### Application of Point Precipitation Frequency Estimates to Watersheds

Presented at

#### The 5<sup>th</sup> Annual Probabilistic Flood Hazard Assessment (PFHA) Research Workshop

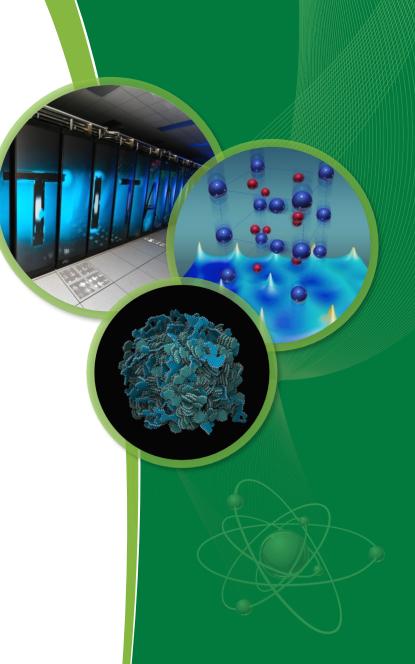
February 19th – February 21st, 2020

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Oak Ridge National Laboratory

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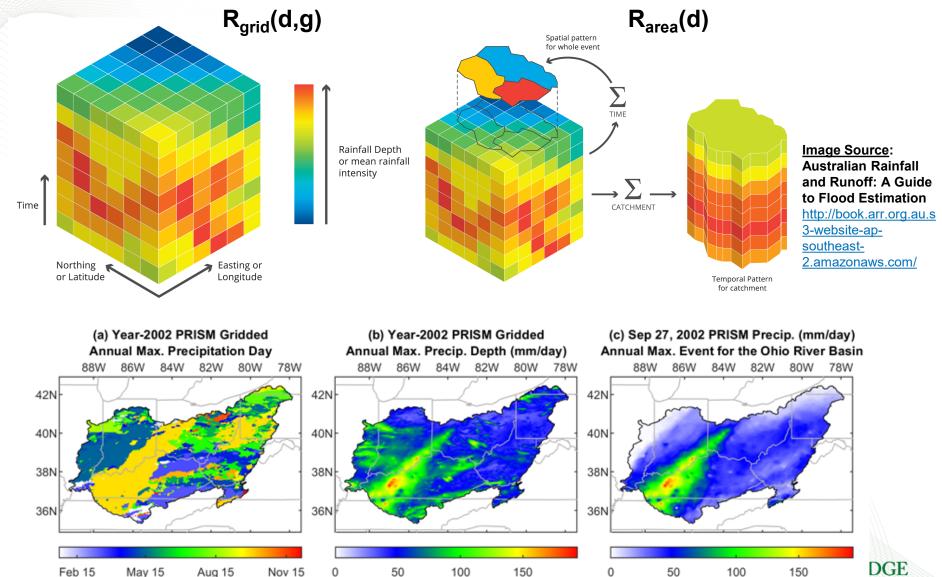


### **Leverage Existing PFA Products**

- To avoid going through the entire chain of precipitation frequency analysis (PFA), we have often opted to look up pre-calculated *T*-year rainfall depths from existing PFA products
  - TP-40 (Hershfield, 1961)
  - National Oceanic and Atmospheric Administration (NOAA) Atlas 14 (Bonnin et al., 2004 and other volumes)
- However, most of the PFA products (including NOAA Atlas 14) provide frequency estimates of "point" precipitation
  - This happens because the annual (or partial duration) maxima are usually identified independently in time.
  - Representative only for a small domain not directly appropriate for large-scale watershed modeling applications.
  - Appropriate conversion factor is hence needed to derive areal-based extreme precipitation estimate.



### **Differences between Grid vs. Areal Maximum**



oratory

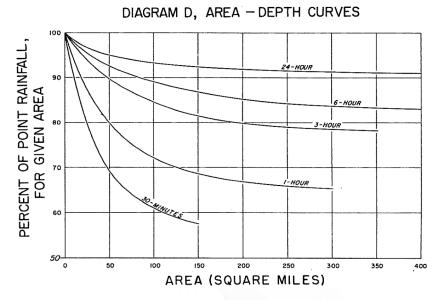
### **Precipitation Areal Reduction Factor (ARF)**

- Existing PFA products (e.g., NOAA Atlas 14) are mostly developed for point rainfall
- Areal reduction factor (ARF) is defined as the ratio of areal extreme rainfall depth (P<sub>area</sub>) to point-based extreme rainfall depth (P<sub>point</sub>)

 $- P_{area} = P_{point} * ARF$ 

- ARFs in common use suffer from several key limitations:
  - Limited / outdated data
  - Small area sizes (up to 400 mi<sup>2</sup>)
  - Do not vary with location, return period, or season

Example ARF curves (from TP-29)



Source: Technical Paper No. 29; noaa.gov



## **Objectives of this Project**

- Understand and demonstrate how ARFs may vary when using different precipitation data products and ARF methods across different geographical locations, durations, areas, return periods, seasons, and etc.
  - Task 1: Provide a summary of available precipitation products that can be used to develop ARFs.
  - Task 2: Provide a critical review of available ARF methods with a view to addressing the deficiencies in the commonly used empirical methods.
  - Task 3: Demonstrate use of the most promising method/dataset combinations through selected test cases.
- Support Nuclear Regulatory Commission (NRC) on the development of future Probabilistic Flood Hazard Assessment (PFHA) guidance on ARFs used by NRC licensees



