

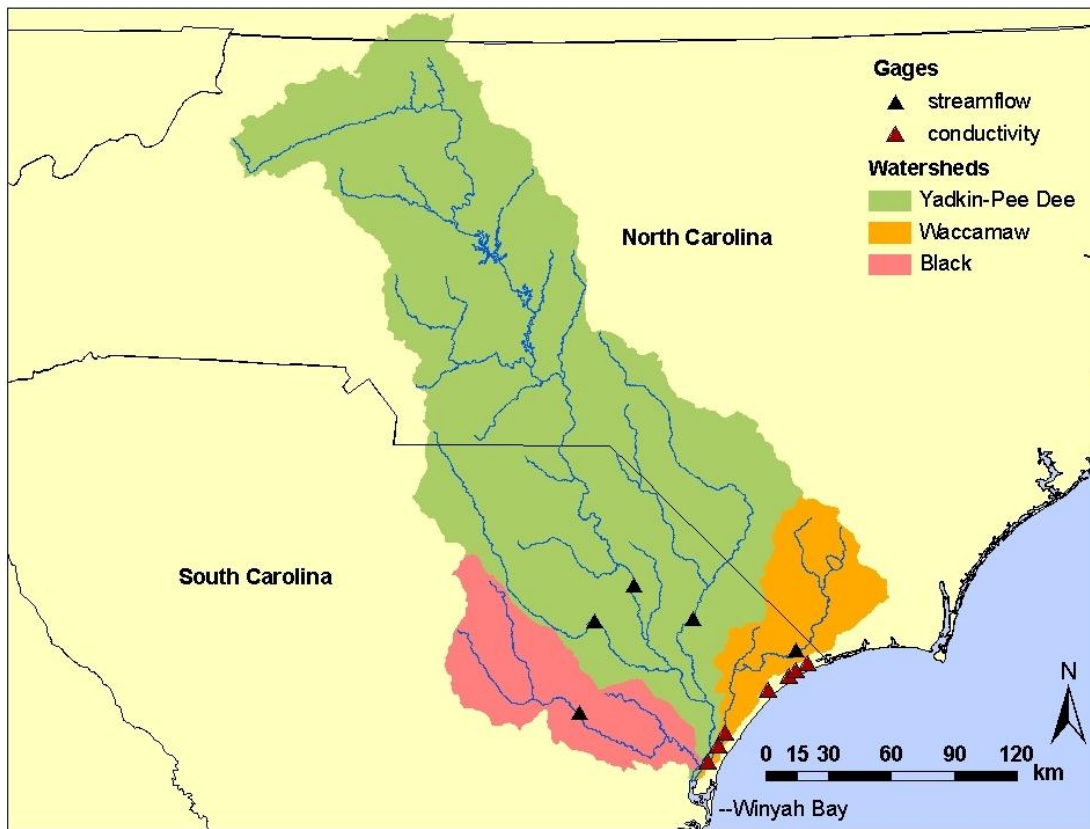
Assessing methods to disaggregate daily precipitation for hydrological simulation

Peng Gao, Gregory Carbone, Daniel Tufford,
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University of South Carolina



Background

◆ CISA (Carolinas Integrated Sciences and Assessments)



◆ Hydrological modeling: how climate affects water supply and quality in major watersheds in Carolinas

