

Quantifying nonstationary extreme rainfall for resilient stormwater design in Calvert County

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Temperature & Precipitation

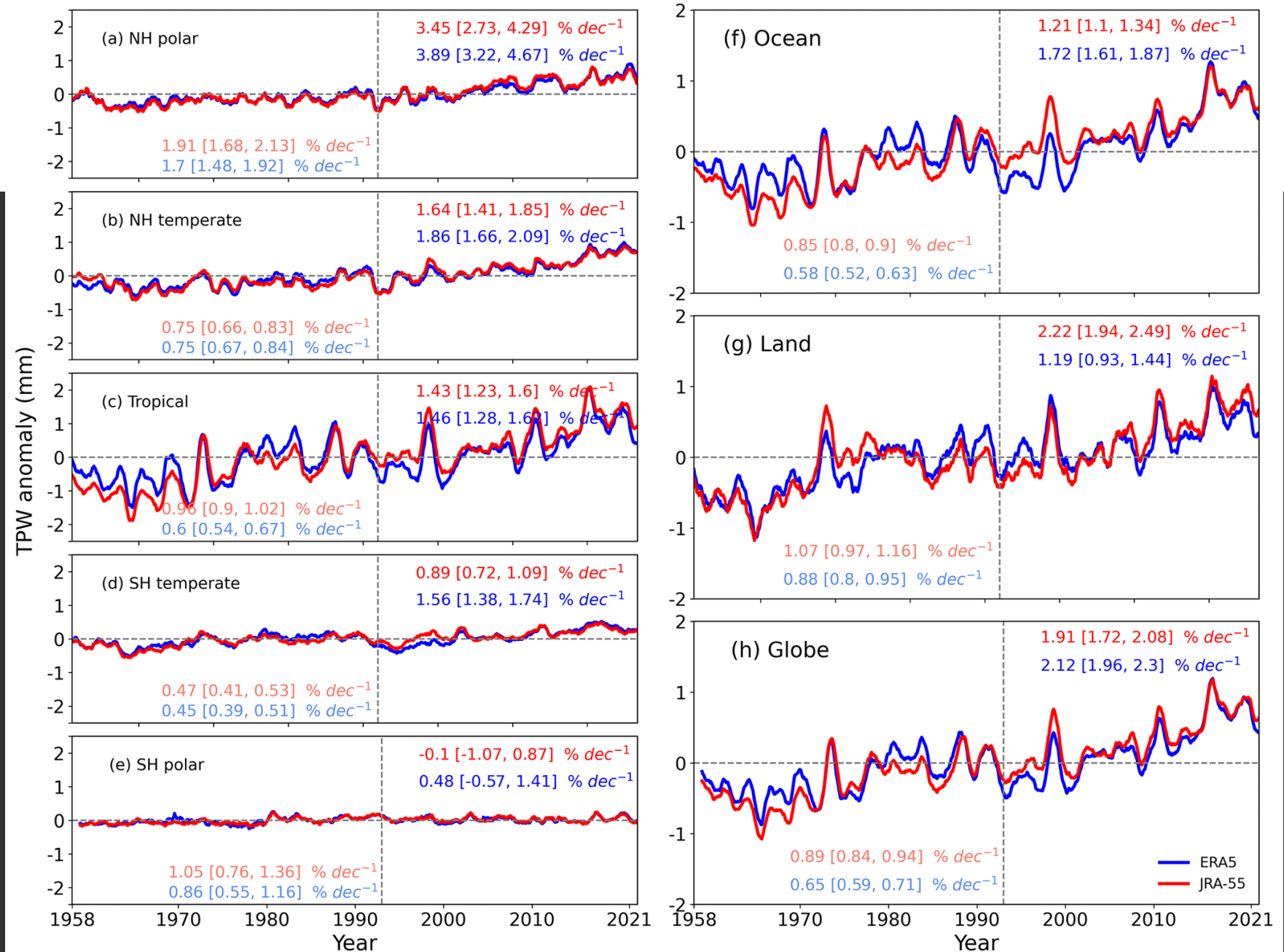
Global temperature has been increasing.

A warmer atmosphere holds more water.

The amount of moisture in the atmosphere available for precipitation has also increased.

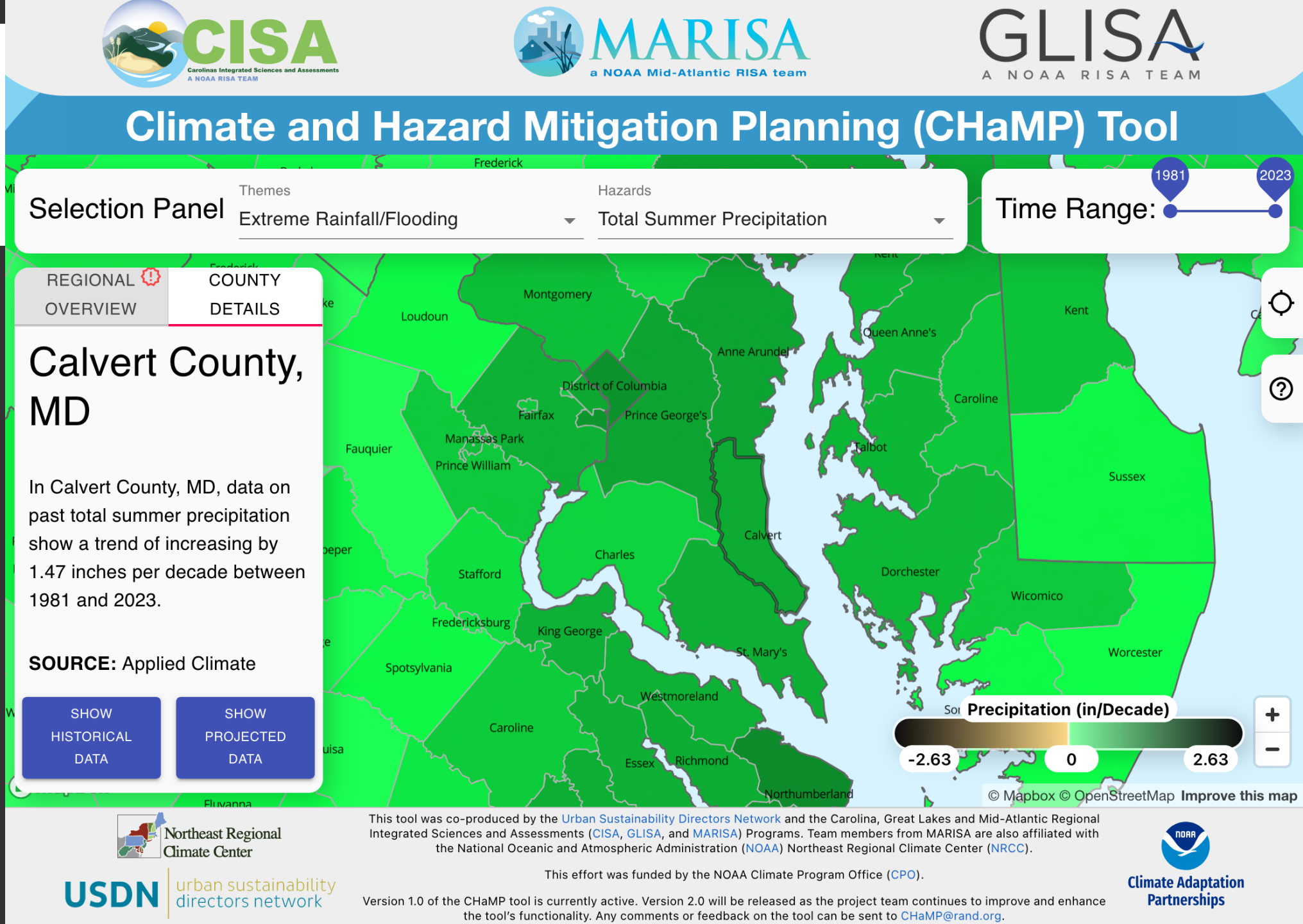
Wan et al 2024

Global Precipitable Water Trends



Local Trends

- Summer rainfall has strongest trend.
- Summer rainfall totals +1.47 in per decade.
- Our summer rains are mostly thunderstorms



Recent Impacts of Extreme Rainfall in Calvert County



Ox Cart Road in Huntingtown after hurricane Isaias, 2020.



