



# Supply-Chain Risks: Extreme Events, Climate Change, and Prospects for Prediction

XXXIX MIT Global Change Forum 15-17 June, 2016, Cambridge, Massachusetts



“INDUSTRIES ARE NO STRANGERS TO... SUPPLY-CHAIN DISRUPTION - WHAT IS CHANGING IS THE COMPLEXITY OF THE RISKS, THEIR INTERDEPENDENCE WITH OTHER RISKS... SET TO EXACERBATE SUPPLY-CHAIN RISK IS CLIMATE CHANGE.” PWC

“IF THERE IS ONE THING CLIMATE CHANGE TEACHES US, IT IS THAT WE CANNOT PROSPER IN ISOLATION... MODERN BUSINESSES DEPEND ON SUPPLY CHAINS STRETCHING AROUND THE GLOBE... THEY APPRECIATE THAT FLOODS... OR DROUGHT STRIKING A DISTANT WATERSHED, CAN MAKE THE DIFFERENCE BETWEEN PROFIT AND LOSS.” UNFCCC

# DISRUPTION AND RISK OF SUPPLY CHAINS FROM EXTREME EVENTS: GLOBAL AWARENESS AND STRATEGIC PLANNING IS GROWING

NatCatSERVICE

## Loss events worldwide 2014 Geographical overview

Munich RE 



Source: Munich Re, NatCatSERVICE, 2015

- Loss events
- Selection of catastrophes  
Overall losses ≥ US\$ 1,500m
- Geophysical events  
(Earthquake, tsunami, volcanic activity)
- Meteorological events  
(Tropical storm, extratropical storm, convective storm, local storm)
- Hydrological events  
(Flood, mass movement)
- Climatological events  
(Extreme temperature, drought, wildfire)

## OTHER NOTABLE GLOBAL EVENTS

2010 Russia severe heat wave:  
Drought/wildfires destroyed wheat yields - export restrictions led to global price increases. Estimated US\$15bn in losses.

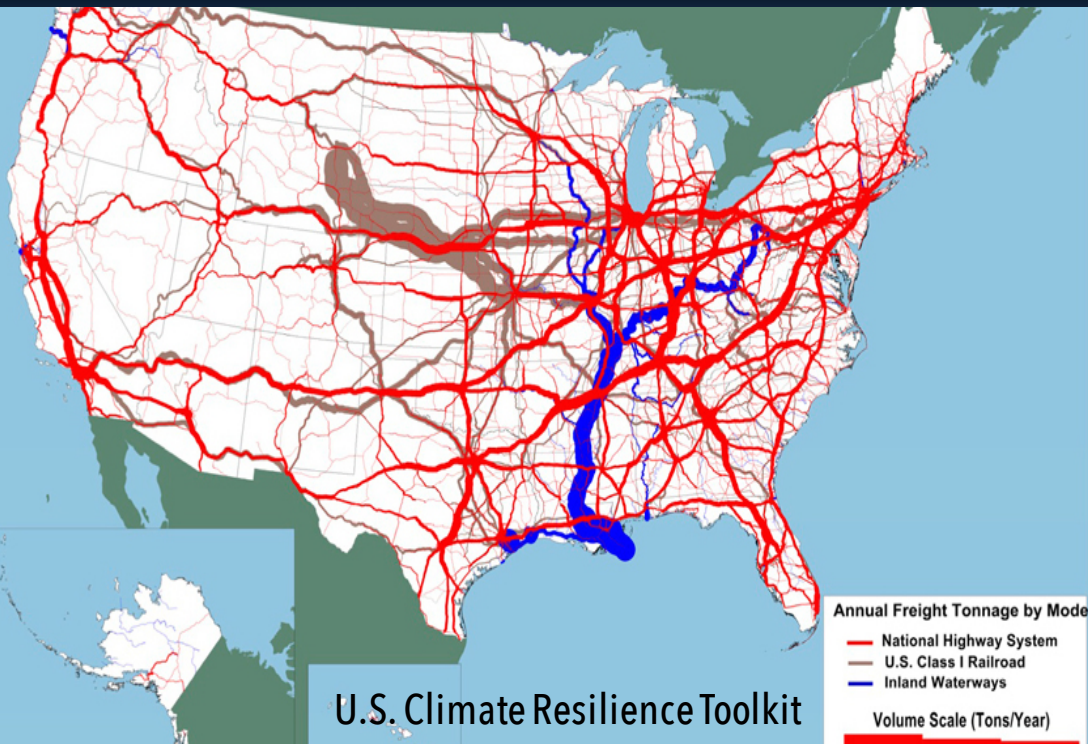
2011 Thailand floods: Disrupted global auto industry. Caused global shortage of hard-disk drives (supplies 40% of global market).

2010-11 Australia: Heavy rainfall and Cyclone Yasi stopped coal exploration in Queensland - prices rose by 25%.

2011 Russia/Pakistan/Australia:  
Droughts and floods cause global food prices to climb

2013 Philippines: Typhoon Haiyan likely to affect global trade and manufacturing

# National Supply Chain Risks

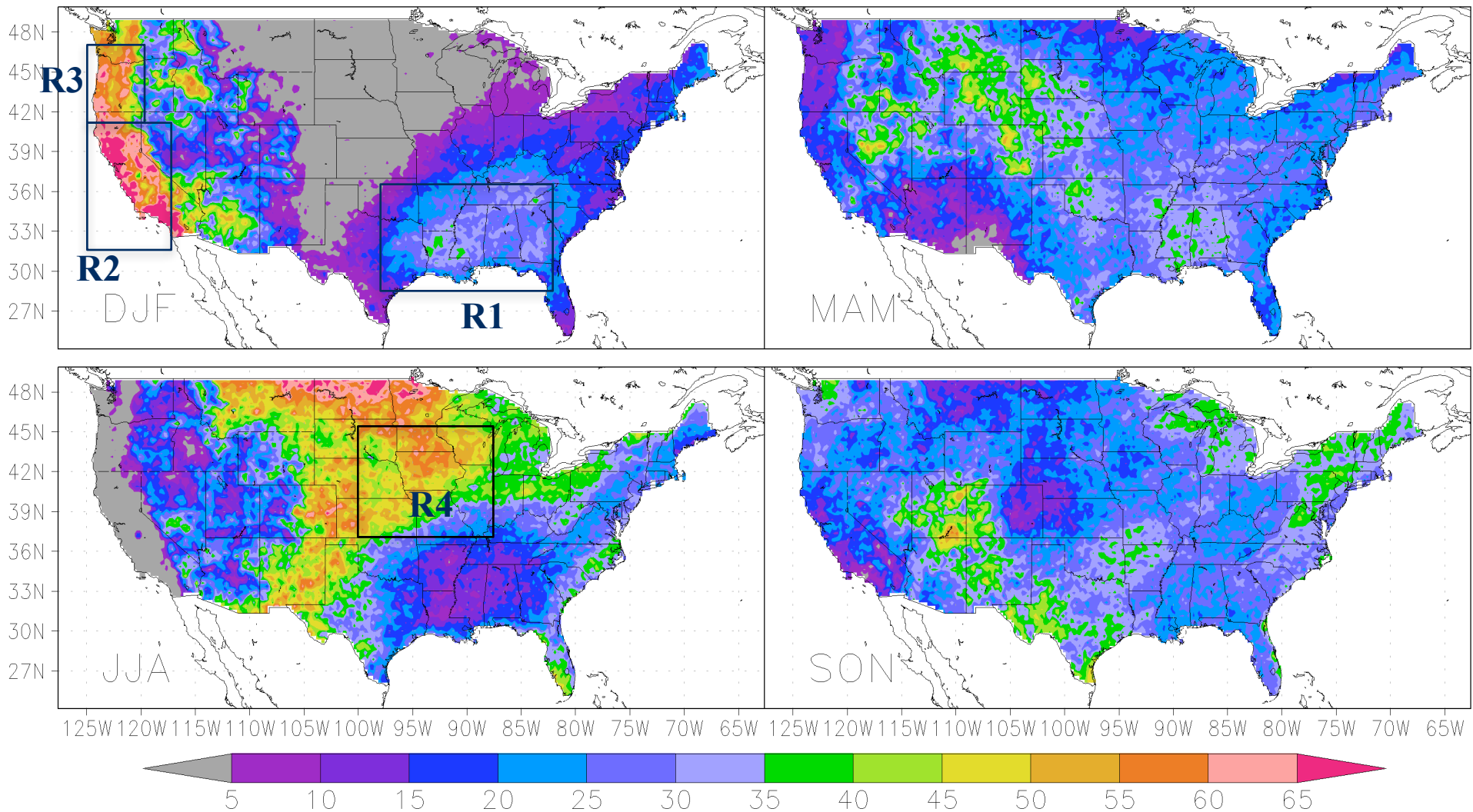


In 2016 – Climate and weather disruptions are expected to be among the biggest threats to freight and shipping supply chain.