Background

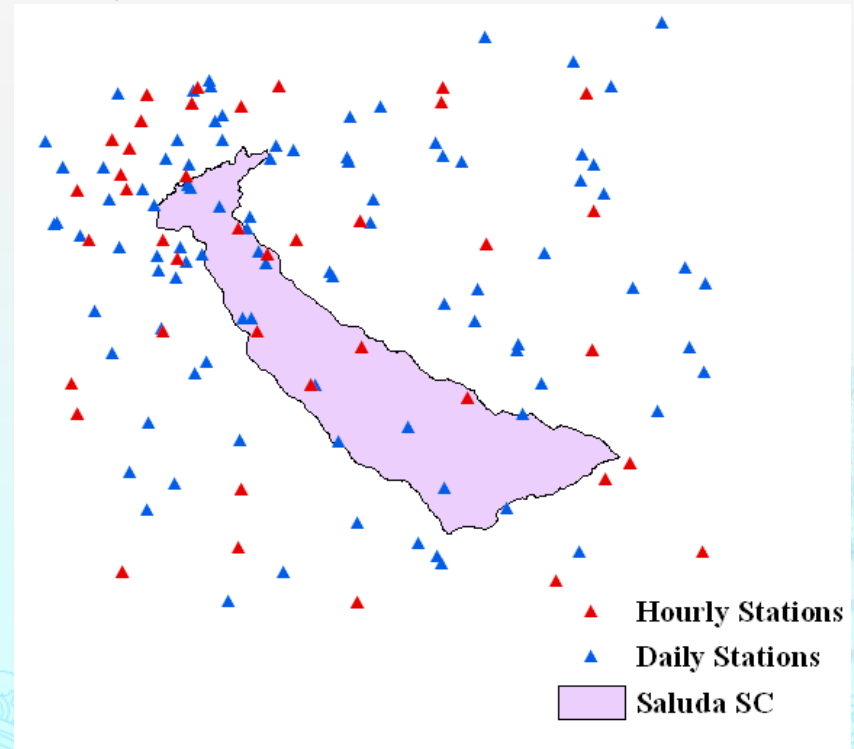
Continuous simulation modeling

(e.g. Hydrologic Simulation Program-Fortran (HSPF))

- ◆ **a principle tool** to investigate the impacts of climate change on water resources
- ◆ **high spatial and temporal** resolution (e.g. hourly or subdaily) rainfall data

Challenges - the constraint of data availability

- ◆ Precipitation data are often available only at **coarser** levels (i.e., daily) (**25,000** daily recording stations, **8,000** hourly stations in U.S.) (Booner, 1998)



Challenges - the constraint of data availability

- ❖ **Meteorological variables from the GCMs (General Circulation Models) needed for hydrological simulation - typically at monthly or **daily** scales**



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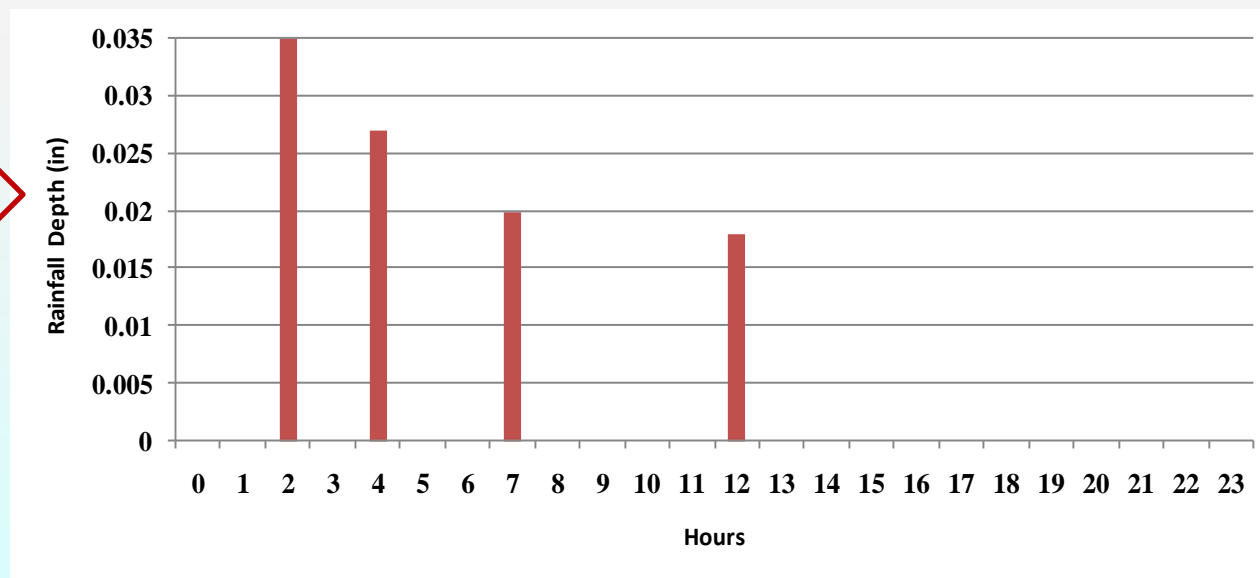
Downscaled Climate Projections by Katharine Hayhoe

