

Factors Affecting the Development of Precipitation Areal Reduction Factors

Presented at

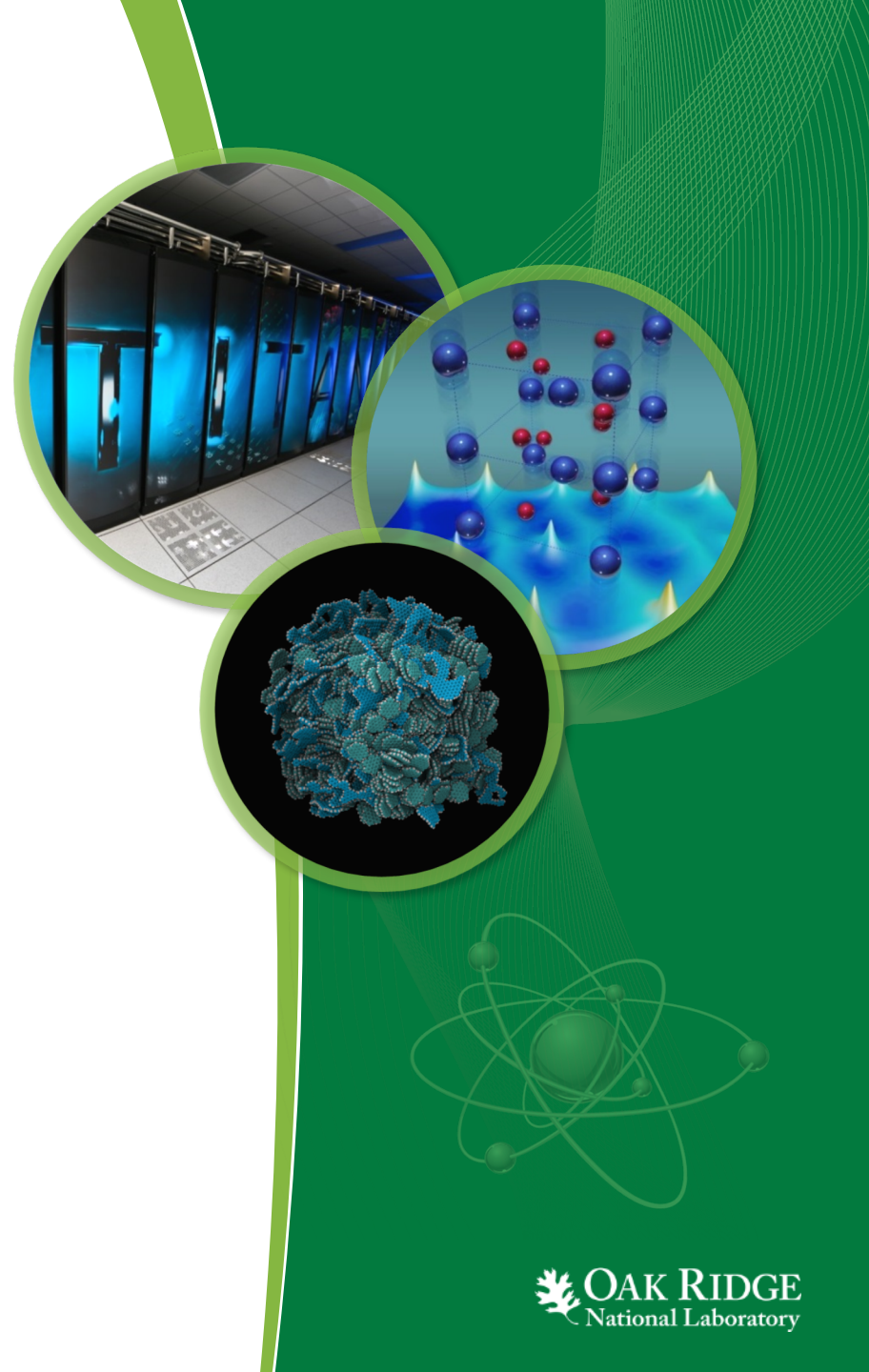
The 4th Annual Probabilistic Flood Hazard Assessment (PFHA) Research Workshop

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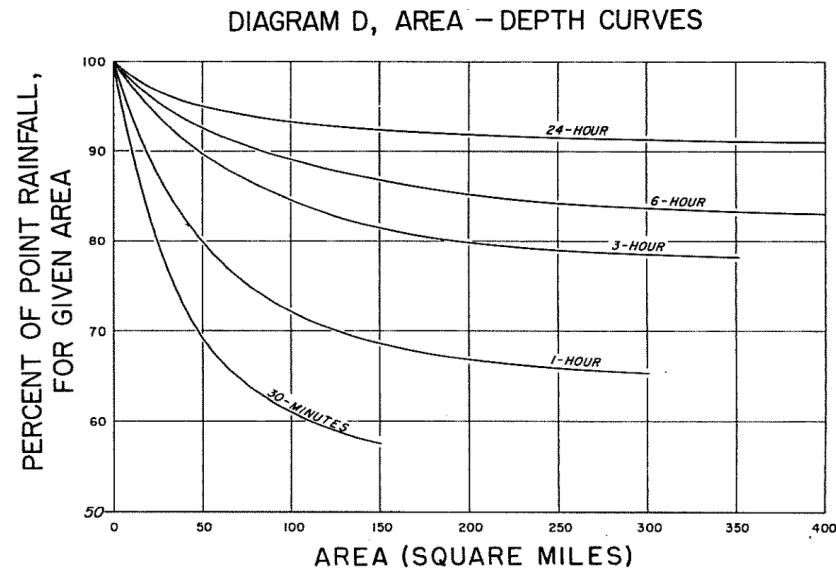
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Background – Areal Reduction Factors (ARFs)

- **Current precipitation frequency products (e.g., NOAA Atlas 14) are mostly developed for point rainfall**
 - Not directly applicable for many nuclear power plant H&H applications
- **Areal reduction factors (ARFs) are needed to convert these point estimates to watershed estimates for H&H modeling**
- **Use “geographically-fixed-area” ARF**
 - NOT “storm-centered” ARF
- **ARFs in common use suffer from several key limitations:**
 - Limited / outdated data
 - Small area sizes (up to 400 mi²)
 - 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**

Study Approach

- **Factors affecting ARFs**

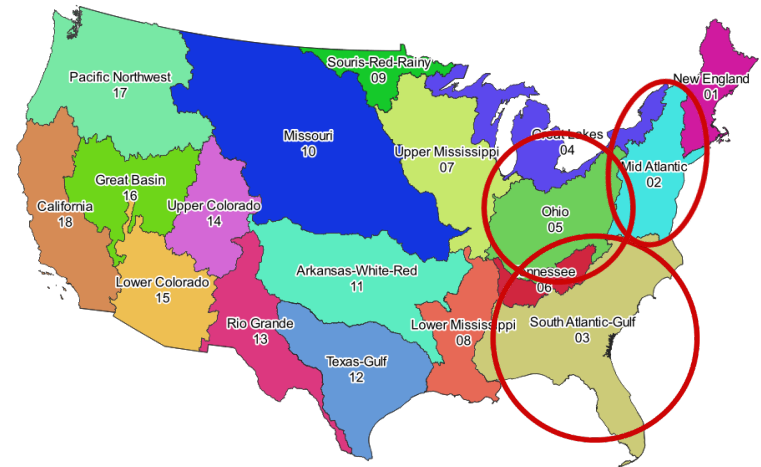
- Area, duration, and return period
- Different ARF methods
- Precipitation products to use
- Geographical locations
- Seasonality

