

Conceptual Framework

- ▶ Projections of future extreme precipitation remain highly uncertain [1]
 - ▶ Rainfall (esp. extreme) poorly represented in GCMs [i.e. 2]
 - ▶ Precipitation fields often used for hydrological and decision models after bias correction [e.g. quantile-quantile mapping 3]) is applied; however model deficiencies not identified, persistence characteristics in precipitation fields poorly represented [e.g. 4].
- Is there a way to use credibly simulated state variables from GCM simulations to derive or simulate credible sequences of regional intense precipitation events associated with societal impacts?*

Research Questions

- We hypothesize that GCMs may simulate the frequency and intensity of atmospheric circulation patterns associated with regional intense precipitation events better than the statistics of the precipitation events themselves.
- Q1** For the Ohio River basin, are the intense springtime precipitation events relevant for extreme floods well simulated by the GCM? If not, why?
 - Q2** If no to **Q1**, can we find atmospheric indices that are associated with the onset of the regional intense precipitation events?
 - Q3** If they are not, are suitably derived atmospheric indices associated with such events in atmospheric re-analysis relatively well simulated by the GCM?
 - Q4** If the GCM simulations of atmospheric indices are better, can they provide more credible projections of regional intense precipitation occurrence than the GCM can directly?

Methods & Data

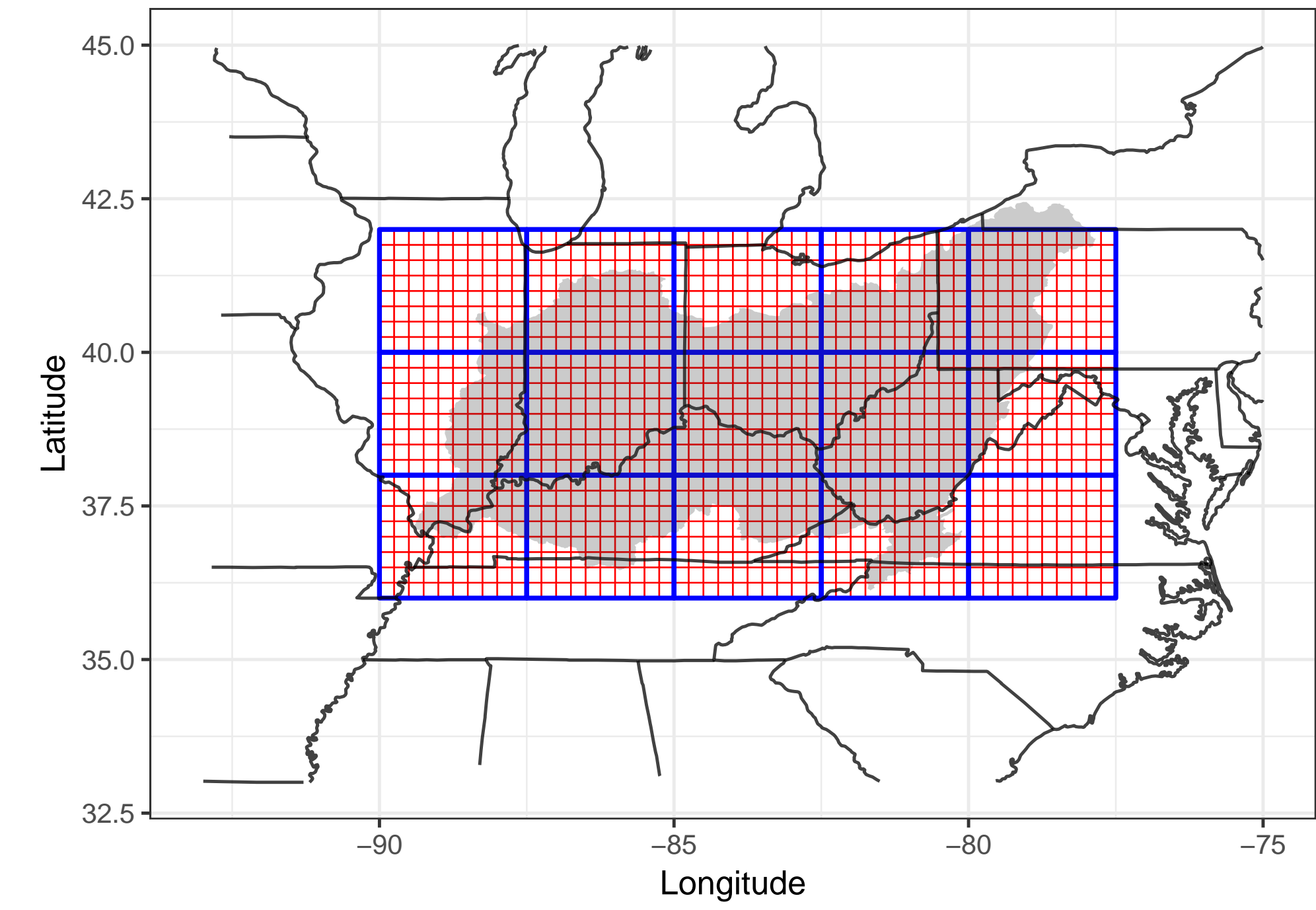


Figure 1: Map of study area and Geophysical Fluid Dynamics Laboratory CM3 coupled model cells (blue grid). The Climate Prediction Center precipitation data (red grid) was upscaled to match the grid of the CM3 coupled model (blue grid), by taking the spatial average of the red cells inside each of the blue cells. The shaded area indicates the Ohio River Basin (~ 530 000 km²) as defined by the United States Geological Survey.

- ▶ MAM season in the Ohio River Basin (Figure 1). “Historical” from 01 March 1950 through 30 May 2005, “future” study period from 01 March 2006 through 30 May 2100.
- ▶ “Dynamical Model” refers to GFDL global coupled model [5] (CM3).
- ▶ CPC US unified gauge-based precipitation data, upscaled from 0.250° by 0.250° to match CM3 (2.50° longitude by 2.00° latitude).
- ▶ Regional Intense Precipitation (RIP) days were defined as any day when over 20% of the region receives experiences a 99th percentile exceedance of precipitation.
- ▶ Reanalysis data from NCEP/NCAR Reanalysis I [6].

RIP Events in a GCM & Observations

- ▶ CM3: too many MAM RIP days, too few back-to-back RIP days
 - ▶ Seasonality bias: too many (few) RIP days in MAM (JJA)
 - ▶ When CM3 produces intense precipitation in any part of the study region, it has a tendency to simultaneously produce intense precipitation in several grid cells
 - ▶ Discrepancy between the GCM runs and the observed RIP records is even more stark when the observed precipitation data is used to calculate the 99th percentile thresholds for the model and RIP records
- Conclusion: **relevant precipitation events not well-simulated by CM3 – no to Q1.**