### **Fixed-area ARF**

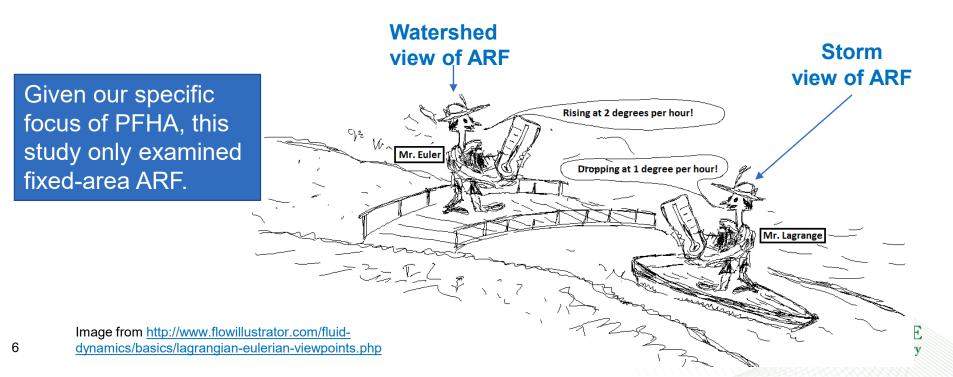
#### Following a watershed

- Find the maximum rainfall depth for a watershed
- Maximum rainfall may capture one or multiple storms
- More suitable for PHFA applications

### **Storm-centered ARF**

#### Following a storm

- Describe the maximum rainfall depth of a moving storm
- Storm may move across multiple watersheds
- More suitable for deterministic storm analysis (e.g., PMP)



## **Study Approach**

#### Factors affecting ARFs

- Area, duration, and return period
- Different ARF methods
- Precipitation products to use
- Geographical locations
- Seasonality

#### Case study application

- Regional comparison
  - 3 hydrologic regions (HUC02), 5 precipitation products, and 6 ARF methods
- National comparison
  - 18 hydrologic regions (HUC02), 1 precipitation product, and 1 ARF method
- Evaluation through fitting statistics (e.g., NSE, RMSE, R<sup>2</sup>)
- Only consider "geographically-fixed-area" ARF





## **Key Metrics for Data Consideration**

#### Accuracy/precision

– How reliable are the precipitation estimates available from the product, and what sources of error and uncertainty exist?

#### Temporal coverage

– For what time period are the precipitation estimates available, and are there any gaps in temporal coverage?

#### Data latency

– How regularly are the precipitation estimates uploaded online?

#### Spatial coverage

- For what regions are the precipitation estimates available?

#### Temporal resolution

– How frequently are precipitation estimates provided?

#### Spatial resolution

For what horizontal spacing or area size are individual precipitation estimates available?



## **Selected Precipitation Products in Case Study**

Precipitation Products	Provider	Dataset Type	Coverage Start	Coverage End	Data Latency	Spatial Coverage	Temporal Resolution	Spatial Resolution
Gauge-only Data	asets							
Hourly Precipitation Data (DSI3240)	NOAA National Centers for Environmental Information (NCEI)	Gauge observation	1940	2013	Data since 2014 have not been released (checked 10/17/2017)	U.S. (including AK, HI, PR)	Hourly	Gauge
Gauge-driven Pr	oducts							
Daymet version 3 (Daymet)	Oak Ridge National Laboratory (ORNL)	Gridded from gauge observation	1980	2017	Annual update	North America	Daily	1 km * 1 km
Daily PRISM Dataset (PRISM)	Oregon State University	Gridded from gauge observation (and partially with radar)	1981	present	Operational (updated automatically)	U.S. (48 states)	Daily	1/24 deg * 1/24 deg (~ 4 km * 4 km)
Livneh CONUS Near-surface Meteorological Data (Livneh)	University of Colorado, Boulder	Gridded from gauge observation	1950	2013	No scheduled update (checked 10/17/2017)	U.S. (48 states), Mexico, & Canada (south of 53N)	Daily	1/16 deg * 1/16 deg (~ 6 km * 6 km)
Radar-driven Pro	oducts							
NCEP National Stage IV Analyses (ST4)	NOAA National Centers for Environmental Prediction (NCEP)	Merged radar and gauges (with QC)	2002	present	Operational (updated automatically)	U.S. (48 states), excluding California-Nevada & Northwest RFCs	Hourly	4 km * 4 km

- These precipitation products exhibit long temporal coverage, broad spatial coverage, and sufficient temporal/spatial resolution.
- DSI3240 is only analyzed for Region 05 (Ohio).



## **Case Study Assessment Procedures**

#### Annual maximum series (AMS) searching

- Data
  - PRISM (1981–2017), Daymet (1980–2017), ST4 (2002–2017), Livneh (1950–2013), DSI3240 (1950–2013)
- Duration
  - All: 1-day, 2-day, 3-day
  - Additionally for ST4 & DSI3240: 1-hr, 2-hr, 3-hr, 6-hr, 12-hr, 18-hr
- Season
  - All season, Warm season (May–Oct), Cool season (Jan–Apr, Nov–Dec)
- Grid AMS (P<sub>grid</sub>): annually at each grid
- Areal AMS (P<sub>area</sub>): annually at each HUC08, HUC06, HUC04, HUCac

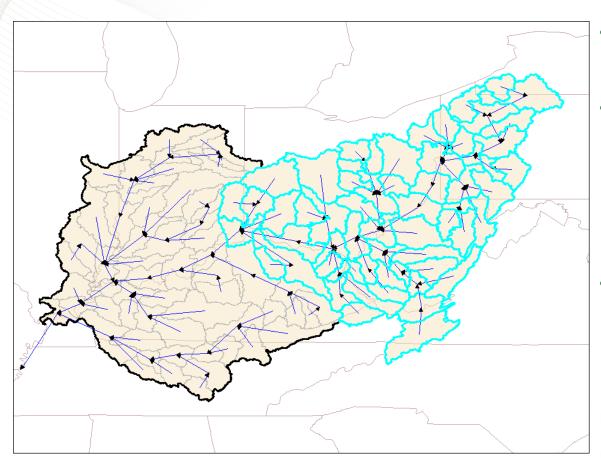
#### • Sample ARF at each areal units (HUCs)