North Beach July 26, 2018
Photo credit: Amy Elliot (SOMD News)

The Challenge of Changing Rainfall

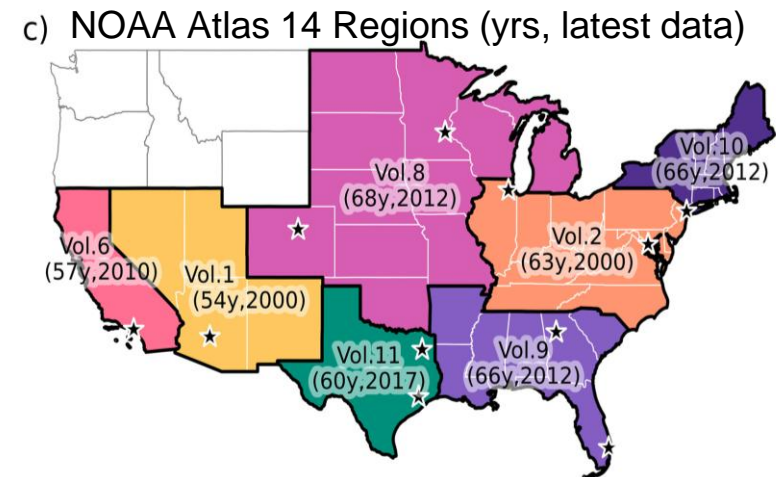
Problem: Escalating impacts of climate change on extreme rainfall events

Traditional Approach: Stormwater infrastructure designed based on historical data (e.g., NOAA Atlas 14)

Reality: Historical records are increasingly insufficient due to:

- Increased frequency and intensity of extreme rainfall
- New weather extremes set annually

Consequence: Underestimation of risk, inadequate local planning, and challenges for the insurance industry



The Problem: Nonstationary Risk & Pluvial Flooding

Climate-Driven Intensification: Mounting evidence of flood intensification

Pluvial Flooding: Flooding from excessive rainfall overwhelming drainage

- Often underestimated and inadequately mitigated
- Major cause of U.S. flood insurance claims (1978-2021 data)

Exacerbating Human Factors

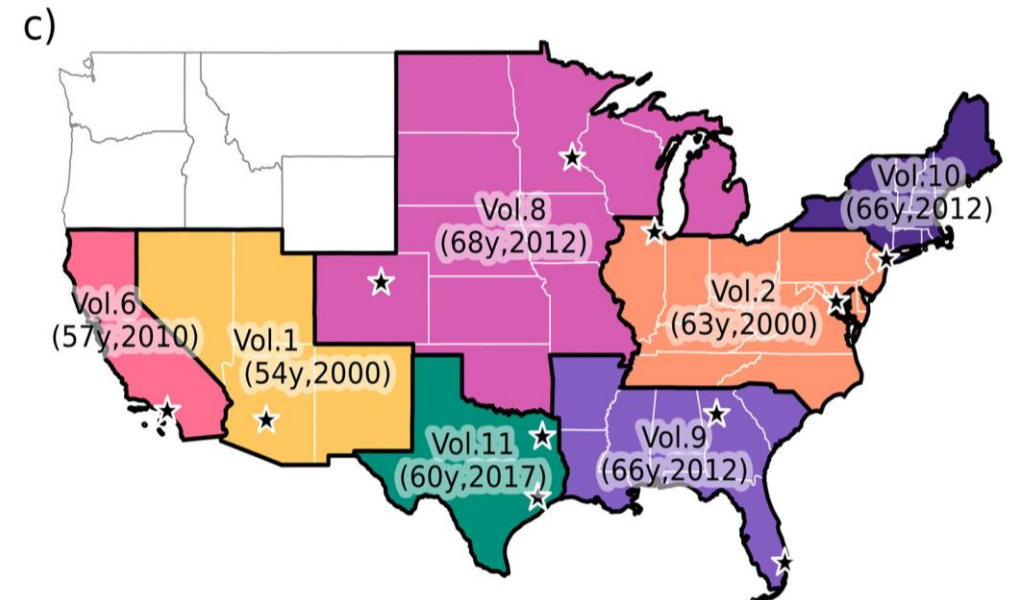
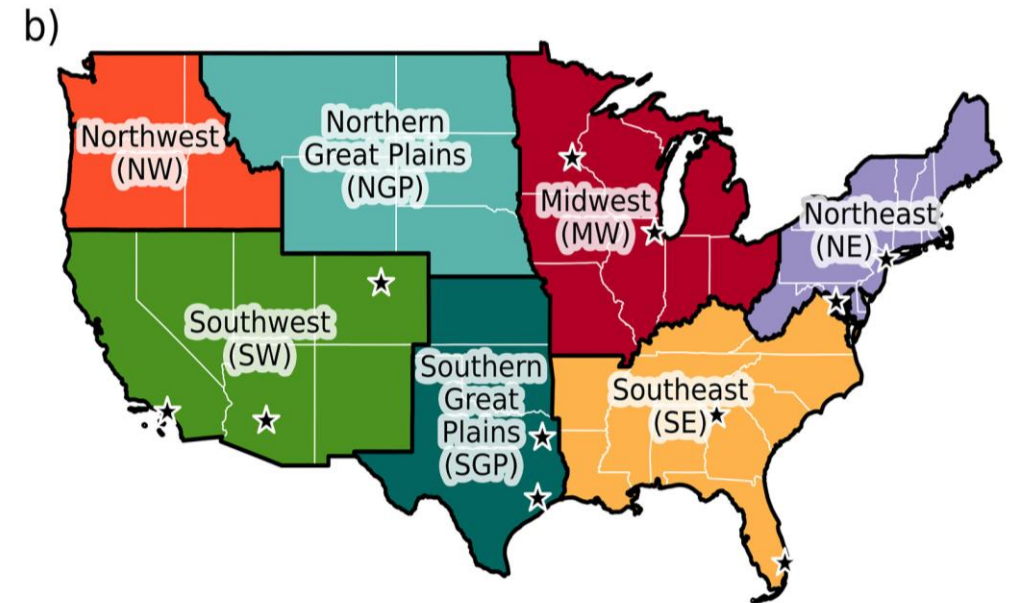
- Increased Impervious Surfaces: Reduced infiltration, enhanced runoff
- Inadequate Stormwater Infrastructure: Catastrophic failures (e.g., Hurricanes Katrina, Harvey, St. Louis 2022)
- Climate Warming: Directly increases rainfall rates and pluvial flooding frequency

How do we adjust?

- **Update the data more frequently.**
 - Atlas 14 IDF curves used by many entities in the US are outdated
 - Atlas 15 is in process for the entire US with updated methods and data
- **Use projections of current and expected conditions to estimate design thresholds.**
- **Scale existing guidance up by some factor – depends on:**
 - How we think future changes will develop (largely dependent on GHG policies and implementation).
 - Different models and analysis techniques give slightly different results.
 - The timeline of the project (how long in the future do we build for).
 - Risk of failure (high consequence of failure projects need lower probability of failure designs).

Scales of the problem: Atlas 14

- Atlas 14 is what we still have in most local ordinance.
- It did not include the northwestern states.
- It generally used ~60 years of data
- The most recent data in our region are from 2000.



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Atlas 15

- Brings the analysis into the 21st century digital data world.
- Seamless national analysis instead of regional.
- Updated every 10 years.
- Includes best available projections of future IDF.
- Enhanced digital availability of data.

Website: <https://www.weather.gov/owp/hdsc>

Email: hdsc.questions@noaa.gov

Locations: Tuscaloosa, AL – Silver Spring, MD – Chanhassen, MN



OWP OFFICE OF WATER PREDICTION

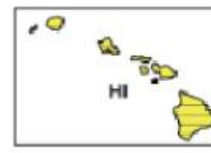
NOAA ATLAS 15:

Update to the National Precipitation Frequency Standard



NOAA is recognized by the engineering and floodplain management communities as the authoritative source of precipitation frequency data, and has a long history of generating these data that serve as the foundation for built infrastructure nationwide.

The [National Weather Service \(NWS\) Office of Water Prediction \(OWP\)](#) has produced an authoritative atlas of precipitation frequency estimates, published as volumes of the NOAA Atlas 14 Precipitation-Frequency Atlas of the United States. These estimates are currently posted on the NOAA [Precipitation Frequency Data Server \(PFDS\)](#), with interactive tables and charts. Precipitation frequency estimates are defined as the precipitation depth at a particular location, for a given storm duration, that has a statistically-expected 1-in-YY chance of being exceeded in any given year, where YY is the statistical annual recurrence interval.



NOAA Atlas 14 estimates are used to design, plan, and manage much of the Nation's infrastructure for a wide variety of purposes under federal, state, and local regulations.