2012 Drought: Destruction of crops and feed stock (corn) caused 10% rise in global food prices (during June and July). Low water on the Mississippi River substantially reduced barge traffic – affecting U.S. grain and coal exports, resulting in substantial economic losses.

2013-2014 Winter Season: Winter weather events disrupted supply chains due to slow outbound and inbound deliveries.

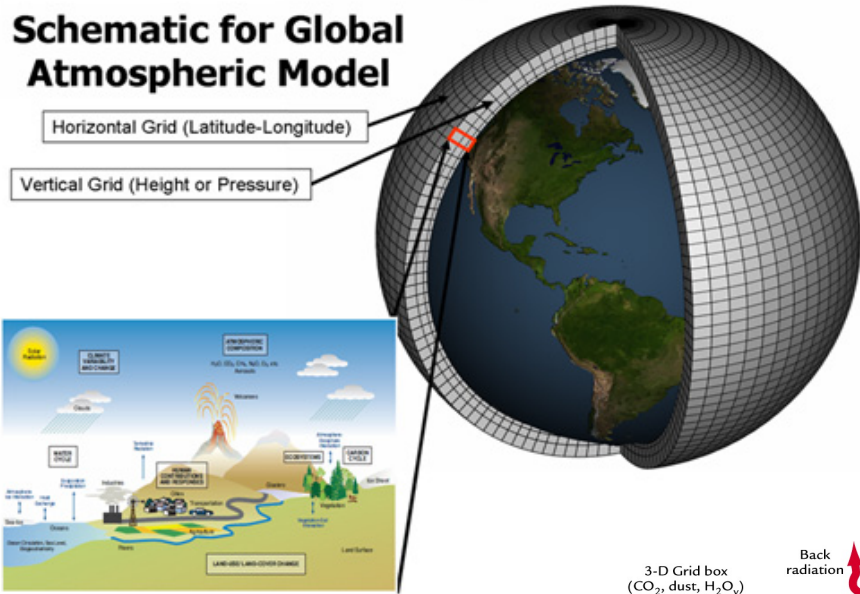
# Percentage of Precipitation Events Exceeding 95th Percentile



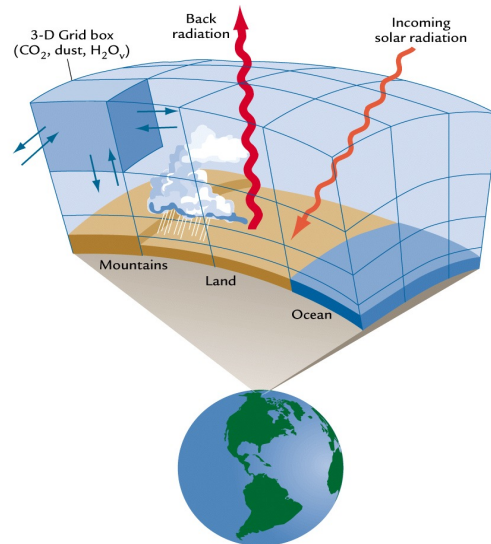
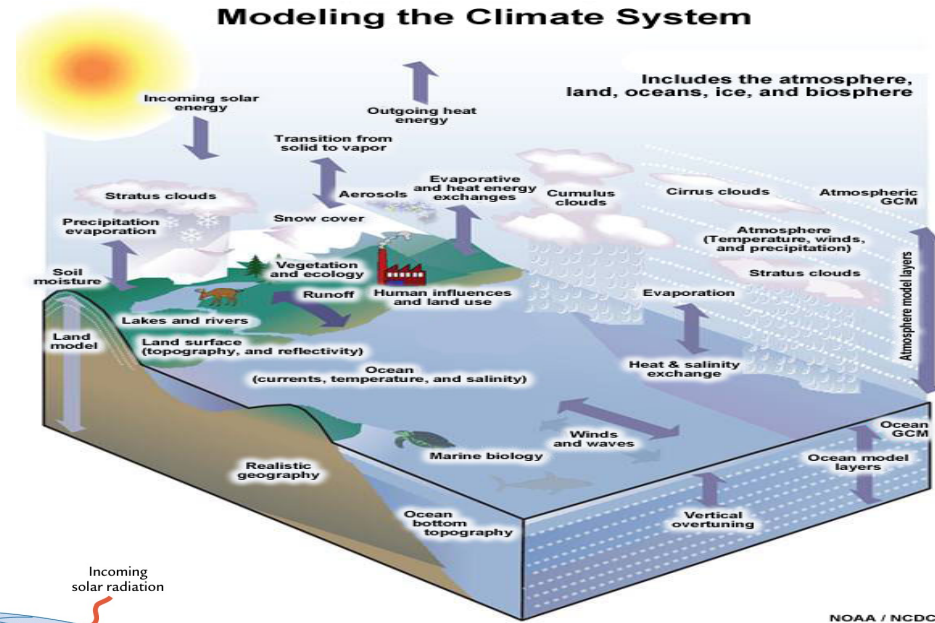
R1: South-Central United States (SCUS) R2: Pacific Coast California (PCCA)  
R3: Washington and Oregon (WAOR) R4: Midwest United States (MWST)

# Extreme Events: The Prediction Challenge

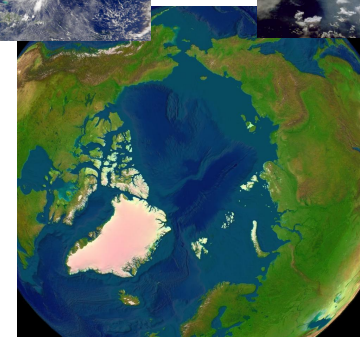
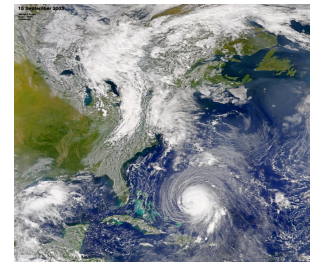
## Schematic for Global Atmospheric Model



