



# Large-sample, high-resolution climate model data sets and flood modeling (rainfall runoff) of warm season floods in mountainous terrain

NASEM Workshop: Extreme Rainfall in Mountainous Terrain: Modeling and observational challenges for warm-season precipitation

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# Introduction

- Warm season extreme precipitation and subsequent floods are high impact. Globally, annual average losses (1979-2021) associated with flooding total \$388 billion. WMO, 2023
- Increasing in frequency and severity
- Need to understand future change and our risk profiles



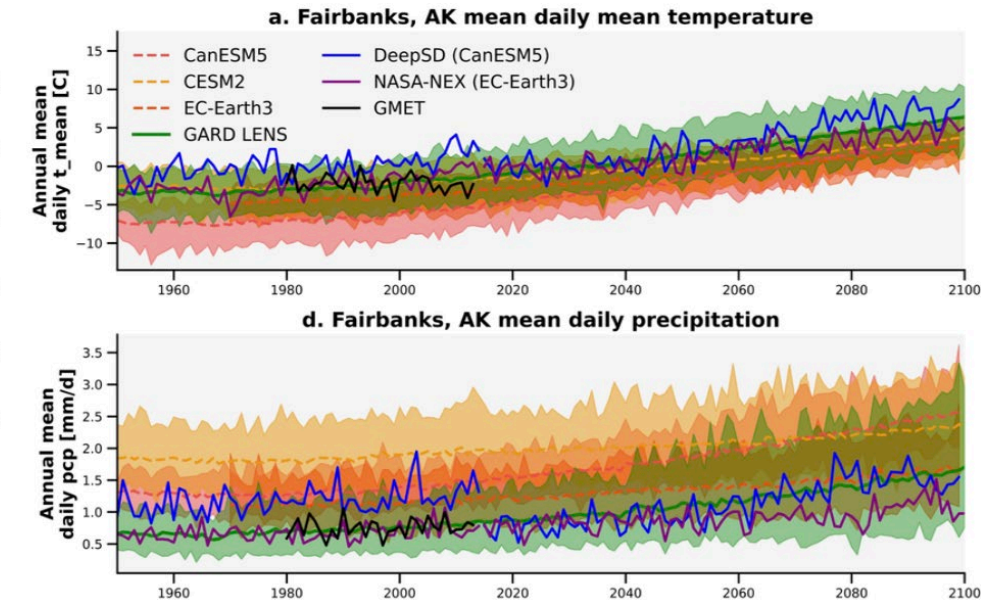
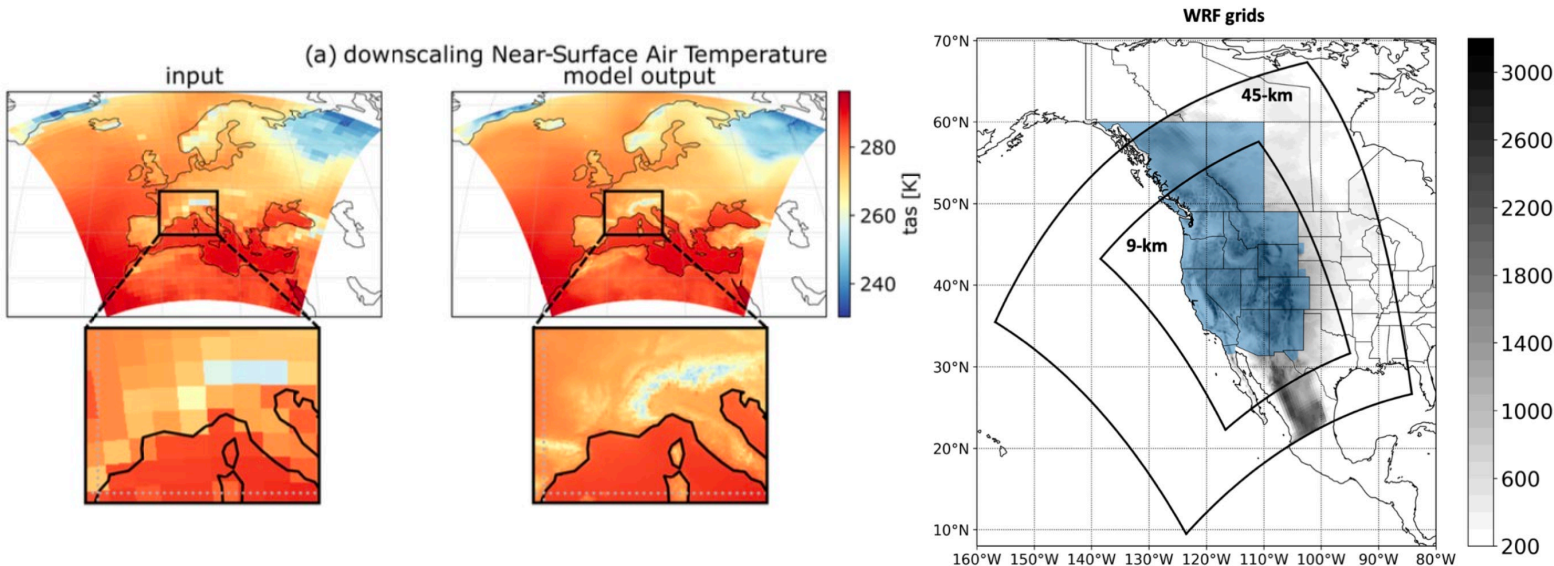
- High-resolution for this discussion:
  - Atmosphere: Orography, storm, meso-beta resolving ( $< 5\text{-}12$  km grid spacing)
  - Hydrology: Mesoscale hydrologic modeling on the small catchment (HUC12  $\sim 100$  km<sup>2</sup>) or similar grid spacing (5-10 km) scale (e.g. elevation gradients, headwaters)
  - Sub daily to daily output
- Large-sample definitions for this discussion:
  - Atmosphere: regional to continental scale; decades to centuries of simulation years
  - Hydrology: Hundreds to thousands of catchments or regional to continental scale; hundreds to thousands of events/hundreds to thousands of simulation years
- Why are these datasets important?
  - Diversity of events
  - Capture non-stationarities such as forced trends and changes in variability
  - Robust statistical sampling and evaluation