Precipitation. The downscaling model for precipitation is similar to that for temperature in many aspects, but with some key differences. First, for practical reasons an AOGCM predictor had to be chosen that was commonly archived at the daily scale. Although upper-level humidity and geopotential height have shown promise in downscaling precipitation, few AOGCMs have preserved daily outputs. Thus, 24h cumulative precipitation was selected as the predictor for precipitation, with the additional refinement of incorporating convective and large-scale precipitation if both predictors were available. For models with these variables, the downscaling approach selects from three possible predictors the one best suited to each month: convective, large-scale, or total. This refinement significantly improved the method's ability to simulate precipitation over arid and semi-tropical regions. Second, EOF filtering of the GCM output is not performed since we found that to degrade the results along with introducing negative values for precipitation. Finally, the logarithm of precipitation values is used instead of raw precipitation amount. This was found to decrease the residuals of the regression.

Solutions

- ◆ Disaggregate the daily rainfall to hourly time series

Date	Prec. (inch)
Jun 16	0
Jun 17	0.1
Jun 18	0
et al.	



Background

- **Many disaggregation methods**
- **Few tests to assess the performance of these methods on hydrological simulations**



Overview of the Study

- ◆ Examine **three** different disaggregation methods to construct **hourly** precipitation time series from **daily** precipitation
- ◆ Use those time series as input and compare simulated flows against observed flows

Three Disaggregation Methods



Method1 – Triangular by HSPF

Daily rainfall needs to be disaggregated: 0.10

daily total		0	0.01	0.02	0.04	0.08	0.16	0.32	...
ratio for each hour	10	0	0	0	0	0	0.01	0.01	...
	11	0	0	0	0.01	0.01	0.04	0.05	...
	12	0	0.01	0.01	0.02	0.03	0.06	0.1	...
	13	0	0	0.01	0.01	0.03	0.04	0.1	...
	14	0	0	0	0	0.01	0.01	0.05	...
	15	0	0	0	0	0	0	0.01	...

- Find the daily total closest to but larger than the daily rainfall that needs to be disaggregated
- Distribute the daily rainfall proportionally to ratio for each hour