- **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^2)**

- **Only consider “geographically-fixed-area” ARF**



Visualizing Spatial and Temporal Rainfall

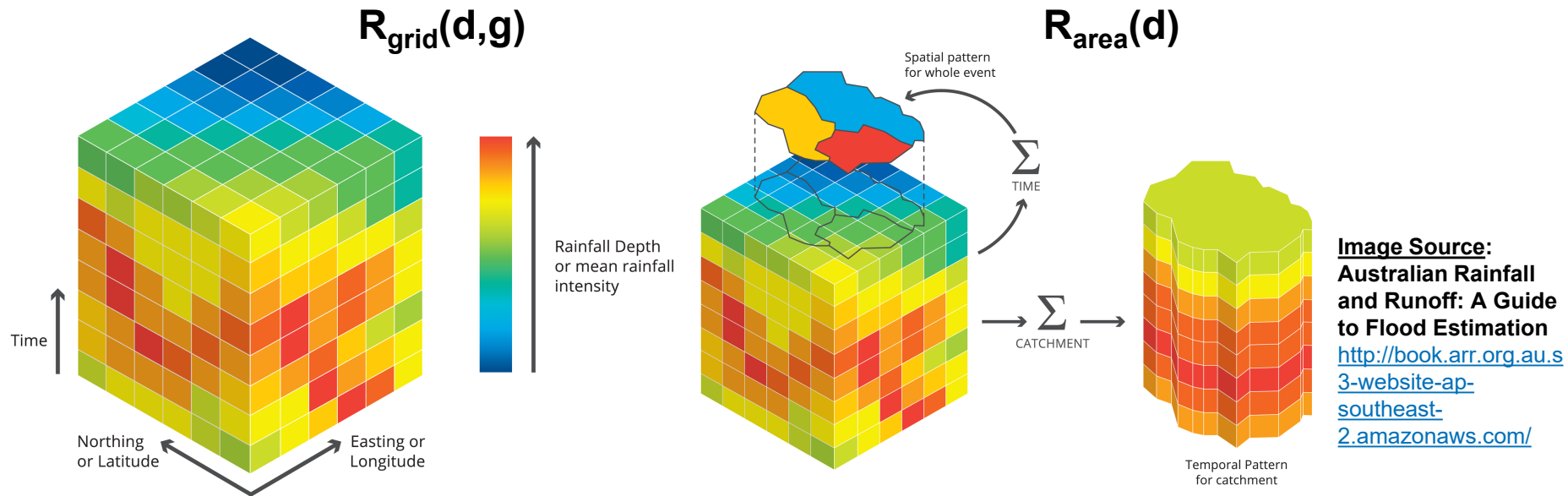
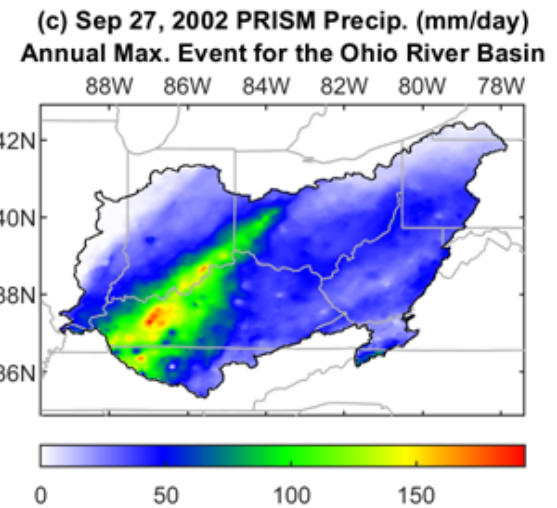
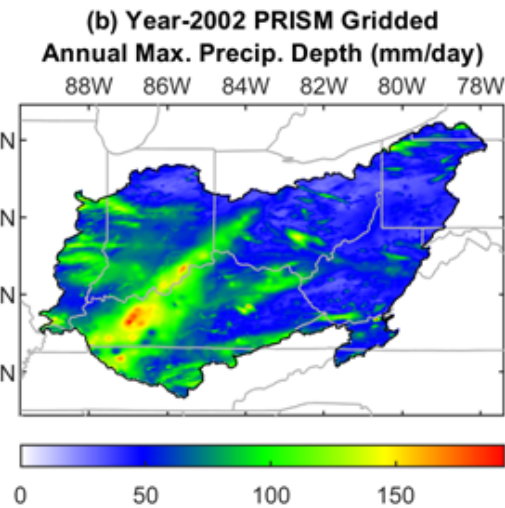
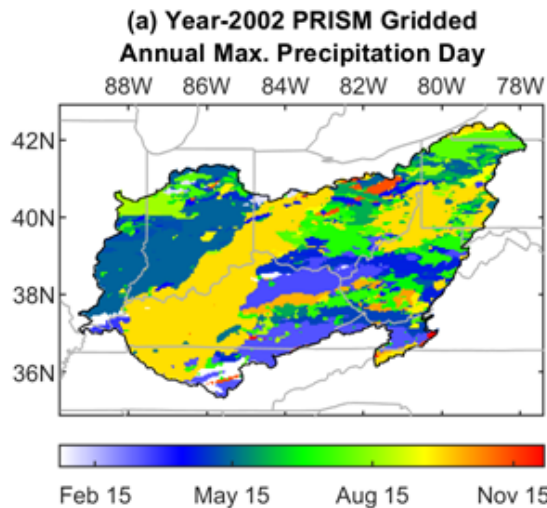


Image Source:
Australian Rainfall and Runoff: A Guide to Flood Estimation
<http://book.arr.org.au.s3-website-ap-southeast-2.amazonaws.com/>



