Detecting multiple anthropogenic forcing agents for attribution of regional precipitation change

Mark D. Risser

Climate and Ecosystem Sciences Division

Berkeley National Laboratory, Berkeley, CA, USA

Statistical Methods for the Physical Sciences Seminar
April 19, 2024

Support provided by the

US Department of Energy Regional and Global Model Analysis Program

Key takeaways:

1. We break down how human-induced greenhouse gas and aerosol emissions influence heavy rainfall events in the United States
2. Greenhouse gas emissions increase rainfall, while aerosols have a long-term drying effect as well as short-term impacts that vary with the seasons
3. As aerosols decrease, their long-term drying effect will likely diminish, causing rainfall extremes to rapidly increase

Outline

Motivation: regional D&A for extreme precipitation

Part I: novel framework for observations-based D&A

Part II: D&A for extreme regional precipitation over the CONUS

Outline

Motivation: regional D&A for extreme precipitation

Part I: novel framework for observations-based D&A

Part II: D&A for extreme regional precipitation over the CONUS

Two primary topics for today's talk:

1. D&A $=$ Detection & Attribution of anthropogenic climate change
2. Extreme value theory for analyzing measurements of precipitation

Two primary topics for today's talk:

1. D&A = Detection & Attribution of anthropogenic climate change
2. Extreme value theory for analyzing measurements of precipitation

Let's dive into some background on each of these topics...

D&A = Detection & Attribution of anthropogenic climate change

Two part exercise:

1. Can we detect systematic changes in the distribution of a climate variable of interest?
2. (If yes,) Can we attribute changes to human activity?

D&A = Detection & Attribution of anthropogenic climate change

Two part exercise:

1. Can we detect systematic changes in the distribution of a climate variable of interest?
2. (If yes,) Can we attribute changes to human activity?

At its core, D&A seeks to make **cause and effect** statements about **if, how, and why** different aspects of the global climate system have changed due to human-induced factors (D&A = causal inference)

D&A = Detection & Attribution of anthropogenic climate change

Two part exercise:

1. Can we detect systematic changes in the distribution of a climate variable of interest?
2. (If yes,) Can we attribute changes to human activity?

At its core, D&A seeks to make **cause and effect** statements about **if, how, and why** different aspects of the global climate system have changed due to human-induced factors (D&A = causal inference)

Many decades of D&A literature: significant changes to surface air temperature, sea level pressure, tropopause height, free atmospheric temperature, ocean heat content, ...

D&A = Detection & Attribution of anthropogenic climate change

Two part exercise:

1. Can we detect systematic changes in the distribution of a climate variable of interest?
2. (If yes,) Can we attribute changes to human activity?

At its core, D&A seeks to make **cause and effect** statements about **if, how, and why** different aspects of the global climate system have changed due to human-induced factors (D&A = causal inference)

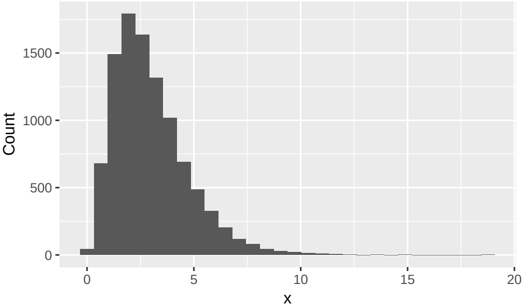
Many decades of D&A literature: significant changes to surface air temperature, sea level pressure, tropopause height, free atmospheric temperature, ocean heat content, ...

Still an active area of research: inconclusive evidence for regional climate change, certain types of extreme events, ...

Extreme value analysis: the study of rare events

Ordinary statistics: characterize the mean (average)

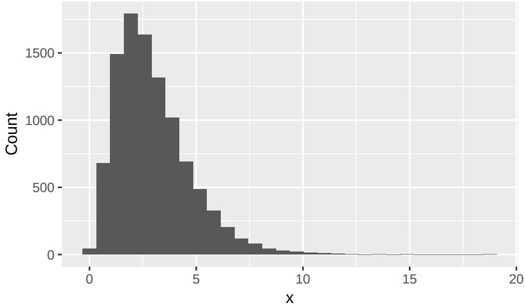
EVA: characterize the “tail” of the distribution (extremes)



Extreme value analysis: the study of rare events

Ordinary statistics: characterize the mean (average)

EVA: characterize the "tail" of the distribution (extremes)



Examples:

- Portfolio adjustment in the insurance industry
- Risk assessment on financial markets
- Engineering: wind, dams, bridges
- **Weather: heavy rainfall, heat waves, hurricanes**

Extreme precipitation: a blessing and a curse

- Extreme precipitation = periods of heavy rainfall or snowfall that are **much larger than what happens on a typical day**

Extreme precipitation: a blessing and a curse

- Extreme precipitation = periods of heavy rainfall or snowfall that are **much larger than what happens on a typical day**
- Unusual or unexpected precipitation events are usually the most costly

Hurricane Harvery, Houston, 2017

Vermont, Summer 2023

Motivation: regional D&A for extreme precipitation

Extreme precipitation: a blessing and a curse

- Extreme precipitation = periods of heavy rainfall or snowfall that are **much larger than what happens on a typical day**
- Unusual or unexpected precipitation events are usually the most costly

Hurricane Harvery, Houston, 2017

Vermont, Summer 2023

- Heavy rainfall can be a boon: series of Jan., 2023 successive storms in California lifted the state out of drought conditions

Extreme precipitation: a blessing and a curse

- Extreme precipitation = periods of heavy rainfall or snowfall that are **much larger than what happens on a typical day**
- Unusual or unexpected precipitation events are usually the most costly

Hurricane Harvery, Houston, 2017

Vermont, Summer 2023

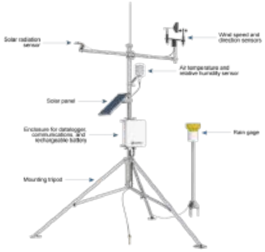
- Heavy rainfall can be a boon: series of Jan., 2023 successive storms in California lifted the state out of drought conditions

*** Understanding of extremes (and changes!) is important for planning and management of resources

How do we make D&A conclusions? Different types of climate data

#1. Observations: measurements collected from monitoring stations

- One example: Global Historical Climate Network = database of daily measurements from land surface stations
- In the United States: relatively dense network of stations with century-length, high-quality records (1900-present)



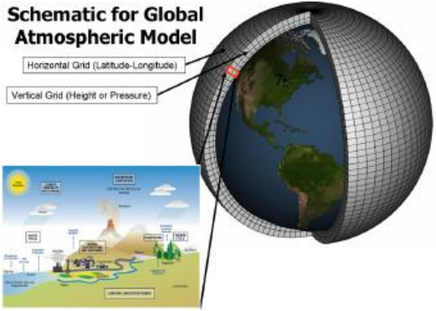
How do we make D&A conclusions? Different types of climate data