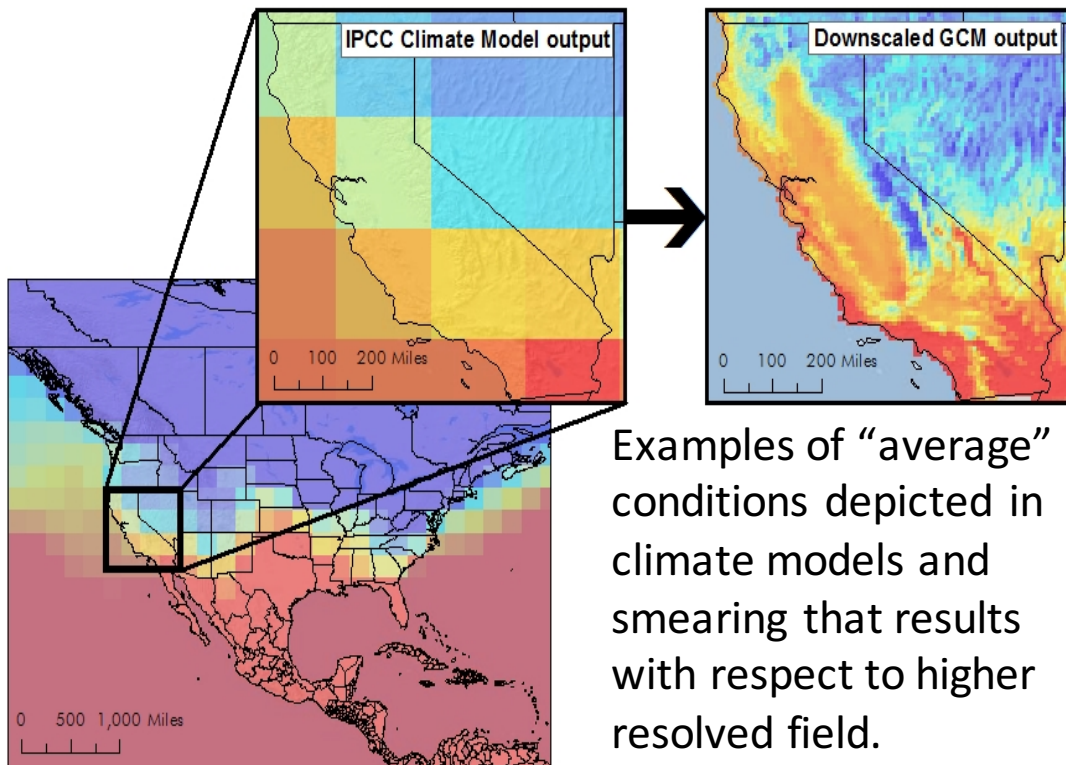
## Modeling the Climate System



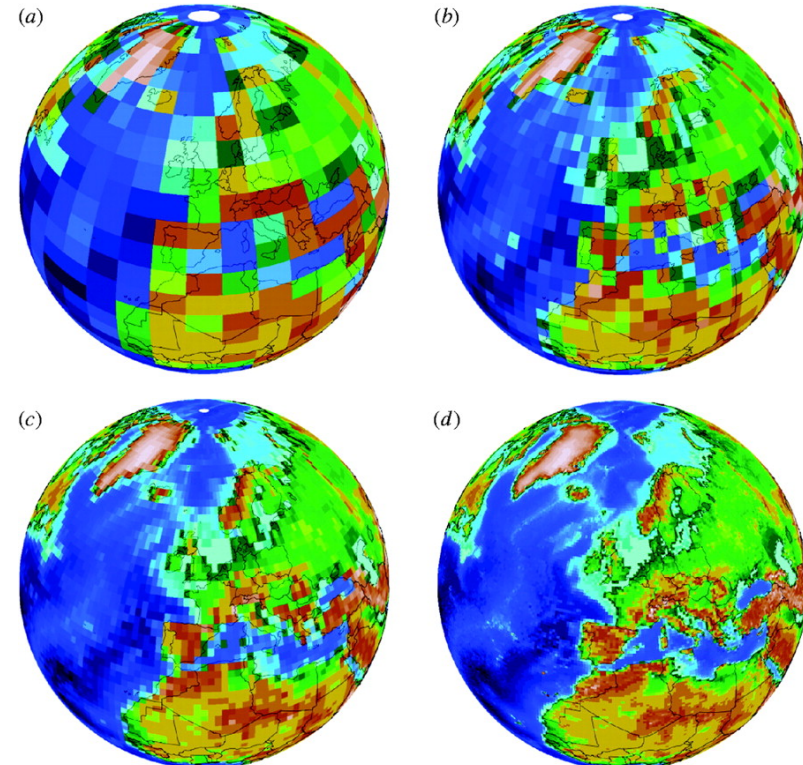
NOAA / NCDC



# THE CHALLENGE OF SIMULATING EXTREME EVENTS



Examples of “average” conditions depicted in climate models and smearing that results with respect to higher resolved field.



EXTREME EVENTS CAN BE LOCALIZED – OCCUR AT SPATIAL SCALES MUCH SMALLER THAN CLIMATE MODEL RESOLUTIONS

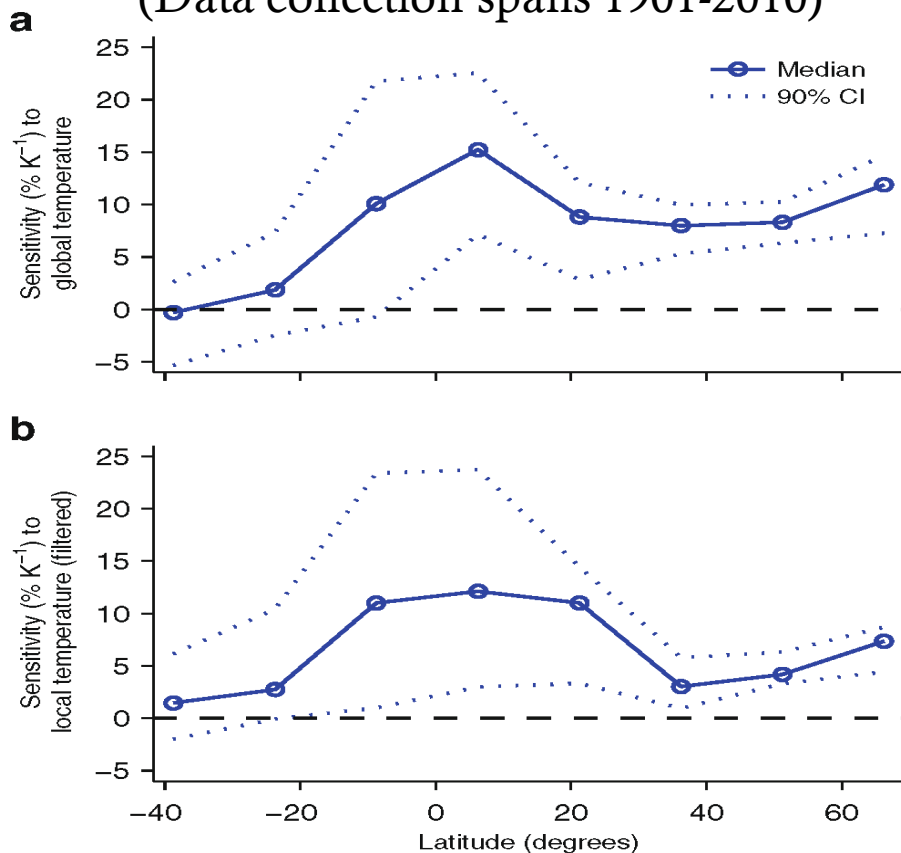
FOR PRECIPITATION GCMs MUST CONSERVE MASS AT THE GRID AND THEREFORE IT MUST SPREAD OR “SMEAR” THE SMALL/LOCAL-SCALE PRECIPITATION AMOUNT ACROSS THE ENTIRE GRID SURFACE.

SUN ET AL. (2006) FOUND GCMs TYPICALLY PRODUCE LIGHT PRECIPITATION MORE OFTEN THAN OBSERVED, TOO FEW HEAVY PRECIPITATION EVENTS AND TOO LITTLE PRECIPITATION IN HEAVY EVENTS

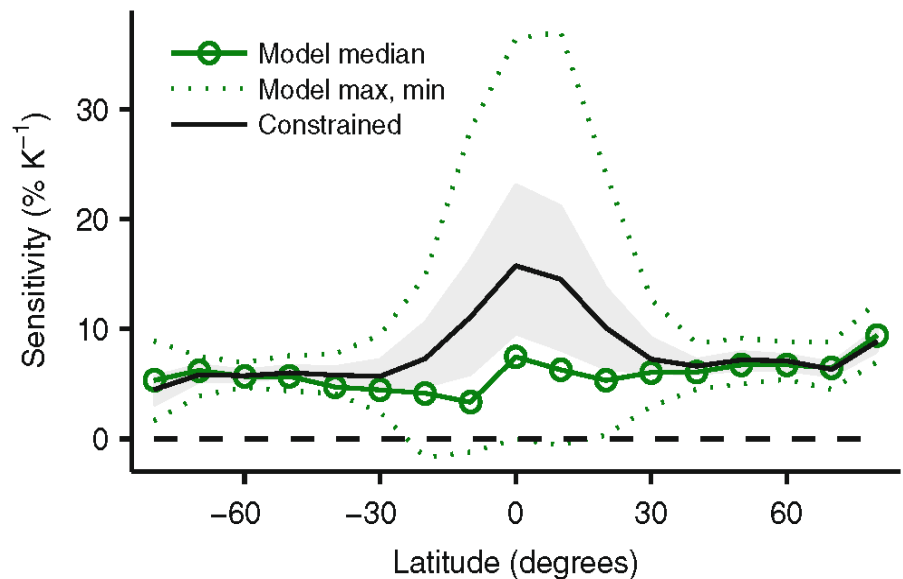
# SENSITIVITY OF PRECIPITATION EXTREMES TO WARMING: MODELS NOT WELL CONSTRAINED IN THE TROPICS. EXTRATROPICS FOLLOW 'THERMODYNAMIC' SCALING

## Observation-Based Regression

Annual-maximum daily land precipitation  
(Data collection spans 1901-2010)



RCP8.5 CMIP5 model results  
99.9<sup>th</sup> percentile of daily precipitation  
Sensitivity to global-mean surface temperature



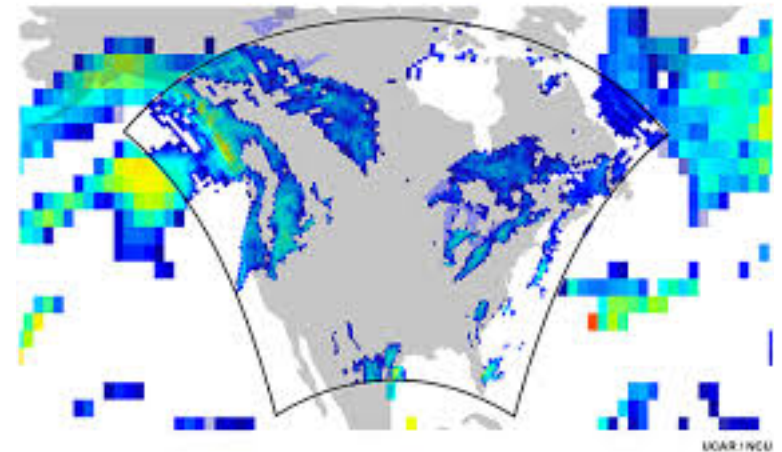
# DYNAMICAL DOWNSCALING

## Pros:

- Fully explicit dynamics and physics
- Not anchored to statistical assumptions (e.g. distribution, stationarity)