Method 2 and 3

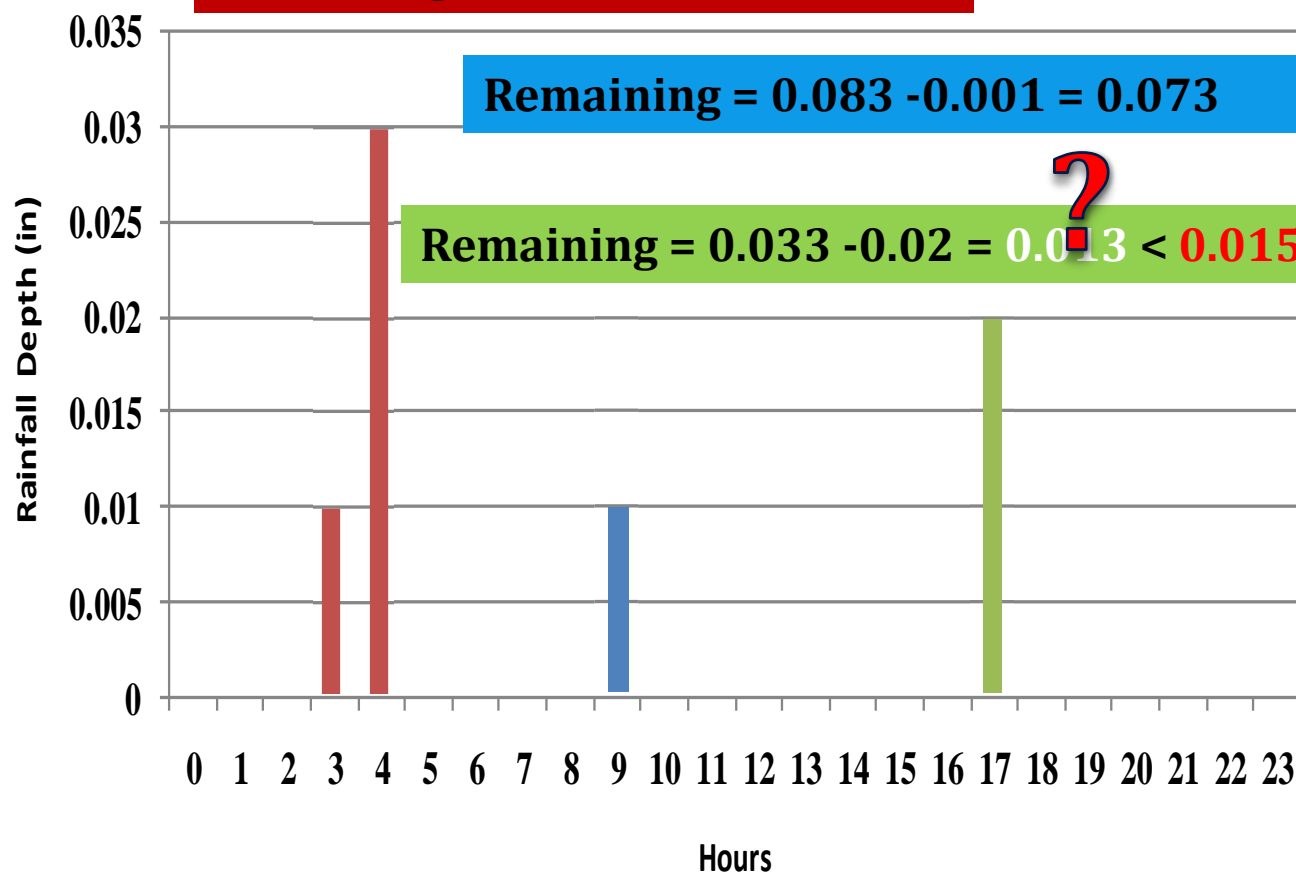
DISAGGREGATION OF DAILY RAINFALL FOR CONTINUOUS WATERSHED MODELING

By Scott Socolofsky,¹ E. Eric Adams,² Members, ASCE, and Dara Entekhabi³

- ◆ It iteratively searches the rainfall events from **the existing rainfall event database** until the remaining amount is lower than **an assigned minimum threshold**
- ◆ The disaggregated hourly rainfalls **reserve the probability distribution** of the existing rainfall event database

To disaggregate a 0.083 inch daily total
with the assigned minimum threshold:
0.015 inch

Remaining = $0.073 - 0.04 = 0.033$



Rainfall events

Total: 0.04 inch
(0.01 inch at 3 o'clock and 0.03 inch at 4 o'clock)

Total: 0.02 inch
(0.02 inch at 8 o'clock)

Total: 0.01 inch
(0.01 inch at 9 o'clock)

Total: 0.01 inch
(0.01 inch at 6 o'clock)