#2. Dynamical models: physical/numerical representations of the globe or a subregion

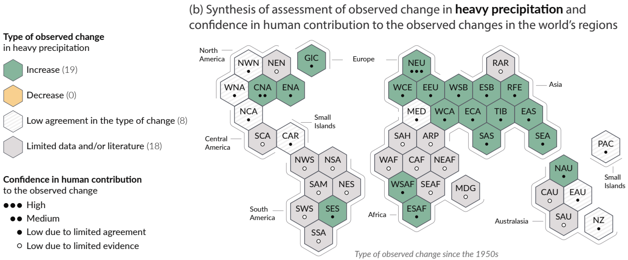
Global climate models (GCMs): global in scope, usually a coarse horizontal resolution ($\approx$ 100-200km grid boxes)

Used as a test bed for understanding how the Earth system responds to hypothetical versions of reality

- World without humans?
- Future world?
- World with some human factors "turned off"?



Low confidence in the human influence on extreme precipitation over North America



IPCC AR6 Summary for Policymakers Fig. SPM.3

Why? Traditional D&A methods rely on global climate models $\rightarrow$ simulated changes in regional precipitation are highly uncertain

Key question: what do measurements of the real world tell us?

New approach:

1. Use climate models in a perfect data sense to develop a robust formula for conducting regional D&A for changes in extreme precipitation

   $\rightarrow$ Climate models used as a test bed: ensure we're getting the right answers for the right reasons

2. Apply flexible statistical methods to conduct local D&A and maximize SNR using weather station data

   $\rightarrow$ No longer using dynamical climate models: a purely data-driven approach

   $\rightarrow$ Side-steps climate model uncertainty, which undermines traditional D&A for extreme precipitation

*** In combination: #1 and #2 yield a conclusive statement about the role of anthropogenic climate change on extreme precipitation over the United States

Outline

Motivation: regional D&A for extreme precipitation

Part I: novel framework for observations-based D&A

Part II: D&A for extreme regional precipitation over the CONUS

D&A formula for extreme precipitation in the United States, 1900-present

For a given geospatial location $\mathbf{s}$ and year $t = 1900, \ldots, 2020$:

$$\underbrace{P(\mathbf{s},t)}_{\text{Observations}} = \underbrace{P_0(\mathbf{s})}_{\text{Pre-indust.}} + \underbrace{P_F(\mathbf{s},t)}_{\text{Forced}} + \underbrace{\underbrace{P_D(\mathbf{s},t)}_{\text{Low-freq. Drivers}} + \underbrace{P_W(\mathbf{s},t)}_{\text{Weather}}}_{\text{Internal variability}}$$

D&A formula for extreme precipitation in the United States, 1900-present

For a given geospatial location $\mathbf{s}$ and year $t = 1900, \ldots, 2020$:

$$\underbrace{P(\mathbf{s}, t)}_{\text{Observations}} = \underbrace{P_0(\mathbf{s})}_{\text{Pre-indust.}} + \underbrace{P_F(\mathbf{s}, t)}_{\text{Forced}} + \underbrace{\underbrace{P_D(\mathbf{s}, t)}_{\text{Low-freq. Drivers}} + \underbrace{P_W(\mathbf{s}, t)}_{\text{Weather}}}_{\text{Internal variability}}$$

- $P(\mathbf{s}, t)$ = input data (max. daily precipitation measurement)

D&A formula for extreme precipitation in the United States, 1900-present

For a given geospatial location $\mathbf{s}$ and year $t = 1900, \dots, 2020$:

$$\underbrace{P(\mathbf{s},t)}_{\text{Observations}} = \underbrace{P_0(\mathbf{s})}_{\text{Pre-indust.}} + \underbrace{P_F(\mathbf{s},t)}_{\text{Forced}} + \underbrace{\underbrace{P_D(\mathbf{s},t)}_{\text{Low-freq. Drivers}} + \underbrace{P_W(\mathbf{s},t)}_{\text{Weather}}}_{\text{Internal variability}}$$

- $P(\mathbf{s}, t)$ = input data (max. daily precipitation measurement)
- $P_0(\mathbf{s})$ = pre-industrial average $\rightarrow$ unperturbed by human influence

D&A formula for extreme precipitation in the United States, 1900-present

For a given geospatial location $\mathbf{s}$ and year $t = 1900, \dots, 2020$:

$$\underbrace{P(\mathbf{s},t)}_{\text{Observations}} = \underbrace{P_0(\mathbf{s})}_{\text{Pre-indust.}} + \underbrace{P_F(\mathbf{s},t)}_{\text{Forced}} + \underbrace{\underbrace{P_D(\mathbf{s},t)}_{\text{Low-freq. Drivers}} + \underbrace{P_W(\mathbf{s},t)}_{\text{Weather}}}_{\text{Internal variability}}$$

- $P(\mathbf{s}, t)$ = input data (max. daily precipitation measurement)
- $P_0(\mathbf{s})$ = pre-industrial average → unperturbed by human influence
- $P_F(\mathbf{s}, t)$ = externally-forced, secular changes over time (human or natural)

D&A formula for extreme precipitation in the United States, 1900-present

For a given geospatial location $\mathbf{s}$ and year $t = 1900, \dots, 2020$:

$$\underbrace{P(\mathbf{s},t)}_{\text{Observations}} = \underbrace{P_0(\mathbf{s})}_{\text{Pre-indust.}} + \underbrace{P_F(\mathbf{s},t)}_{\text{Forced}} + \underbrace{\underbrace{P_D(\mathbf{s},t)}_{\text{Low-freq. Drivers}} + \underbrace{P_W(\mathbf{s},t)}_{\text{Weather}}}_{\text{Internal variability}}$$

- $P(\mathbf{s}, t)$ = input data (max. daily precipitation measurement)
- $P_0(\mathbf{s})$ = pre-industrial average $\rightarrow$ unperturbed by human influence
- $P_F(\mathbf{s}, t)$ = externally-forced, secular changes over time (human or natural)
- $P_D(\mathbf{s}, t)$ and $P_W(\mathbf{s}, t)$ = everything else (the noise) $\rightarrow$ year-to-year changes from atmospheric/ocean dynamics

D&A formula for extreme precipitation in the United States, 1900-present

$$P_F(\mathbf{s}, t) = \text{externally-forced, secular changes over time (human or natural)}$$

Our **perfect data tests** using global climate models concluded (Risser et al., 2022):

D&A formula for extreme precipitation in the United States, 1900-present

$$P_F(\mathbf{s}, t) = \text{externally-forced, secular changes over time (human or natural)}$$