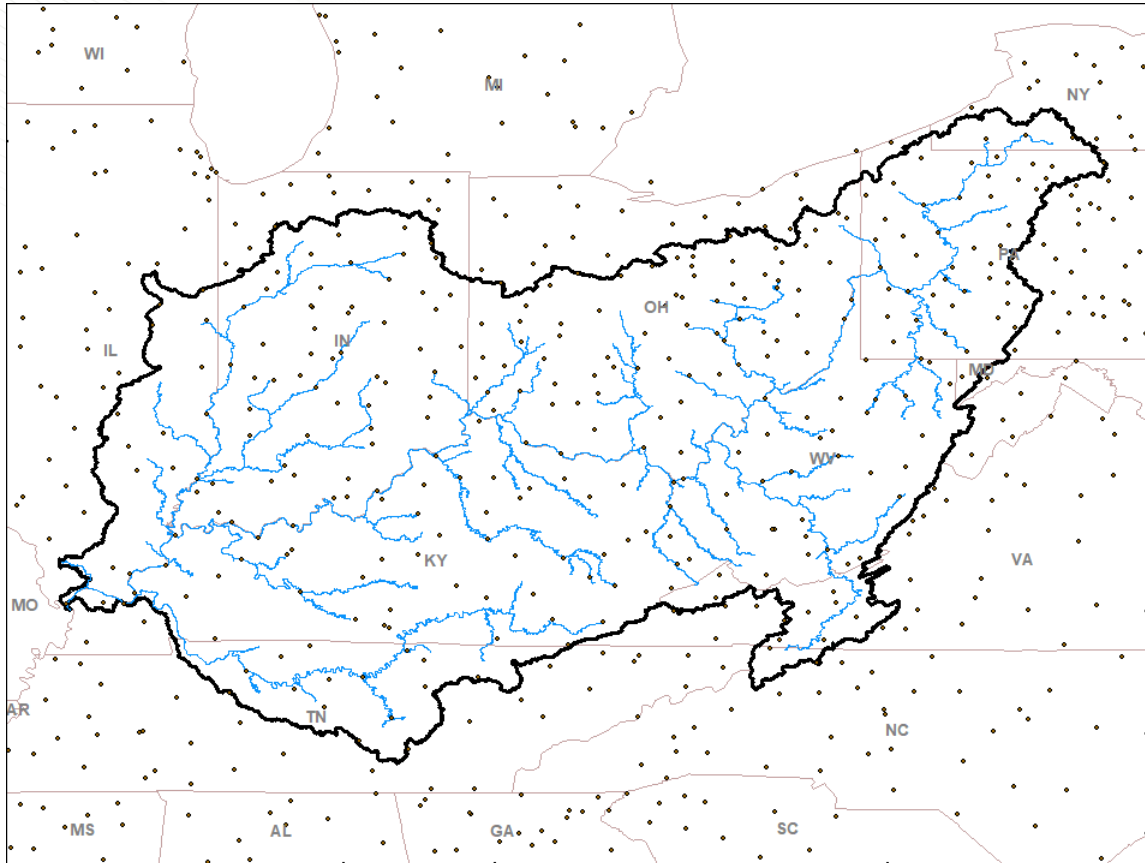
Precipitation Products

Precipitation Products	Provider	Dataset Type	Coverage Start	Coverage End	Data Latency	Spatial Coverage	Temporal Resolution	Spatial Resolution
Gauge-only Datasets								
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 Products								
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 Products								
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).

DSI3240 Assessment Approach

Ohio River Basin (Hydrologic Region 05)



*Dots illustrate NCEI hourly rainfall stations which have 30+ years of record

- **Process 1950–2013 hourly precipitation dataset**
 - 64 years of data
- **Bilinear interpolation of non-missing hourly precipitation to 4-km PRISM grids**
 - Acceptable in the Ohio region given smoother topography. Topographic adjustment shall be needed in other regions.
- **Analyze ARF using the existing PRISM setup**

General 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_{grid}): annually at each grid
 - *Areal AMS* (P_{area}): annually at each HUC08, HUC06, HUC04, HUCac
- **Sample ARF at each areal units (HUCs)**
 - Average AMS
 - (Temporal average of P_{area}) / (Temporal and spatial average of P_{grid})
 - T-year estimate
 - Fitting AMS by GEV, and getting T-year estimates (e.g., $P_{\text{area},10\text{yr}}$)
 - $P_{\text{area},\text{Tyr}} / (\text{Spatial average of } P_{g11,\text{Tyr}})$
- **Regional fitting by different ARF models**

Sample ARF Calculation

- **$R_{grid}(d,g)$**

- Daily rainfall at each grid
- d , a day
- g , a grid location within an Area

- **$P_{grid}(y,g)$**

- Annual max. rainfall at each grid
- $P_{grid}(y,g) = \max_{d \in \mathcal{Y}} R_{grid}(d,g)$
- y , a year
- N_y , total number of years

- **$R_{Area}(d)$**

- Daily rainfall at each Area
- $R_{Area}(d) = \frac{\sum_{g \in H} R(d,g)}{N_H}$
- H , the set of all g within an Area
- N_H , number of grid points in an Area

- **$P_{Area}(y)$**

- Annual max. rainfall at each Area
- $P_{Area}(y) = \max_{d \in \mathcal{Y}} R_{Area}(d)$