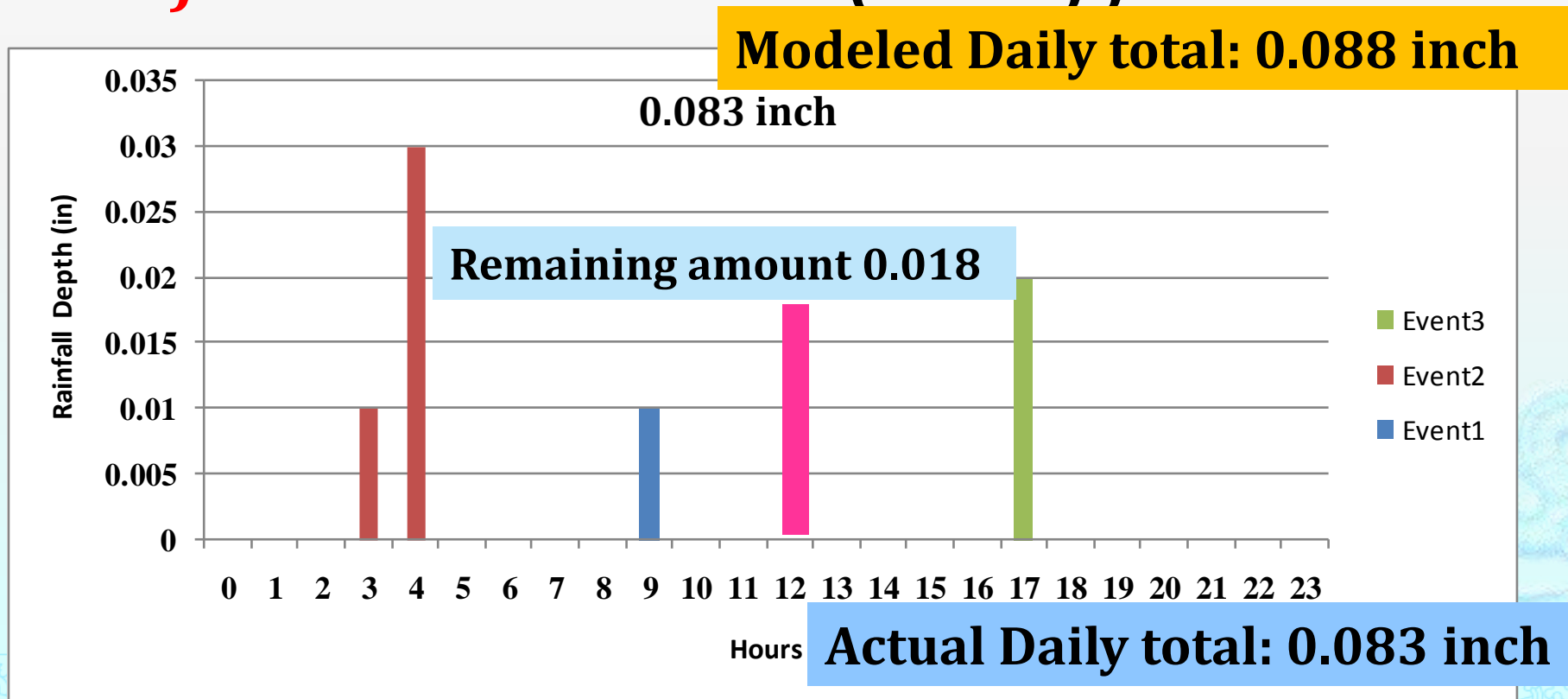
Total: 0.01 inch
(0.01 inch at 17 o'clock)

et al.

How to deal with the remaining amount of 0.013 inch?