Our **perfect data tests** using global climate models concluded (Risser et al., 2022):

- We can safely ignore the effect of natural forcing agents: volcanic activity, solar radiation

D&A formula for extreme precipitation in the United States, 1900-present

$$P_F(\mathbf{s}, t) = \text{externally-forced, secular changes over time (human or natural)}$$

Our **perfect data tests** using global climate models concluded (Risser et al., 2022):

- We can safely ignore the effect of natural forcing agents: volcanic activity, solar radiation
- We can safely ignore the effect of some anthropogenic forcing agents: stratospheric ozone, land-use/land-cover change

D&A formula for extreme precipitation in the United States, 1900-present

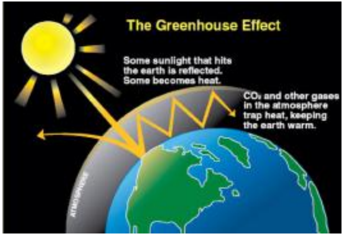
$$P_F(\mathbf{s}, t) = \text{externally-forced, secular changes over time (human or natural)}$$

Our **perfect data tests** using global climate models concluded (Risser et al., 2022):

- We can safely ignore the effect of natural forcing agents: volcanic activity, solar radiation
- We can safely ignore the effect of some anthropogenic forcing agents: stratospheric ozone, land-use/land-cover change
- We must account for two specific anthropogenic forcing agents:
  1. Greenhouse gas (GHG) emissions
  2. Anthropogenic aerosols

Greenhouse gas emissions

One factor driving changes in precipitation: the greenhouse effect



- The "greenhouse effect" refers to the process of atmospheric radiation warming the Earth's surface
- Greenhouse gases (GHG): CO_2, CH_4, N_2O, halocarbons
- Human activities **enhance** this effect: burning of fossil fuels, deforestation, cement production, etc.
- Clausius-Clapeyron equation: extreme precipitation increases by $\approx 6\%$ per 1°C warming

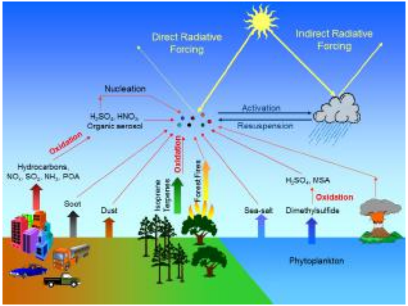
Radiative forcing from GHG emissions: "slow" precipitation response $\rightarrow$ affects rainfall via long-term warming of the atmosphere/ocean

Anthropogenic aerosols

Aerosols: tiny particles with a big impact on our climate and human health

- The air is filled with millions of tiny solid particles and liquid droplets: aerosols
- 90% are "natural": sea salt, dust, volcanic ash, smoke from forest fires
- 10% are man-made: byproducts of fossil fuel combustion, autos, and power plants; biomass burning → **air pollution** or **smog**
- Complicated impacts on weather and climate!

Anthropogenic aerosols: two primary impacts on the Earth system



❶ Aerosols + incoming sunlight

- → Reflection/scattering of solar energy
- → More aerosols = offset global warming
- → Same effect everywhere: **global effects**

❷ Aerosols + clouds

- → Impact the rate at which clouds form and what type of clouds form
- → Depends on source proximity: **local effects**

Effect on extreme precipitation:

- "Slow" precipitation response from reduced radiative forcing
- "Fast" precipitation response from alteration of cloud properties

D&A formula for extreme precipitation in the United States, 1900-present

$$P_F(\mathbf{s}, t) \approx \beta_{\text{Slow}}(\mathbf{s}) \underbrace{\Big[F_{\text{GHG}}(t) + F_{\text{AER-glob}}(t)\Big]}_{\text{Slow response}} + \beta_{\text{Fast}}(\mathbf{s}) \underbrace{F_{\text{AER-local}}(\mathbf{s}, t)}_{\text{Fast response}}$$

D&A formula for extreme precipitation in the United States, 1900-present

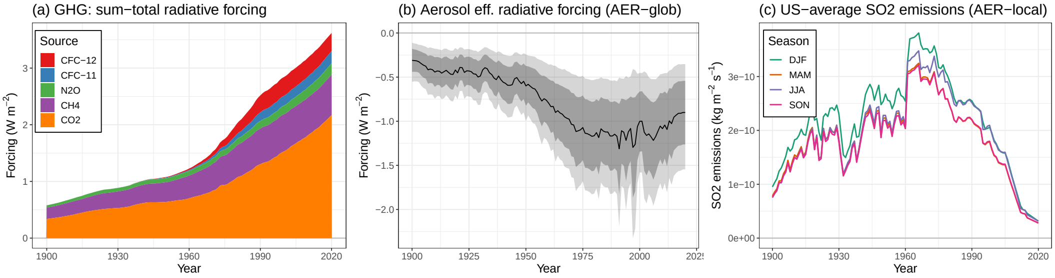
$$P_F(\mathbf{s}, t) \approx \beta_{\text{Slow}}(\mathbf{s}) \underbrace{\Big[F_{\text{GHG}}(t) + F_{\text{AER-glob}}(t)\Big]}_{\text{Slow response}} + \beta_{\text{Fast}}(\mathbf{s}) \underbrace{F_{\text{AER-local}}(\mathbf{s}, t)}_{\text{Fast response}}$$

- $\beta_{\text{Slow}}(\mathbf{s})$, $\beta_{\text{Fast}}(\mathbf{s})$: **local attribution coefficients** $\rightarrow$ describe magnitude/sign of response

D&A formula for extreme precipitation in the United States, 1900-present

$$P_F(\mathbf{s},t) \approx \underbrace{\beta_{\text{Slow}}(\mathbf{s})\left[F_{\text{GHG}}(t) + F_{\text{AER-glob}}(t)\right]}_{\text{Slow response}} + \beta_{\text{Fast}}(\mathbf{s})\underbrace{F_{\text{AER-local}}(\mathbf{s},t)}_{\text{Fast response}}$$

- $\beta_{\text{Slow}}(\mathbf{s})$, $\beta_{\text{Fast}}(\mathbf{s})$: **local attribution coefficients** $\rightarrow$ describe magnitude/sign of response
- $F_f(\cdot) \rightarrow$ fixed forcing time series:



Statistical methods

Step 1: Spatial extremes analysis with UQ (Risser et al., 2019a)

- Apply D&A formula from Part I with GEV regression per station
- Scalable, nonstationary Gaussian processes for spatial modeling of GEV coefficients (Risser and Calder, 2017)
- Nonparametric bootstrap methods for quantifying uncertainty (Risser et al., 2019a)

Step 2: Detection & attribution of human influence (Risser et al., 2019b)