NOAA Atlas 14 estimates replace estimates previously published by NOAA in the early 1960s and '70s and cover a range of storm durations from 5-minutes through 60-days, for average recurrence intervals of 1-year through 1,000-year. Compared to previous volumes

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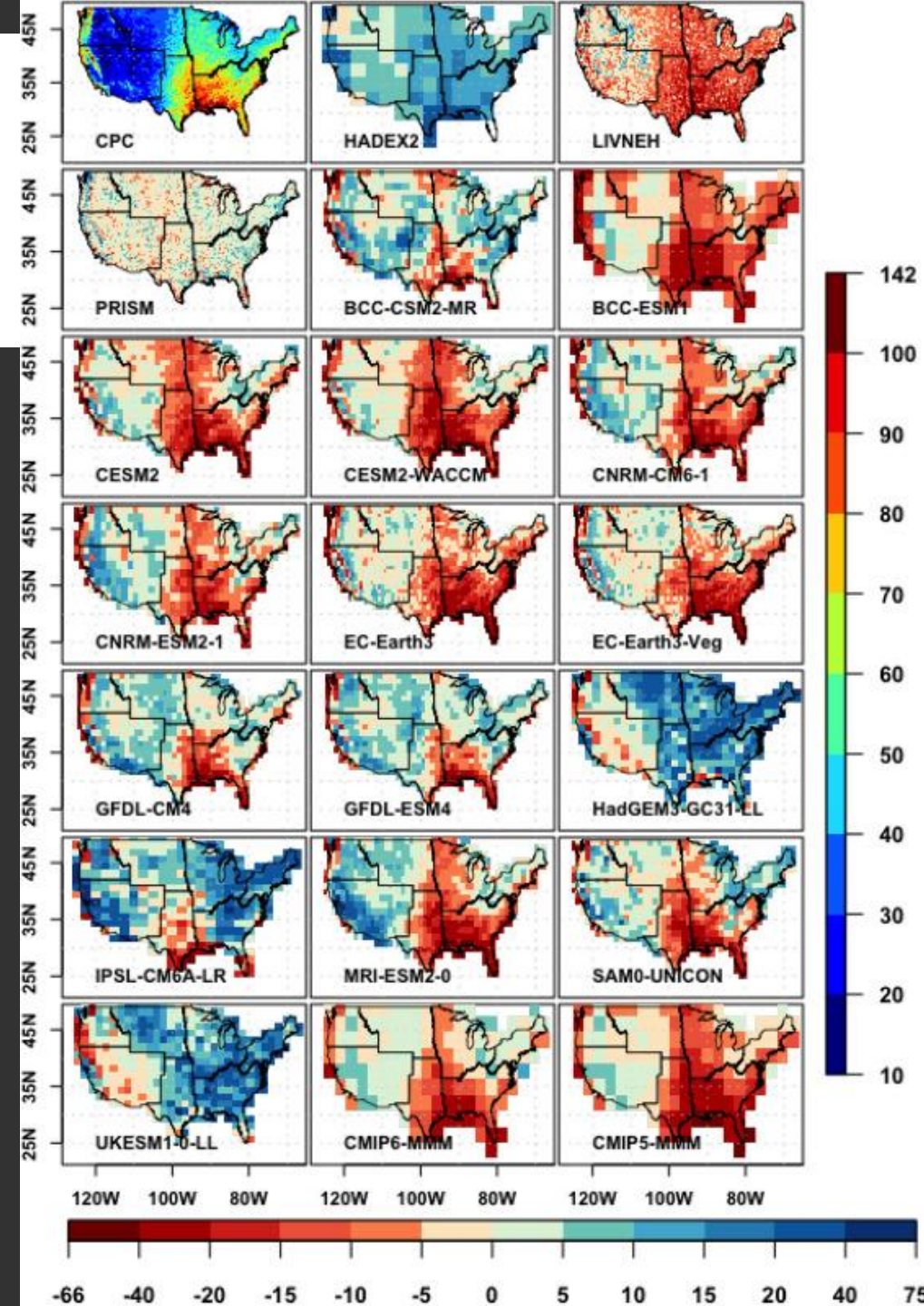
All models are wrong, but some are useful



G. E. P. Box

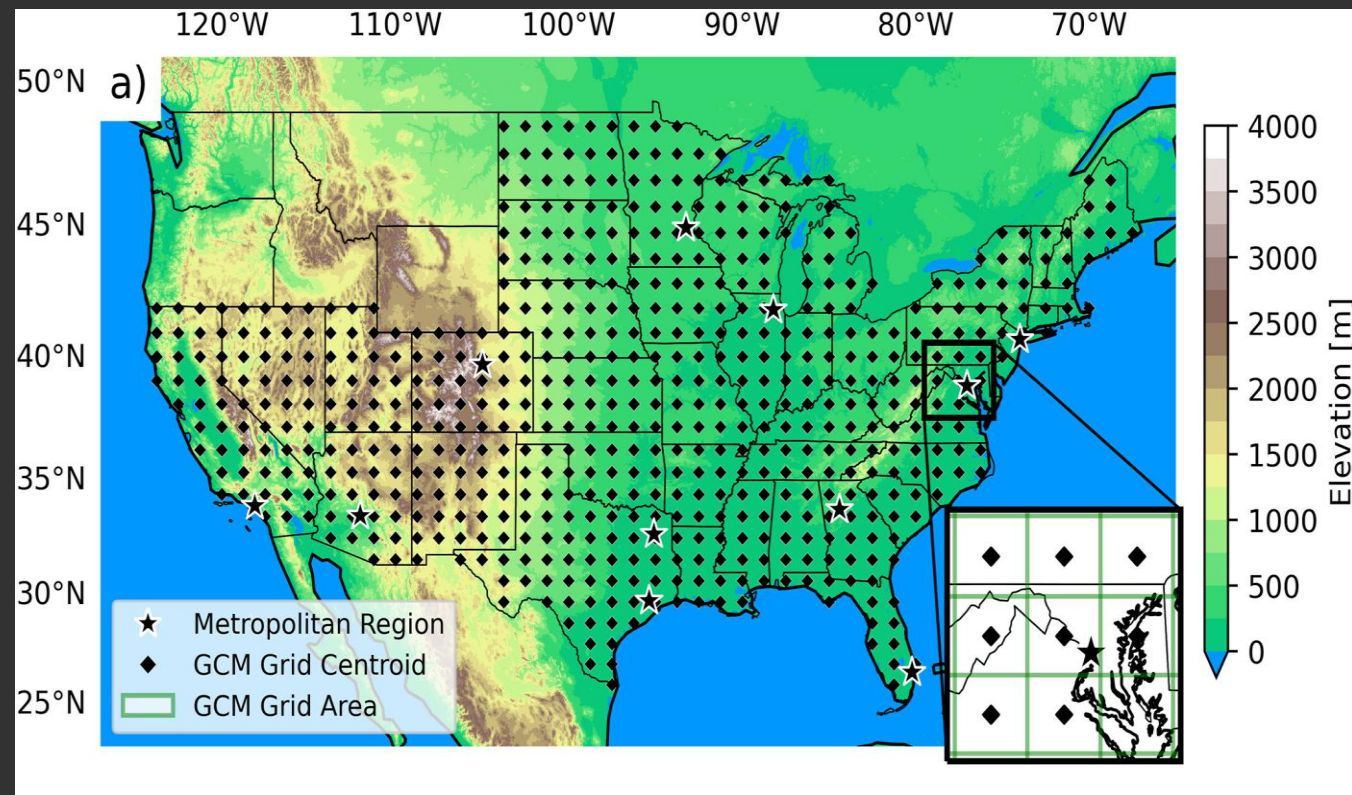
- Different global climate prediction models have different biases in their extreme rainfall.
- Most have a low-bias in the East and Southeast, where convective rainfall is a substantial source of extreme rain and a cause of recent trends.
- Summertime convective rain (thunderstorms) have to be parameterized at this scale.

