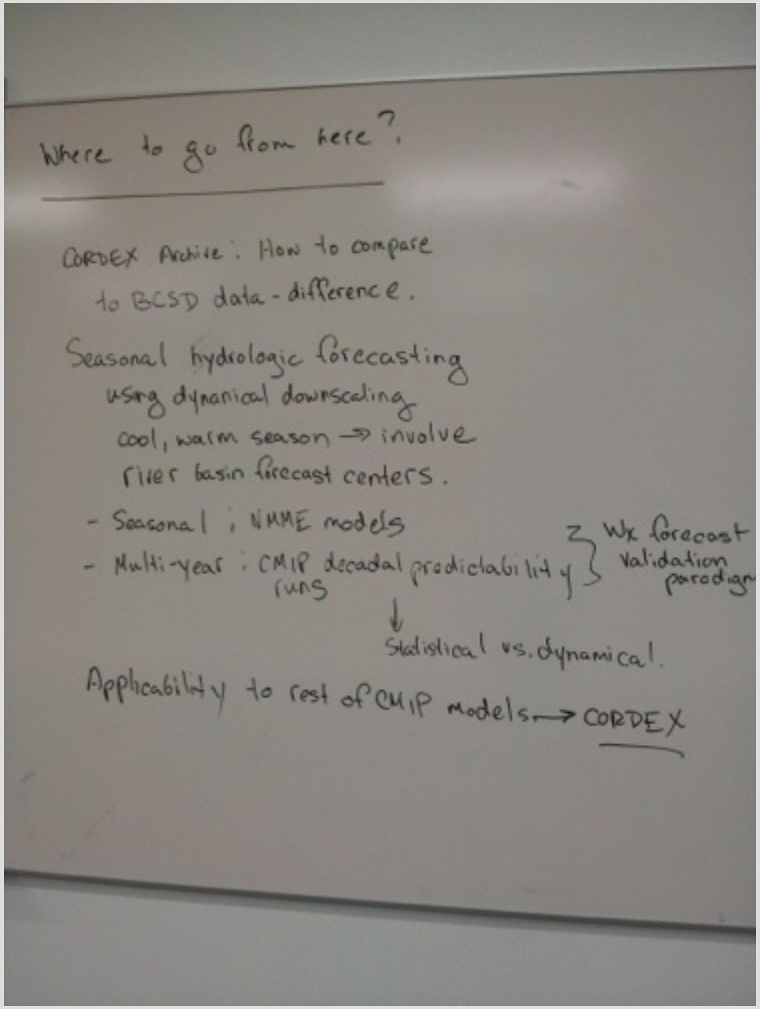
Data needs: Data format, analyses,

Data products related to critical sensitivities.

More explicit analysis to isolate periods of
→ "Critical thersholds": long-term drought
that would require mitigative action.
(change water management)
BoR, CAP vs. SRP; upper vs. lower basin

Equal priority to sub-basins in upper &
lower systems.
→ Natural flow points in system in <u>BOTH</u>

Analysis of hydrologic processes → get list
consistent w/ Technical Report B Basin
Study.



<u>Where to go from here?</u>

CORDEX Archive: How to compare
to BCSD data - difference.

Seasonal hydrologic forecasting
using dynamical downscaling
cool, warm season → involve
river basin forecast centers.
- Seasonal; NMME models
- Multi-year: CMIP decadal predictability runs } Wx forecast validation paradigm
↓
Statistical vs. dynamical.

Applicability to rest of CMIP models → <u>CORDEX</u>

Vision of a potential future at the University of Washington

Assume a leadership role in developing the idea of regional climate modeling center, for producing customized, client-driven applied science deliverables and research needs.

In a teaching capacity, to develop or maintain existing graduate courses in the department in regional atmospheric modeling and climate data analysis, with greater emphasis on statistical characterization of extremes. Additionally, a translational course that would emphasize stakeholder engagement.

Improve the projection of hydroclimate, using integrated high resolution atmospheric and hydrologic physical modeling with ensemble approaches, demonstrating the potential value added. Intraseasonal to seasonal timescales is a ripe opportunity and highly desired.

Emphasize international outreach in my research activities, with special emphasis on Latin America, that builds on my recent Fulbright Fellowship at the National Autonomous University in Mexico City.

To work with UW faculty to develop outreach programs in atmospheric and related sciences to underrepresented groups.