- Permutation/resampling methods to define null distributions
- Multiple testing adjustment for spatially-correlated tests

Statistical methods

Step 1: Spatial extremes analysis with UQ (Risser et al., 2019a)

- Apply D&A formula from Part I with GEV regression per station
- Scalable, nonstationary Gaussian processes for spatial modeling of GEV coefficients (Risser and Calder, 2017)
- Nonparametric bootstrap methods for quantifying uncertainty (Risser et al., 2019a)

Step 2: Detection & attribution of human influence (Risser et al., 2019b)

- Permutation/resampling methods to define null distributions
- Multiple testing adjustment for spatially-correlated tests

Ultimate goal: assess spatial patterns and time-to-emergence of the human influence on extreme precipitation

- Separate conclusions for each three-month season $\rightarrow$ account for different mechanisms for extreme precipitation

Motivation: regional D&A for extreme precipitation

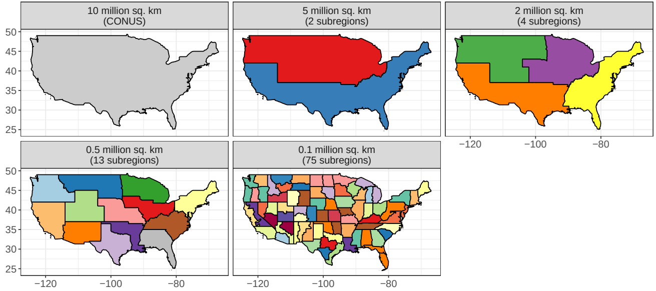
Part I: novel framework for observations-based D&A

Part II: D&A for extreme regional precipitation over the CONUS

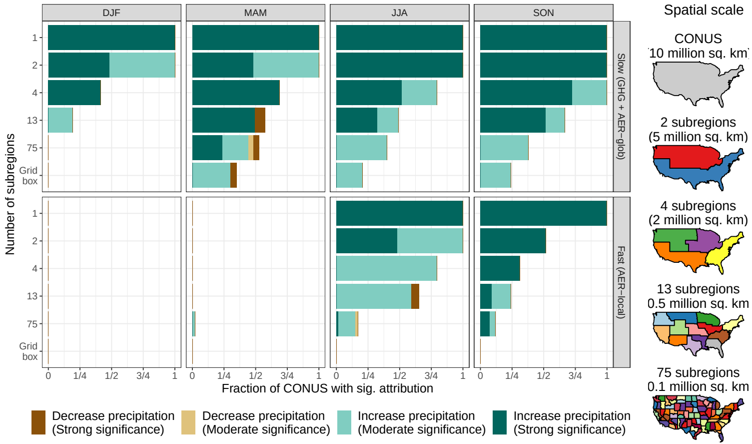
Result #1: spatial scales of attribution, fast vs. slow response

Detection & Attribution is inherently a signal-to-noise exercise

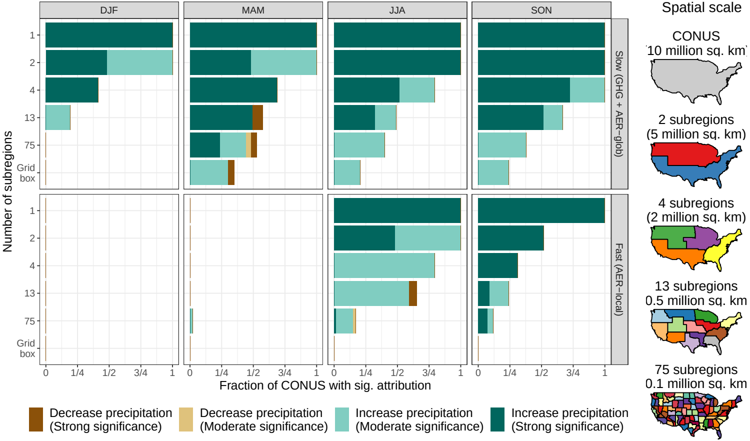
- Averaging over larger areas reduces statistical noise
- At what spatial scales can we detect/attribute human influence?
- Consider a set of attribution regions: all of the U.S., two regions, four regions, . . . , down to individual grid boxes



Result #1: spatial scales of attribution, fast vs. slow response

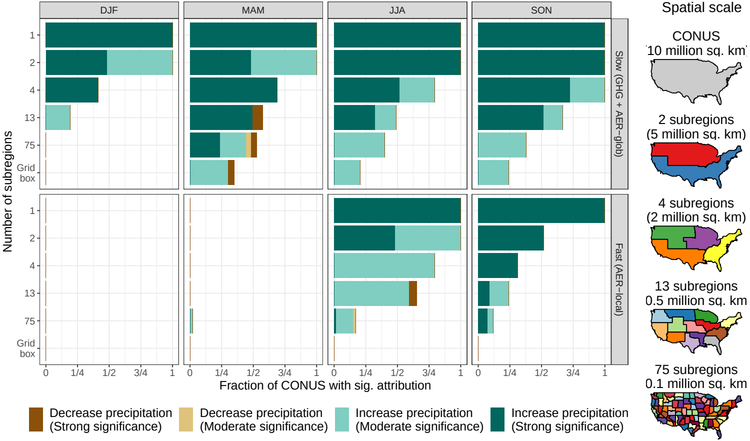


Result #1: spatial scales of attribution, fast vs. slow response



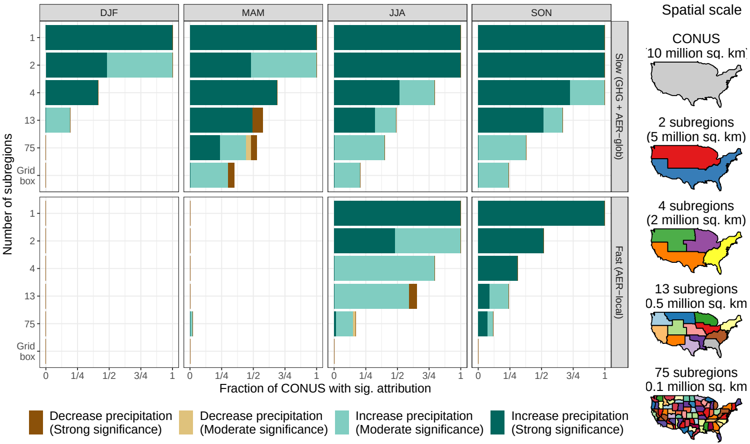
- For all of CONUS: significant attribution across seasons for both fast and slow response

Result #1: spatial scales of attribution, fast vs. slow response



- For all of CONUS: significant attribution across seasons for both fast and slow response
- As expected: strength of signal ↓ as spatial scale ↓