Fig. 6. Bias in the 1981–2005 time mean of bias in annual maximum 1-day precipitation amount (Rx1day). The first panel shows mean annual maximum 1-day precipitation in the reference (CPC) dataset on its native $0.25^\circ \times 0.25^\circ$ grid and uses the color scale along the right edge of the figure. The other panels show bias (dataset minus CPC) on each dataset's native grid and use the color scale along the bottom edge of the figure. Units are in mm/day. Srivastava et al., 2020 (<https://doi.org/10.1016/j.wace.2020.100268>)



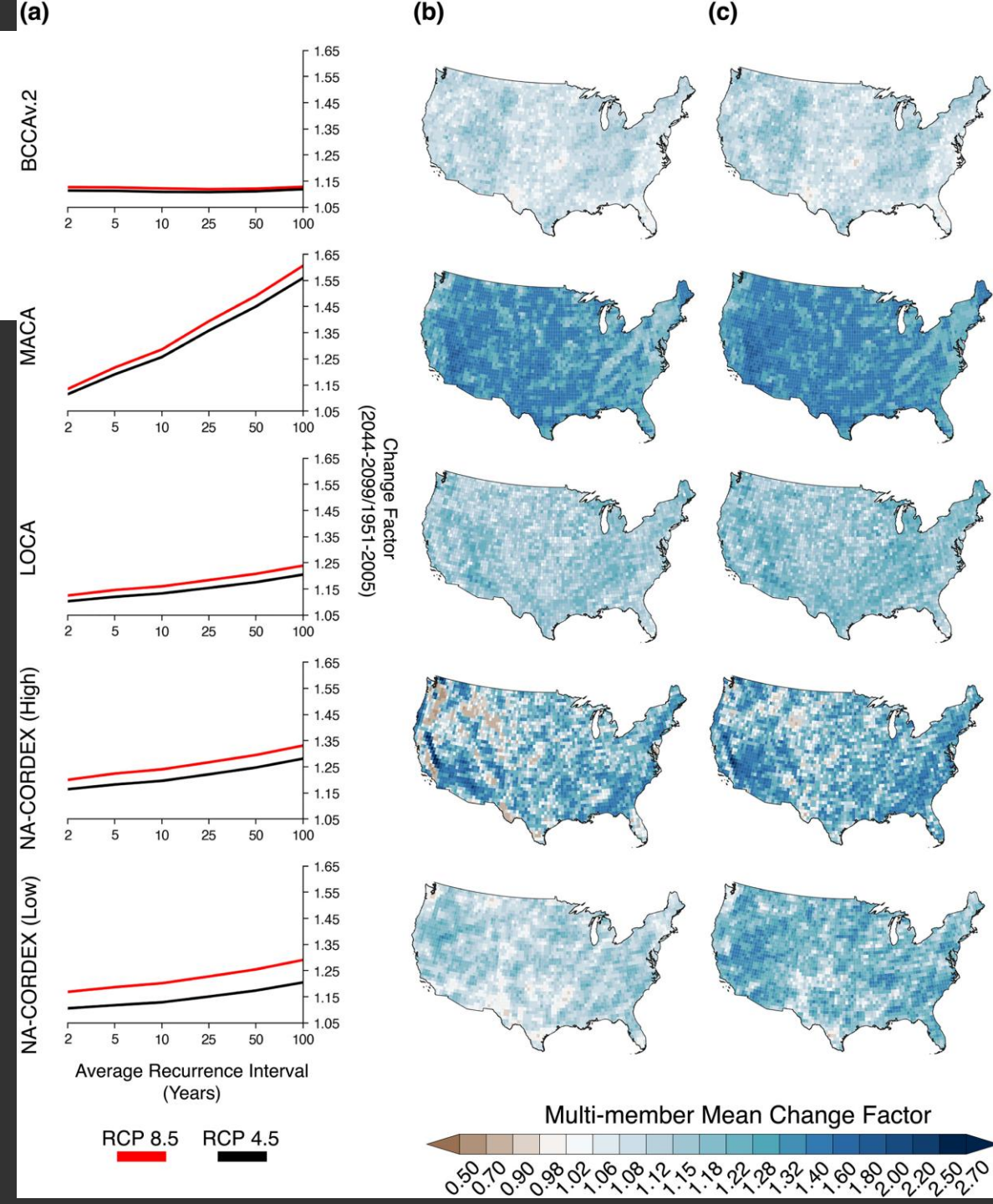
Scales of the problem: GCM

- The grid for global scale models is coarse.
- Grid boxes sometimes average physiographically different locations.
- Thunderstorms are not dynamically modeled and thus don't respond dynamically to changing background conditions.



Uncertainties in Future U.S. Extreme Precipitation From Downscaled Climate Projections

- Dynamical and statistical downscaling of global GCM could be helpful.
- Extreme rainfall trends from different downscaled models differ a lot in both space and the frequency distribution of the rainfall.
- They also differ in their sensitivity to GHG forcing.



Convection Permitting Model Projections: Weather Model Run with Future Conditions

- Model run 13 yrs with modern background conditions based on obs 2001-2013.
- Model run 13 yrs with background conditions based on CMIP6 2070-2100, RCP8.5 (business as usual).
- Difference maps indicate future:
 - Mostly wetter conditions
 - Summertime drying in the moderate rainfall
 - More extreme rainfall.

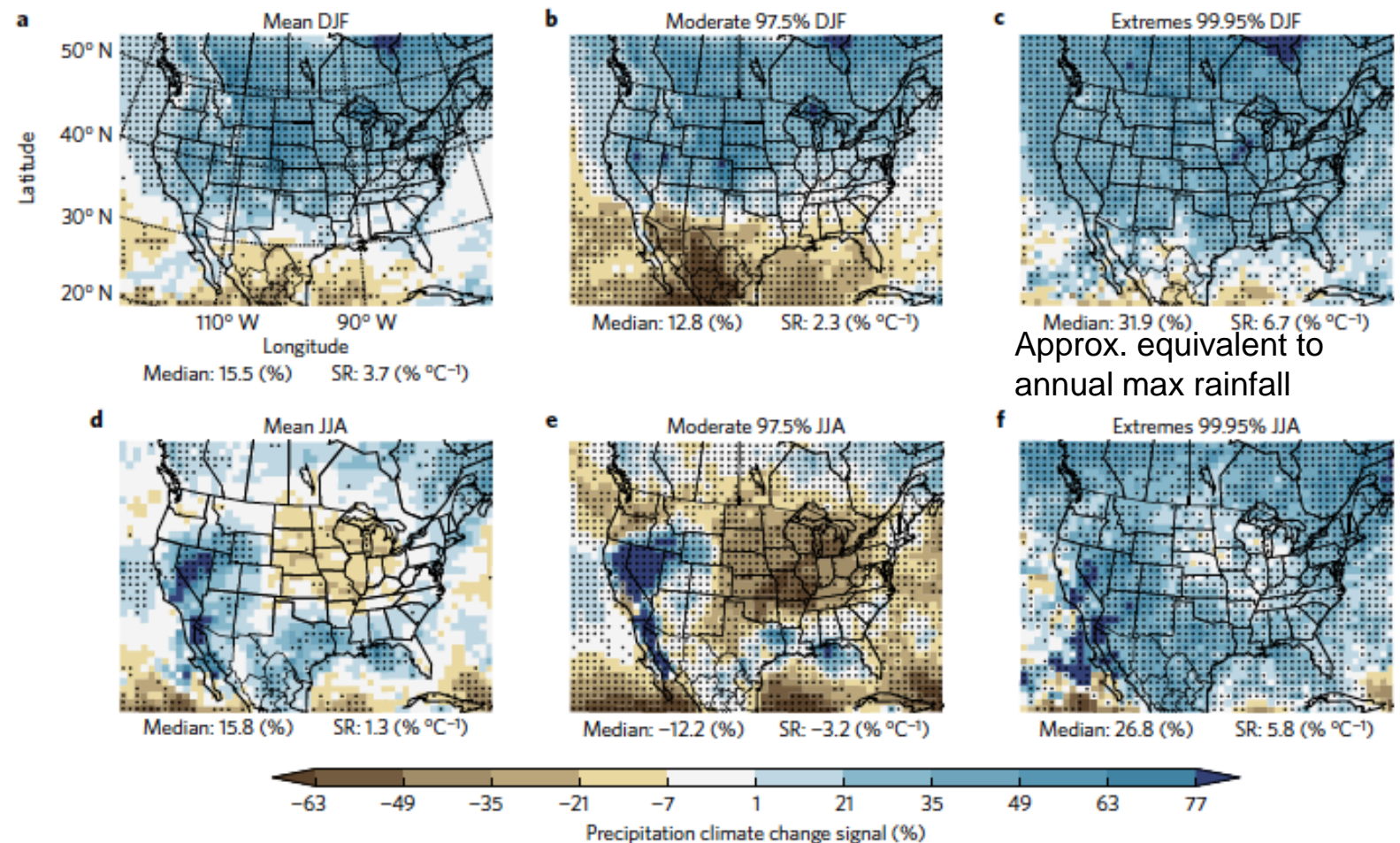


Figure 1 | Hourly extreme precipitation is increasing in the majority of the domain, while mean and moderate intense precipitation are substantially decreasing in large areas. Relative changes are shown for averages of 25×25 grid boxes ($\sim 100 \text{ km} \times \sim 100 \text{ km}$) to improve the signal-to-noise ratio for mean (a,d), moderate (97.5th percentile; b,e), and extreme precipitation (99.95th percentile; c,f). The spatial median change and average scaling rate (SR; precipitation change divided by seasonal mean temperature change) are shown below each map. Results are shown for December, January and February (DJF) (a-c) and June, July and August (JJA) (d-f). Dots highlight regions with significant changes. The investigated period is January 2001 to September 2013.