# Current Large-Sample Climate Modeling and Datasets

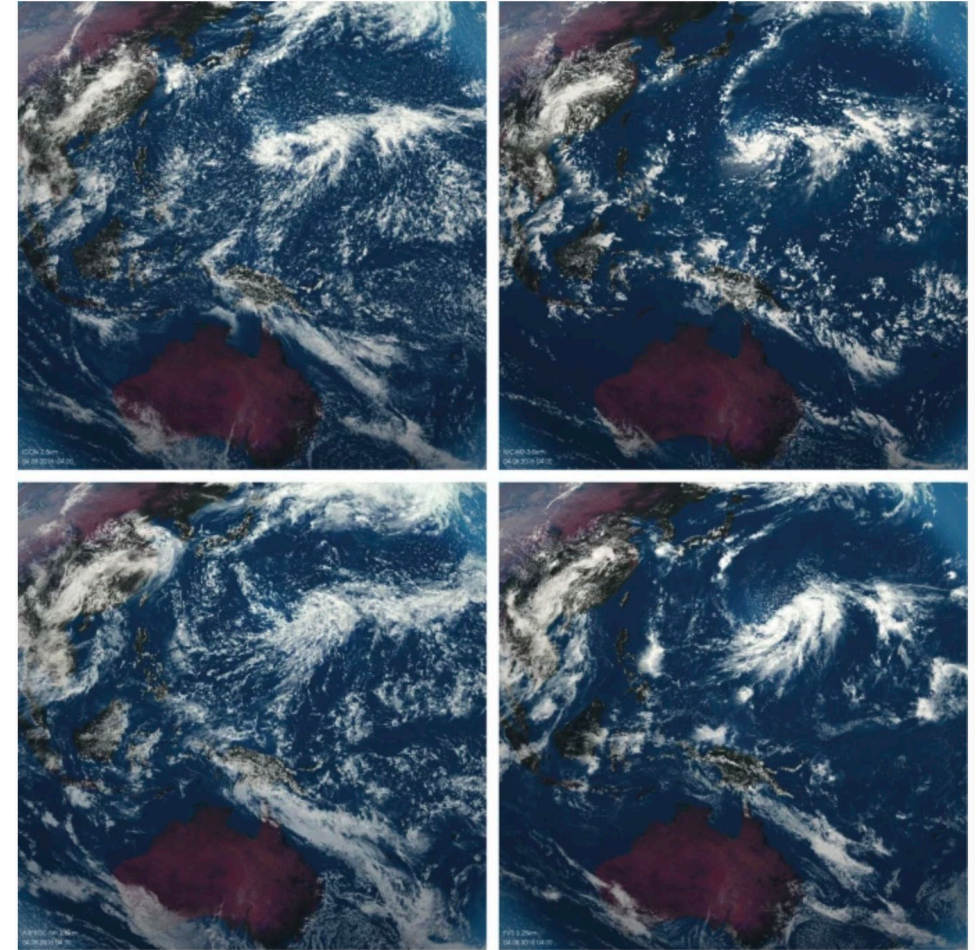
- Rapid development of high-resolution regional and global datasets
  - Continuum of methods – simpler statistical, dynamic, AI/ML (downscaling and emulators)
- Downscaling of global Earth System Models and their large ensembles (e.g. SMILEs)
  - LOCA2, GARD-LENS, WUS-D3, d4PDF, CONUS-404

Downscaling Method Class	Class Definition	Method Examples
Simple Statistical	Statistical methods that primarily correct or adjust the mismatch between large- and local-scale (or model and observation) climatologies.	Bias Corrected Spatially Disaggregated (BCSD), Quantile Delta Method (QDM), Quantile-Quantile Delta Change Method (QQDC)
Complex Statistical	Statistical methods that use a form of linear or complex non-linear regression (machine learning) or analog methods to filter the information transfer between large- and local-scale (or model and observation) climatologies.	Statistical DownScaling Model (SDSM), LOcally Constructed Analogs (LOCA), Multivariate Bias Correction (MBCn), EnGARD, Convolutional Neural Networks (CNNs), Random Forests
Quasi-dynamical	Hybrid methods that combine statistical and dynamical tools to perform downscaling	Intermediate Complexity Atmospheric Research (ICAR) model
Fully Dynamical	The application of mesoscale atmospheric models using GCM or ESM boundary conditions to generate outcomes at local scales.	Weather Research and Forecasting (WRF) model



# Current Large-Sample Climate Modeling and Datasets

- Global storm resolving model (GSRM) simulations
  - DYAMOND simulations, other single model simulations (e.g. NICAM, SCREAM, MPAS-A)
  - Very limited temporal length, atmosphere only

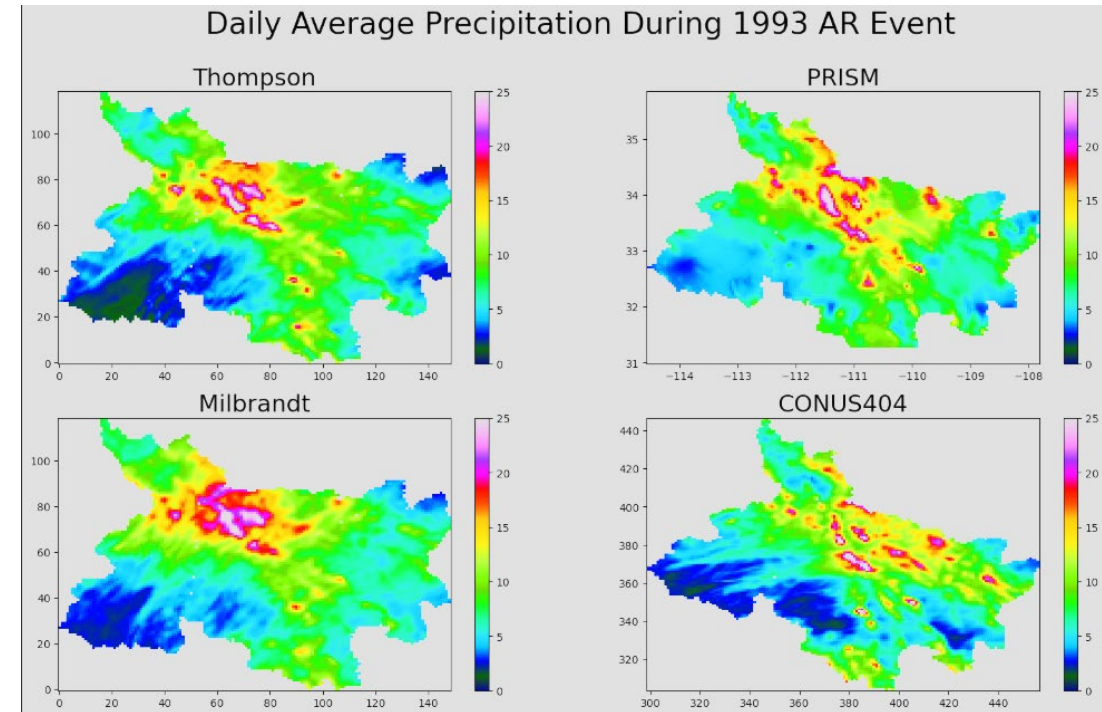


Stevens et al. (2019)