- Average AMS
  - (Temporal average of P<sub>area</sub>) / (Temporal and spatial average of P<sub>grid</sub>)
- T-year estimate
  - Fitting AMS by GEV, and getting T-year estimates (e.g., P<sub>area,10yr</sub>)
  - P<sub>area,Tyr</sub> / (Spatial average of P<sub>g11,Tyr</sub>)

#### Regional fitting by different ARF models



## Watershed-based AMS Searching Approach



Increase AMS samples to cover a wider range of watershed sizes

- Define additional spatial unit HUCac based on watershed connectivity
  - For each HUC08, using its connectivity with other HUC08s to identify the entire upstream contributing watershed as HUCac
  - Use HUCac to search AMS
- Use HUC08, HUC06, HUC04, and HUCac AMS to fit different ARF models
  - 120 HUC08: 290 840 km<sup>2</sup>
  - $\quad 21 \ HUC06: \ 4,400 54,000 \ km^2$
  - 7 HUC04: 15,000 85,000 km<sup>2</sup>
  - 46 HUCac: 4,600 420,000 km<sup>2</sup>



### **Selected ARF Models**

#### Empirical Methods

- M1: Leclerc & Schaake (1972) fitted formula of US Weather Bureau TP-29
- M2: Koutsoyiannis and Xanthopoulos (1999) – fitted UK-NERC ARF relationship (NERC, 1975)
- M3: Hydrological Atlas of Switzerland Model (Grebner et al., 1998)
- M4: Australian Rainfall & Runoff (ARR) Guideline (Nathan and Weinmann, 2016)
- Dynamic Scaling Model
  - M5: De Michele et al. (2001)
- Extreme Value Theory
  - M6: Overeem et al. (2010)

 $ARF(A,D) = 1 - e^{aD^b} + e^{(aD^b - cA)}$  $aA^{(b-c\ln A)}$  $ARF(A, D) = 1 - \frac{a}{2}$  $ARF(A) = \frac{a_0}{(A+a_2)^{a_1}} + a_3 e^{-a_4 A}$ ARF(A, D, AEP) $= 1 - a(A^b - c \log_{10} D)D^{-d}$  $+ eA^{f}D^{g}(0.3 + \log_{10}AEP)$  $+ h10^{iAD}(0.3 + \log_{10} AEP)$  $ARF(A,D) = \left| 1 + w \left( \frac{A^z}{D} \right)^b \right|$  $ARF(A, D, AEP) = P(A, D, AEP)/P(A^*, D, AEP)$  $P(A, D, AEP) = GEV^{-1}(1 - AEP|\mu, \gamma, \kappa)$  $\mu(A, D) = aD^b + (c + d \ln D)A^e$  $\gamma(A, D) = f \ln A + g \ln D + h$  $\kappa(A) = i \ln A + j$ 

## M5: De Michele Dynamic Scaling Model

#### • De Michele et al. (2001) and (2011)

 Uses the concepts of dynamic scaling and statistical self-affinity to find a general expression for the mean annual maxima precipitation as a function of the rainfall duration and area

• 
$$ARF(A, D) = \left[1 + w\left(\frac{A^z}{D}\right)^b\right]^{-\nu/b}$$

- A, area (km<sup>2</sup>)
- D, duration (hr)
- Four parameters: v, b, w, z

### ORNL Fitting

- Minimize the root mean square error (RMSE) between ARF samples and ARF model using Matlab *fminsearch* function (Nelder-Mead simplex algorithm; Lagarias et al., 1998)
- Performance evaluated by Nash–Sutcliffe efficiency (NSE)
- (4 fitted parameters) \* (# of frequency levels)



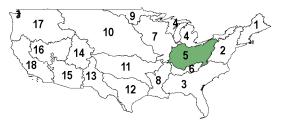
## **Summary of Overall Findings**

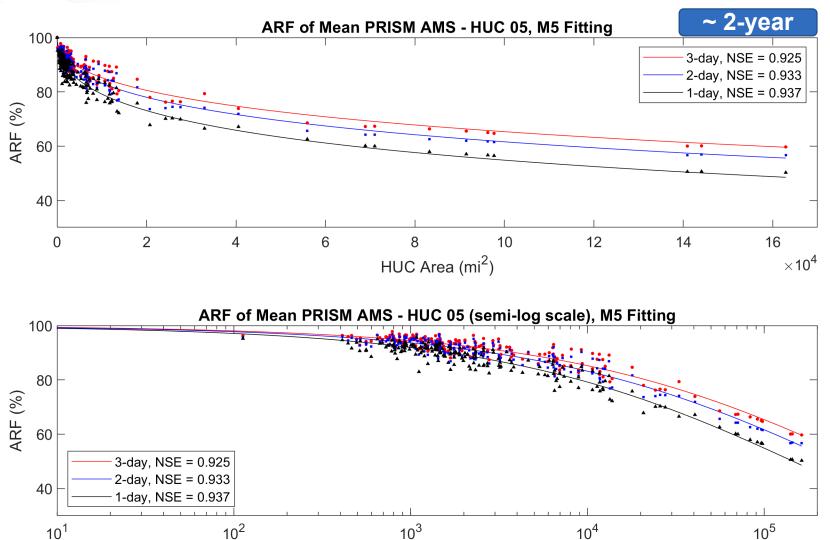
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### Region 05 M5 De Michele Model

- Data: PRISM (all seasons)
- Duration: 1-day, 2-day, 3-day
- Frequency level: AMS
- ARF Fitting: M5



