Modern Statistical Techniques for Characterization of Extreme Precipitation during Atmospheric River Events

EARTH SCIENCES DIVISION

CASCADE

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SCIENCE DRIVER

Scientific Questions of CASCADE SFA

- How will current extreme climate change in frequency, duration, intensity, and spatial scale in the future?
- Can future climate extremes be reliably attributed to anthropogenic influences?

➢ Specific Focus on Analysis of Spatial Extremes and Their Dependence Pattern

Hypotheses:

1. The spatial relationship of extremes can be more readily quantified with a robust description of the spatial dependence of extremes.
2. Climate change can affect region/location of extreme phenomena, implying changes in spatial scale of extremes and impact of extreme events. There might be anthropogenic influences on the spatial association of extremes.

Objectives:

- ◆ Characterization of Atmospheric Rivers (ARs) and extreme outcomes
- ◆ Spatial analysis within statistical framework of extreme value theory
- ◆ Impact of climate change on spatial coherence of AR events
- ◆ Connections between large scale atmospheric systems and climate extremes

DESIGN OF METHODS

Data Description

Event Detection and Extreme Precipitation using CMIP5

- Model: GFDL-ESM2M, HadGEM2-CC, MIROC5, CCSM4
- Variable: max AR precipitation (annual maximum precipitation during AR events)
- Time Periods: historical run (1981-2005) and future RCP8.5 run (2076-2100)
- Region of interest: California, United States

Detection of Atmospheric Rivers

We have software to detect atmospheric rivers in large climate datasets [1]. We use the TECA framework [2] for parallelizing the detection procedure across multiple nodes on an HPC cluster. The code is written in C++ and uses MPI for distributed memory execution.

We use the following criteria for detecting atmospheric rivers:

- Search for band of precipitable water originating in tropics
- Band should make landfall on the US West Coast
- Integrated Water Vapor > 2cm
- Length of Band > 2000 Km
- Width of Band < 1000 Km

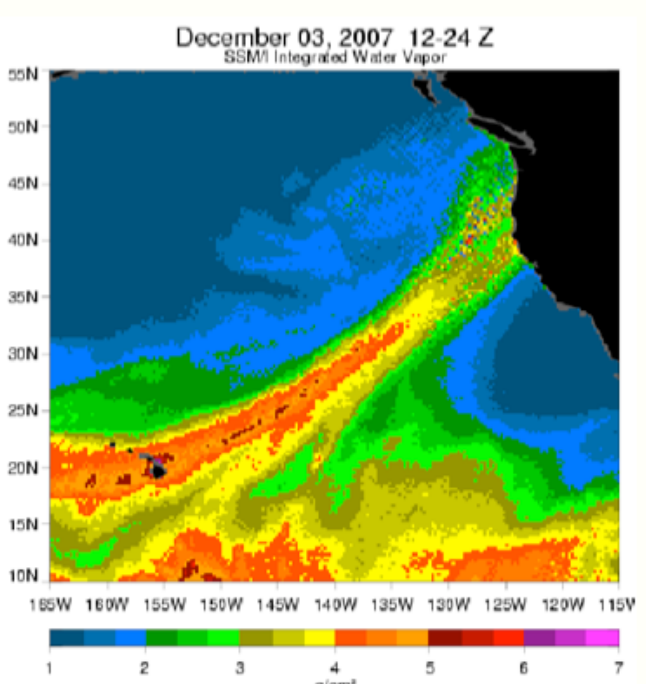


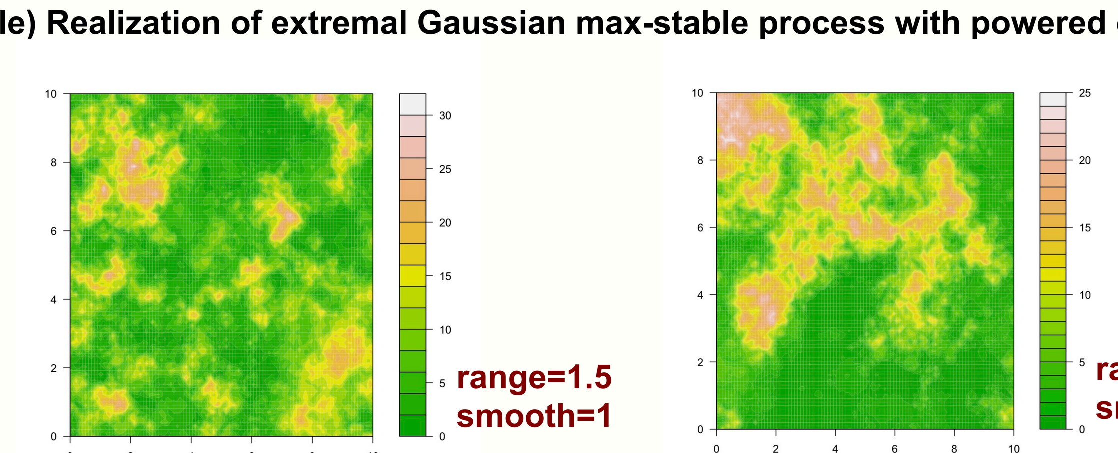
Fig 1: AR event making landfall over CA

Design of Statistical Extreme Value Analysis

Max-stable Process – Statistical Modeling of Extreme Phenomena at Multiple Locations

- Consider a spatial process $Y(s), s \in S \subseteq \Re^d$ satisfying max-stability. Covariance structure of the max-stable process can be characterized by valid correlation function or variogram with smooth and range parameters.