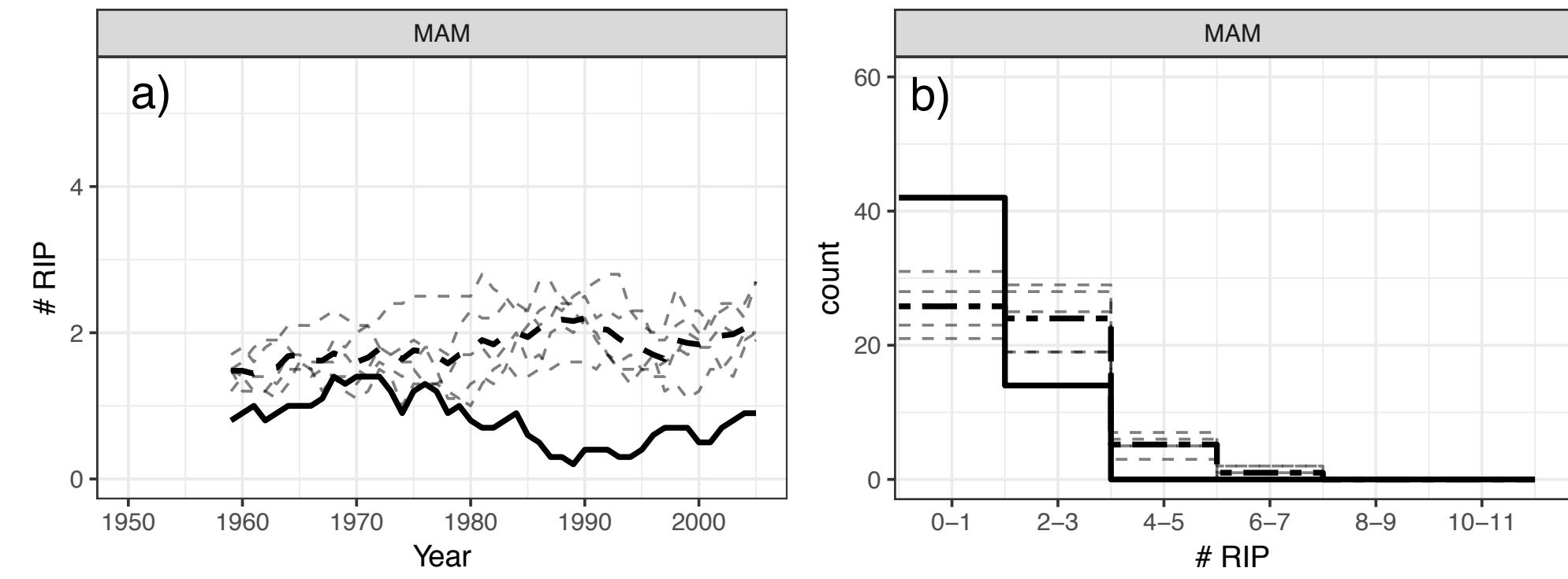


Figure 2: (a) 10-year moving average of the number of MAM RIP days by year for the observed record (black solid line), the five GFDL CM3 ensemble members (light dashed lines), and the ensemble mean (heavy dashed line). (b) The counts for the number of MAM RIP days by year for the observed record (black solid line), the five GFDL CM3 ensemble members (light dashed lines), and the ensemble mean (heavy dashed line).

Circulation Patterns Associated with RIP Events

GCMs represent observed dipole pattern, with some latitudinal bias in storm track and geometry of high pressure system