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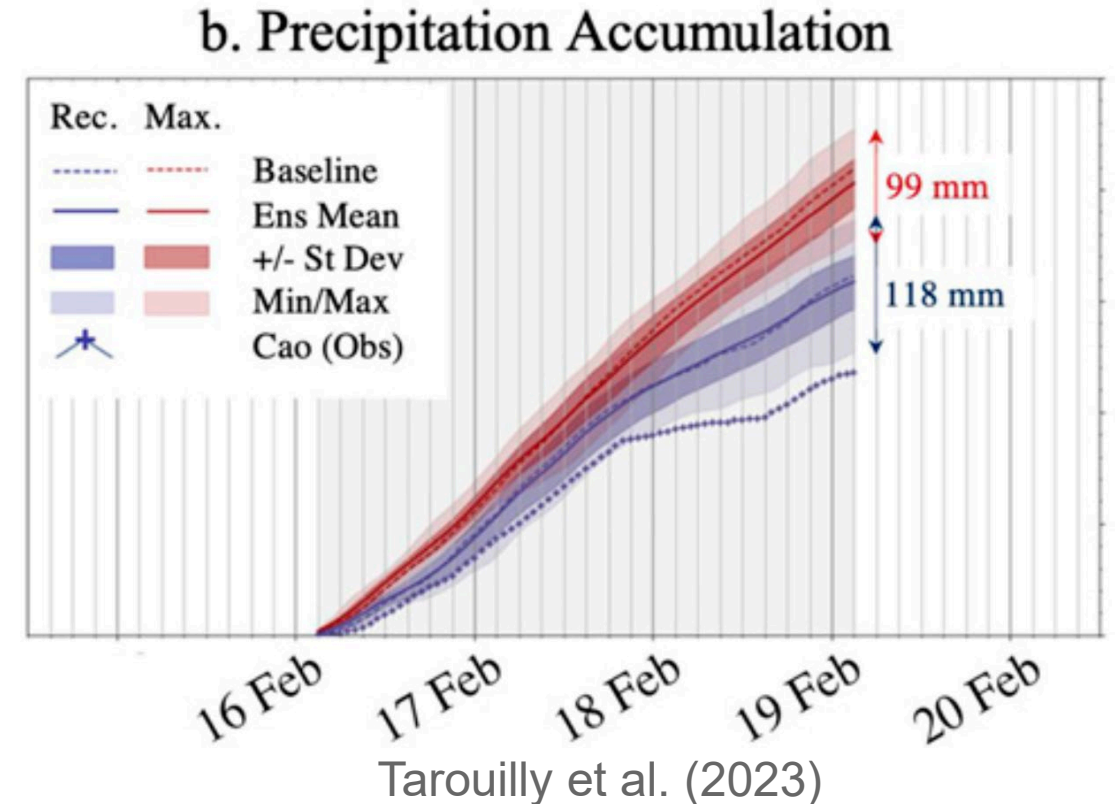
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- Event based datasets
  - Regional simulations of only events of interest
    - Boost event sample sizes
    - Process studies



Lybarger et al. (2025), in prep

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    - Boost event sample sizes
    - Process studies
  - PMP method development and evaluation
    - Uncertainty quantification
    - Model evaluation
    - Non-stationarity



# Large-Sample Climate Modeling and Datasets - Gaps

- What methods are fit (or adequate) for purpose?
  - Comprehensive evaluation and benchmarking is hard, but essential
  - Relative and absolute performance criteria needed
    - Better than previous model?
    - Good enough for decision making?

## METViewer CAM Scorecard

for GFDLHV3\_NSSLFV3grid and NSSLFV3

2018-04-30 00:00:00 – 2018-06-01 00:00:00

			Daily Domain									
				12 hr	15 hr	18 hr	21 hr	24 hr	27 hr	30 hr	33 hr	36 hr
Fraction Skill Score	Composite Reflectivity	49	>=25.0	▽	▽	▽			▽	▽	▽	
			>=30.0	▽	▽	▽			▽	▽	▽	
			>=35.0	▽	▽	▽			▽	▽	▽	
			>=40.0		▽	▽			▽	▽	▽	
			>=45.0		▽	▽						
			>=50.0		▽							
CSI	Composite Reflectivity	1	>=25.0	▽	▽	▽			▽	▽	▽	
			>=30.0	▽	▽	▽			▽	▽	▽	
			>=35.0	▽	▽	▽			▽	▽	▽	
			>=40.0		▽	▽			▽		▽	
			>=45.0									
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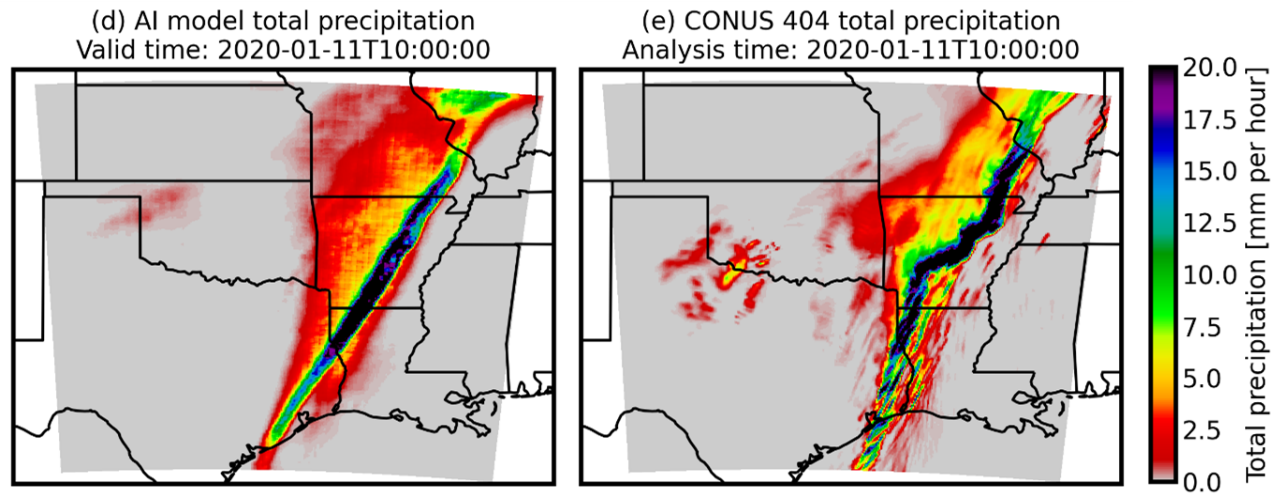
△	GFDLHV3_NSSLFV3grid is better than NSSLFV3 at the 99% significance
▲	GFDLHV3_NSSLFV3grid is better than NSSLFV3 at the 95% significance
	No statistically significant difference between GFDLHV3_NSSLFV3grid
▽	GFDLHV3_NSSLFV3grid is worse than NSSLFV3 at the 95% significance
▽	GFDLHV3_NSSLFV3grid is worse than NSSLFV3 at the 99% significance
	Not statistically relevant