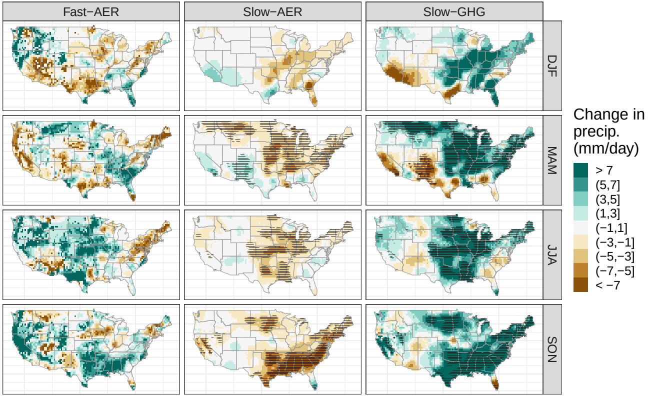
Result #1: spatial scales of attribution, fast vs. slow response



- For all of CONUS: significant attribution across seasons for both fast and slow response
- As expected: strength of signal ↓ as spatial scale ↓
- Slow response is still detectable at very small spatial scales!

Result #2: grid-box attribution

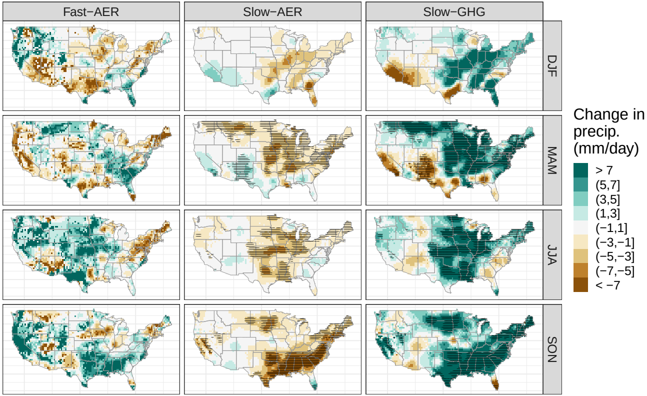
Start with individual grid boxes: assess spatial patterns of climate change



- Hatching = statistically significant attribution for moderate (−) and strong (+) significance
- Green = extreme events larger for high forcing levels
- Brown = extreme events smaller for high forcing levels

Result #2: grid-box attribution

Spatial patterns of **GHG forcing** (Slow-GHG) on extreme precipitation



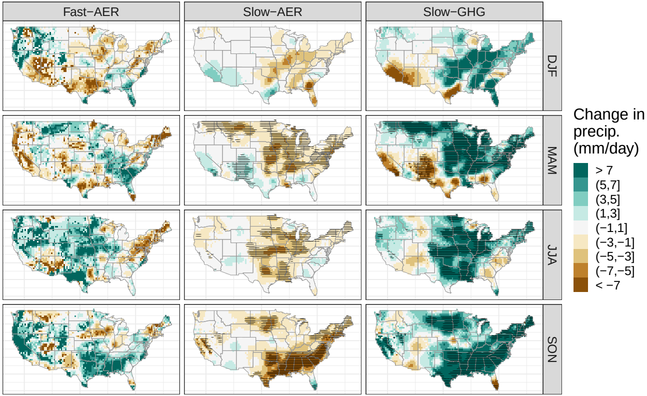
- Dominant color is **GREEN**:

  ↑ GHG forcing ⇒ ↑ Precip.

  (as expected: see C-C scaling)

Result #2: grid-box attribution

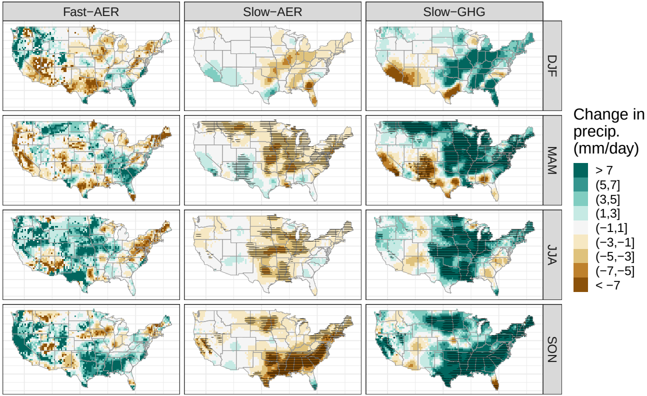
Spatial patterns of **GHG forcing** (Slow-GHG) on extreme precipitation



- Dominant color is **GREEN**:
  $\uparrow$ GHG forcing $\Rightarrow \uparrow$ Precip.
  (as expected: see C-C scaling)
- Heavy rainfall events increase by $>$ 10mm

Result #2: grid-box attribution

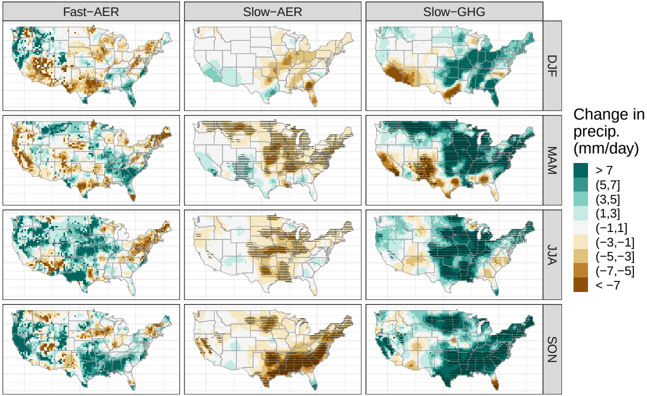
Spatial patterns of **GHG forcing** (Slow-GHG) on extreme precipitation



- Dominant color is **GREEN**:
  $\uparrow$ GHG forcing $\Rightarrow \uparrow$ Precip.
  (as expected: see C-C scaling)
- Heavy rainfall events increase by $>$ 10mm
- Effect is often **statistically significant** (hatching)

Result #2: grid-box attribution

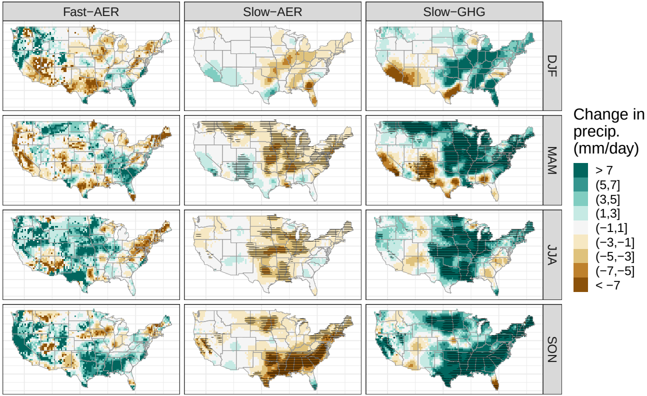
Spatial patterns of **GHG forcing** (Slow-GHG) on extreme precipitation



- Dominant color is **GREEN**:
  $\uparrow$ GHG forcing $\Rightarrow$ $\uparrow$ Precip.
  (as expected: see C-C scaling)
- Heavy rainfall events increase by $>$ 10mm
- Effect is often **statistically significant** (hatching)
- Not always true: sometimes
  $\uparrow$ GHG forcing $\Rightarrow$ $\downarrow$ Precip.