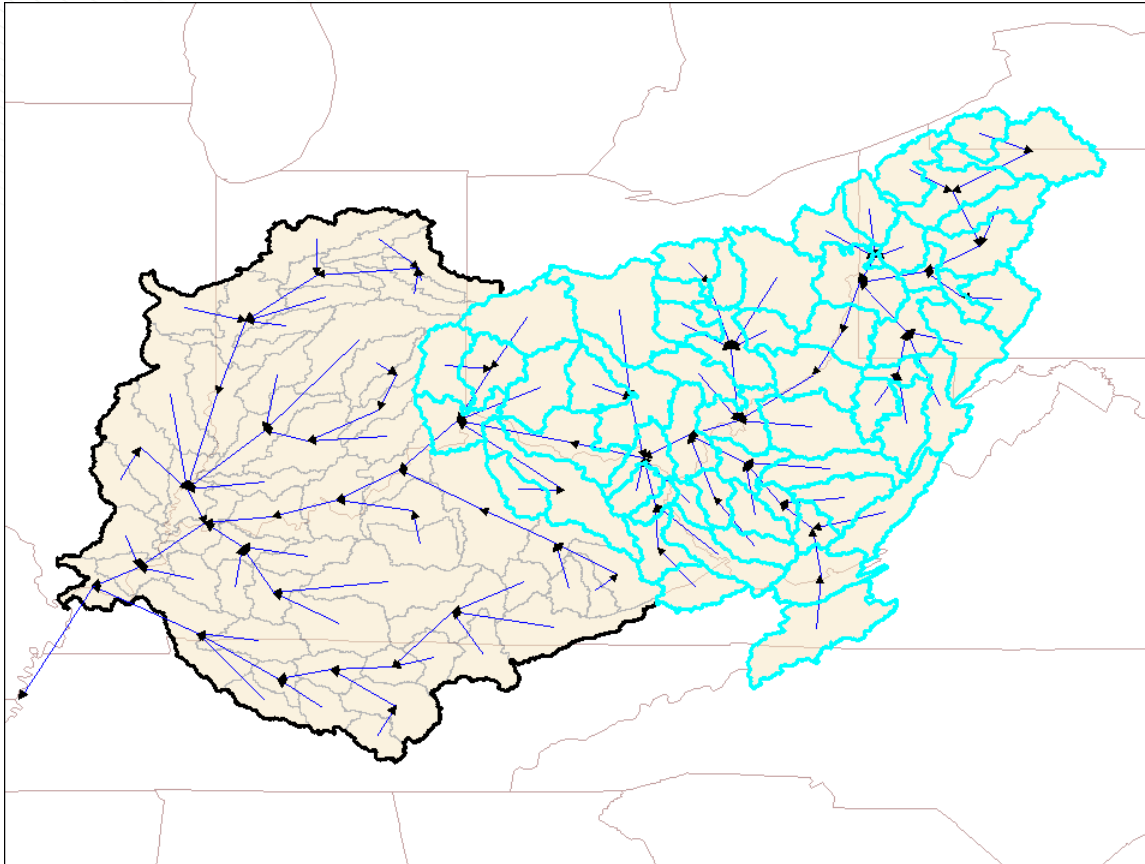
- **Sample ARF of average AMS**

- $P_{grid,avg1}(y) = \frac{\sum_{g \in H} P_{grid}(y,g)}{N_H}$
- $P_{grid,avg2} = \frac{\sum_{y=1}^{N_y} P_{grid,avg1}(y)}{N_y}$
- $P_{HUC,avg} = \frac{\sum_{y=1}^{N_y} P_{HUC}(y)}{N_y}$
- $ARF_{AMS} = \frac{P_{HUC,avg}}{P_{grid,avg2}}$

- **Sample ARF of T-year estimates**

- $P_{grid,Tyr}(g) = GEV(P_{grid}(y,g), Tyr)$
- $P_{grid,Tyr,avg} = \frac{\sum_{g \in H} P_{grid,Tyr}(g)}{N_H}$
- $P_{Area,Tyr} = GEV(P_{Area}(y), Tyr)$
- $ARF_{Tyr} = \frac{P_{Area,Tyr}}{P_{grid,Tyr,avg}}$

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 km²
 - 21 HUC06: 4,400 – 54,000 km²
 - 7 HUC04: 15,000 – 85,000 km²
 - 46 HUCac: 4,600 – 420,000 km²

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)

$$ARF(A, D) = 1 - e^{aD^b} + e^{(aD^b - cA)}$$

$$ARF(A, D) = 1 - \frac{aA^{(b-c \ln A)}}{D^d}$$

$$ARF(A) = \frac{a_0}{(A + a_2)^{a_1}} + a_3 e^{-a_4 A}$$

$$\begin{aligned} ARF(A, D, AEP) &= 1 - a(A^b - c \log_{10} D)D^{-d} \\ &+ eA^f D^g (0.3 + \log_{10} AEP) \\ &+ h10^{iAD} (0.3 + \log_{10} AEP) \end{aligned}$$

• Dynamic Scaling Model

- M5: De Michele et al. (2001)

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

• Extreme Value Theory

- M6: Overeem et al. (2010)

$$\begin{aligned} ARF(A, D, AEP) &= P(A, D, AEP) / P(A^*, D, AEP) \\ P(A, D, AEP) &= GEV^{-1}(1 - AEP | \mu, \gamma, \kappa) \\ \mu(A, D) &= aD^b + (c + d \ln D)A^e \\ \gamma(A, D) &= f \ln A + g \ln D + h \\ \kappa(A) &= i \ln A + j \end{aligned}$$

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

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

- A , area (km²)
- D , duration (hr)
- Four parameters: v , b , w , z

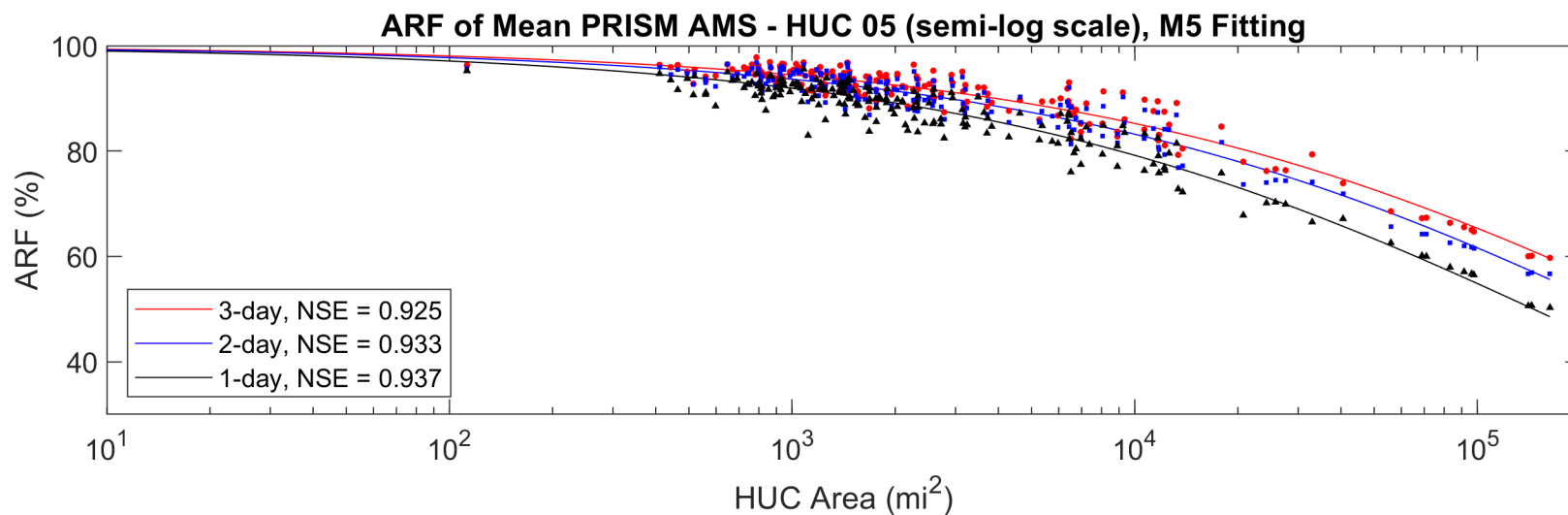
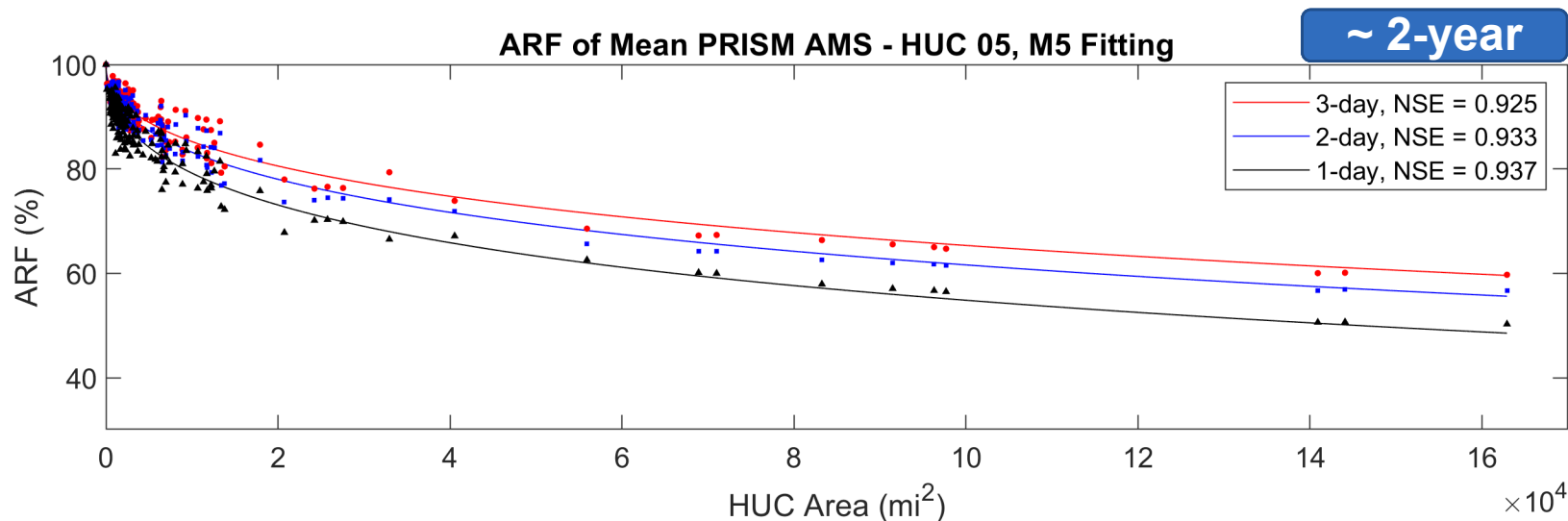
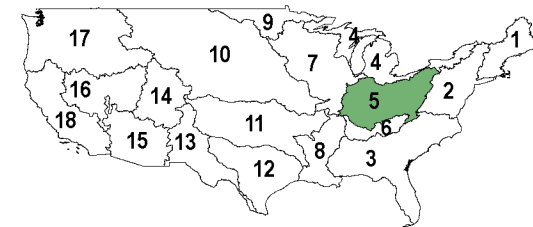
- **ORNL Fitting**