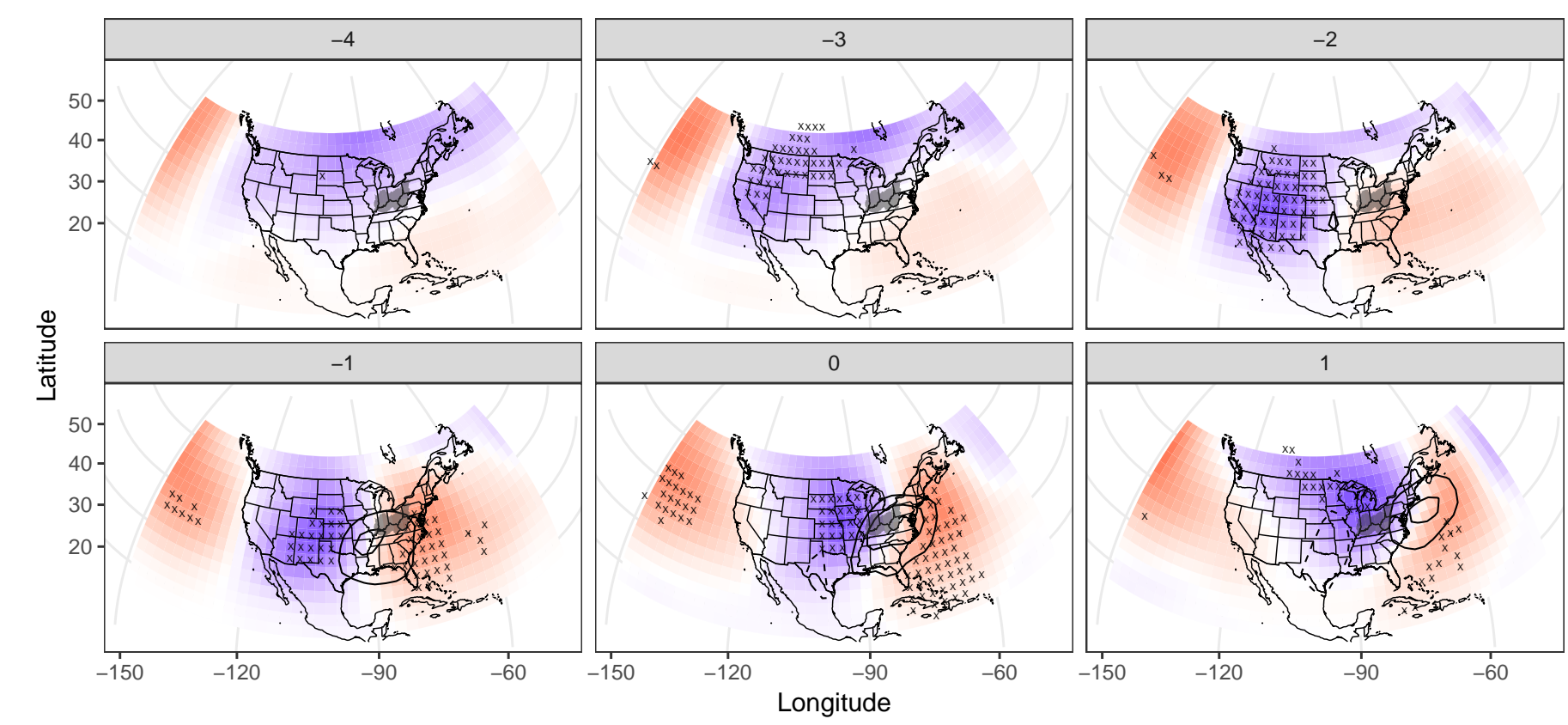


Figure 3: Daily composites of Z_{700} anomalies (shades) and integrated precipitable water content anomaly (contours at 3 kg m⁻²) from four days before each spring (MAM) RIP event to one day following the event. Solid contours represent positive anomalies and dashed contours represent negative anomalies. An “X” indicates that at least 80% of composite members had anomalies of the same sign in that location.