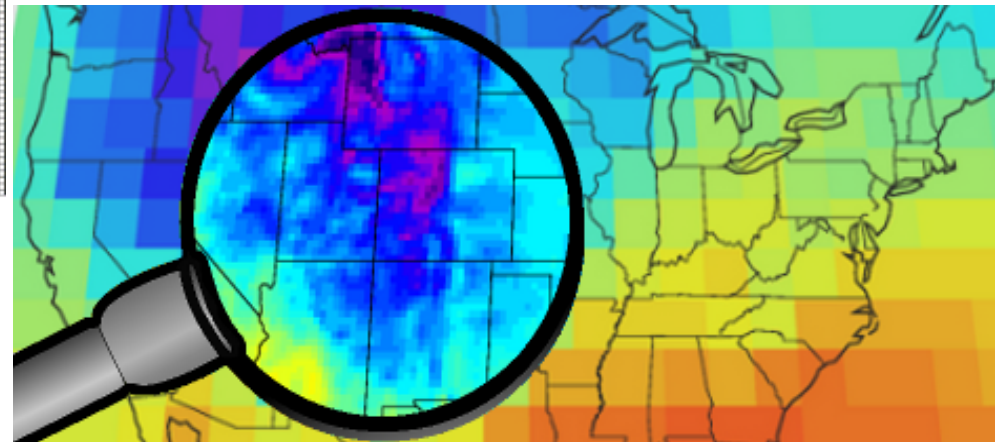
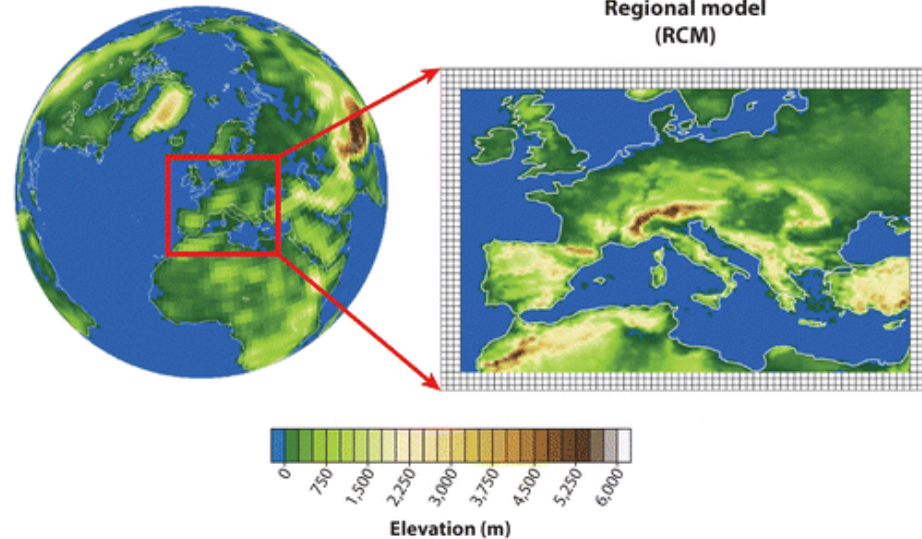
## Cons:

- Computationally expensive
- Limited Domain
- Model dependencies



Global model  
(AOGCM)

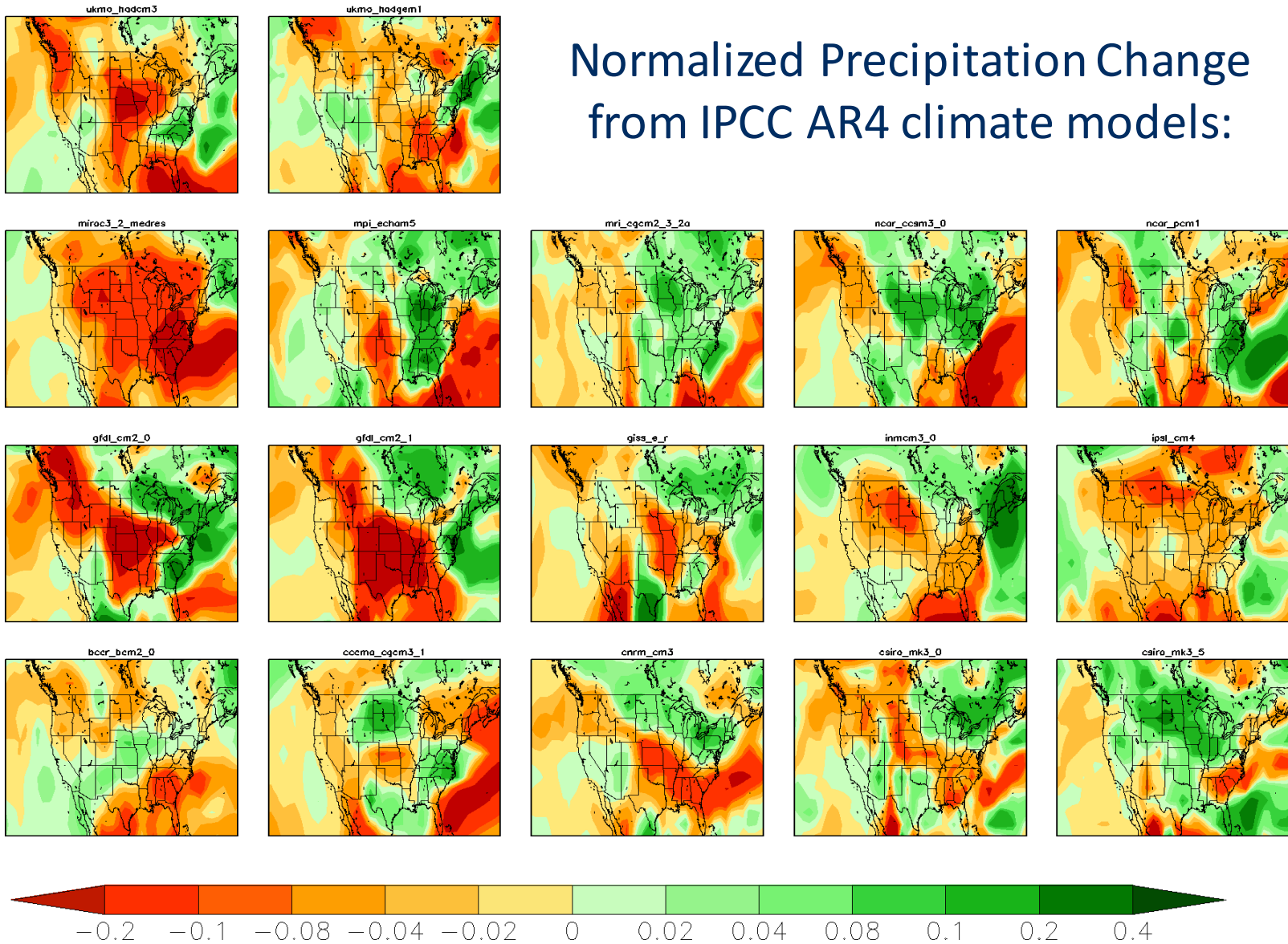
Regional model  
(RCM)





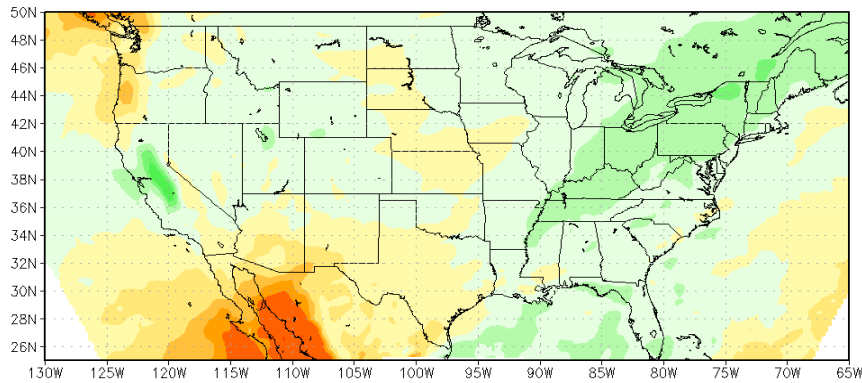
# SUBSTANTIAL RANGE OF "PLAUSIBLE" PATTERNS OF CHANGE FROM GLOBAL CLIMATE MODELS

Normalized Precipitation Change  
from IPCC AR4 climate models:

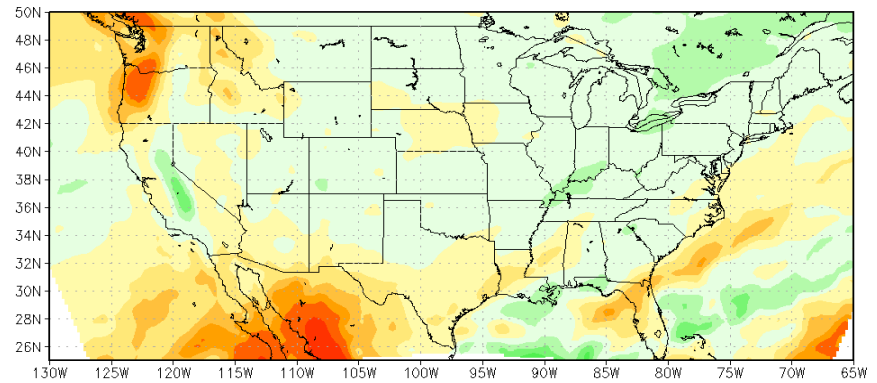


# BENEFITS OF HIGHER SPATIAL RESOLUTION DJF PRECIPITATION CHANGES

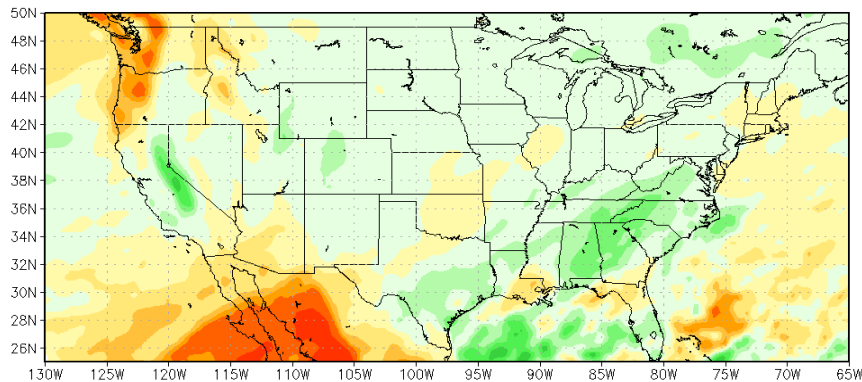
## CRCM-CCSM



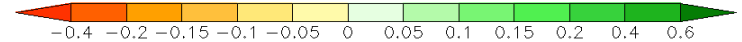
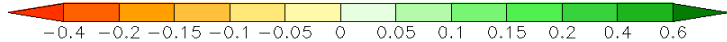
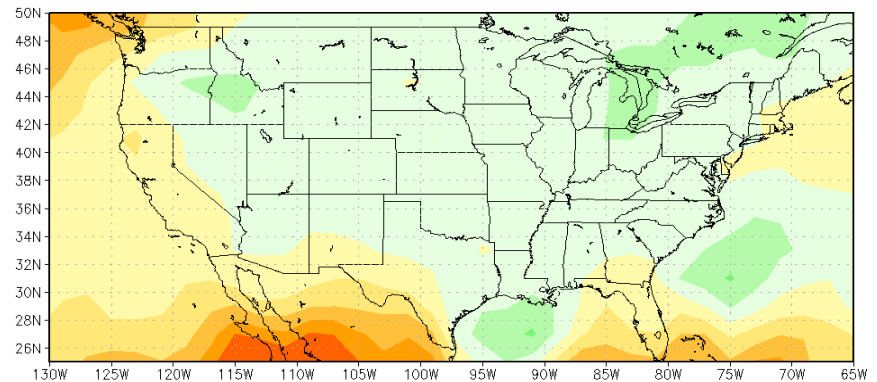
## MM5I-CCSM



## WRFG-CCSM



## CCSM



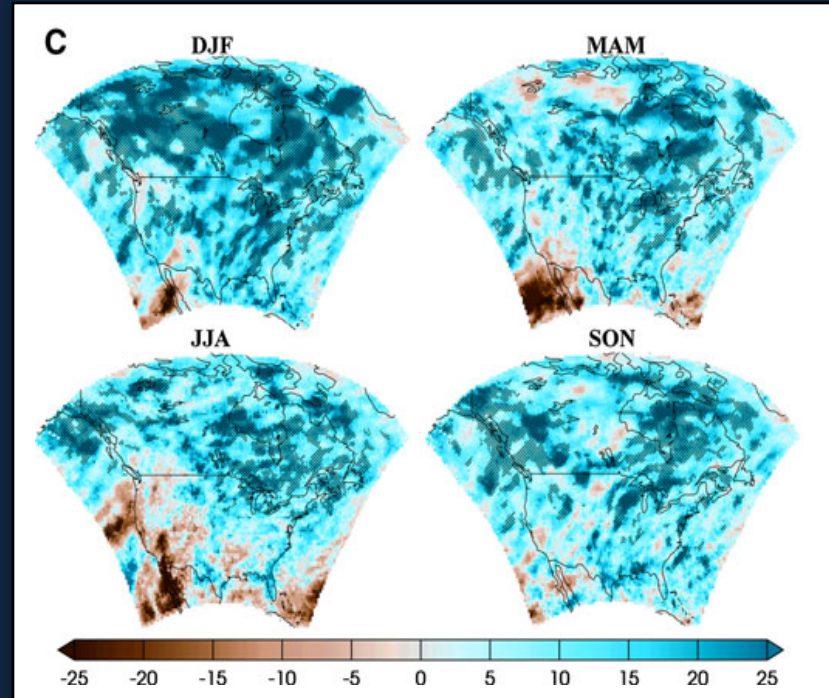
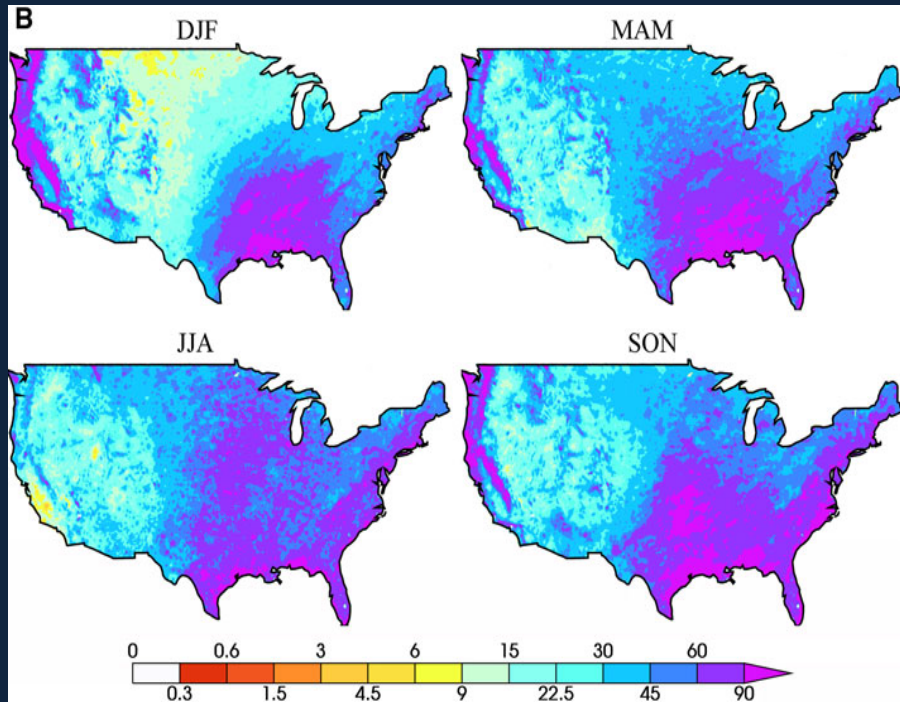
**SALIENT PATTERNS OVER MAJOR WESTERN MOUNTAIN RANGES**

# REGIONAL CLIMATE MODELS ADD CONSIDERABLE TEXTURE TO REGIONAL PROJECTIONS – BUT WITH IMPORTANT CAVEATS

## 20-YEAR RETURN VALUES OF SEASONAL MAXIMUM DAILY PRECIPITATION

Observations: 1968-1999 (mm/day)

NARCCAP Model-Average Change (%)  
SRES A2: 2038-2070



Wehner, 2013 (*Climate Dynamics*)

NOT ALL OF THE RCMs OUTPERFORM THEIR HOST GCMs IN TERMS OF CORRELATION SKILL. (E.G. HALMSTAD ET AL., 2012)

# STATISTICAL DOWNSCALING

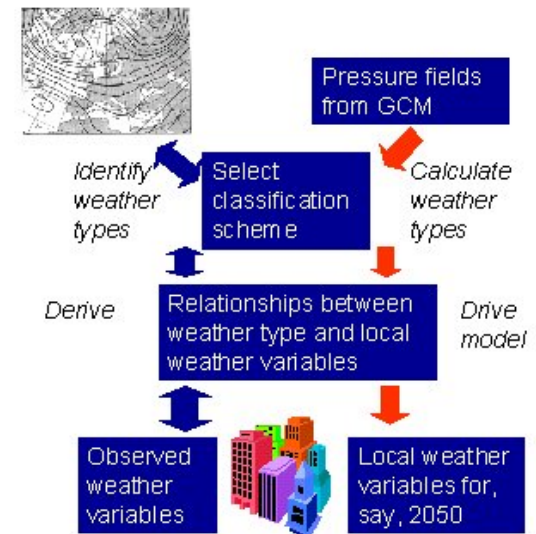
- Most methods founded upon the concept of “Model Output Statistic” (MOS - Glahn and Lowry, 1972) – multiple linear regression between large-scale (from forecast models) and small-scale (observed) variables.