Method2: Socolofsky method

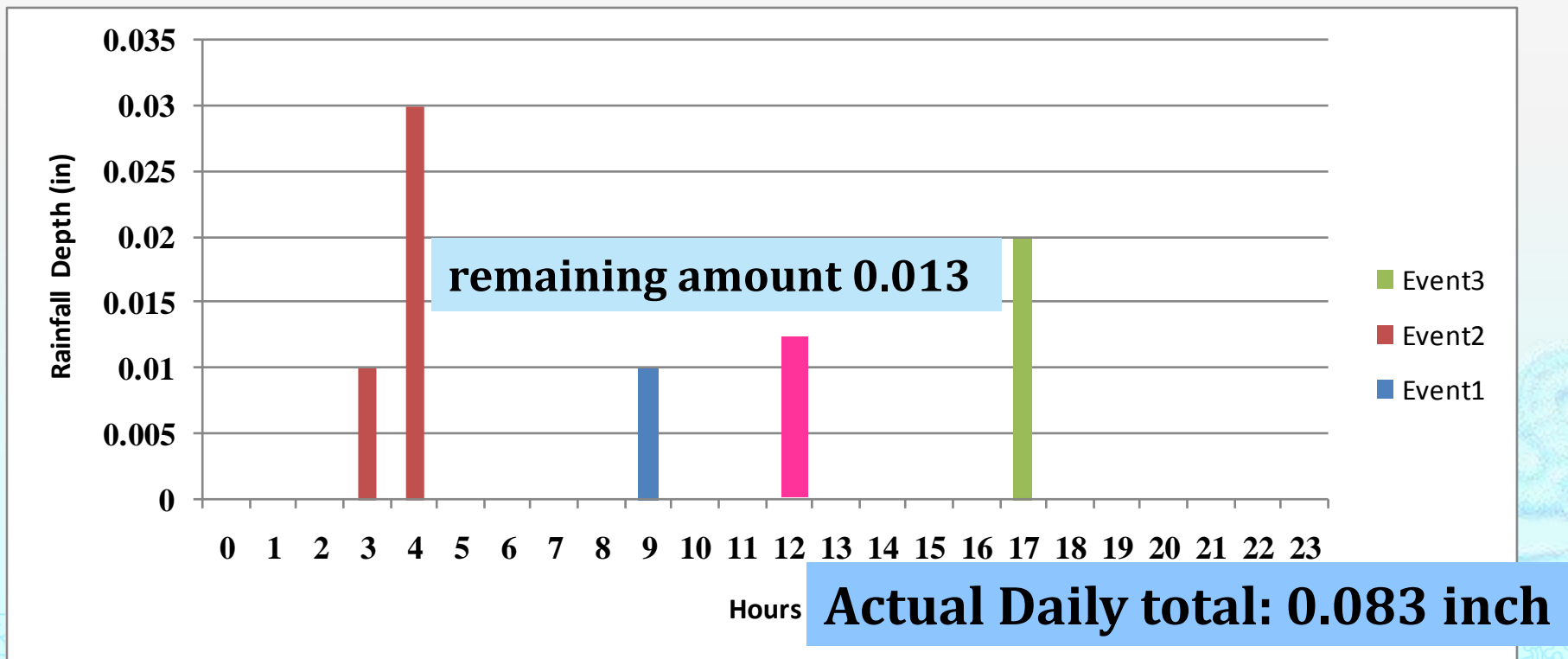
- ◆ The remaining amount follows exponential distribution (e.g. Modeled remaining amount = - Actual remaining amount (*i.e.*, -0.013)***log (random seed)** at random hour from (0 to23))



Method3: Adjusted Socolofsky method

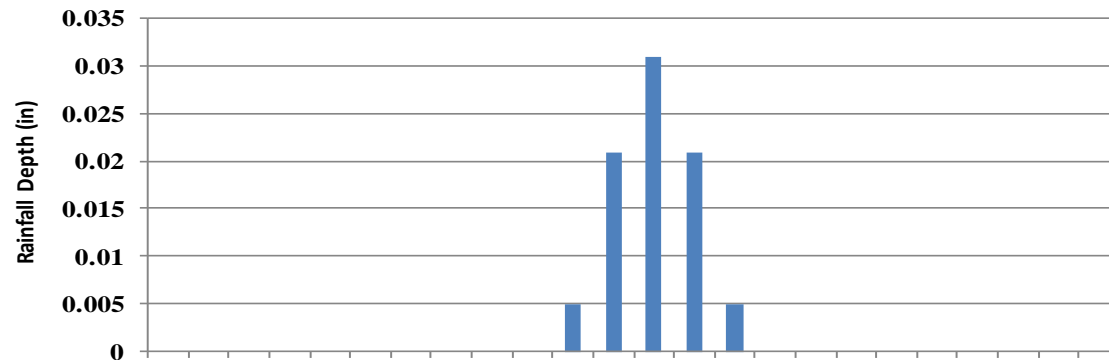
- ◆ The remaining amount is directly placed into a one-hour storm event