- 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)

Preliminary Results

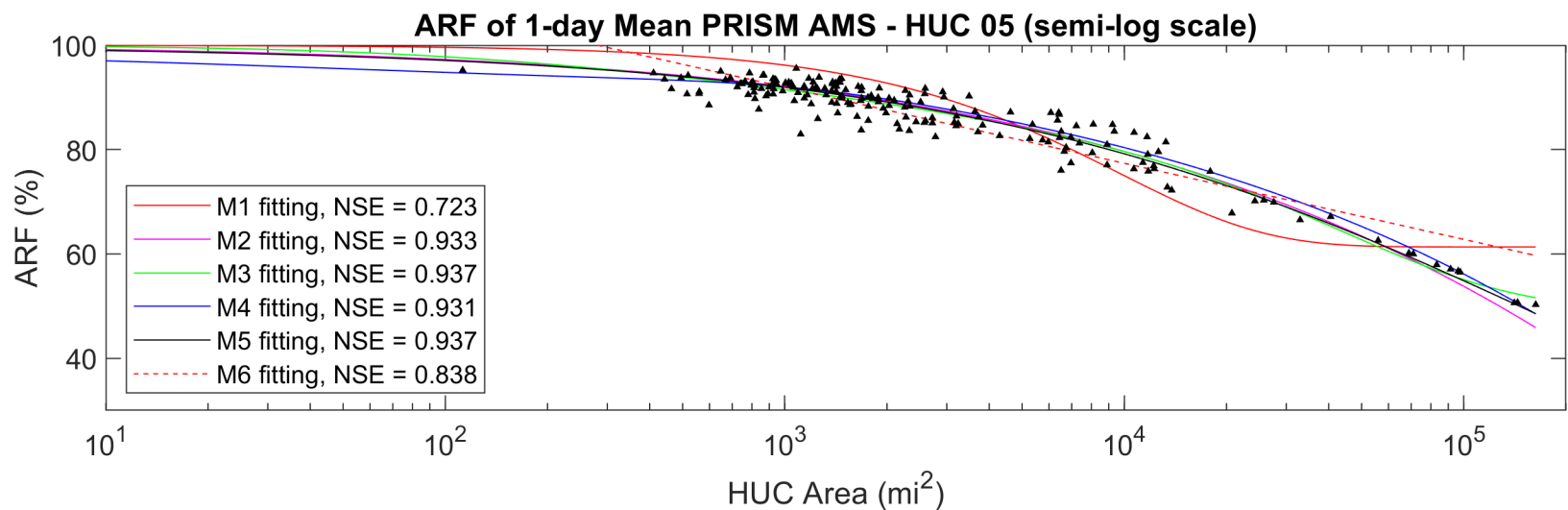
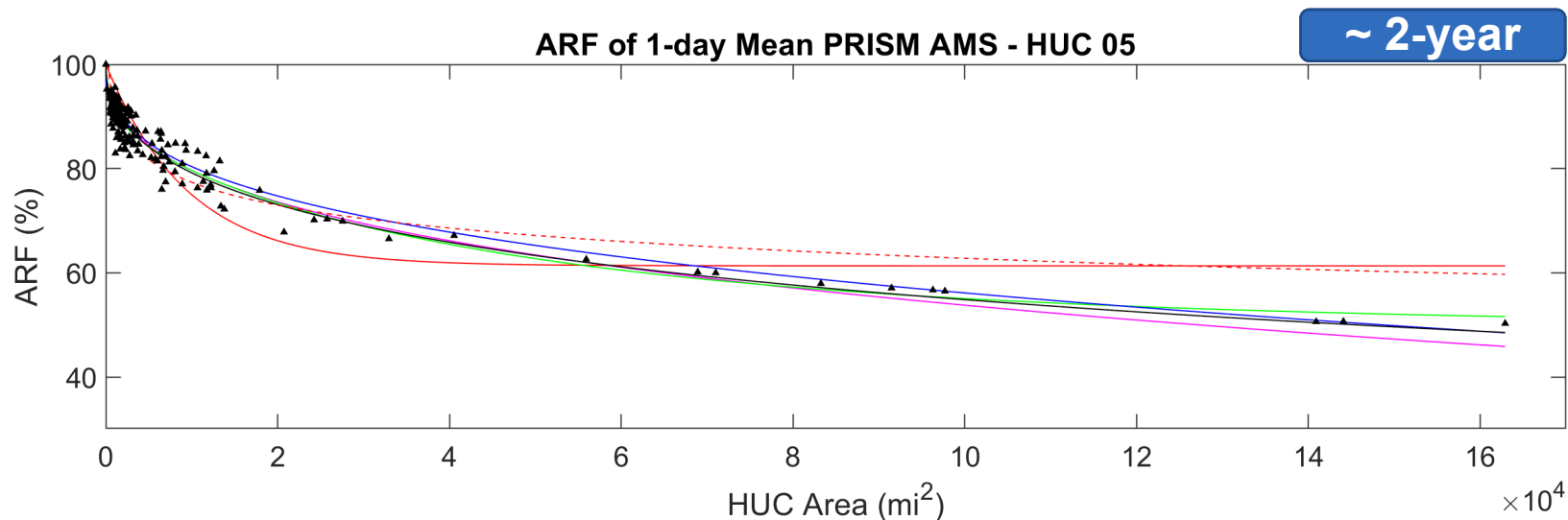
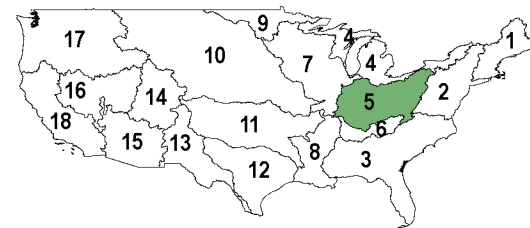
M5: De Michele Dynamic Scaling Model