- Example) Realization of extremal Gaussian max-stable process with powered exponential correlation [3]:



Extremal Coefficient – A Metric of Spatial Dependence of Extremes

- Pairwise extremal coefficient: θ, a function of a distance between two locations.

$$P(Y(s_1) \le y, Y(s_2) \le y) = \exp\left\{-\frac{\theta(s_1, s_2)}{y}\right\}$$

➔ 1 (complete dependence) ≤ θ ≤ 2 (complete independence)

- A naïve estimator of extremal coefficient based on Cooley et al [4].

A Map to Summarize Pairwise Spatial Dependence

- Step 1. Calculate pairwise spatial dependence from a focal location to any other grids
- Step 2. Transfer the extremal coefficients to the values between 0 (complete independence) and 1 (dependence)
- Step 3. At each grid point, count # of stations with strong dependence (>0.7)
  -Example) In HadGEM2-CC simulation, we have counts in the interval between 0 (no grid showing strong dependence) and 17 (strongly dependent with 17 grid points).

DEMONSTRATION OF METHODS

Characterization of Atmospheric River and Extreme Precipitation

Results:

- We have longer duration and higher frequency in AR events under RCP8.5 than present-day run (Fig 2).
- Fig 3 shows that AR events in RCP8.5 scenario tend to produce larger maximum rainfall than the events from historical run.
- Range of spatial dependence between extreme precipitation is concentrated on smaller localized area under RCP8.5 than present day (Tables and Fig 4).

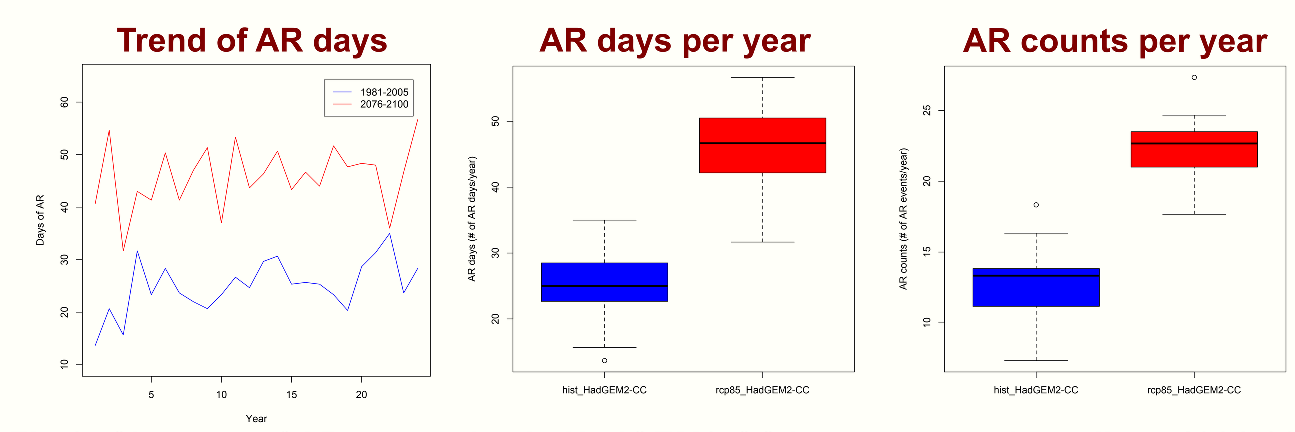


Fig 2: Changes of AR properties in HadGEM2-CC between two time slices 1981-2005 (blue) and 2076-2100 (red).