Modeled Daily total: 0.083 inch

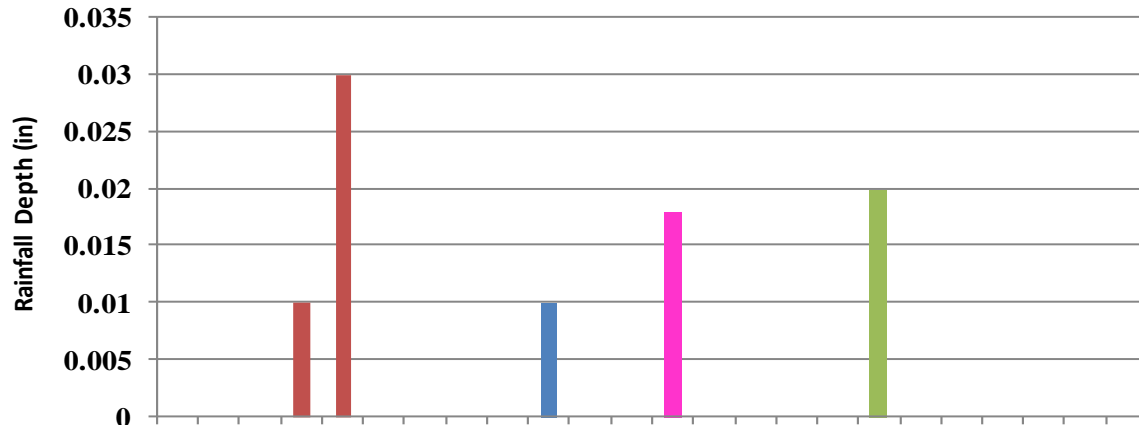


**Daily total:
0.083 inch**

Triangular Distribution

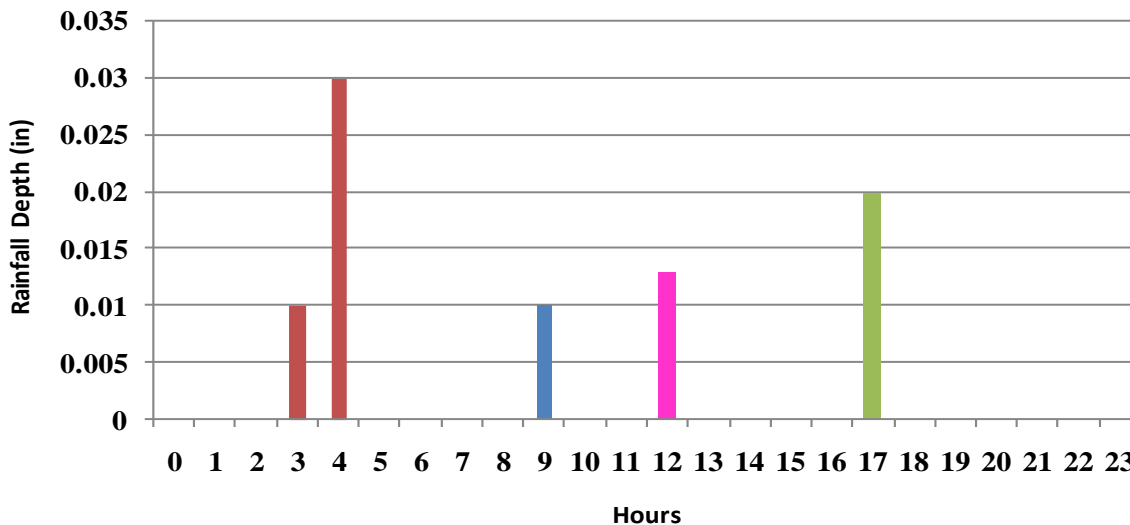