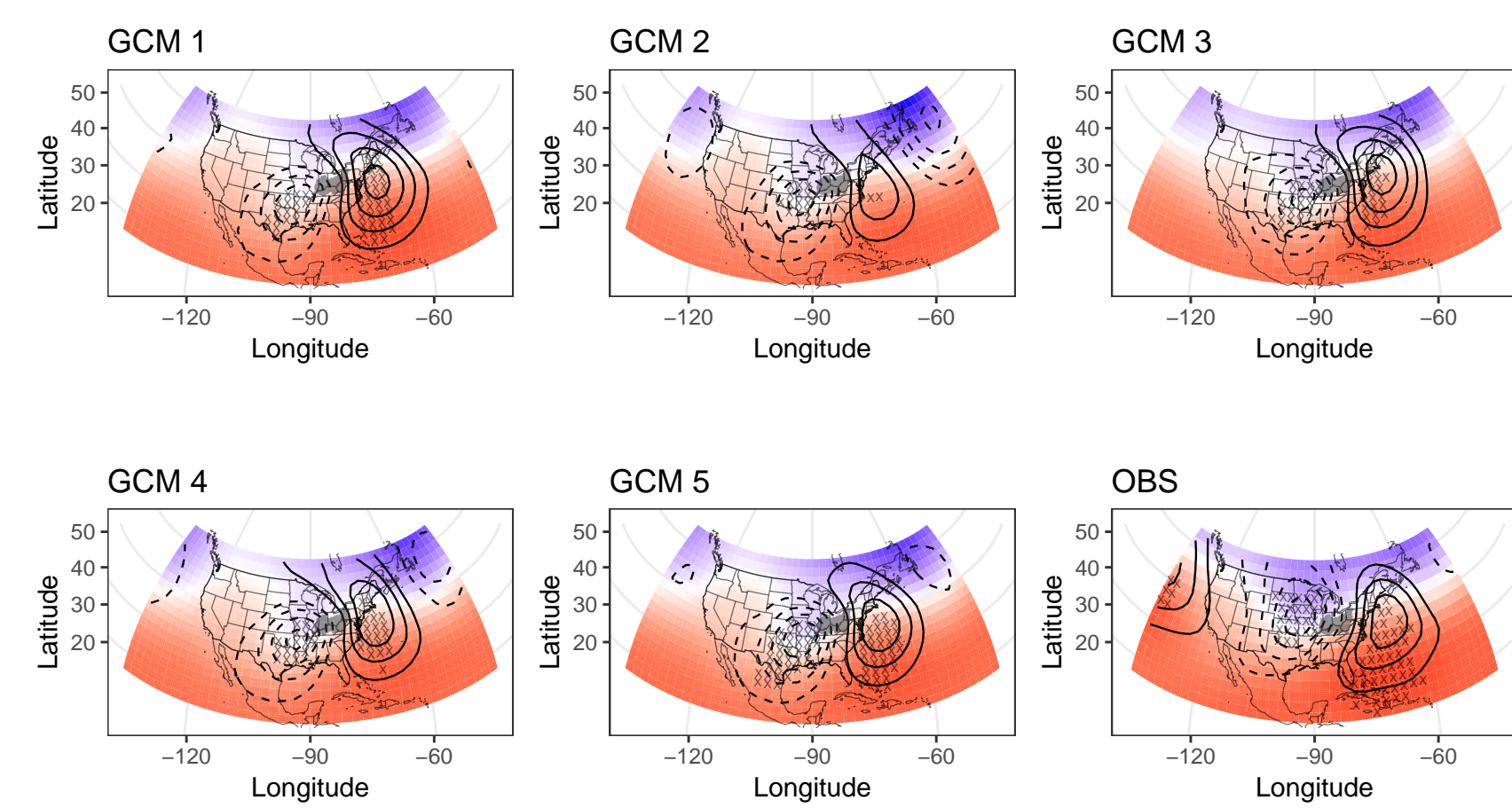


Figure 4: MAM RIP day composites of absolute Z_{700} (shading) and Z_{700} anomalies (contours in 15 m increments) for 5 CM3 members and reanalysis (Obs).