Result #2: grid-box attribution

Spatial patterns of **GHG forcing** (Slow-GHG) on extreme precipitation

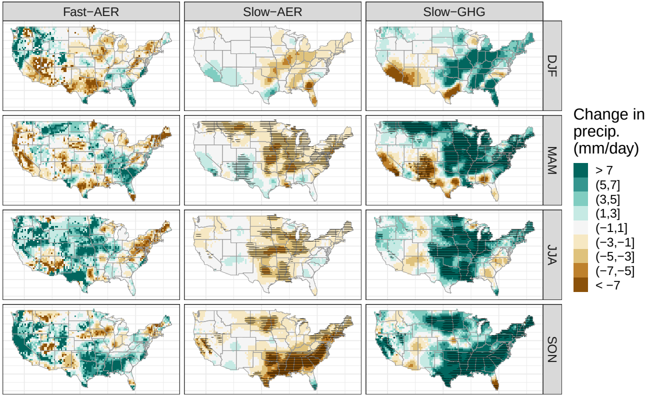


- Dominant color is **GREEN**:
  $\uparrow$ GHG forcing $\Rightarrow \uparrow$ Precip.
  (as expected: see C-C scaling)
- Heavy rainfall events increase by $>$ 10mm
- Effect is often **statistically significant** (hatching)
- Not always true: sometimes
  $\uparrow$ GHG forcing $\Rightarrow \downarrow$ Precip.

*** Importance of **localized** D&A!

Result #2: grid-box attribution

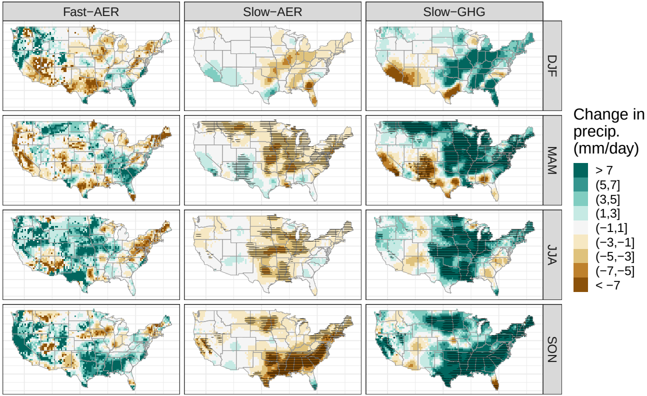
Spatial patterns of the **long-term effect of aerosols** (Slow-AER) on extreme precipitation



- Dominant color is **BROWN**:
  $\uparrow$ Slow-AER $\Rightarrow$ $\downarrow$ Precip.
  (again as expected from atmospheric theory)

Result #2: grid-box attribution

Spatial patterns of the **long-term effect of aerosols** (Slow-AER) on extreme precipitation



- Dominant color is **BROWN**:

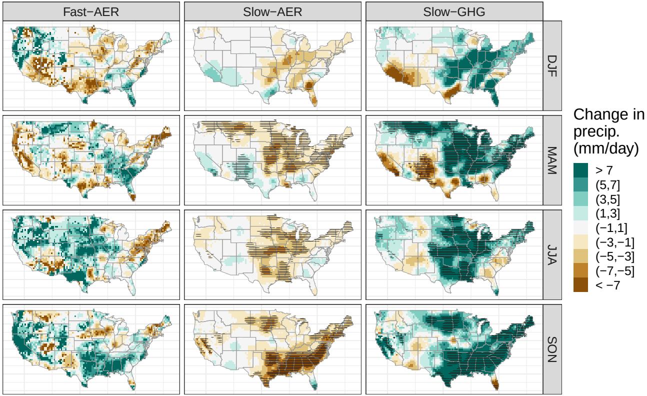
  $\uparrow$ Slow-AER $\Rightarrow \downarrow$ Precip.

  (again as expected from atmospheric theory)

- Note that the signal is the opposite sign as Slow-GHG by construction

Result #2: grid-box attribution

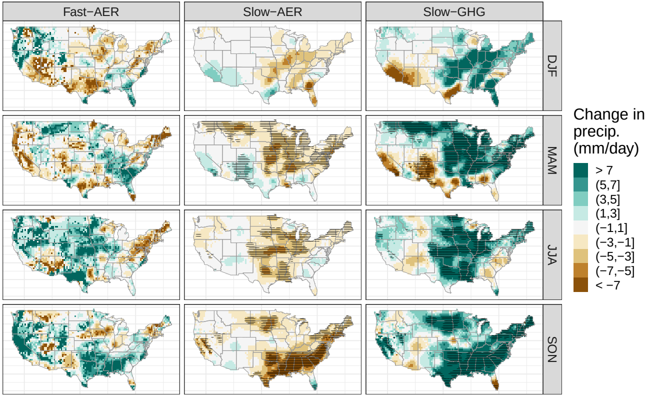
Spatial patterns of the **short-term impact of aerosols** (Fast-AER) on extreme precipitation



- No longer a dominant color!

Result #2: grid-box attribution

Spatial patterns of the **short-term impact of aerosols** (Fast-AER) on extreme precipitation

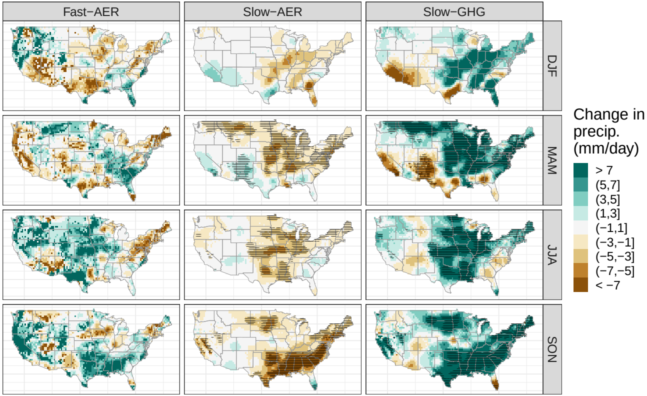


- No longer a dominant color!
- In some places:

  $\uparrow$ Fast-AER $\Rightarrow$ $\downarrow$ Precip.