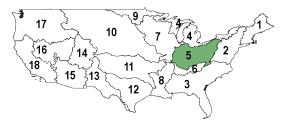


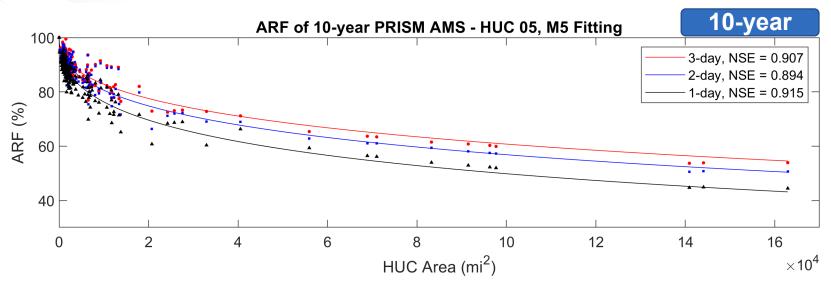
HUC Area (mi<sup>2</sup>)

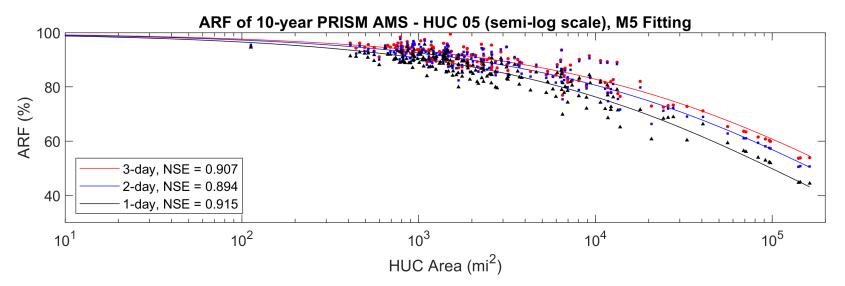
### Region 05 M5 De Michele Model

16

- Data: PRISM (all seasons)
- Duration: 1-day, 2-day, 3-day
- Frequency level: 10-year
- ARF Fitting: M5





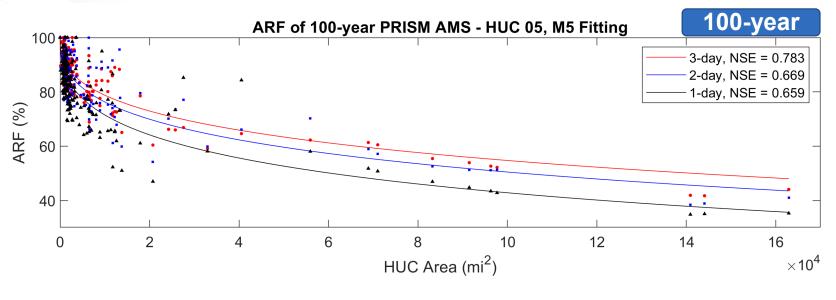


### Region 05 M5 De Michele Model

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- Data: PRISM (all seasons)
- Duration: 1-day, 2-day, 3-day
- Frequency level: 100-year
- ARF Fitting: M5

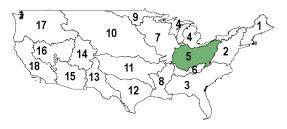




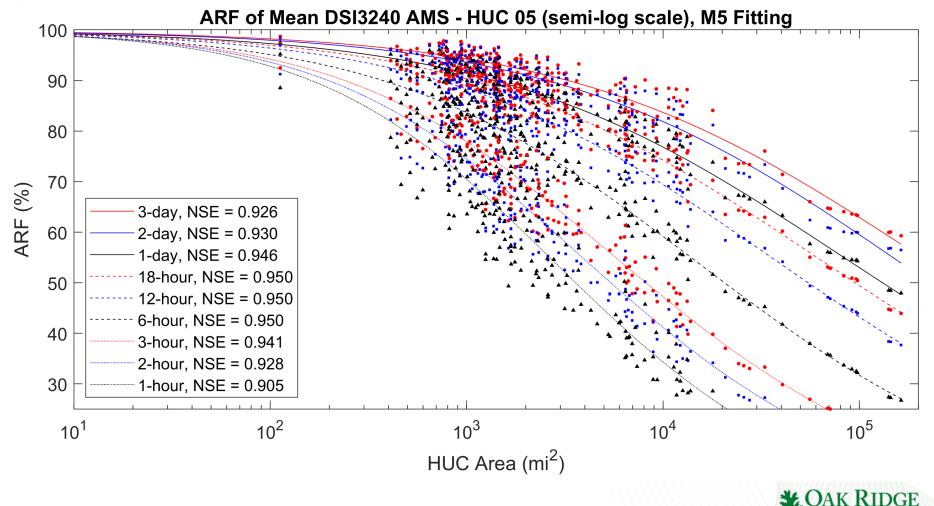
ARF of 100-year PRISM AMS - HUC 05 (semi-log scale), M5 Fitting 100 1 80 ARF (%) 60 3-day, NSE = 0.783 2-day, NSE = 0.669 40 1-day, NSE = 0.659 10<sup>3</sup>  $10^{1}$ 10<sup>2</sup> 10<sup>4</sup> 10<sup>5</sup> HUC Area (mi<sup>2</sup>)

### **Differences across Durations**

- Data: DSI3240 (all seasons)
- Duration: 3-day, 2-day, 1-day, 18hr, 12-hr, 6-hr, 3-hr, 2-hr, 1-hr
- Frequency level: AMS
- ARF Fitting: M5