Defining Indices for RIP Circulations

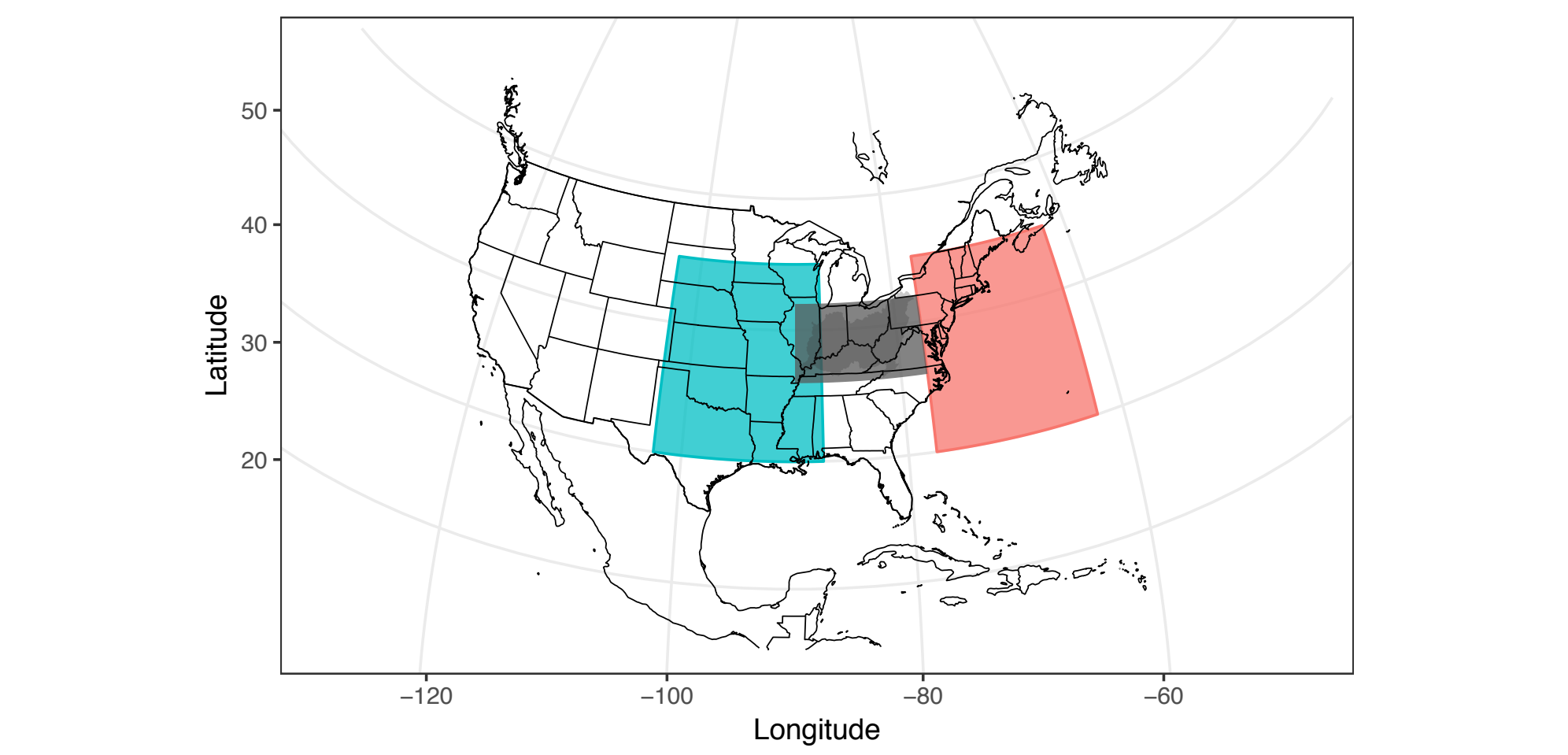


Figure 5: The regions of low and high pressure defining the Eastern U.S.-Western Atlantic Dipole index (EWD), and the region defining the moisture holding capacity index.

- ▶ Define Eastern U.S.-Western Atlantic Dipole (EWD) index: average of high pressure box (red) minus low pressure box (green) (fig. 5)
- ▶ Define moisture-holding capacity (MHC) index using average temperature (brown; fig. 5) $MHC_t = 6.1 \exp \left[\frac{17.67T}{T+243} \right]$