Result #2: grid-box attribution

Spatial patterns of the **short-term impact of aerosols** (Fast-AER) on extreme precipitation



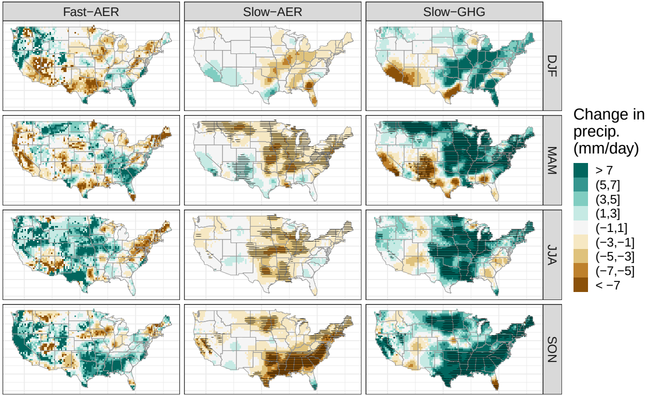
- No longer a dominant color!
- In some places:

  $\uparrow$ Fast-AER $\Rightarrow \downarrow$ Precip.
- In other places:

  $\uparrow$ Fast-AER $\Rightarrow \uparrow$ Precip.

Result #2: grid-box attribution

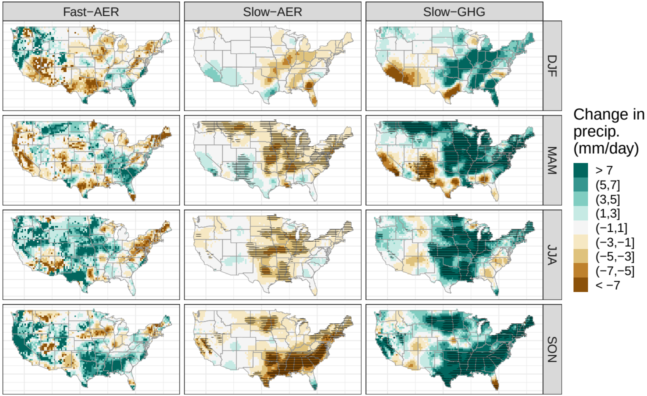
Spatial patterns of the **short-term impact of aerosols** (Fast-AER) on extreme precipitation



- No longer a dominant color!
- In some places:
  $\uparrow$ Fast-AER $\Rightarrow$ $\downarrow$ Precip.
- In other places:
  $\uparrow$ Fast-AER $\Rightarrow$ $\uparrow$ Precip.
- Strong seasonal dependence

Result #2: grid-box attribution

Spatial patterns of the **short-term impact of aerosols** (Fast-AER) on extreme precipitation



- No longer a dominant color!
- In some places:
  $\uparrow$ Fast-AER $\Rightarrow \downarrow$ Precip.
- In other places:
  $\uparrow$ Fast-AER $\Rightarrow \uparrow$ Precip.
- Strong seasonal dependence

*** Evidence for convective invigoration by aerosols (see Samset et al., 2016)

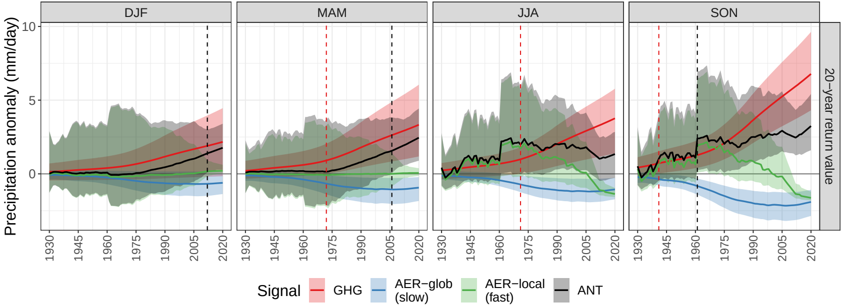
Result #3: time-to-emergence

When do the various anthropogenic signals emerge (if at all)?

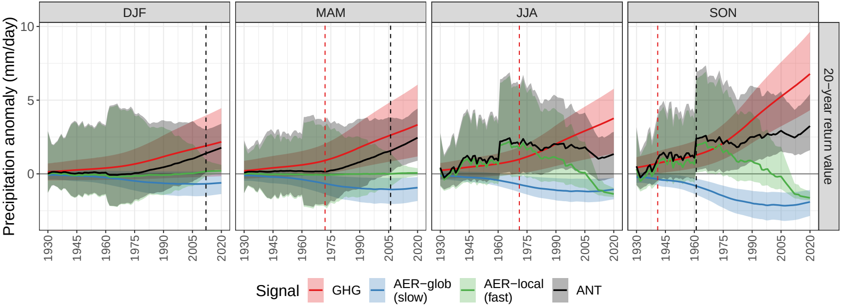
- So far: assessed spatial patterns of the maximum effect of each forcing agent over time
- Now: look at the trajectories over time of each forcing agent, averaged over the U.S.
- **Key question:** when do the individual signals emerge from baseline conditions, after accounting for uncertainty?
- Also assess the **sum-total anthropogenic (ANT)** signal:

$$\text{ANT} = \text{Slow-GHG} + \text{Slow-AER} + \text{Fast-AER}$$

Result #3: time-to-emergence

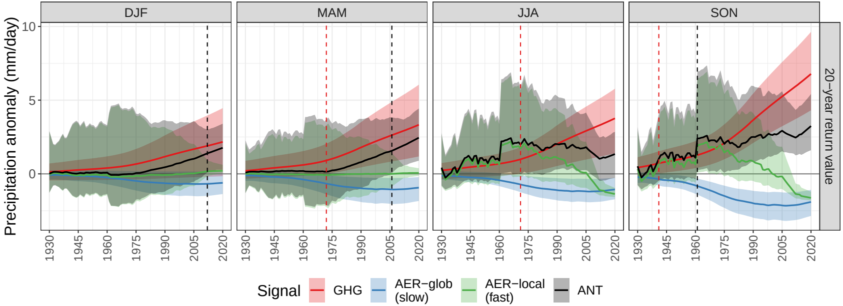


Result #3: time-to-emergence



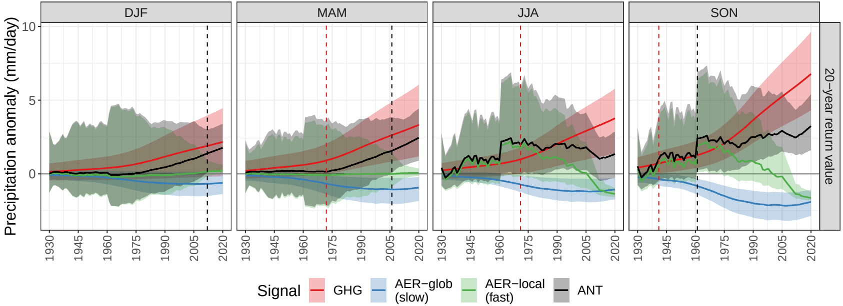
- Dashed vertical lines: first time **GHG signal** and **combined ANT signal** emerge

Result #3: time-to-emergence



- Dashed vertical lines: first time **GHG signal** and **combined ANT signal** emerge
- 3/4 seasons: GHG signal emerges before combined ANT signal . . . i.e., AER masking!