Gallo et al. (2019)



# Large-Sample Climate Modeling and Datasets - Gaps

- What methods are fit (or adequate) for purpose?
  - Comprehensive evaluation and benchmarking is hard, but essential
  - Relative and absolute performance criteria needed
    - Better than previous model?
    - Good enough for decision making?
- Managing the AI/ML frontier
  - AI/ML is poised to exponentially increase methods and data
  - Need robust evaluation
  - Is explainable AI of value?
    - Increase partner trust?



Sha et al., in prep

# Large-Sample Climate Modeling and Datasets - Gaps

- Sample sizes and uncertainty quantification
  - Breaking computational bounds and advanced methods (e.g., Dr. Wright's talk next)
  - Continue GPU transition, how to integrate AI/ML into models, or just emulate everything?

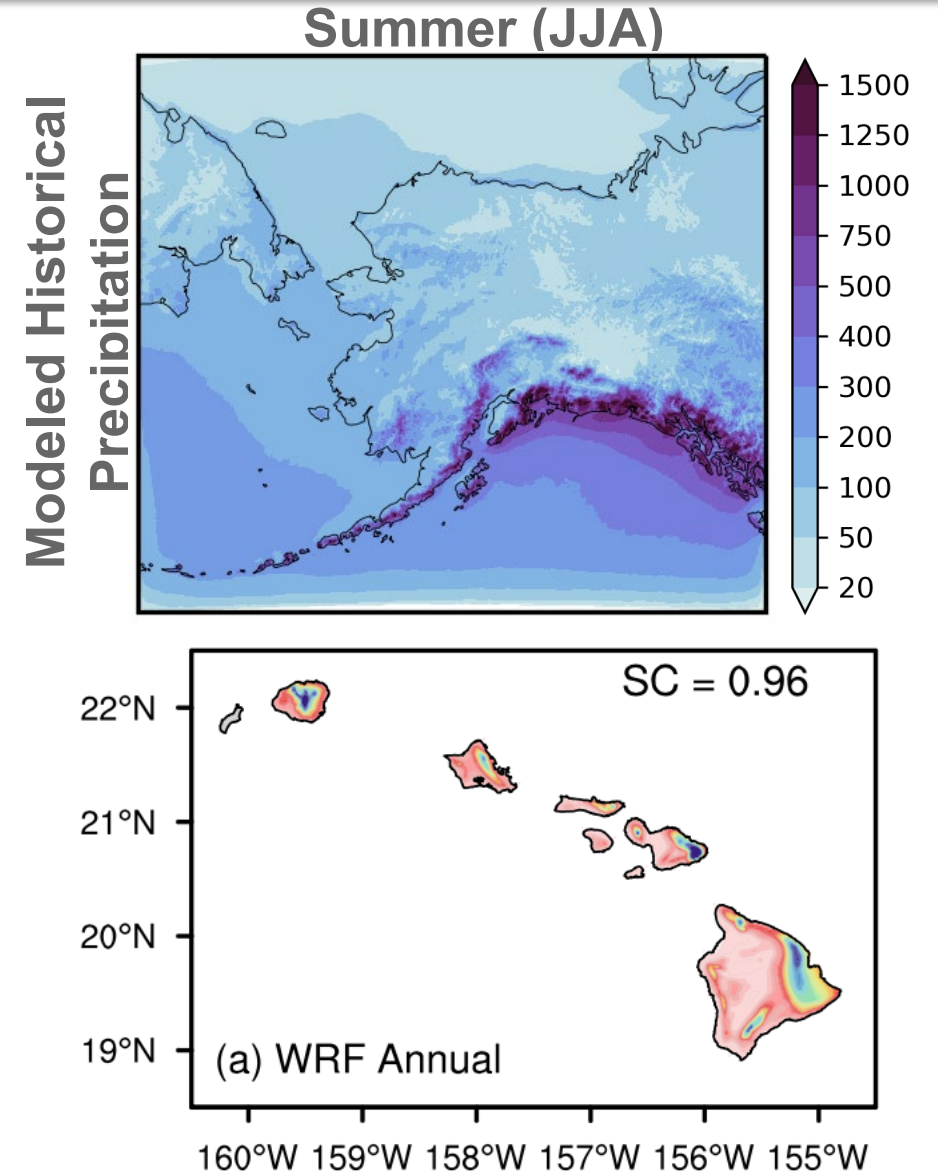


OLCF at ORNL



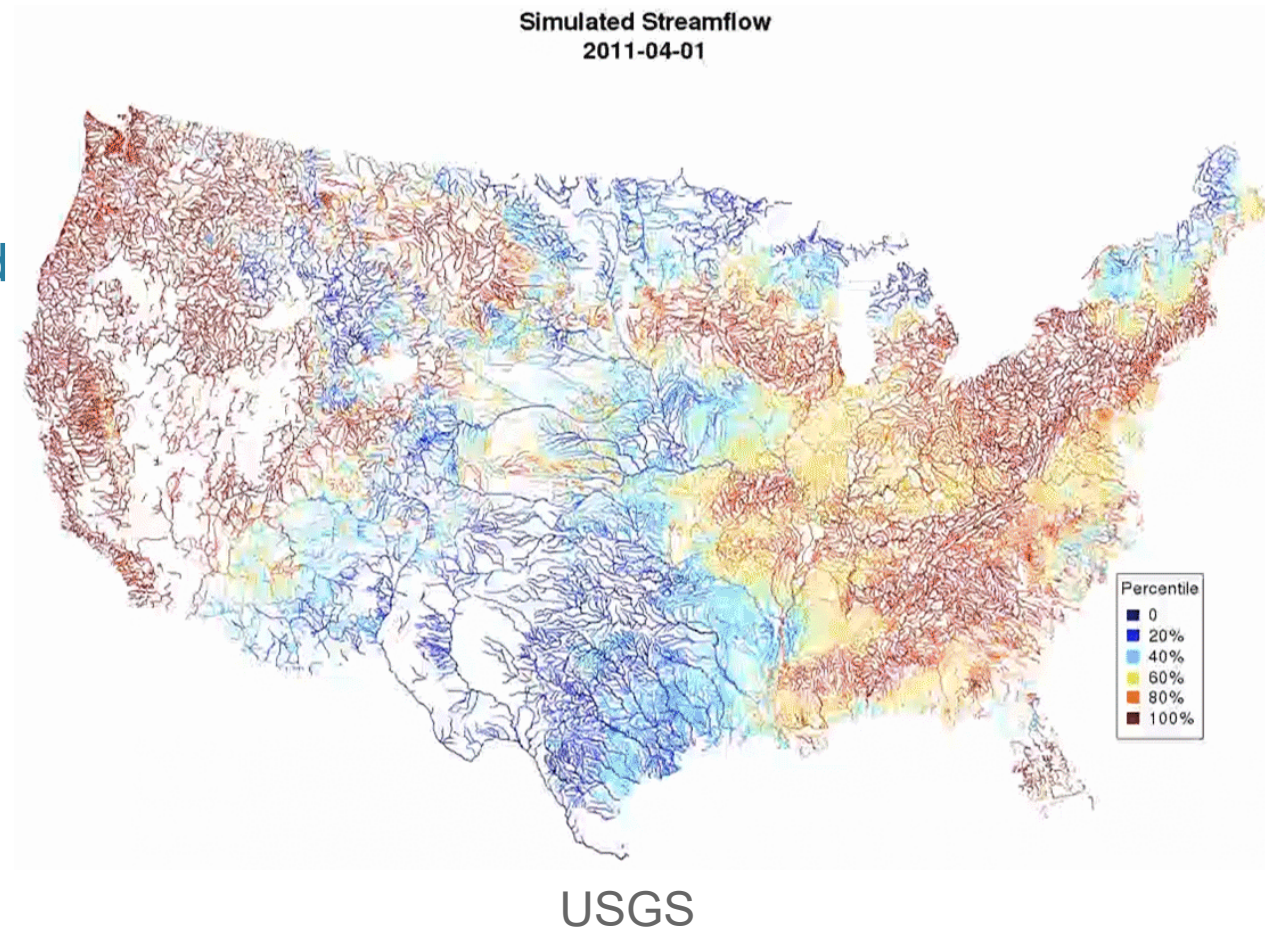
# Large-Sample Climate Modeling and Datasets - Gaps

- Sample sizes and uncertainty quantification
  - Breaking computational bounds and advanced methods (e.g., Dr. Wright's talk next)
  - Continue GPU transition, how to integrate AI/ML into models, or just emulate everything?
- Outside CONUS (OCONUS)
  - Few datasets for Hawai'i and Alaska
  - Fewer for Puerto Rico, other territories and possessions
  - Limited observational training/validation datasets



# Large-Sample Surface Hydrologic Modeling and Datasets

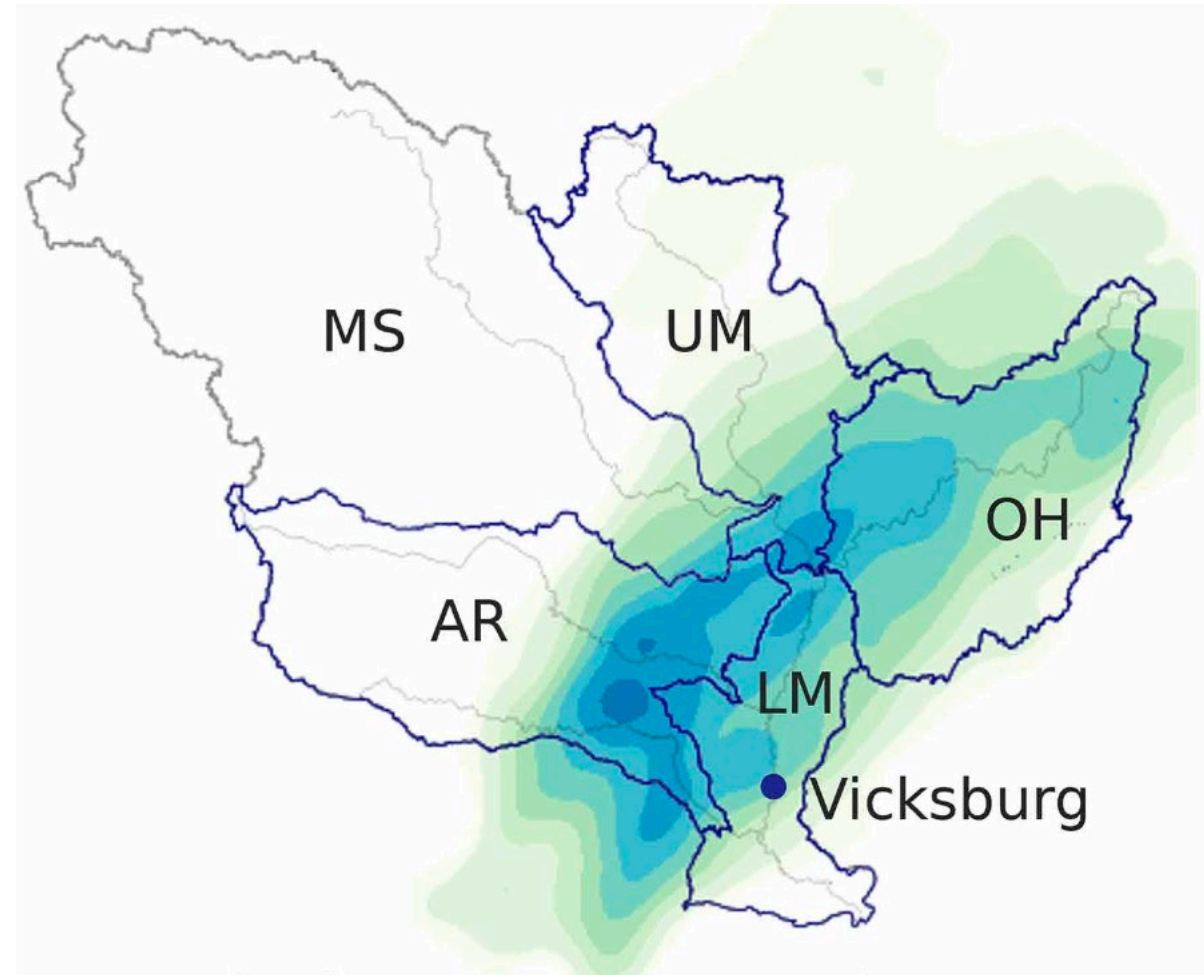
- Many national scale models and historical datasets
  - National Water Model (NWM), National Hydrologic Model (NHM), other models and groups produce retrospectives