Summary and Scientific Motivation for this Project

- Our local rainfall trends are from convective activity (thunderstorms)
- How well do the downscaled models capture summer thunderstorms?
 - Not a strong point
- What tool do we have available that does capture summer thunderstorm physics?
 - Super high resolution models (essentially weather models)
- Does a high resolution model capture recent rainfall patterns and are the projections of future rainfall in the model different from more standard projections?

Project Objectives

1. **Assess Trends:** Evaluate trends in heavy rainfall statistics relevant for stormwater management designs in Calvert County
2. **Suggest Modifications:** Propose revisions to design thresholds by incorporating the most recent regional climate dynamics and uncertainties
3. **Overall Goal:** Enable Calvert County to adjust regulatory standards, thereby reducing flood risks and impacts

Data Sources: A Multi-Dataset Approach

Purpose: Combine historical records with future projections to assess trends

1. NOAA Global Hourly Precipitation (ISD DSI-3505)

Station-based hourly time series (1945–2023); from Calvert, Anne Arundel, St. Mary's Counties; used for long-term trend analysis (24-hour rainfall maxima)

2. NOAA Atlas 14 Annual Maxima

Cleaned and processed historical data (1892–2000); also from the 3 counties; used to assess differences with future expectations using the same IDF estimation methods

3. NASA IMERG Product

Satellite-derived, ground-truthed gridded precipitation (2001–2022); 30-minute temporal, 0.1° (10 km) spatial resolution; represents recent observational period

4. Convection-Permitting Model (CPM) Control Run

Highly-resolved (1-hour, 4 km) historical simulation (2000–2013); baseline for bias correction and comparison with observations. **Novel component:** Explicitly includes thunderstorms

5. CPM Climate Projections (RCP 8.5)

"Business as usual" climate trajectory (average conditions over 2071–2100); used for future rainfall estimates

Methods: Statistical Trend Assessment

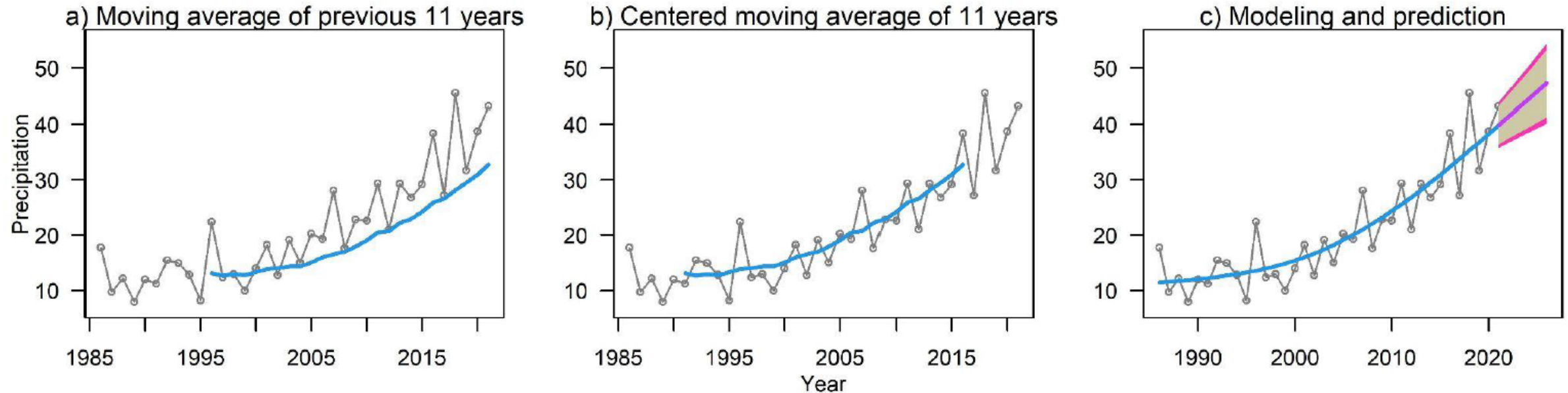


Fig. 1: *In the presence of a trend, (a) aggregation over the past several years lags behind the true risks; (b) centered moving average correctly represents the tendency but fails to represent the most recent years or provide forecasts; (c) statistical tools and climate projections can be used to model dynamics of the risk and provide forecasts.*

Methods: Trend Assessment in Observational Data

1. Generalized Additive Model for Location, Scale, and Shape (GAMLSS) with Generalized Extreme Value (GEV) distribution

$$Precipitation_t \sim GEV(\mu_t, \sigma_t, \nu_t)$$

$$\log(\mu_t) = a_0 + s_1(Year_t)$$

$$\log(\sigma_t) = b_0 + s_2(Year_t)$$

$$\log(\mu_t) = a_0 + a_1 Year_t$$

$$\log(\sigma_t) = b_0 + b_1 Year_t$$

$$\log(\sigma_t) = b_0$$

2. Nonparametric Mann–Kendall Test (Sieve-Bootstrapped)
 - Tests for monotonic trend, accounting for autocorrelation
 - AR(p) model filters autocorrelation; residuals are bootstrapped

Methods: Bias Correction of Climate Model Output

Purpose: Match the distribution of observed precipitation and climate model output for the same period

- Enables accurate estimation of future climate dynamics

Method Selection: 10-fold cross-validation using NASA (observed) and CPM control run (model) hourly precipitation (2001–2012)

Quantile Mapping Methods Assessed

- PTF (Parametric Transformations): Exponential tendency to an asymptote
- DIST (Distribution Derived): Bernoulli-Gamma mixture distribution
- QUANT / RQUANT (Nonparametric Quantile Mapping): Empirical and robust empirical quantiles
- SSPLIN (Smoothing Spline): Smoothing spline fit to quantile-quantile plot

Evaluation Criteria: Smallest Mean Absolute Error (MAE) and Root Mean Square Error (RMSE)

Methods: IDF & DDF Estimation and Uncertainty Quantification

Fit a **Generalized Extreme Value (GEV)** distribution to the annual maxima for each duration

- **DDF Curves:** Calculate return levels for durations and return periods (2, 5, 10, 25, 50, 100 years)
- **IDF Curves:** Derived from DDF curves by adjusting return levels for intensity

Uncertainty Quantification (Bootstrap Procedure)

- **Resampling:** Resample spatial grid cells with replacement 1000 times
- **Re-estimation:** Re-estimate IDF and DDF curves (fitting GEV) for all durations on each dataset
- **Confidence Intervals:** Calculate 2.5th/97.5th percentiles (95% CI) and 10th/90th percentiles (80% CI) from the distribution of estimated return levels

Results: Trend Model Selection

Table 1. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for GEV models with varying specifications for the location and scale parameters. The lowest (optimal) values for each criterion are highlighted in bold.