## – Pros:

- Computationally efficient
- Remove model biases
- Flexible to end-user needs

## – Cons:

- Data limited (space and time)
- Behavioral assumptions (i.e. stationarity, distributional families)
- Inability to explore two-way interactions



# RECENT STUDIES OF STATISTICAL DOWNSCALING

- Methods to date focus on the construction of timeseries of local wind – rather than focused on a particular event (or regime of events) that represent a risk or threat.
- Generalized linear model (GLM) describes large scale to local scale sampling via assumed or best-fit distribution of the local observed data.
  - Regressions between large-scale to local-scale distributions.
  - Pryor et al. (2005) focused on downscaling a Weibull PDF using a regression based approach with relative vorticity and mean sea level pressure gradients as the large-scale predictors.
- Vector generalized linear models: Describe a collection of distribution parameters.
  - Maraun et al. (2010) fit shape parameters to a generalized extreme value (GEV) distribution.
- Generalized additive models (GAMs) employ a sum of non-parametric functions for the predictors. Salameh et al. (2009) used sums of splined (or piece-wise) third-order polynomials.

**The majority of these methods are used to construct timeseries of precipitation.**

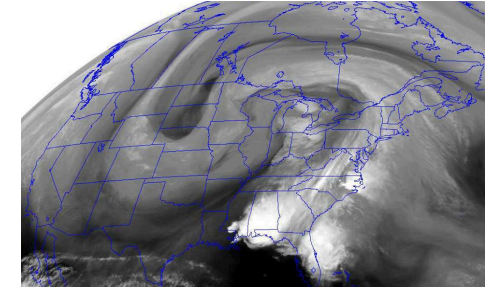
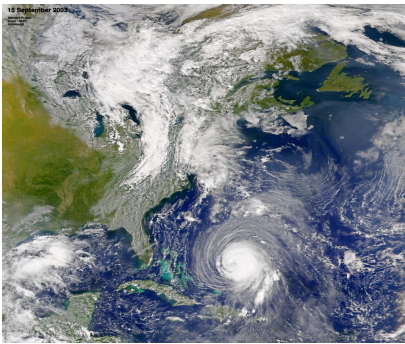
**Focus more on the location and occurrence of an event perceived as a threat.**



# PROJECTION OF EXTREMES THROUGH AN ANALOGUE APPROACH

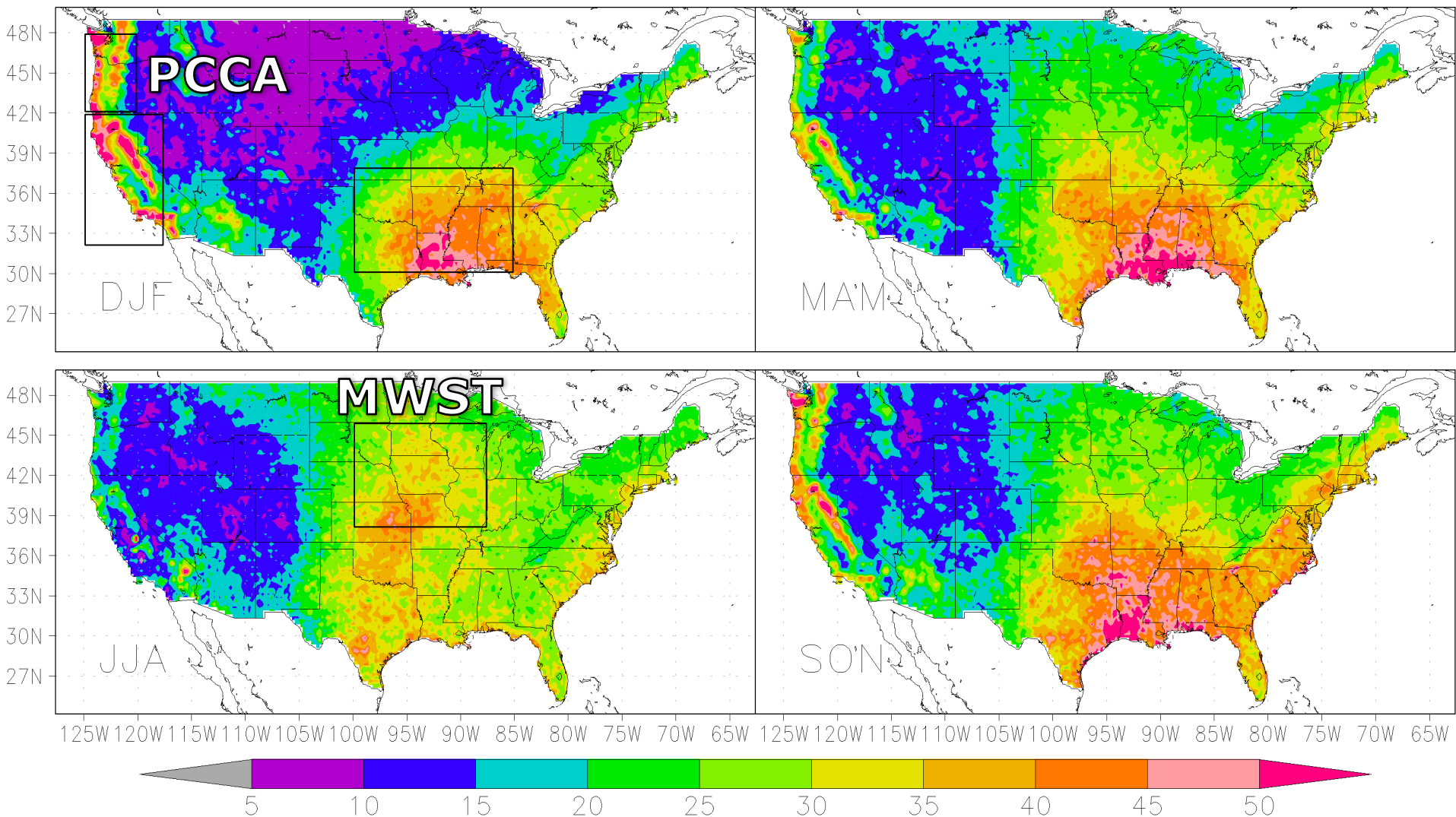
**Analogue (or analog):** *noun* - something seen as comparable to another; *adjective* - relating or using signals or information represented by a continuously variable physical quantity.

Focus more on event of concern or threat - rather than generalized description in space and time.



Gao, X., A. Schlosser, P. Xie, E. Monier, and D. Entekhabi, 2014: An Analogue Approach to Identify heavy Precipitation Events: Evaluation and Application to CMIP5 Climate Models in the United States. *J. Climate*. doi:10.1175/JCLI-D-13-00598.1

# Precipitation Rate for the 95th Percentile

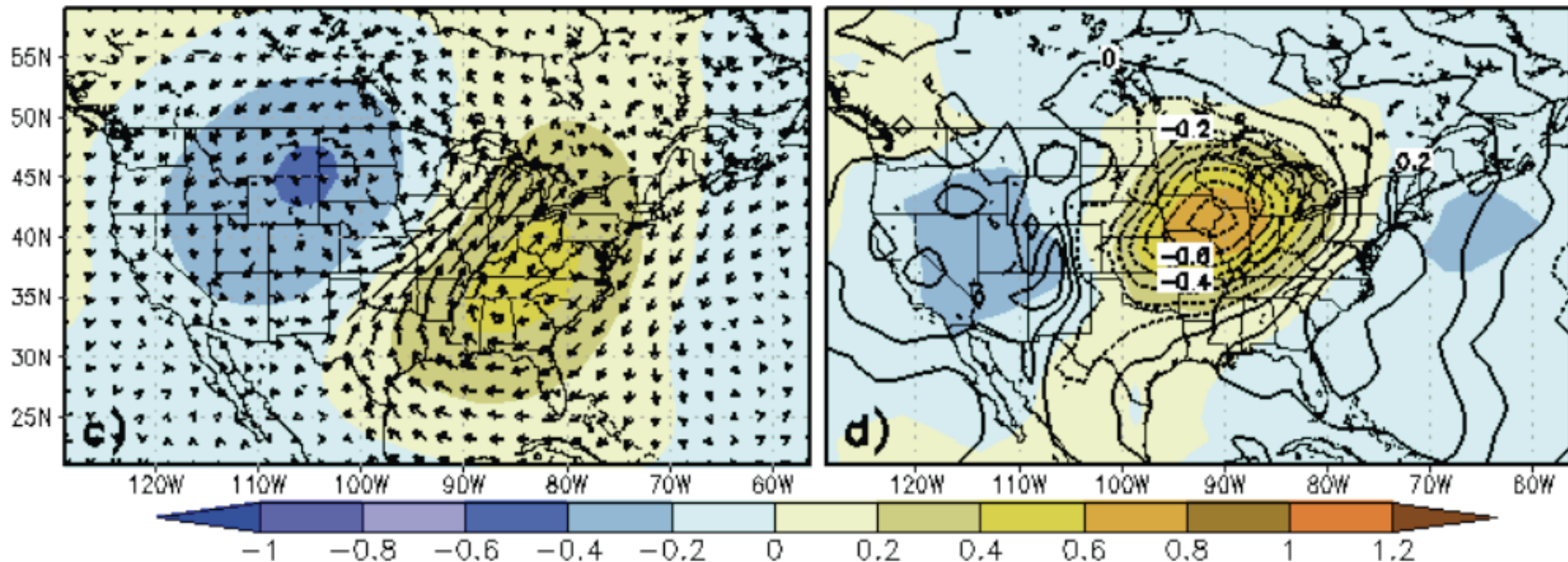


95th percentile (mm/day) of precipitation events ( $> 1$  mm/day) for each season over the contiguous United States. The black rectangles indicate four study regions examined in this study, including the South-Central United States (SCUS), the Mid-western United States (MWST), the northern (WAOR) and southern (PCCA) flank of the Pacific coast.