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



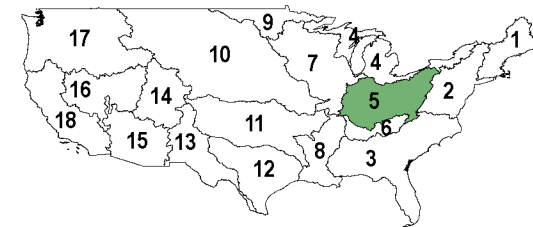
Region 05 Overall M1–M6 Comparison

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



Region 05 Overall M1–M6 Comparison

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

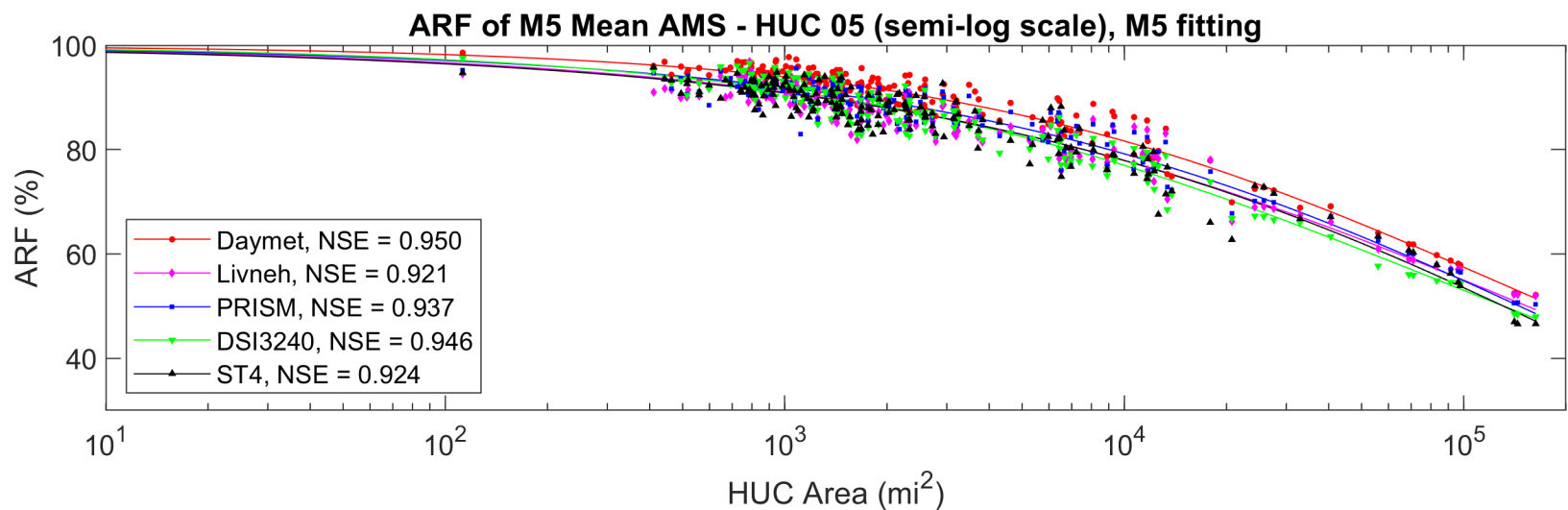
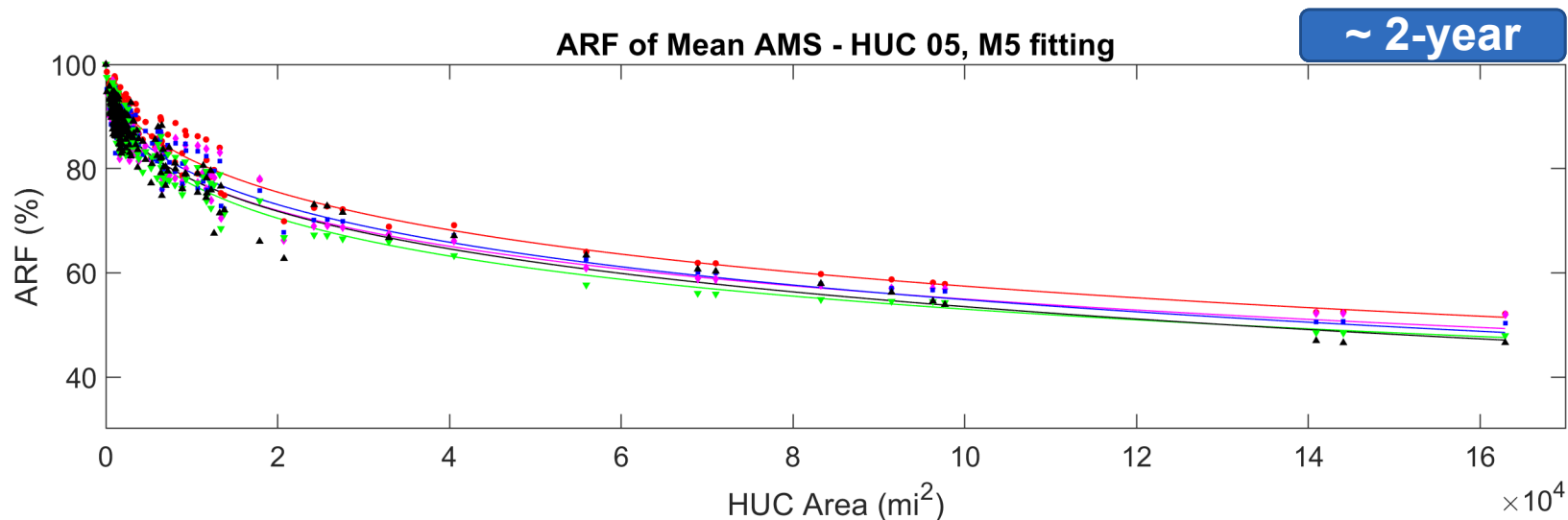
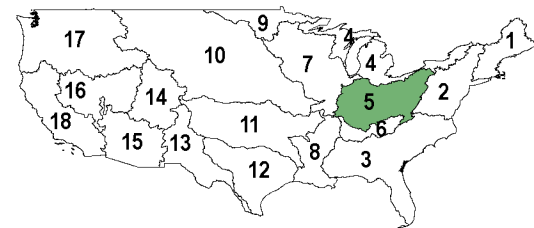