# Large-Sample Surface Hydrologic Modeling and Datasets

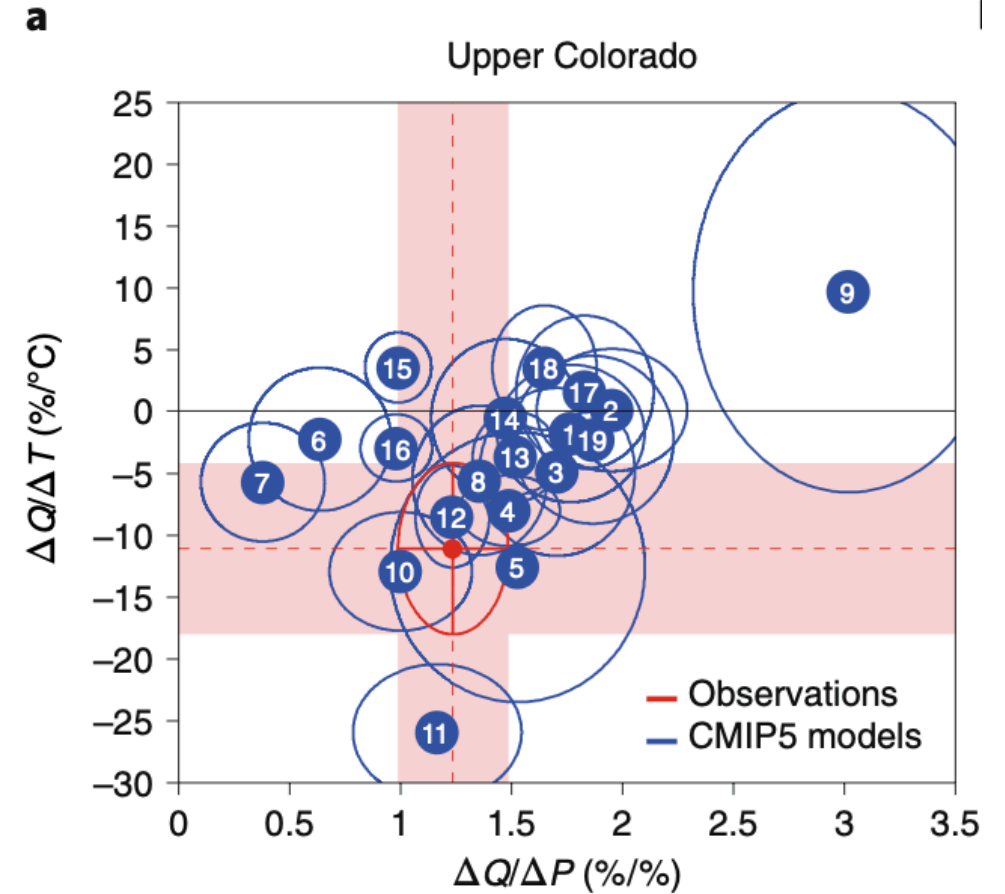
- Many national scale models and historical datasets
  - National Water Model (NWM), National Hydrologic Model (NHM), other models and groups produce retrospectives
- Fewer fit-for-purpose regional to continental scale datasets available for future periods
  - Lack of inputs
  - Model chain complexity
    - Many decision points
  - High computational demands



Liu et al. (2025)

# Large-Sample Surface Hydrologic Modeling and Datasets - Gaps

- Caution using most current land model output directly from high-resolution (or other) models
  - Often little effort is made for hydrologic performance
  - E.g. ESM land models may have unrealistic climate sensitivities (Lehner et al. 2019)