# Composites: Heavy Precipitation (90<sup>th</sup> Percentile) (MWST, JJA, 1979-2005, 570 Events)

500mb Geopotential Height  
(*Shaded*)  
Vapor Flux Vectors (*Arrow*)

Total Precipitable Water  
(*Shaded*)  
500mb Vertical Pressure  
Velocity (*Contour*)



Supported by large-scale lifting and warm, moist fetch of air.



(PCCA, 202 Days)

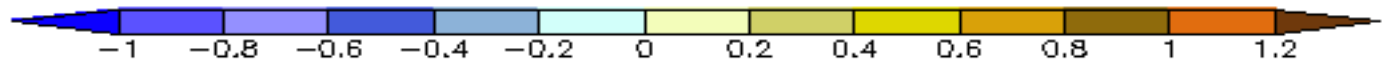
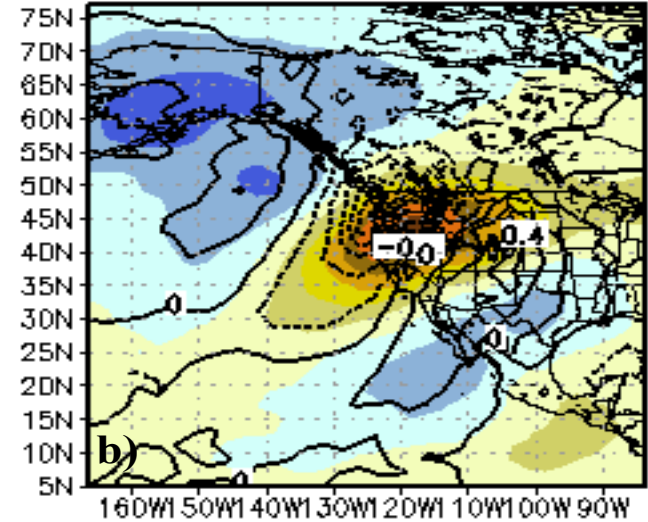
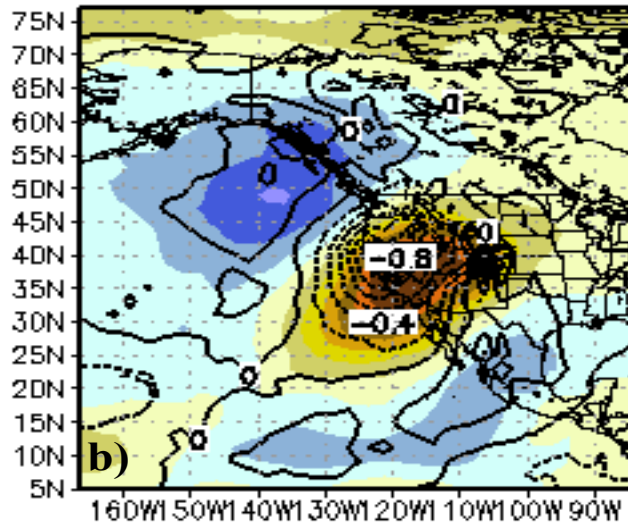
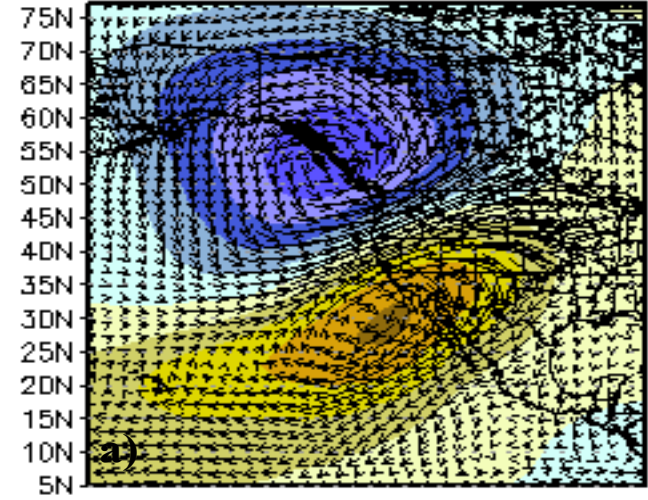
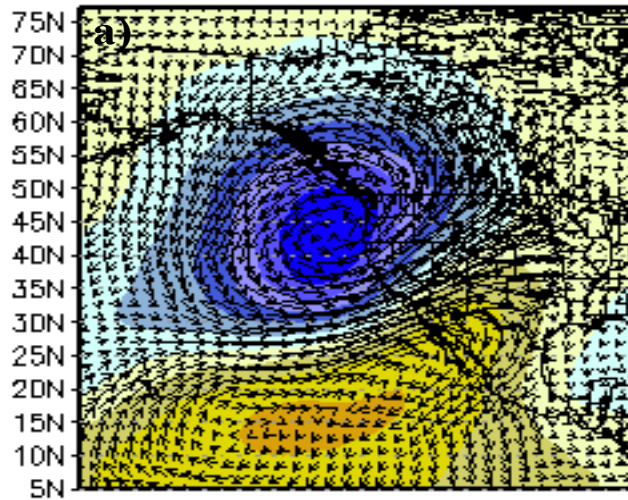
(WAOR, 292 Days)

DJF Z500  
(*Shaded*)

DJF VFV  
(*Arrow*)

DJF TPW  
(*Shaded*)

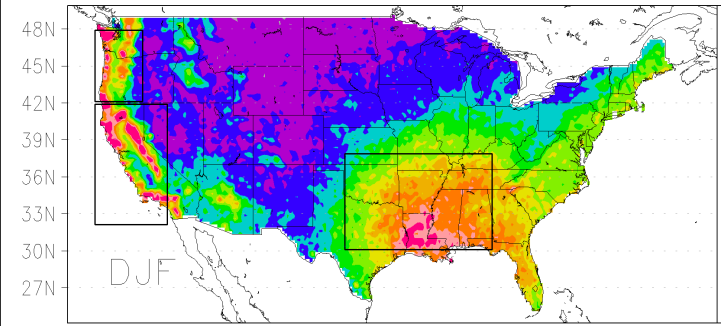
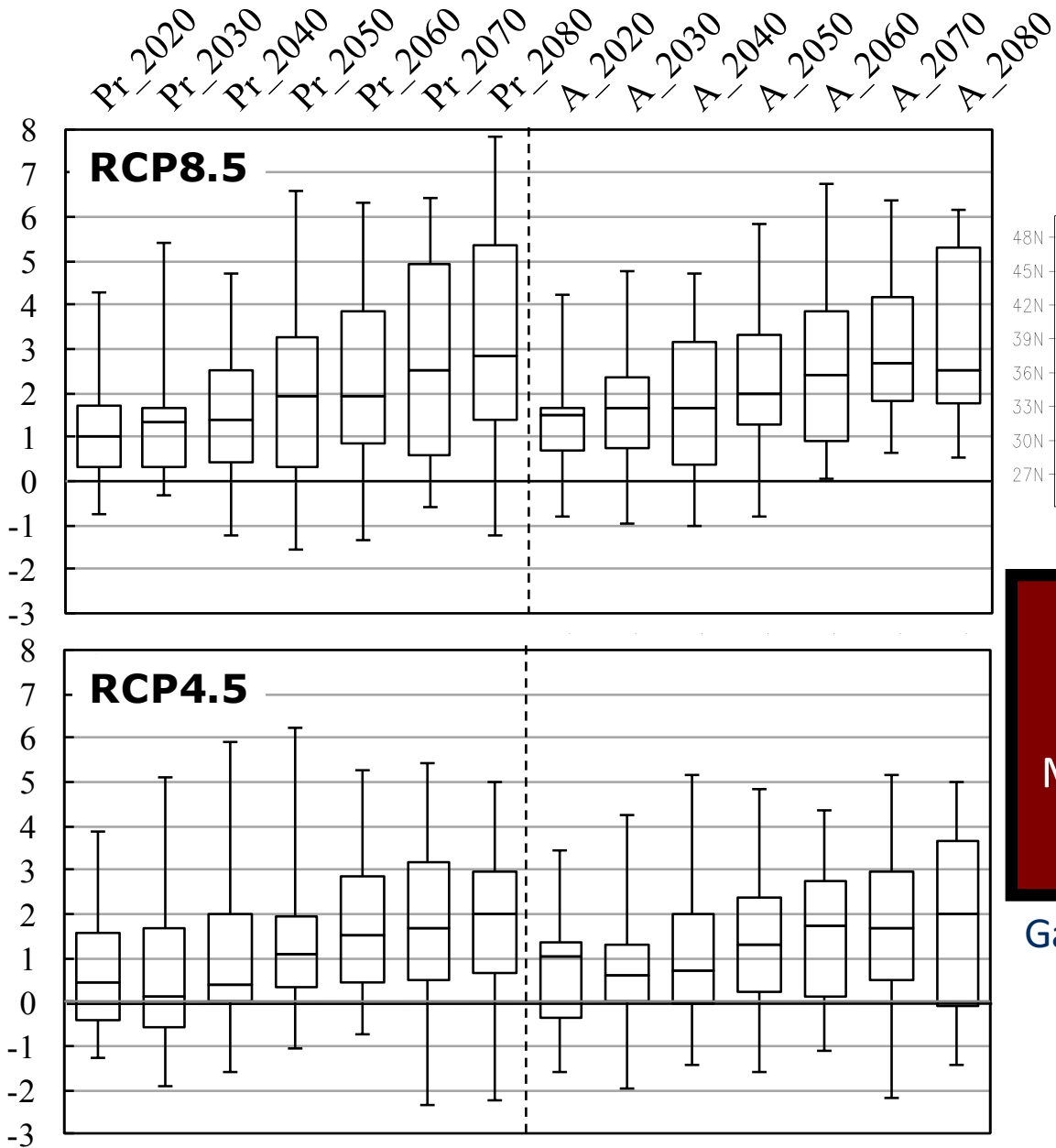
DJF W500  
(*Contour*)