Location μ_t	Scale σ_t		
	Intercept-only $\log(\sigma_t) = b_0$	Linear trend $\log(\sigma_t) = b_0 + b_1 Year_t$	Nonlinear trend $\log(\sigma_t) = b_0 + s_2(Year_t)$
Linear trend $\log(\mu_t) = a_0 + a_1 Year_t$	723.11, 732.32	723.48, 735.00	718.54, 734.95
Nonlinear trend $\log(\mu_t) = a_0 + s_1(Year_t)$	716.03, 729.32	712.22, 728.75	712.65, 730.64

Results: Trend Assessment

Significant **increase in both magnitude and variability** of extreme precipitation over time

$$Precipitation_t \sim GEV(\mu_t, \sigma_t, \nu_t)$$

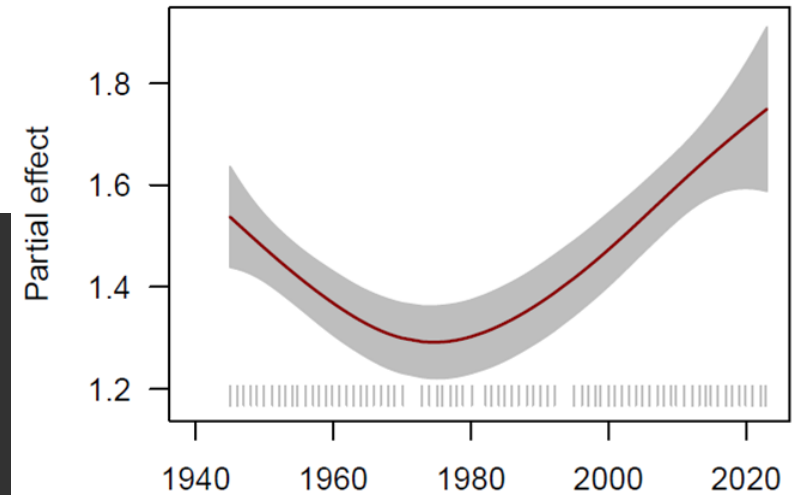
$$\log(\mu_t) = a_0 + s_1(Year_t)$$

$$\log(\sigma_t) = b_0 + b_1 Year_t$$

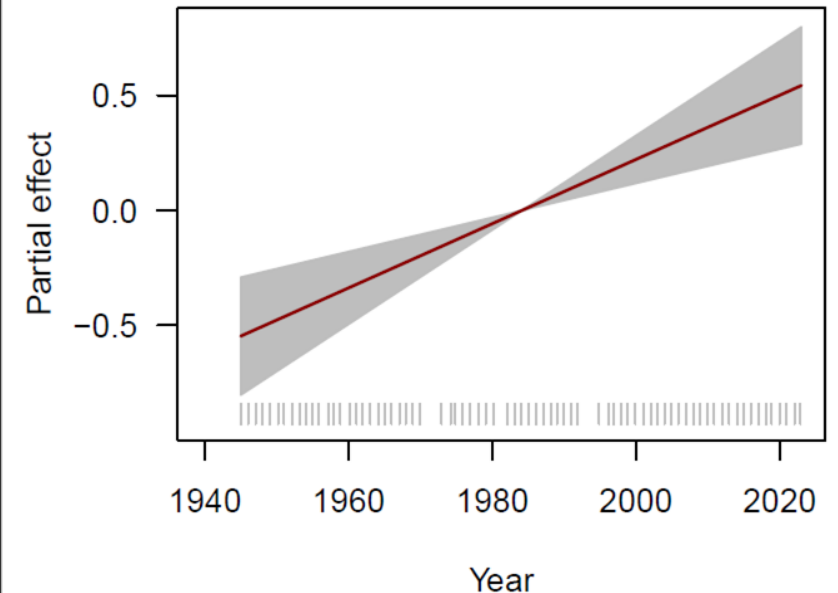
$$\nu_t = c_0$$

Sieve-bootstrapped Mann–Kendall test $\tau = 0.158$, with an associated p-value of 0.047 --> presence of a statistically significant monotonically increasing trend

A) Smooth term for the location parameter



B) Smooth term for the scale parameter



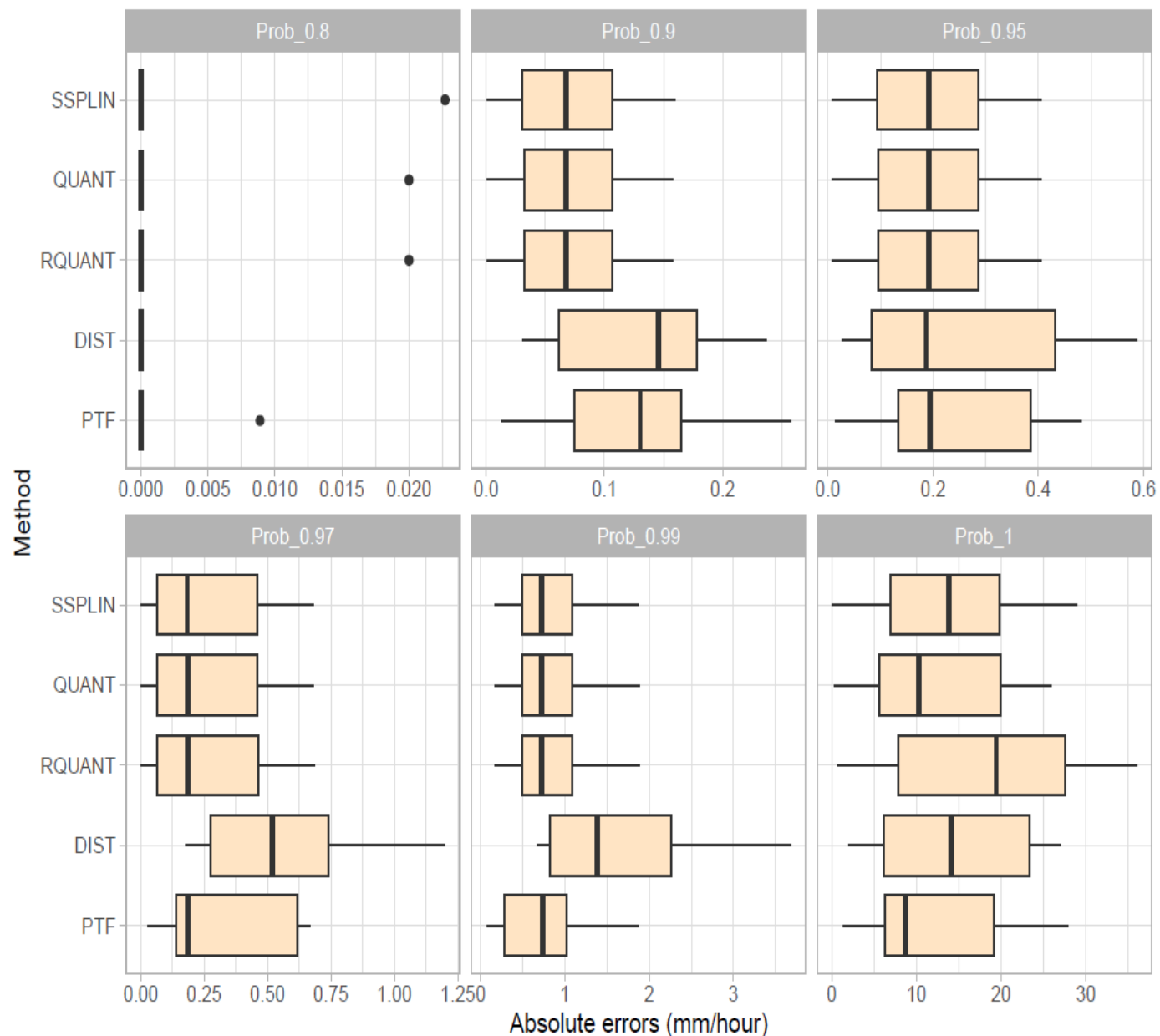
Results: Bias Correction

QUANT method consistently yielded the lowest MAE and RMSE

Verification: Trivial difference between NASA data and bias-corrected model control run quantiles in the 2001–2012 training period

Key Observation: For probabilities > 0.9 , bias-corrected control run quantiles were lower than observed quantiles from the full 2001–2022 NASA data