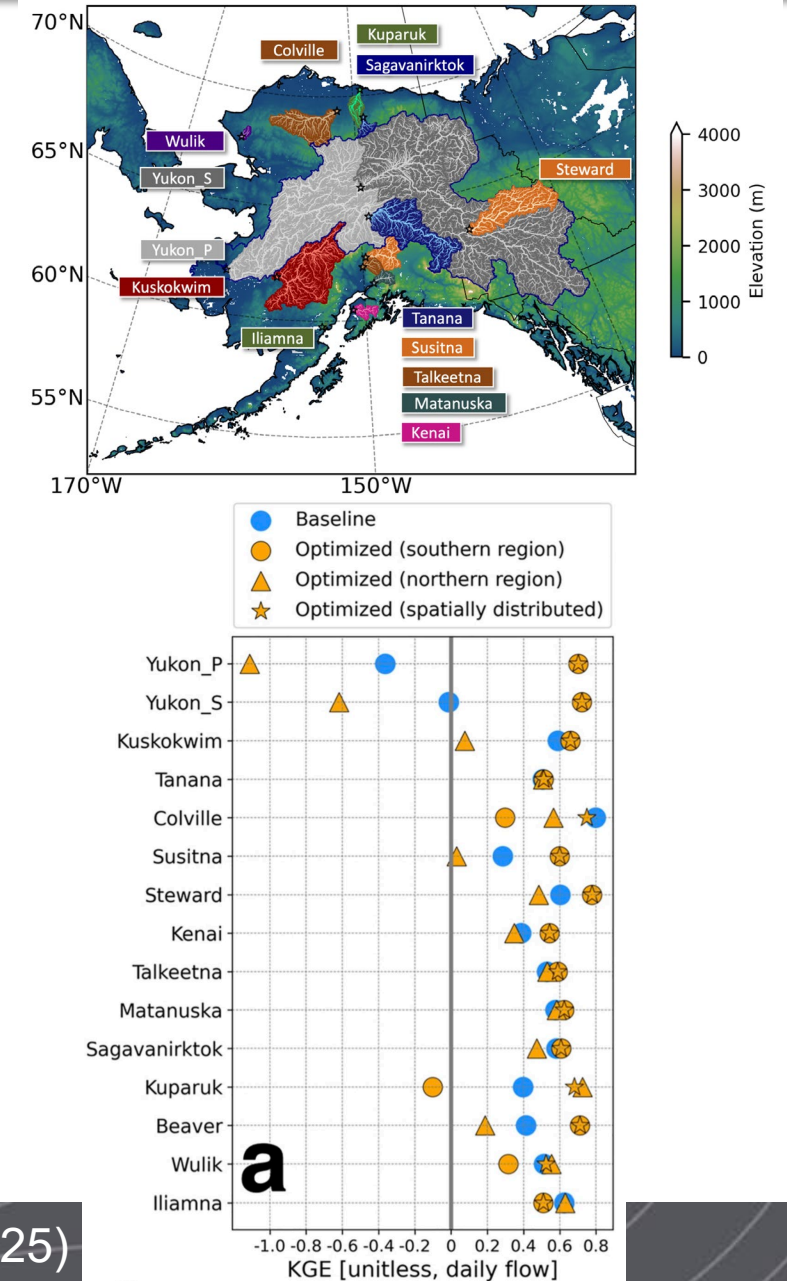


Lehner et al. (2019)



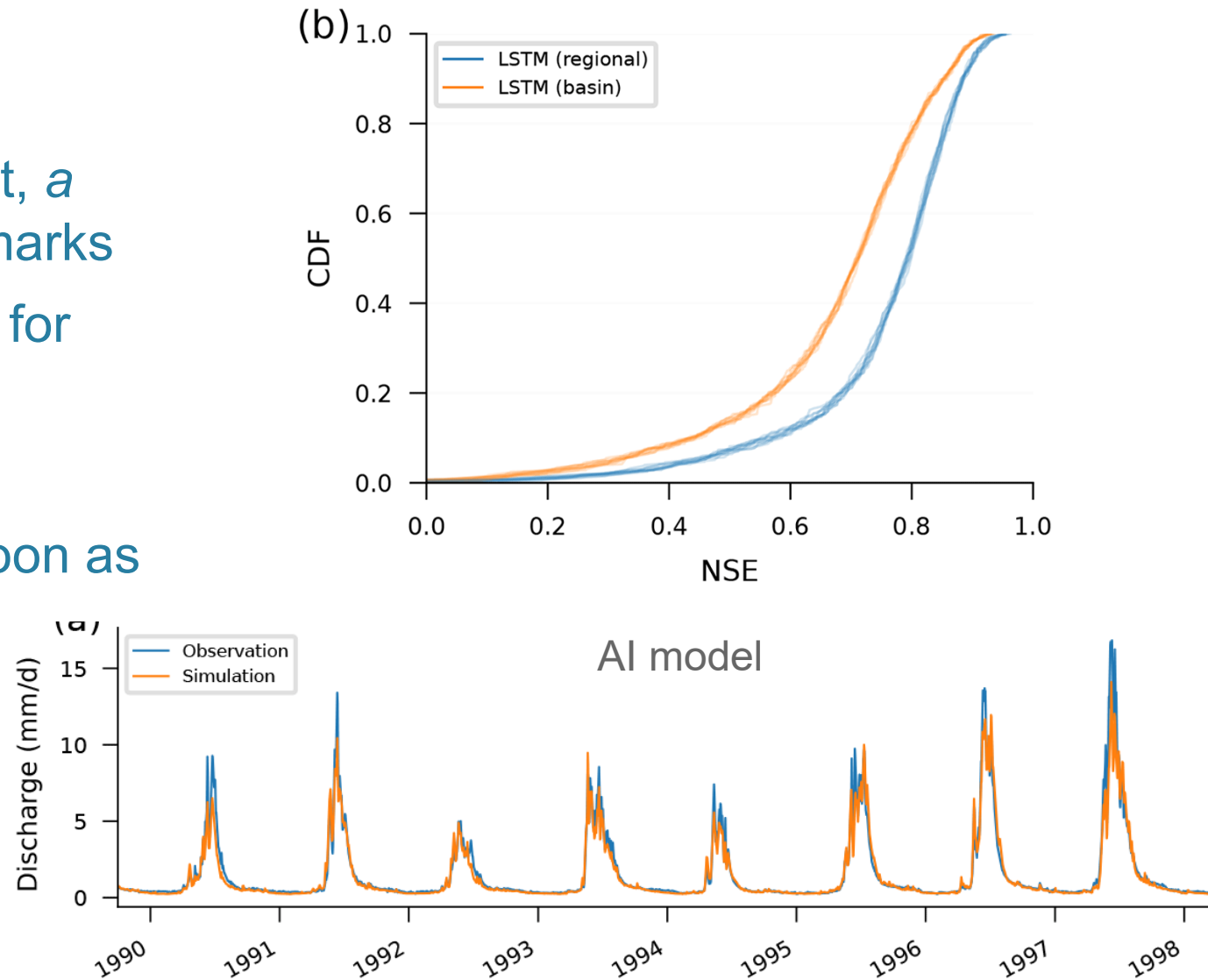
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  - Often little effort is made for hydrologic performance
  - E.g. ESM land models may have unrealistic climate sensitivities (Lehner et al. 2019)
- There are efforts towards improving coupled model hydrology
  - Land-model configuration and optimization for hydrology
  - Fit-for-purpose inspired evaluation



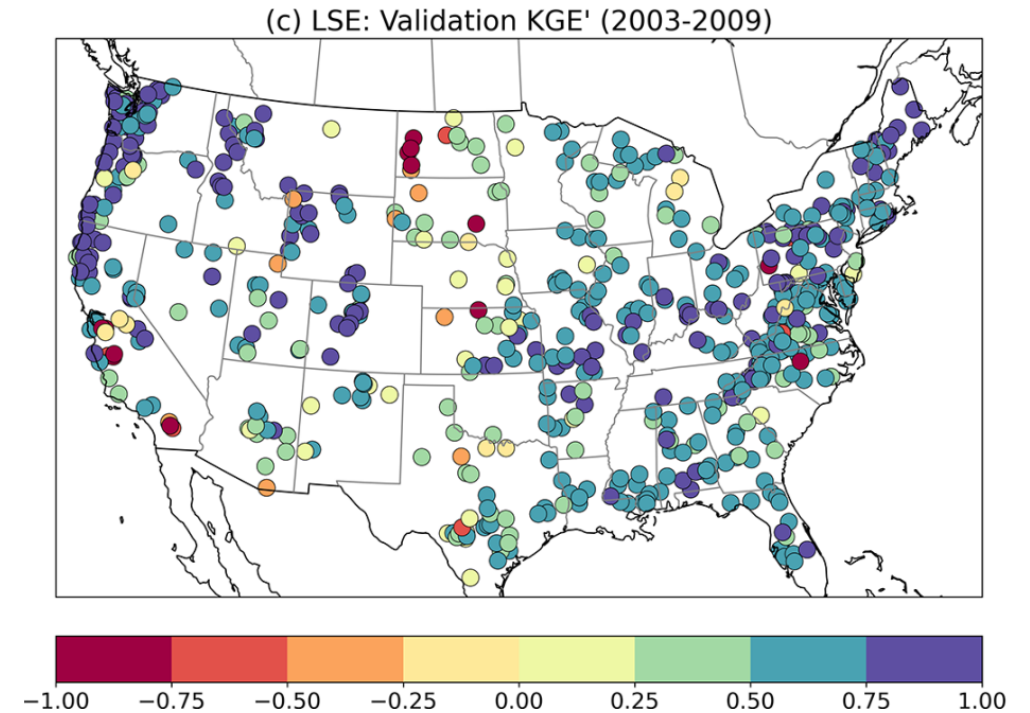
# Large-Sample Surface Hydrologic Modeling and Datasets - Gaps