Strong fetch, convergence, and uplift of moist, maritime air onto the U.S. west coast ("Pineapple Express")

# PCCA: TRENDS IN DJF HEAVY PRECIPITATION

Change in Number of Extreme Days per Year



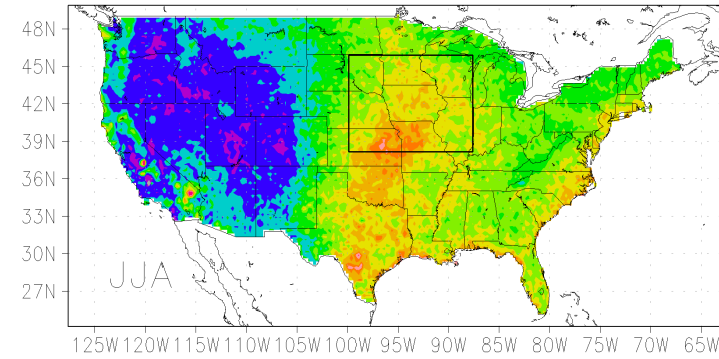
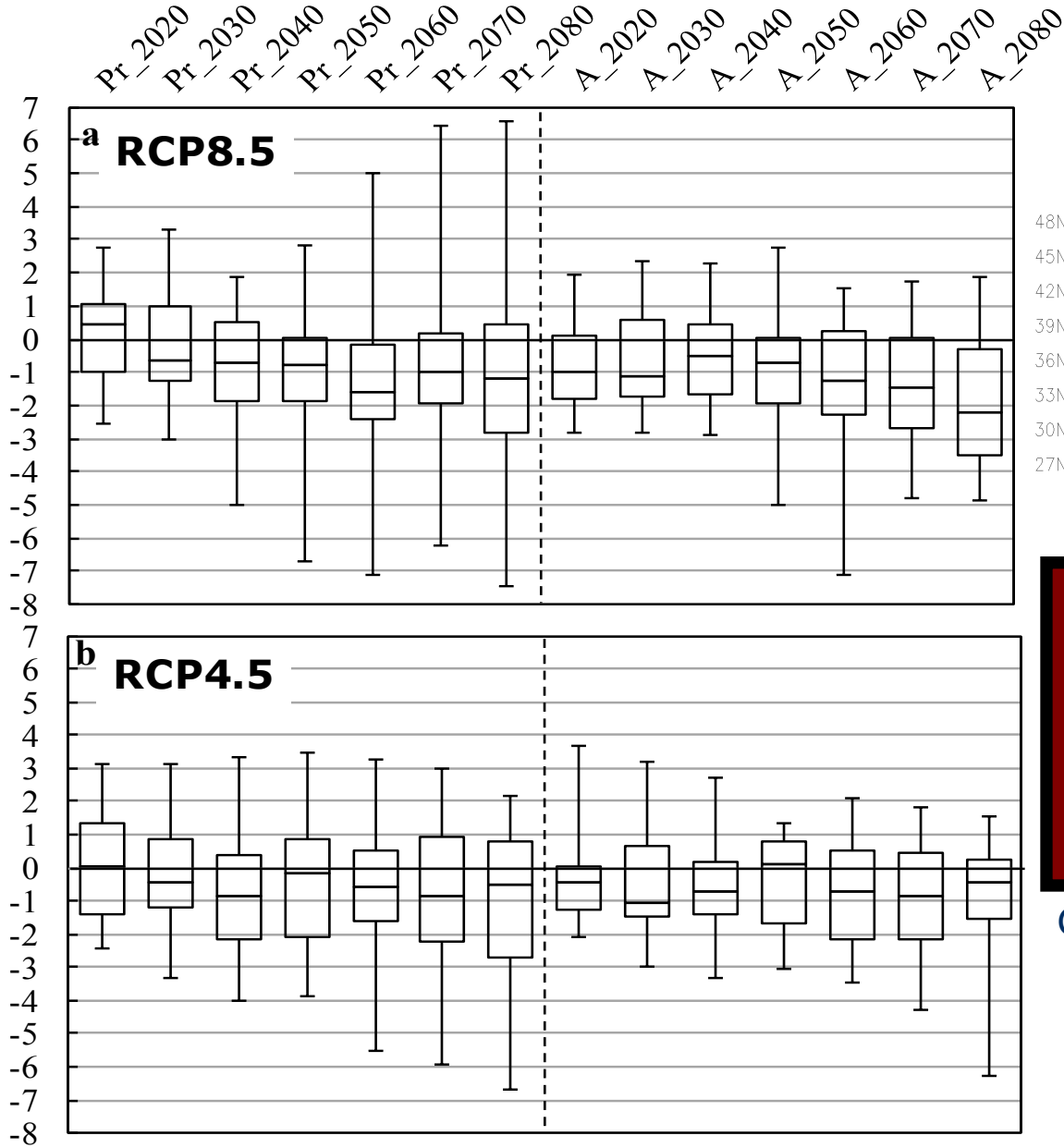
**ANALOGUE PROJECTION  
REDUCES TOTAL RANGE OF  
MODEL SOLUTIONS OF HEAVY  
PRECIPITATION CHANGE**

Gao et al, 2016 (forthcoming)



# MWST: TRENDS IN JJA HEAVY PRECIPITATION

Change in Number of Extreme Days per Year



ANALOGUE PROJECTION  
REDUCES TOTAL RANGE OF  
MODEL SOLUTIONS OF HEAVY  
PRECIPITATION CHANGE

Gao et al, 2016 (forthcoming)

# THANK YOU

- ◆ SUPPLY CHAINS HAVE ALWAYS BEEN UNDER RISK FROM EXTREME EVENTS. CHANGES IN EXTREME EVENTS ARE MORE DISRUPTIVE FOR SOCIETY ON NATIONAL AND GLOBAL TRADE LEVEL THAN GRADUAL CHANGES, WHICH ARE EASIER TO ADAPT AND MORE SO IF SUCH CHANGES ARE FORESEEN.
- ◆ CLIMATE-CHANGE EXTREME IMPACT AMPLIFIED DUE TO INCREASING COMPLEXITY OF SUPPLY-CHAIN AND OVER-RELIANCE OF SINGLE/REGIONAL MANUFACTURING AND ITS INFRASTRUCTURE SUPPORT (I.E. ELECTRIC GRID).
- ◆ TIME HORIZON AND LEAD-TIME OF THREAT-AND-ACTION: CONFIGURATION OF PREDICTION MODELS AND FUNDAMENTAL LIMITS TO PREDICTION REQUIRE CAREFUL SCRUTINY OF CLIMATE-CHANGE PROJECTIONS.
- ◆ A NUMBER OF METHODS EXIST TO "ENHANCE" INFORMATION PROVIDED BY CLIMATE MODELS.
- ◆ HIGHER-RESOLUTION AND/OR PERFORMANCE AGAINST HISTORY MAY NOT TRANSLATE TO FORECAST RELIABILITY.
- ◆ RESILIENCE, ROBUSTNESS, AND FRAGILITY: INTERSECTION OF SUPPLY-CHAIN AND EXTREME PREDICTION EXPERTS.