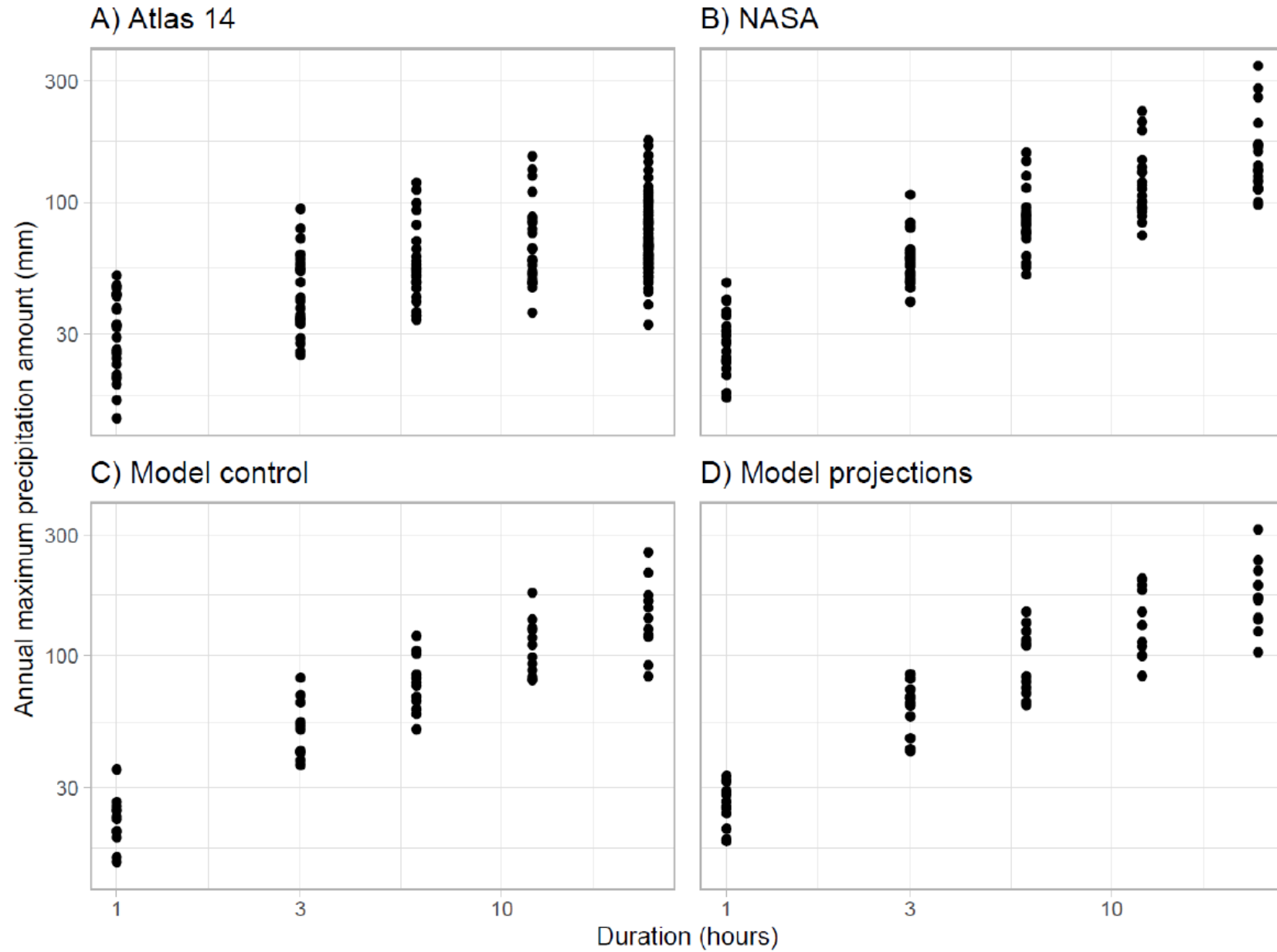
- Suggests an increase in extreme precipitation during 2013–2022, supporting trend inference
- Bias-corrected model projections show a further expected increase in the most extreme precipitation



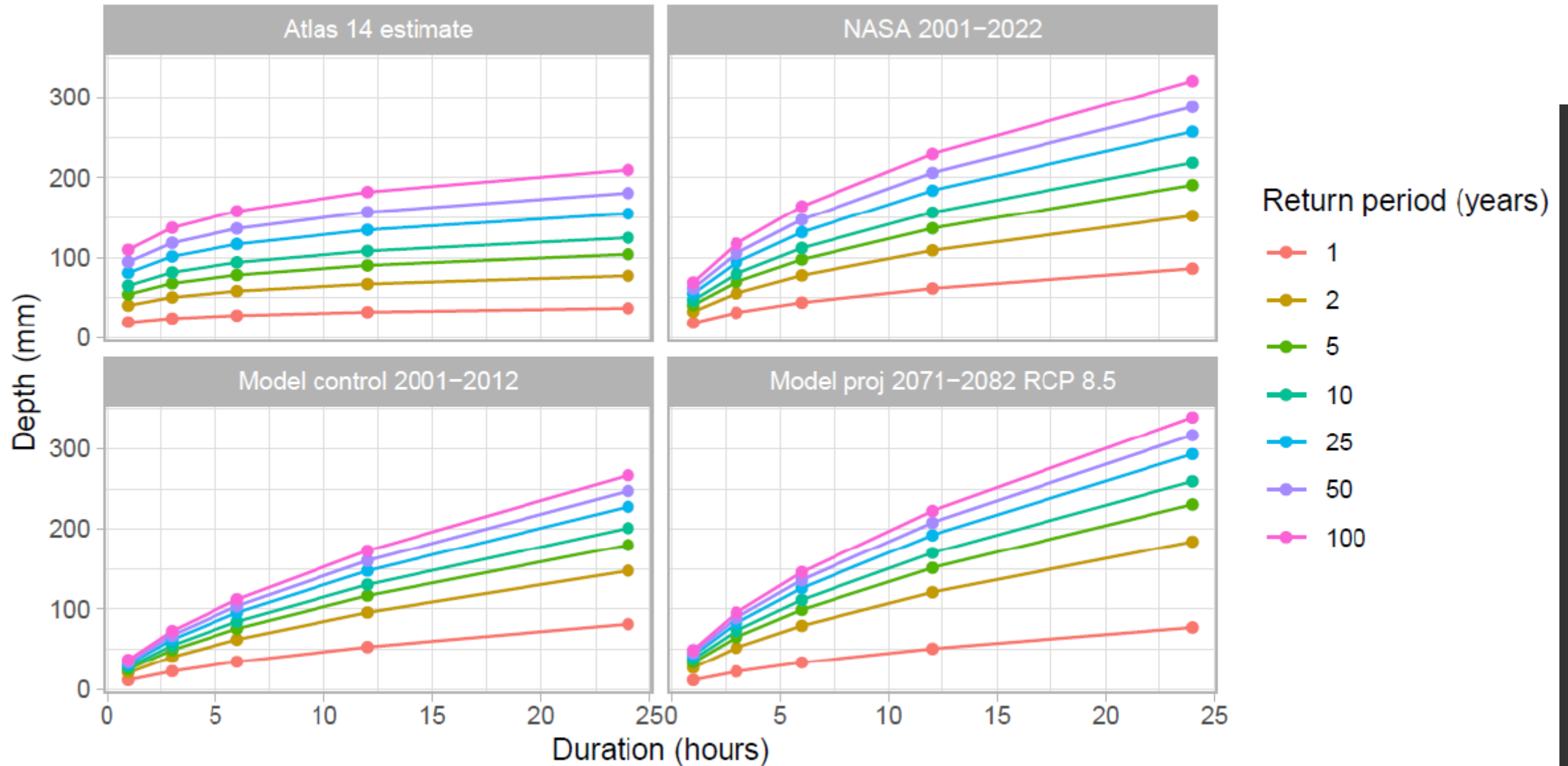
Results: Bias Correction Output

Probability	Observed quantiles (2001–2022)	Bias-corrected model control run quantiles (2001–2012)	Model projection quantiles (2071–2082)	Bias-corrected model projection quantiles (2071–2082)	Difference (Bias- corrected model projection – Bias- corrected model control run quantiles)
0.10	0.00	0.00	0.00	0.00	0.00
0.20	0.00	0.00	0.00	0.00	0.00
0.30	0.00	0.00	0.00	0.00	0.00
0.95	1.41	1.38	0.41	1.28	-0.10
0.96	1.98	1.94	0.66	1.87	-0.07
0.97	2.85	2.81	1.09	2.81	0.00
0.98	4.26	4.20	1.86	4.33	0.13
0.99	6.93	6.81	3.75	7.48	0.67
1.00	82.23	71.62	130.89	84.98	13.36