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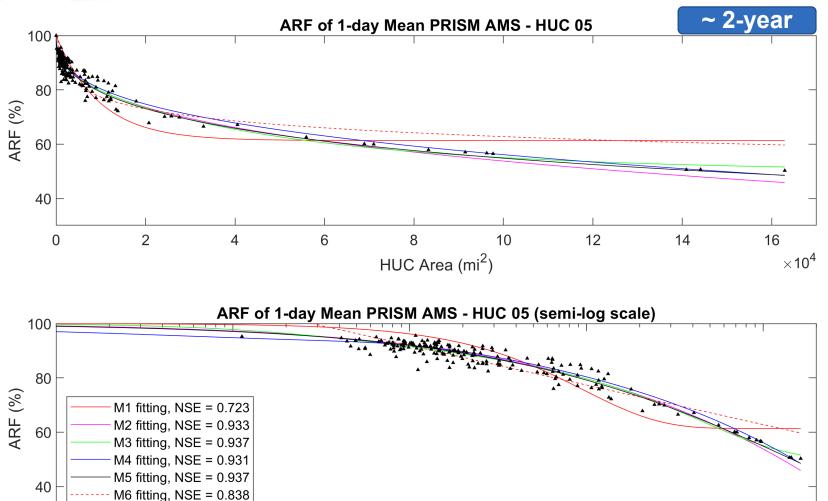
## **Summary of Overall Findings**

- ARF decreases with (1) decreasing duration, (2) increasing area, and (3) increasing return period.
- ARF methods may cause significant differences.
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- Data: PRISM (all seasons)
- Duration: 1-day
- Frequency level: AMS
- ARF Fitting: M1–M6





10<sup>3</sup>

HUC Area (mi<sup>2</sup>)

10<sup>4</sup>

10<sup>2</sup>

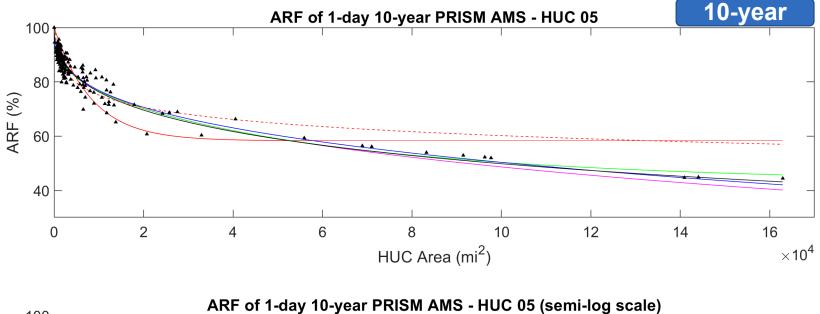
10<sup>5</sup>

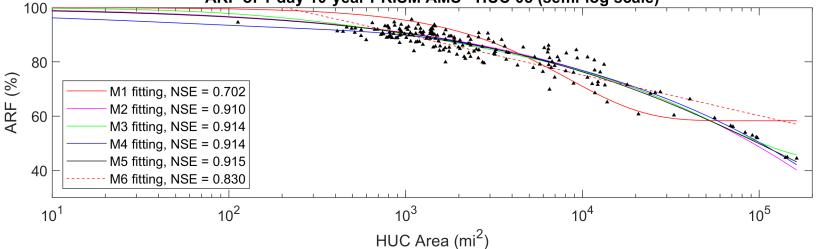
 $10^{1}$ 

21

- Data: PRISM (all seasons)
- Duration: 1-day
- Frequency level: 10-year
- ARF Fitting: M1–M6

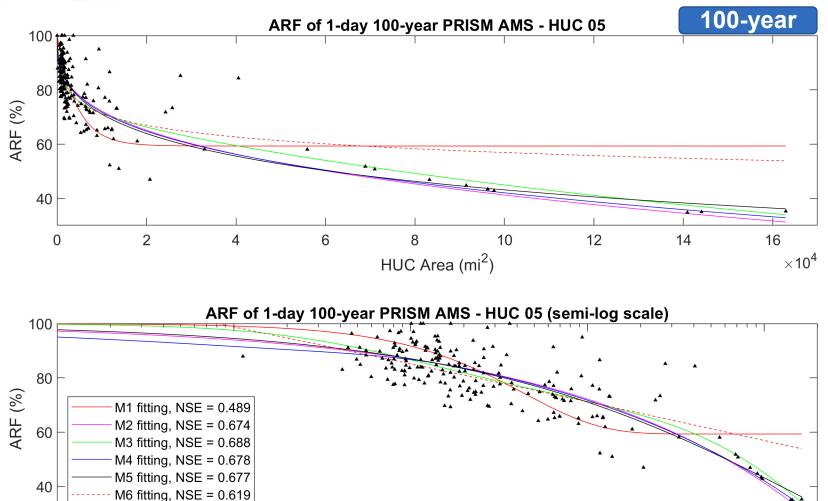






- Data: PRISM (all seasons)
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- Frequency level: 100-year
- ARF Fitting: M1–M6





10<sup>3</sup>

HUC Area (mi<sup>2</sup>)

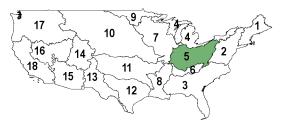
10<sup>4</sup>

10<sup>2</sup>

10<sup>5</sup>

 $10^{1}$ 

- Data: PRISM (all seasons)
- Duration: 1-day, 2-day, 3-day
- Frequency level: AMS, 10-year, 100-year
- ARF Fitting: M1–M6



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Duration	NSE												
Duration	M1	M2	M3	M4	M5	M6							
	Average AMS (approximately 2-year)												
1-day	0.72	0.93	0.94	0.93	0.94	0.84							
2-day	0.76	0.93	0.93	0.93	0.93	0.77							
3-day	0.75	0.92	0.93	0.92	0.93	0.67							
	10-year												
1-day	0.70	0.91	0.91	0.91	0.91	0.83							
2-day	0.69	0.89	0.90	0.89	0.89	0.75							
3-day	0.73	0.90	0.91	0.91	0.91	0.70							
	100-year												
1-day	0.48	0.67	0.69	0.68	0.68	0.62							
2-day	0.45	0.70	0.70	0.70	0.70	0.61							
3-day	0.59	0.80	0.81	0.81	0.80	0.71							