- ▶ CM3 reasonably simulates the distributional (fig. 6) and persistence (not shown) features of two atmospheric indices that modulate the likelihood of RIP events

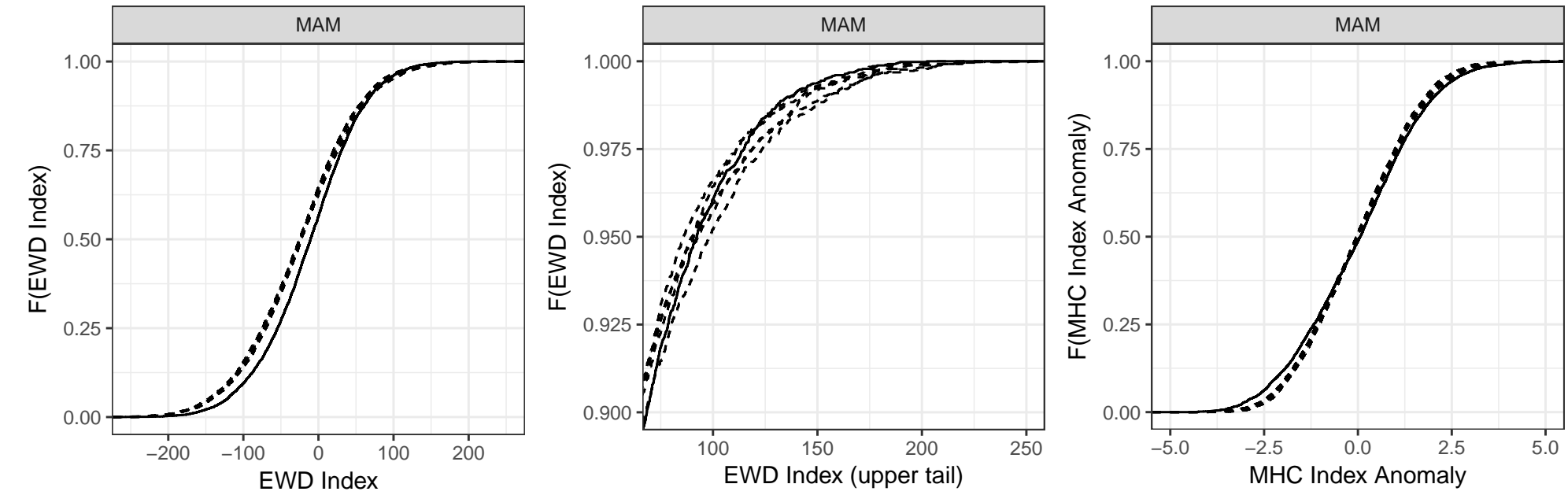


Figure 6: (Left) Cumulative distribution function for the reanalysis based dipole (solid line) and the GFDL GCM ensemble members based dipole (dashed lines) for MAM. (Middle) The positive tail of (Left). (Right) Same as (Left) for the moisture holding capacity.