Results: Data for IDF and DDF Curves



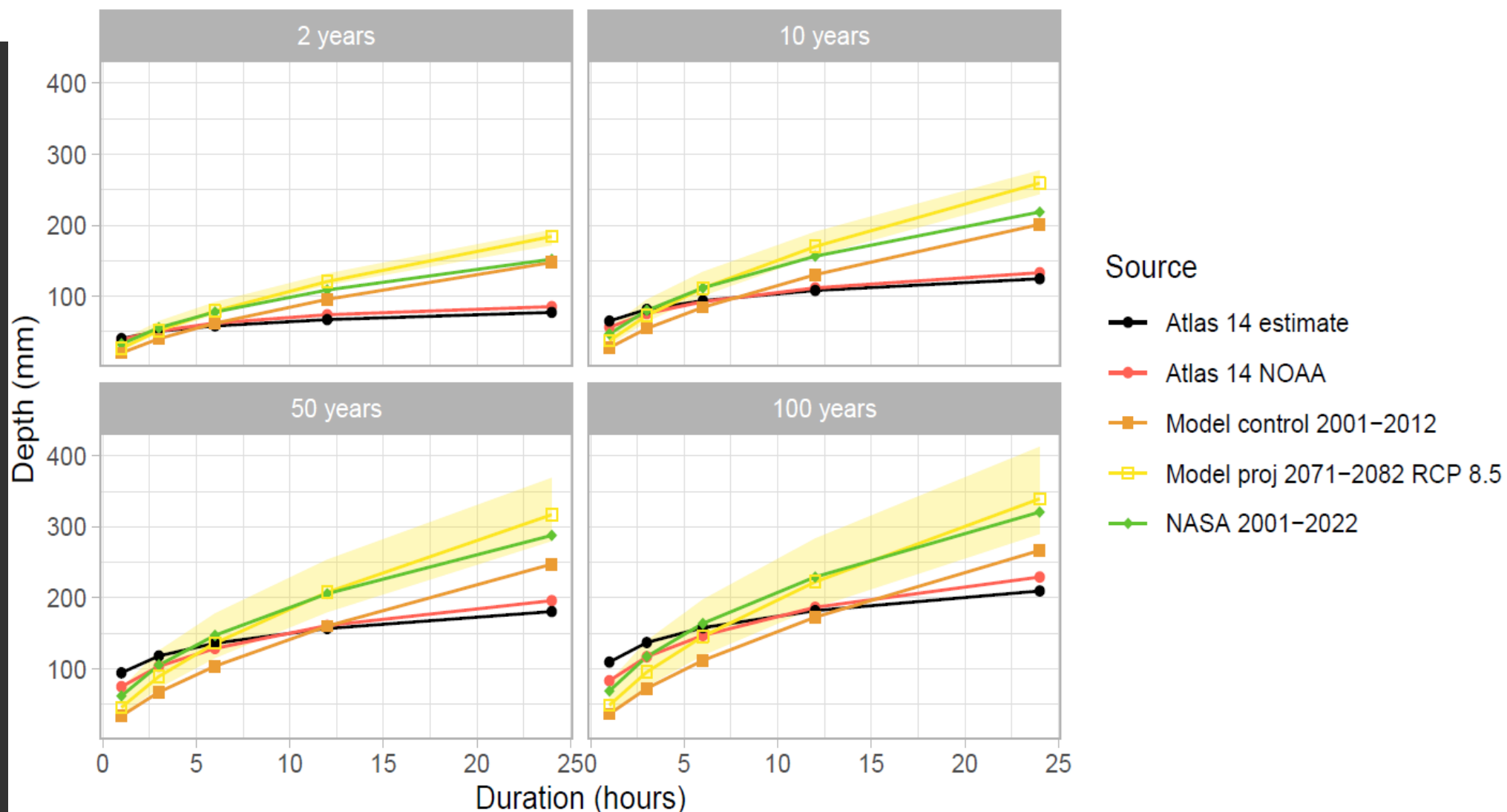
Results: DDF Curves



Results: IDF and DDF Curves

Estimates from **bias-adjusted model projections** are **consistently higher** than observed or control run data

Suggests a **clear pattern towards more extreme rainfall in the future**, warranting further exploration



Discussion: Key Insights

Consistency with Atlas 14: General consistency but notable differences at varying durations

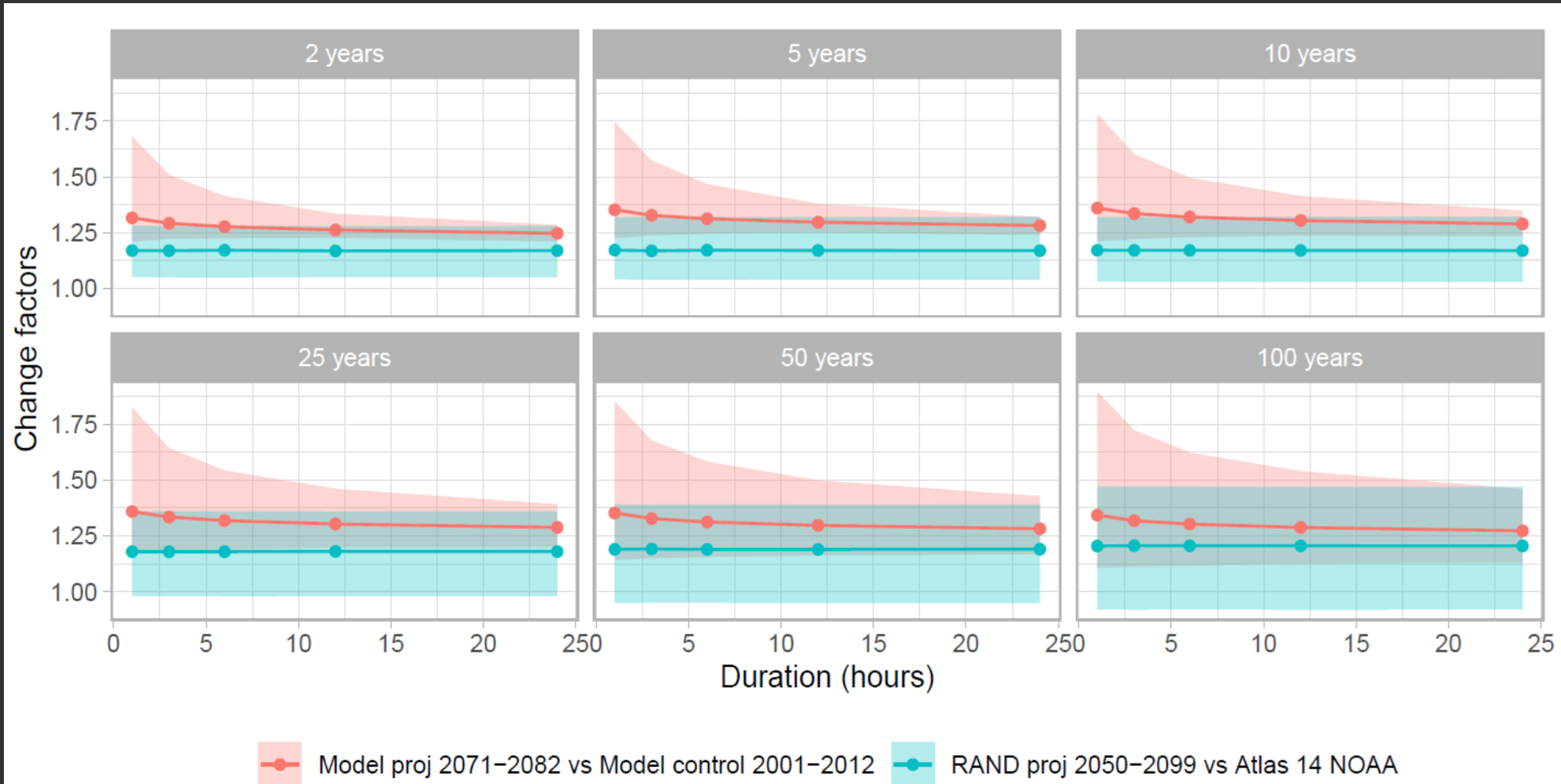
- Recent NASA data (2001–2022) show substantially steeper DDF curves for longer durations (12 and 24 hours) compared to historical Atlas 14 (pre-2000)
- Confirms nonstationary nature of extreme rainfall; historical records underestimate current conditions

Importance of Temporal Consistency: Bias correction effectively aligns quantiles over matched timeframes

- Comparisons must be done over the same period to avoid confounding temporal changes with other data differences

Discussion: Comparison with RAND Study

- RAND (lower-resolution, no convective precipitation): Median change factor of **1.18**
- Our study (CPM, accounts for convection): Median change factor of **1.30**
- Our study's 80% confidence intervals consistently remain above 1, suggesting a consistent increase in rainfall



Conclusion & Future Directions

Key Findings Confirmed: Recent extreme rainfall in Southern Maryland significantly exceeds 20th-century levels, and high-resolution models project even greater future intensities

- Underscores nonstationary nature of extreme precipitation
- Highlights inadequacy of historical Atlas 14 data for stormwater management design

Implications for Risk Management

- Quantitative estimates of current and future risk dynamics are crucial for actuaries and the public
- Current property insurance contracts should integrate up-to-date estimates to maintain viability
- Estimated trends should compel insurers to adjust future products and advocate for climate mitigation

Broader Applicability

- This project offers a science-based template for other jurisdictions nationally
- Fosters dialogue on adopting new methods for developing regulatory standards and risk reduction strategies that explicitly account for projected climate change

Thank you!

Questions?