\*Red cell highlights NSE < 0.5

## **Summary of Overall Findings**

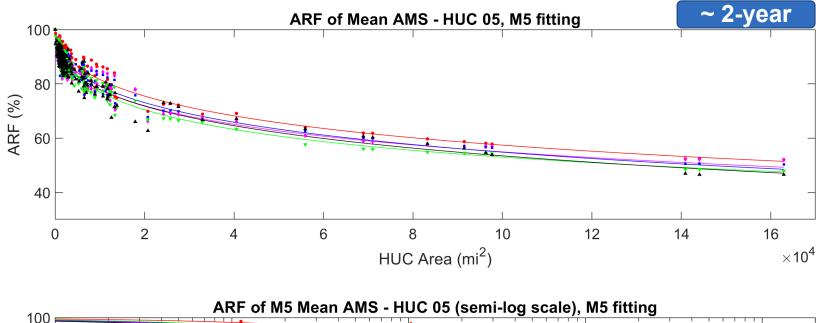
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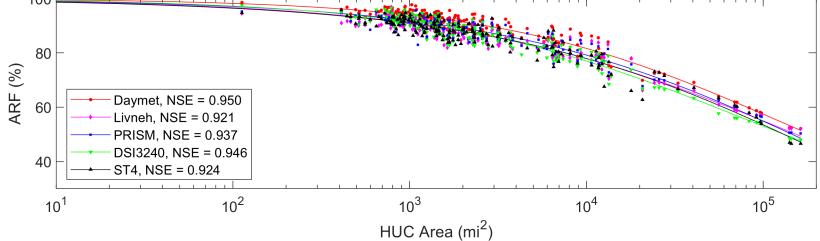


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- Data: All (all seasons)
- Duration: 1-day
- Frequency level: AMS
- ARF Fitting: M5



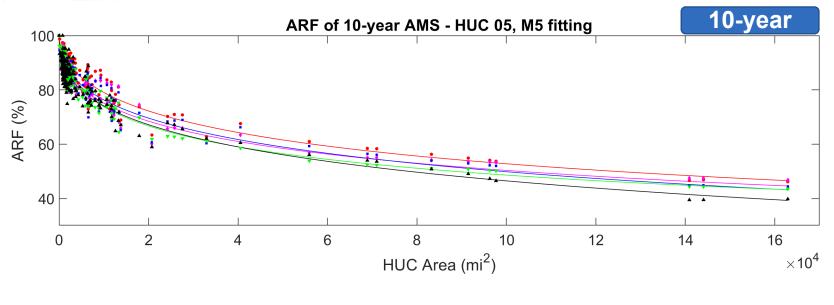




26

- Data: All (all seasons)
- Duration: 1-day
- Frequency level: 10-year
- ARF Fitting: M5

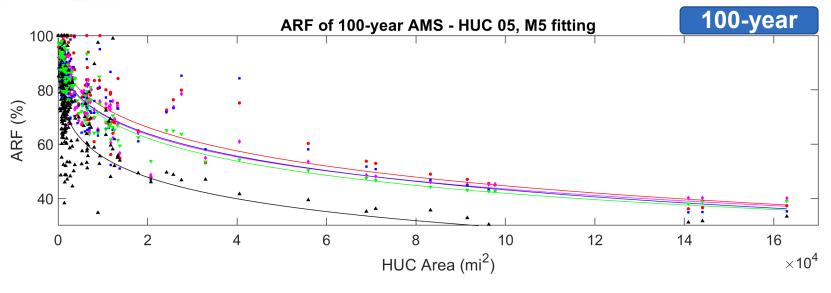




ARF of M5 10-year AMS - HUC 05 (semi-log scale), M5 fitting 100 80 ARF (%) Daymet, NSE = 0.929 60 Livneh, NSE = 0.914PRISM, NSE = 0.915 DSI3240, NSE = 0.934 40 ST4, NSE = 0.891 10<sup>3</sup>  $10^{1}$ 10<sup>2</sup> 10<sup>4</sup> 10<sup>5</sup> HUC Area (mi<sup>2</sup>)

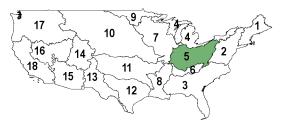
- Data: All (all seasons)
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- Frequency level: 100-year
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ARF of M5 100-year AMS - HUC 05 (semi-log scale), M5 fitting 100 80 ARF (%) Daymet, NSE = 0.737 60 Livneh, NSE = 0.801PRISM, NSE = 0.677 DSI3240, NSE = 0.846 40 ST4, NSE = 0.352 10<sup>3</sup>  $10^{1}$ 10<sup>2</sup> 10<sup>4</sup> 10<sup>5</sup> HUC Area (mi<sup>2</sup>)

- Data: All (all seasons)
- Duration: 1-day, 2-day, 3-day
- Frequency level: AMS, 10-year, 100-year
- ARF Fitting: M5



	NSE												
Duration	PRISM (1981–2017)	Daymet (1980–2017)	ST4 (2002–2017)	Livneh (1950–2013)	DSI3240 (1950–2013)								
	Average AMS (approximately 2-year)												
1-day	0.94	0.95	0.92	0.92	0.95								
2-day	0.93	0.95	0.92	0.93	0.93								
3-day	0.92 0.94		0.92	0.92	0.93								
	10-year												
1-day	0.91	0.93	0.89	0.91	0.93								
2-day	0.89	0.92	0.88	0.92	0.92								
3-day	0.91 0.93		0.87	0.91	0.91								
			100-year										
1-day	0.68	0.74	0.35	0.80	0.85								
2-day	0.70	0.74	0.39	0.77	0.80								
3-day	0.80	0.82	0.36	0.82	0.80								
		*Red cell highli	abts NSE < 0.5		CAK KIDGE								

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\*Red cell highlights NSE < 0.5

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## **Summary of Overall Findings**