Duration	NSE					
	M1	M2	M3	M4	M5	M6
	Average AMS (approximately 2-year)					
1-day	0.72	0.93	0.94	0.93	0.94	0.84
2-day	0.76	0.93	0.93	0.93	0.93	0.78
3-day	0.75	0.92	0.93	0.92	0.93	0.69
	10-year					
1-day	0.70	0.91	0.91	0.91	0.91	0.82
2-day	0.69	0.89	0.90	0.89	0.89	0.68
3-day	0.73	0.90	0.91	0.91	0.91	0.61
	100-year					
1-day	0.48	0.66	0.67	0.66	0.66	0.60
2-day	0.44	0.67	0.67	0.67	0.67	0.38
3-day	0.60	0.78	0.79	0.79	0.78	0.45

*Red cell highlights NSE < 0.5

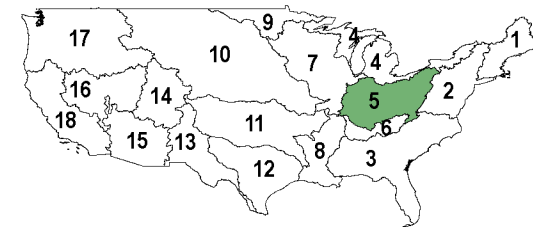
Region 05 Data Source Comparison

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



Region 05 Data Source Comparison

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

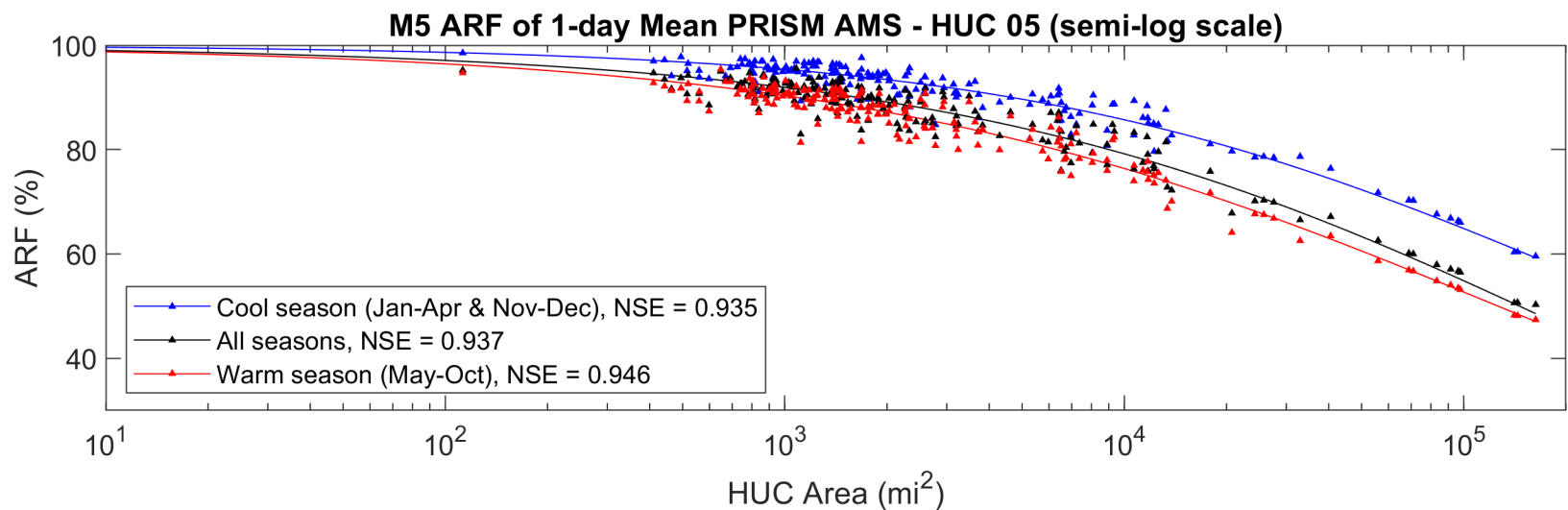
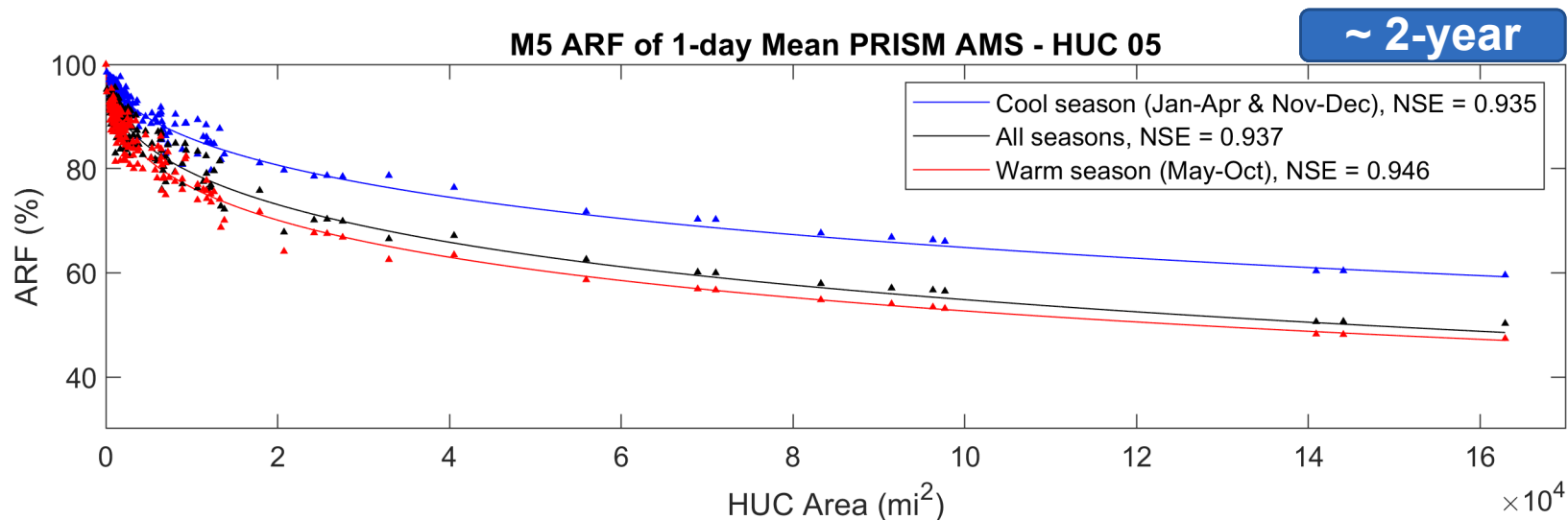
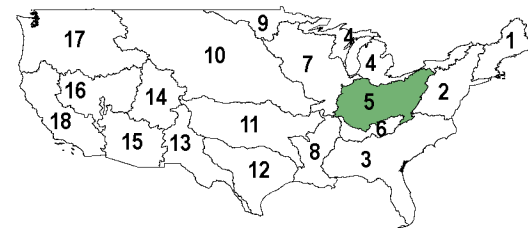