- Benchmarking
  - Need to continue to push for robust, *a priori*, partner co-produced benchmarks
  - Open-source, community software for hydrology à la ILAMB or METplus
- AI/ML modeling
  - Continue integrating partners as soon as possible in development process
  - Explainability to build trust
  - Robust benchmarking and model intercomparisons



# Large-Sample Surface Hydrologic Modeling and Datasets - Gaps

- Regionalization and optimization
  - Model structure, process parameterization, and parameter optimization are unconstrained problems
  - AI/ML based optimization and regionalization is promising

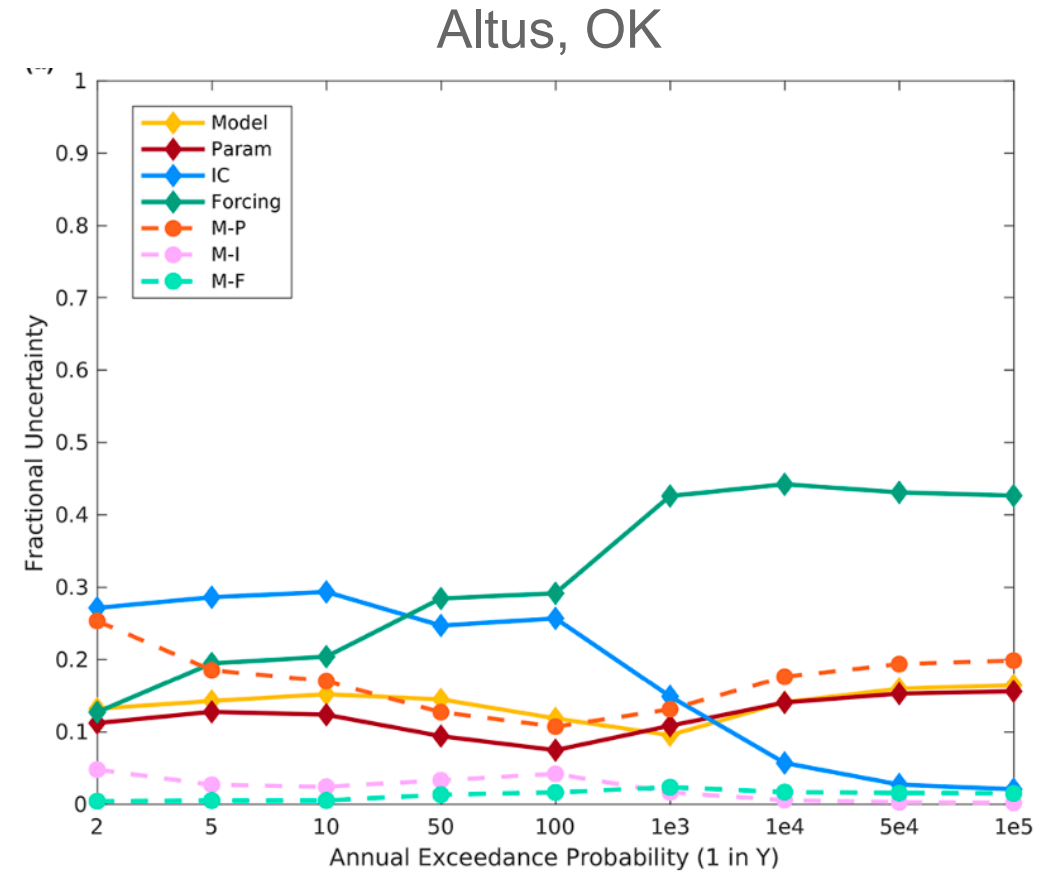


Farahani et al. (2025)



# Large-Sample Surface Hydrologic Modeling and Datasets - Gaps

- Regionalization and optimization
  - Model structure, process parameterization, and parameter optimization are unconstrained problems
  - AI/ML based optimization and regionalization is promising
- Ensemble simulations and uncertainty quantification
  - Need much larger regional continuous and event based ensembles
  - Formal uncertainty analysis across all dimensions of flood simulation



Newman et al. (2021)

# Opportunities to Connect to PMP Modernization

- Model Evaluation Project (MEP)
  - Comprehensive benchmarking of both atmospheric and hydrologic models across a range of metrics (5-2, 5-12)
    - **Co-designed *a priori* performance criteria and benchmark models (5-2)**
      - What are meaningful metrics?
      - What are meaningful improvements (e.g. practical significance)?
    - Climate sensitivities
    - Right answer for the right reasons - process representation (5-8, 5-12)
- Uncertainty quantification
  - Large ensembles (5-7, 5-10)
  - Multi-method evaluation and assessment for near-term change factors (5-9)
- Emulators and other computational infrastructure advances (e.g. GPU based physical models) (5-10)

# Key Take-Home Messages

- Method and data explosion is an opportunity for analysis
  - Need to quantify adequate/fit-for-purpose (MEP is critical)
  - Move to multi-century record lengths; increasing model process representation using AI/ML and computational hardware advances
- Improving hydrology, both in offline and coupled models
  - Need optimization and regionalization of model structure and parameters
  - Need large-scale benchmarking studies – Do our models respond realistically?
- Improving uncertainty quantification
  - Need more formal uncertainty analysis across scenario, model structure and parameters, meteorology, and hydrologic states
- Partner input and participation is strong in places
  - Need deeper partner co-design of models, experiments, and data