Conditional Simulation

- Goal: condition the RIP events (poorly represented in CM3) on EWD and MHC indices (better represented in CM3). Assume:
- ▶ Linear model for EWD and MHC indices
 - ▶ MHC is secondary: if $EWD < 0$, do not consider MHC
 - ▶ Logistic regression model: $p(RIP_t) \sim f(EWD_t, MHC_t)$
 - ▶ Fit model on reanalysis temperature and pressure fields, and observed RIP events
 - ▶ Simulate from model using CM3 temperature and pressure fields
- Comparing fig. 7 with fig. 2, we see a marked improvement in model skill by conditioning on large-scale circulation features

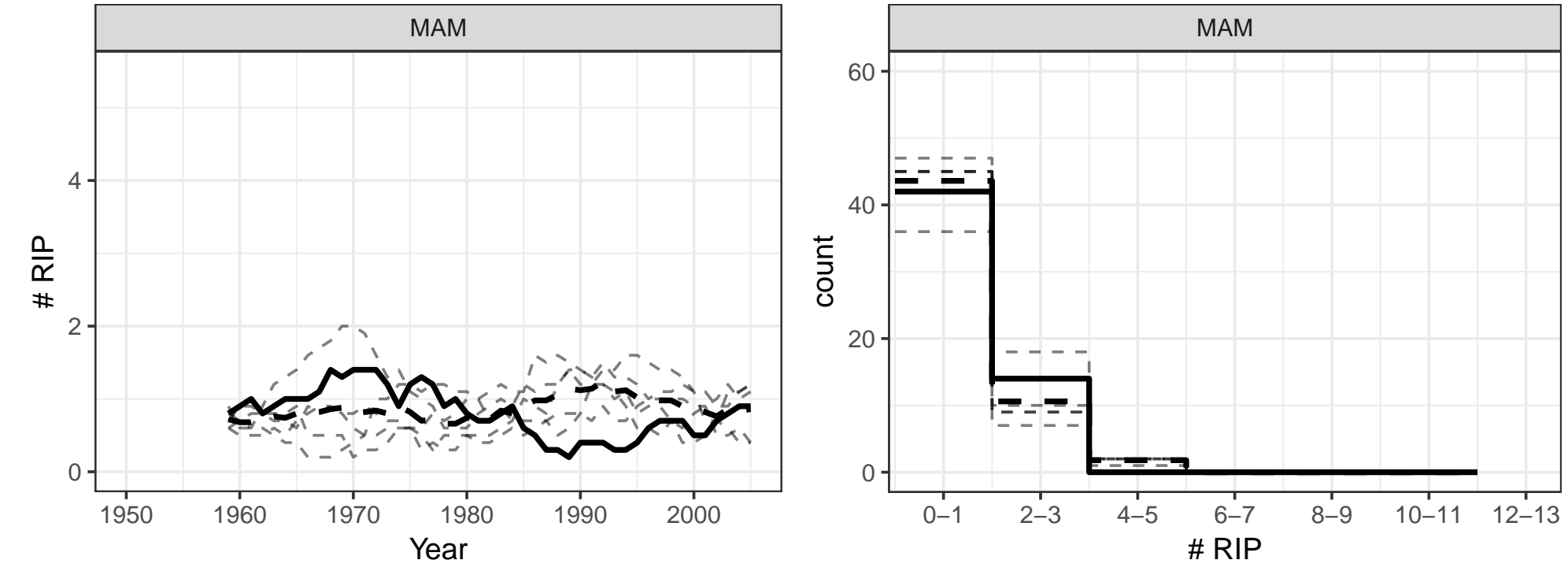


Figure 7: (a) 10-year moving average of the number of MAM RIP days by year for the observed record (black solid line), the five conditional simulated RIP days. (b) Counts for the number of MAM RIP days by year for the observed record (black solid line), the five conditional simulated RIP records based on the GFDL CM3 ensemble member's geopotential height and temperature fields (light dashed lines), and the ensemble mean (thick dashed line).