Duration	NSE				
	PRISM (1981–2017)	Daymet (1980–2017)	ST4 (2002–2017)	Livneh (1950–2013)	DSI3240 (1950–2013)
	Average AMS (approximately 2-year)				
1-day	0.94	0.95	0.92	0.92	0.95
2-day	0.93	0.95	0.92	0.93	0.93
3-day	0.92	0.94	0.92	0.93	0.93
	10-year				
1-day	0.91	0.93	0.89	0.91	0.93
2-day	0.89	0.92	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 highlights NSE < 0.5

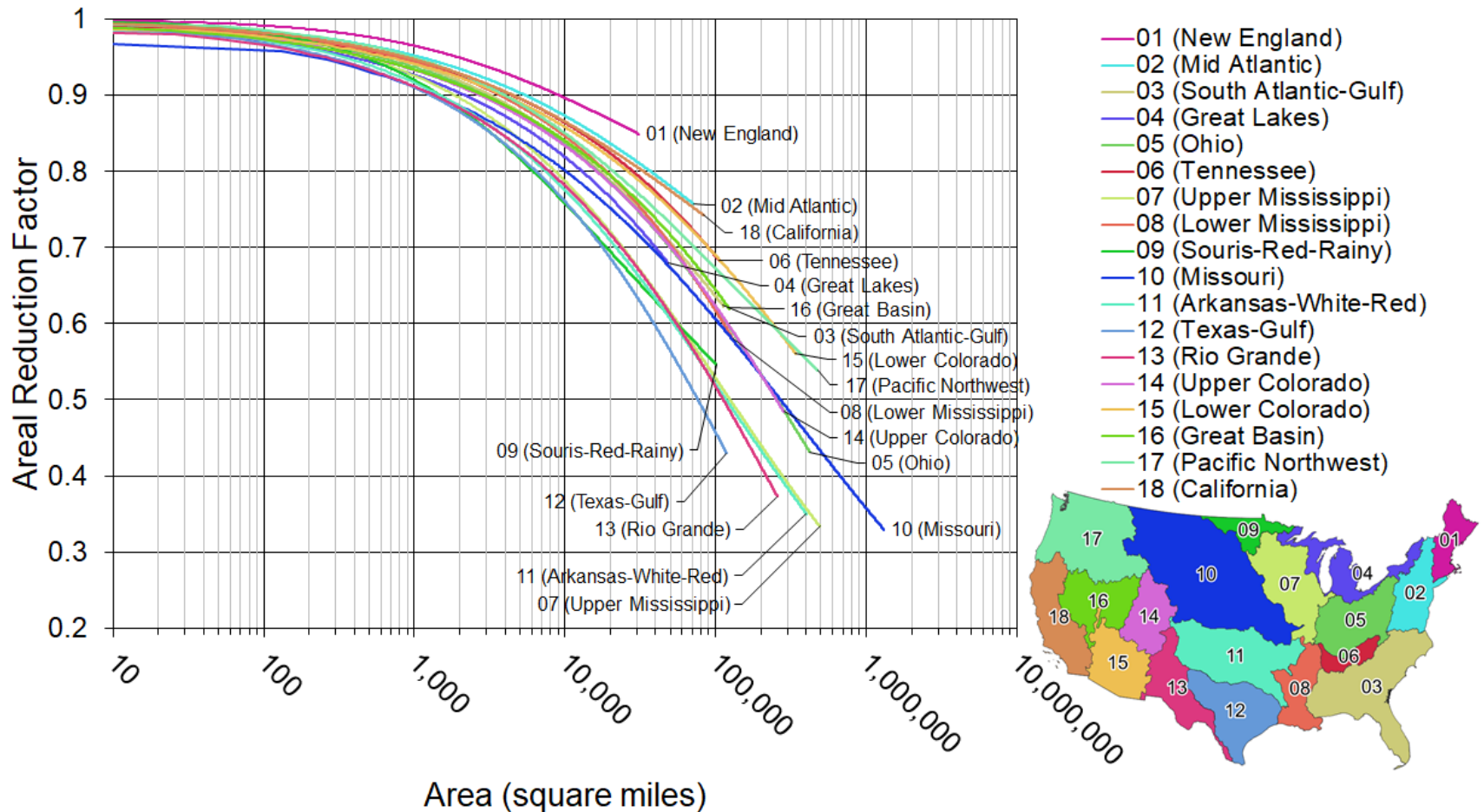
Region 05 Seasonal Variability

- Data: PRISM (all, warm, cool)
- Duration: 1-day
- Frequency level: AMS, 10-year, 100-year
- ARF Fitting: M5



National Comparison (I)

Areal Reduction Factors by HUC02 using PRISM-daily data and M5 fitting
1-day Duration | 10-y Return Period



Preliminary Observations (I)

- **General**

- Shorter duration, lower ARF
- Larger area, lower ARF
- Higher return period, lower ARF
- Cool season ARF > All season ARF > Warm season ARF

- **Regarding ARF methods**

- Different ARF methods matter
- M2 (K&X), M3 (Switzerland), M4 (ARR), and M5 (De Michele) provide better fitting.
- While M3 (Switzerland) can fit well, it does not include duration as a variable and hence can be more sensitive to sample size and data quality.
- M4 (ARR) is more difficult to fit (8 parameters), but it includes frequency levels in the model and can be overall more robust.
- M5 (De Michele) can fit well and has a good underlying theory.
- While M6 (GEV) has a good underlying theory, it's more challenging for the ARF application. Further ad hoc adjustment is needed.

Preliminary Observations (II)

- **Regarding data sources**

- Smaller ARF differences are found, but the differences are not negligible.
- Data length plays an important role, especially for higher return level ARFs.
- Difficult to fit one set of parameters for both longer and shorter durations.
- While gauge data is harder to process, it leads to the best ARF model fitting in Region 05.

- **Regarding inter-regional differences**

- ARFs are lower in the central US, higher in eastern & western US
- Texas-Gulf (R12) & Souris-Red-Rainy (R09) are generally the lowest.

- **Overall**

- The proposed HUCac watershed AMS searching approach work across different regions.
- High return level ARF remains a major challenge, mostly due to relatively short data record length.

Thank you!

Questions?

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