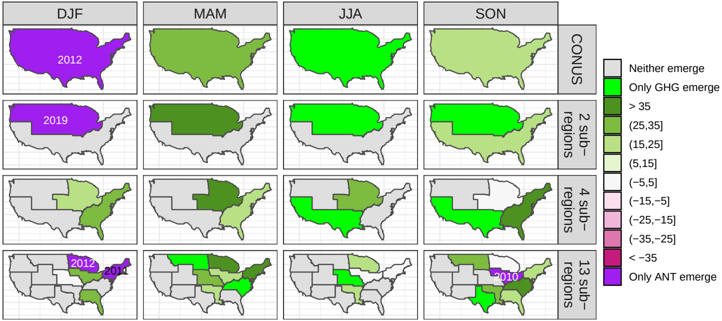
Result #3: time-to-emergence



- Dashed vertical lines: first time **GHG signal** and **combined ANT signal** emerge
- 3/4 seasons: GHG signal emerges before combined ANT signal . . . i.e., AER masking!
- **Key result:** expected increases to extreme precipitation from GHG forcing have been offset/masked by aerosols!

Result #3: time-to-emergence

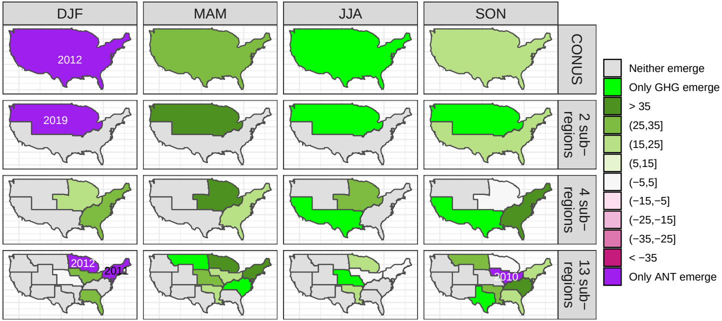
Clear evidence for aerosol masking at scale of U.S. → what about smaller scales?



- Plotted color = ANT emerge time minus GHG emerge time

Result #3: time-to-emergence

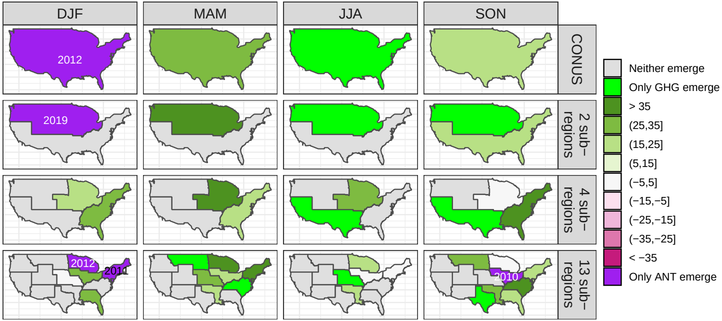
Clear evidence for aerosol masking at scale of U.S. → what about smaller scales?



- Plotted color = ANT emerge time minus GHG emerge time
- GREEN = masking by aerosols

Result #3: time-to-emergence

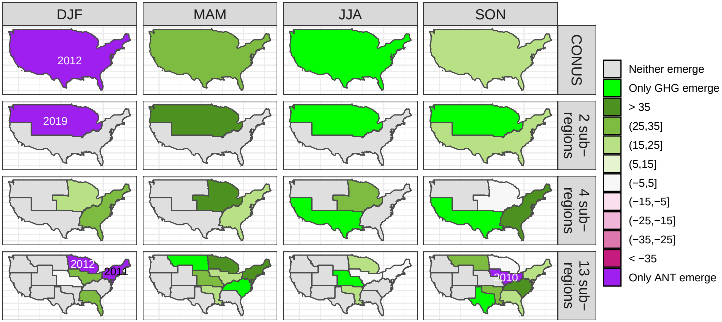
Clear evidence for aerosol masking at scale of U.S. → what about smaller scales?



- Plotted color = ANT emerge time minus GHG emerge time
- GREEN = masking by aerosols
- The aerosol masking is **statistically significant for areas as small as 100,000 km^2**

Result #3: time-to-emergence

Clear evidence for aerosol masking at scale of U.S. → what about smaller scales?



- Plotted color = ANT emerge time minus GHG emerge time
- GREEN = masking by aerosols
- The aerosol masking is **statistically significant for areas as small as 100,000 km^2**
- If combined ANT signal only: happens no earlier than 2010

Implications for risk of natural hazards

We show: GHG-driven increases to rainfall are offset by aerosol emissions up through 1970s

- Last 50 years: masking effect has gradually disappeared due to sharp decreases in sulfur dioxide emissions over the United States
- Greenhouse gas signal dominates recent changes in precipitation

Implications for risk of natural hazards

We show: GHG-driven increases to rainfall are offset by aerosol emissions up through 1970s

- Last 50 years: masking effect has gradually disappeared due to sharp decreases in sulfur dioxide emissions over the United States
- Greenhouse gas signal dominates recent changes in precipitation

These results contribute to mounting evidence of anthropogenically-driven increases in flood risk

- Natural masking of flood risk (Bass et al., 2022) + amplified of natural circulation variability from large-scale warming (O'Brien et al., 2022) → dramatic increases in flood risk in the near future
- July/August 2022: five unprecedented flooding events in the US and the catastrophic events in Pakistan

Thank you!

Key takeaways:

1. We break down how human-induced greenhouse gas and aerosol emissions influence heavy rainfall events in the United States
2. Greenhouse gas emissions increase rainfall, while aerosols have a long-term drying effect as well as short-term impacts that vary with the seasons
3. As aerosols decrease, their long-term drying effect will likely diminish, causing rainfall extremes to rapidly increase

Contact: Mark D. Risser, `mdrisser@lbl.gov`

DOIs for relevant papers

- Using GCM output for perfect data experiments: 10.1007/s00382-022-06321-1
- Statistical methods for D&A: 10.1007/s00382-019-04636-0, 10.1175/JCLI-D-19-0077.1
- More on methods and results from Part II: 10.1038/s41467-024-45504-8