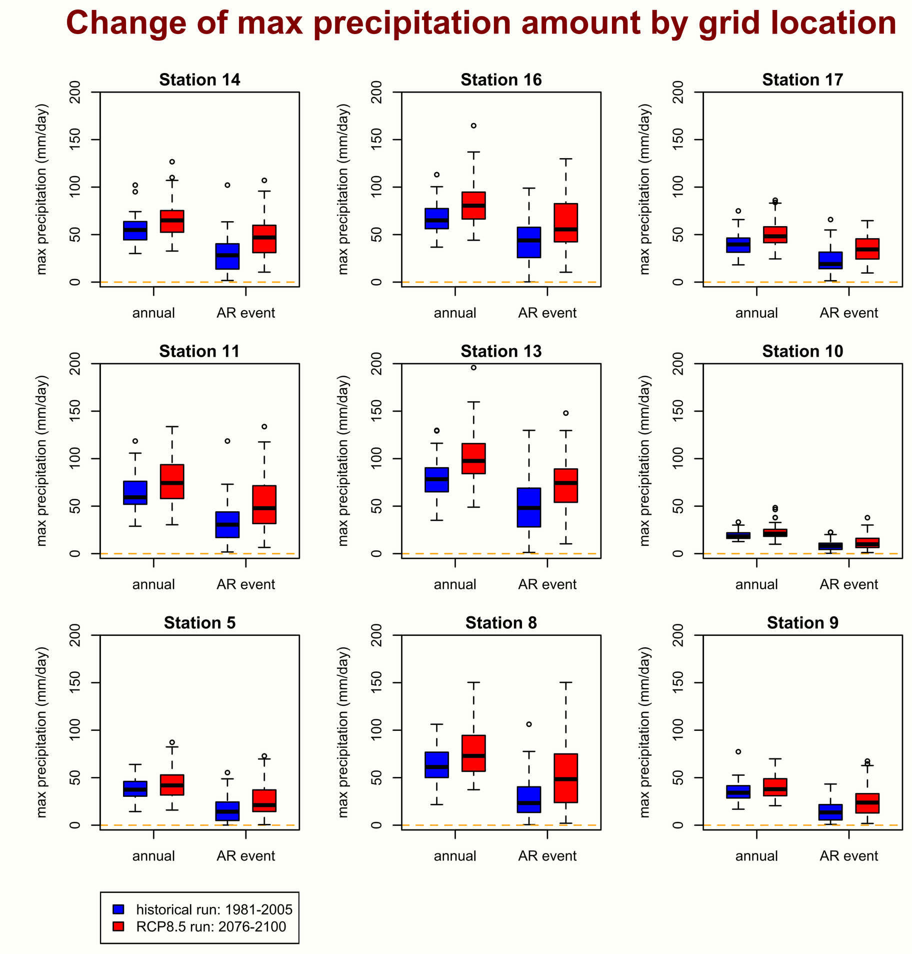


Fig 3: Boxplot of annual max precipitation and max AR precipitation from HadGEM2-CC during 25-year time periods at nine grids.

historical	GFDL	HadGEM	MIROC	CCSM4
range	3.825	2.883	3.773	2.805
smooth	1.615	1.999	1.076	1.998

RCP8.5	GFDL	HadGEM	MIROC	CCSM4
range	2.649	2.527	3.505	2.362
smooth	1.999	1.999	1.585	1.999

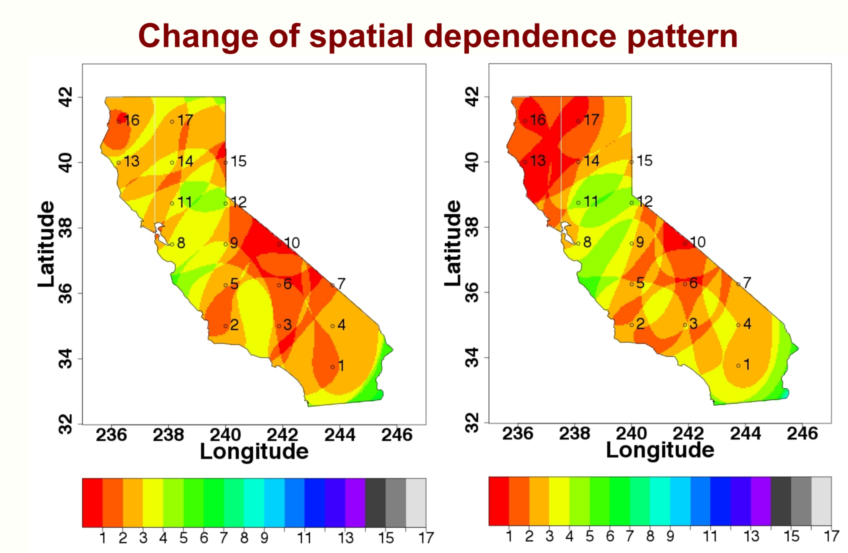


Fig 4: Maps to summarize change in pairwise spatial dependence in HadGEM2-CC simulation from 1981-2005 (left) to 2076-2100 (right). Discrete color at each location represents the number of grid locations with strong dependence.

Summary: Change of Atmospheric River Properties within a Warmer Climate

	GFDL-ESM2M	HadGEM2-CC	MIROC5	CCSM4
AR duration (days/year)	+10 (+39%)	+20 (+83%)	+12 (+43%)	+24 (+76%)
AR counts (events/year)	+5 (+35%)	+9 (+73%)	+5 (+33%)	+6 (+36%)
max AR precipitation	heavier	heavier	smaller	heavier
range of spatial dependence	narrower over the region	narrower, especially over northern CA	narrower	narrower, especially over northern CA

SCIENCE IMPACT

Impact on Climate Science

Influence of regional atmospheric systems on spatial coherence of extreme events

- Refinement of analytical methods and new metrics of spatial dependence for extreme events
- Investigation into spatial coherence of future extremes within a changing climate
- Better understanding of mechanisms and large meteorological patterns driving extremes
- Implications of spatial range of events on impacts / damages driven by extreme phenomena

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