Future Simulations

- ▶ A conditional simulation model using GCM atmospheric circulation and temperature projections for 21st century shows increasing trends for such events and
- ▶ Conditional simulation model attributes increasing RIP events approximately 1/3 to circulation changes and 2/3 to temperature changes
- ▶ Results differ significantly from RIP events based only on MAM precipitation field

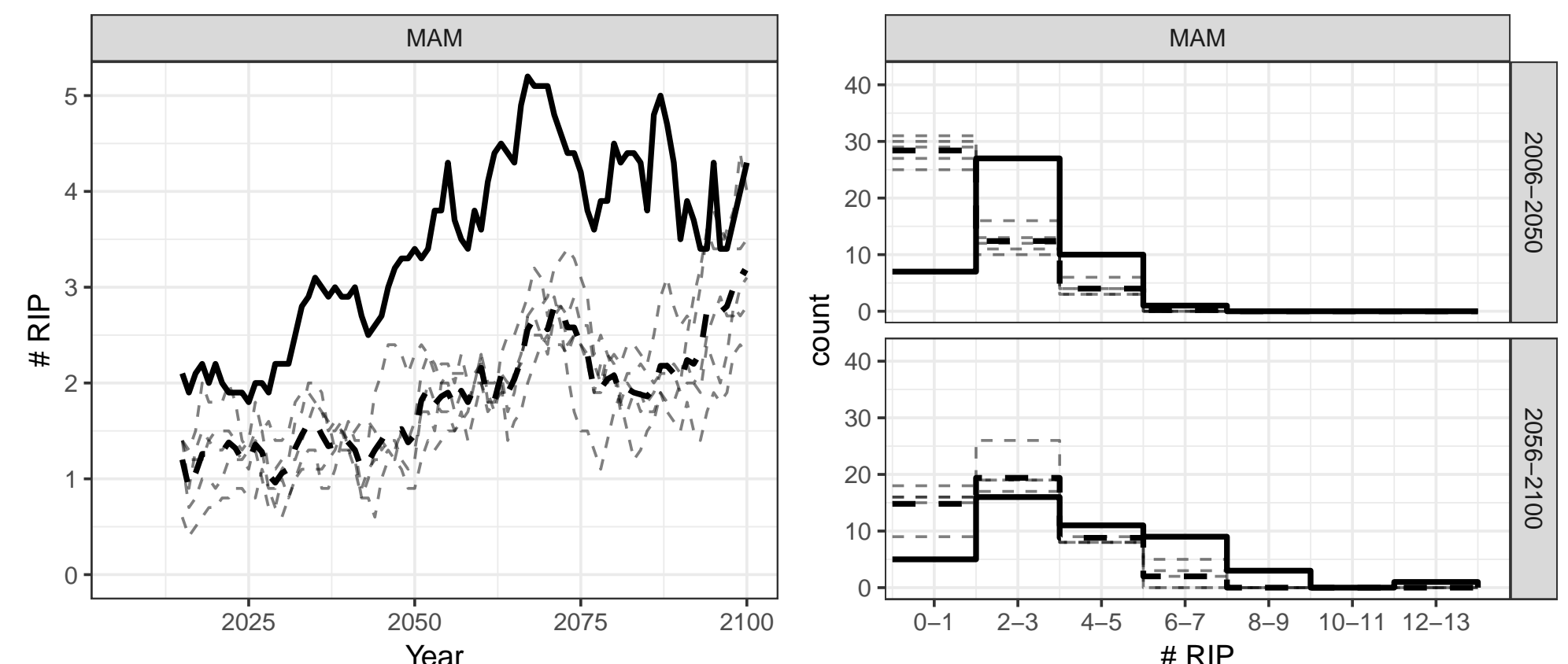


Figure 8: (Left) 10-year moving average projections from 2006 to 2100 of MAM RIP counts by year from CM3 precipitation field (black solid line), conditional simulation based on CM3 temperature and pressure fields (light dashed lines show five simulations based on the one ensemble field and the dark dashed line shows the mean of these simulations). (Right top) Distribution of RIP counts by year for 2006-2050. (Right bottom) As (Right top) but for 2056-2100.

Summary

- ▶ Recurrent atmospheric circulation patterns that correspond to regional intense precipitation events in the Ohio River Basin are identified
- ▶ GCM biases in predicting regional intense precipitation frequency are largely overcome by conditioning these events on GCM atmospheric circulation patterns
- ▶ GCM frequency bias in RIP record appears a manifestation of inflated spatial correlation of high intensity precipitation

This *framework for conditional simulation* is an alternative to grid-scale statistical downscaling

Next Steps

- ▶ Increase complexity of statistical model
- ▶ Sub-seasonal to seasonal predictors of RIP activity (i.e. PNA)
- ▶ Assess other models

This *framework for conditional simulation* is a robust alternative to grid-scale statistical downscaling

References

- [1] IPCC. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. 2012.
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Acknowledgements

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