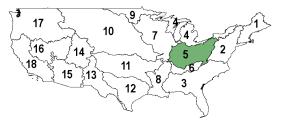
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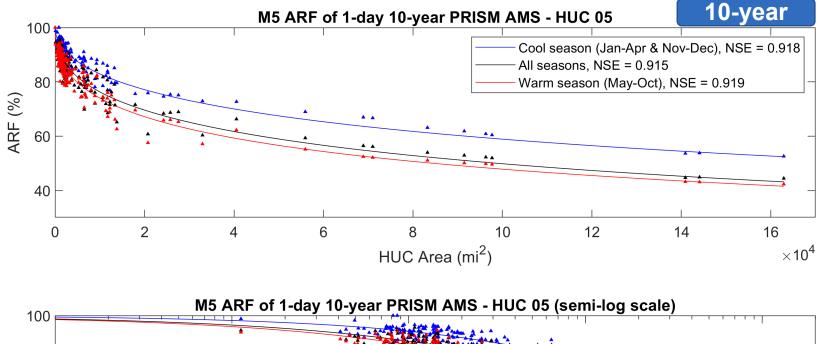


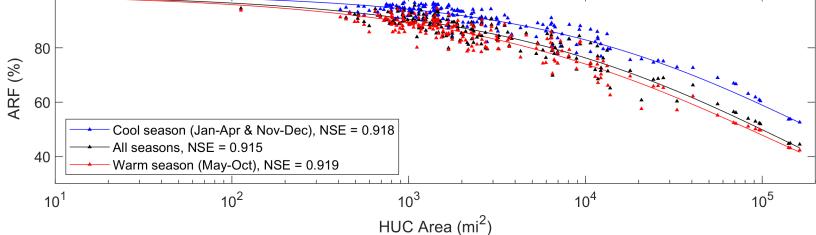
### Region 05 Seasonal Variability

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- Data: PRISM (all, warm, cool)
- Duration: 1-day
- Frequency level: 10-year
- ARF Fitting: M5





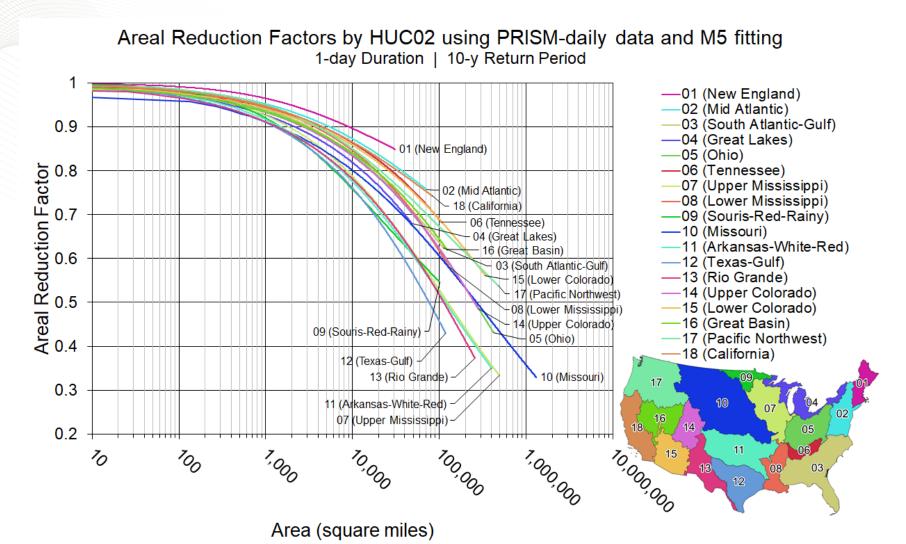


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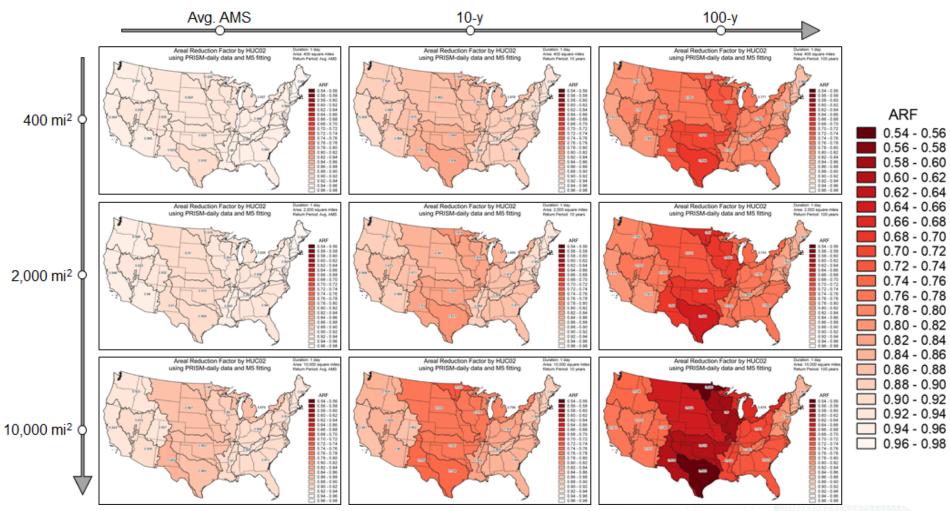
## National Comparison Results: 1-day 10-year



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### **National Comparison Results: 1-day**

Areal Reduction Factors by HUC02 using PRISM-daily data and M5 fitting 1-day Duration



## **National Comparison Results: 1-day NSE**

Comparison of 1-day CONUS regional M5 ARF fitting using PRISM precipitation across different return periods.

									N	SE								
<b>Return Period</b>		Region Number															-	
	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18
Avg. AMS	0.68	0.80	0.72	0.69	0.94	0.91	0.93	0.87	0.88	0.85	0.87	0.88	0.92	0.83	0.84	0.81	0.85	0.72
GEV 10-yr	0.66	0.67	0.72	0.58	0.91	0.89	0.90	0.83	0.85	0.78	0.81	0.89	0.90	0.81	0.79	0.77	0.84	0.74
GEV 100-yr	0.20	0.15	0.44	0.31	0.68	0.46	0.72	0.59	0.73	0.57	0.59	0.70	0.72	0.65	0.51	0.37	0.70	0.63



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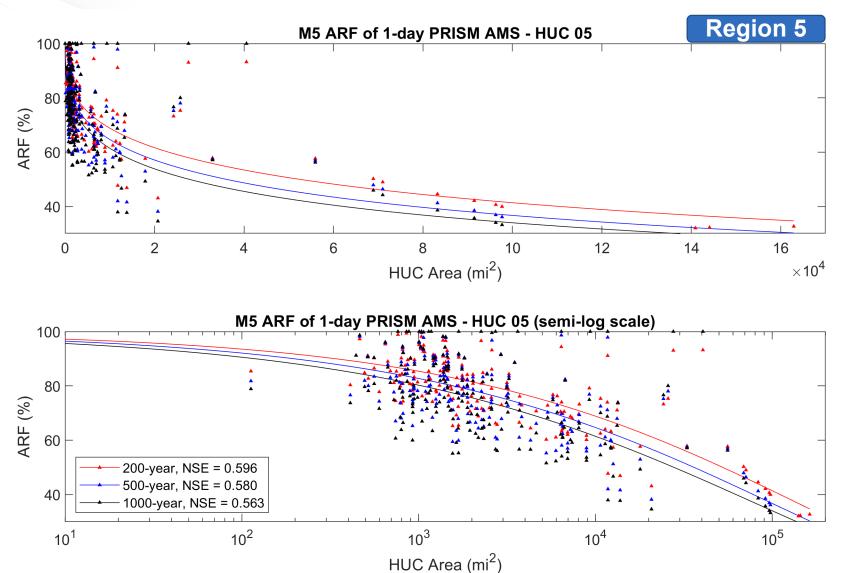
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### High Return Levels

- Data: PRISM (all seasons)
- Duration: 1-day
- Frequency level: 200-year, 500year, 1000-year
- ARF Fitting: M5

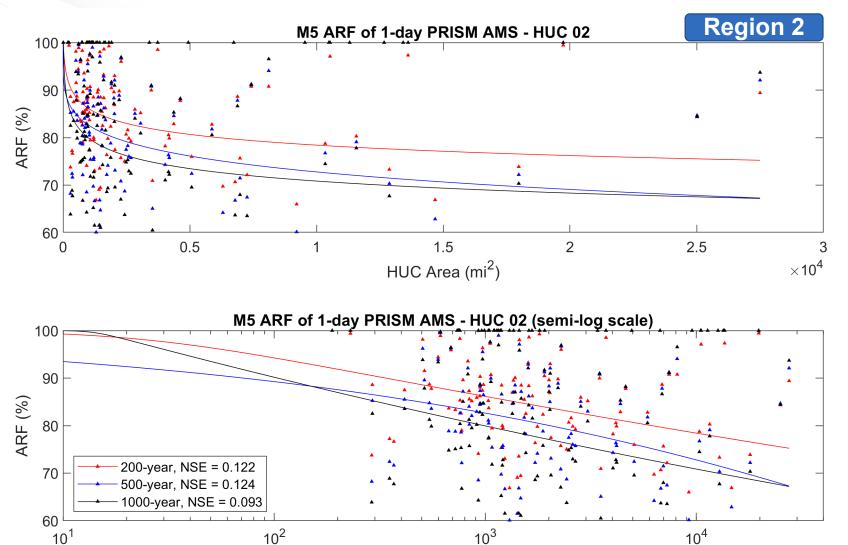




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- Frequency level: 200-year, 500year, 1000-year
- ARF Fitting: M5



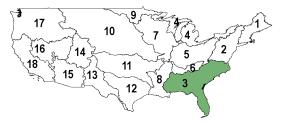


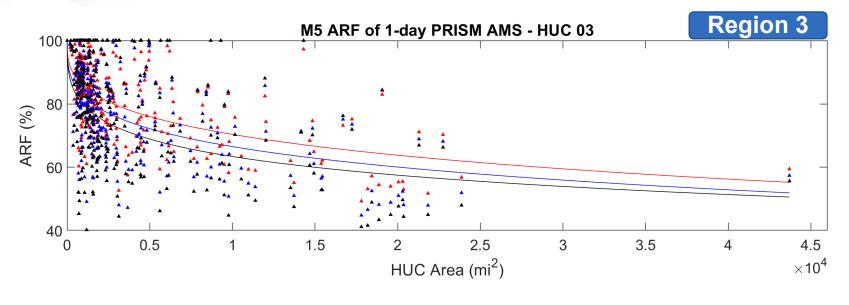
HUC Area (mi<sup>2</sup>)

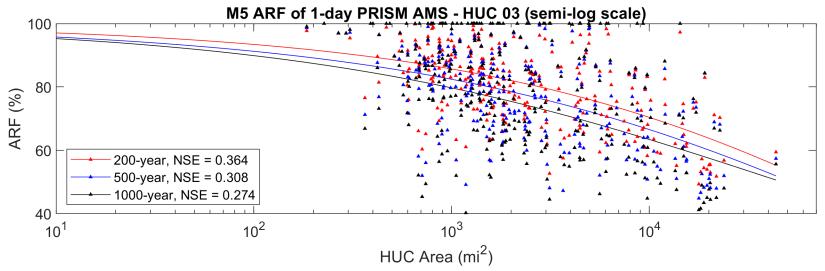
### High Return Levels

38

- Data: PRISM (all seasons)
- Duration: 1-day
- Frequency level: 200-year, 500year, 1000-year
- ARF Fitting: M5







### **Issues to be Explored**

- Development of ARF for long return period
- Uncertainty quantification
- Lack of long-term, high spatiotemporal resolution dataset
- Subwatershed application
- Need for a national ARF product



# Thank you!

## **Questions?**

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