Socolofsky method



Rest Amount
Event3
Event2
Event1

Adjusted Socolofsky method

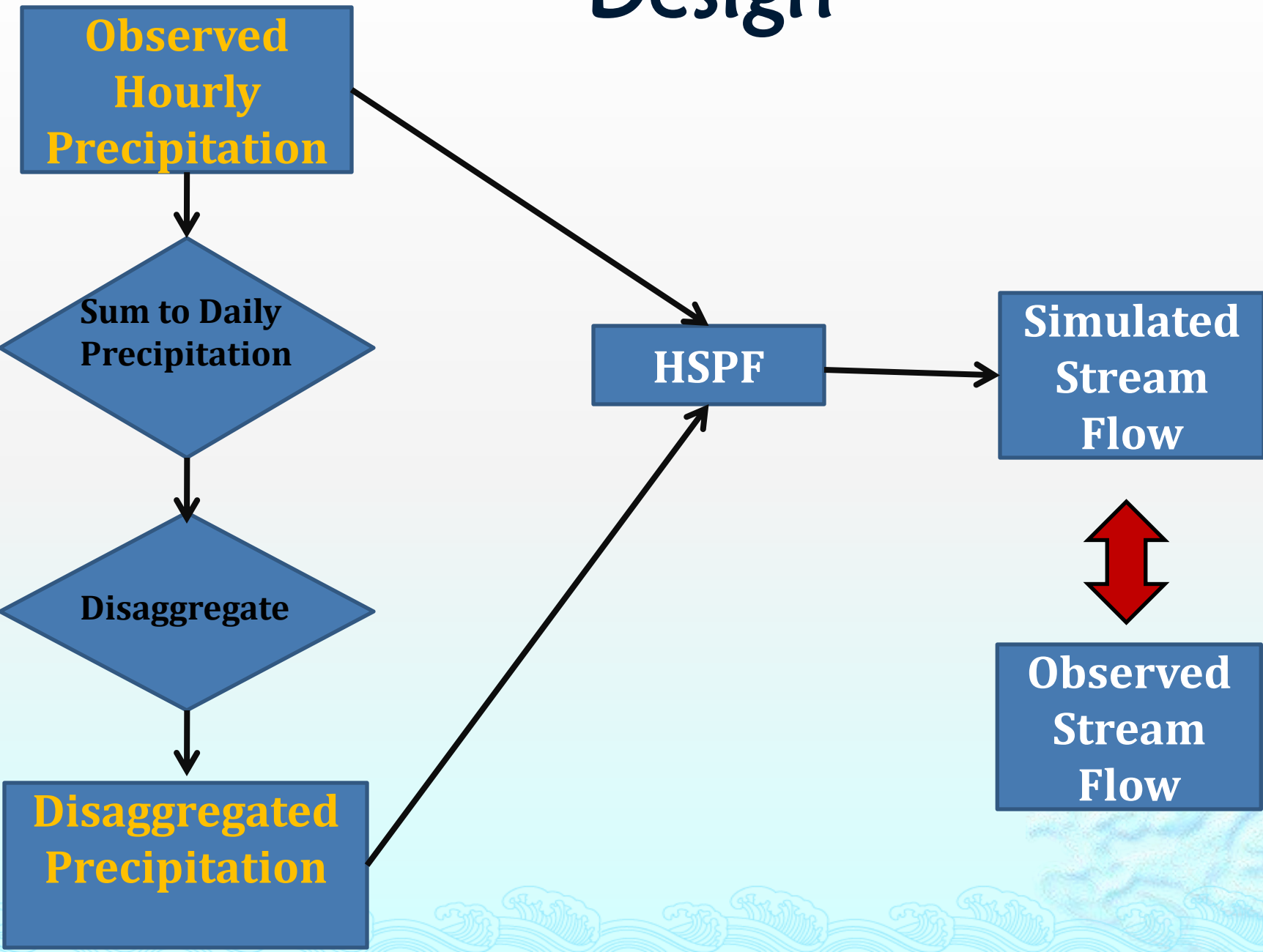


Rest Amount
Event3
Event2
Event1

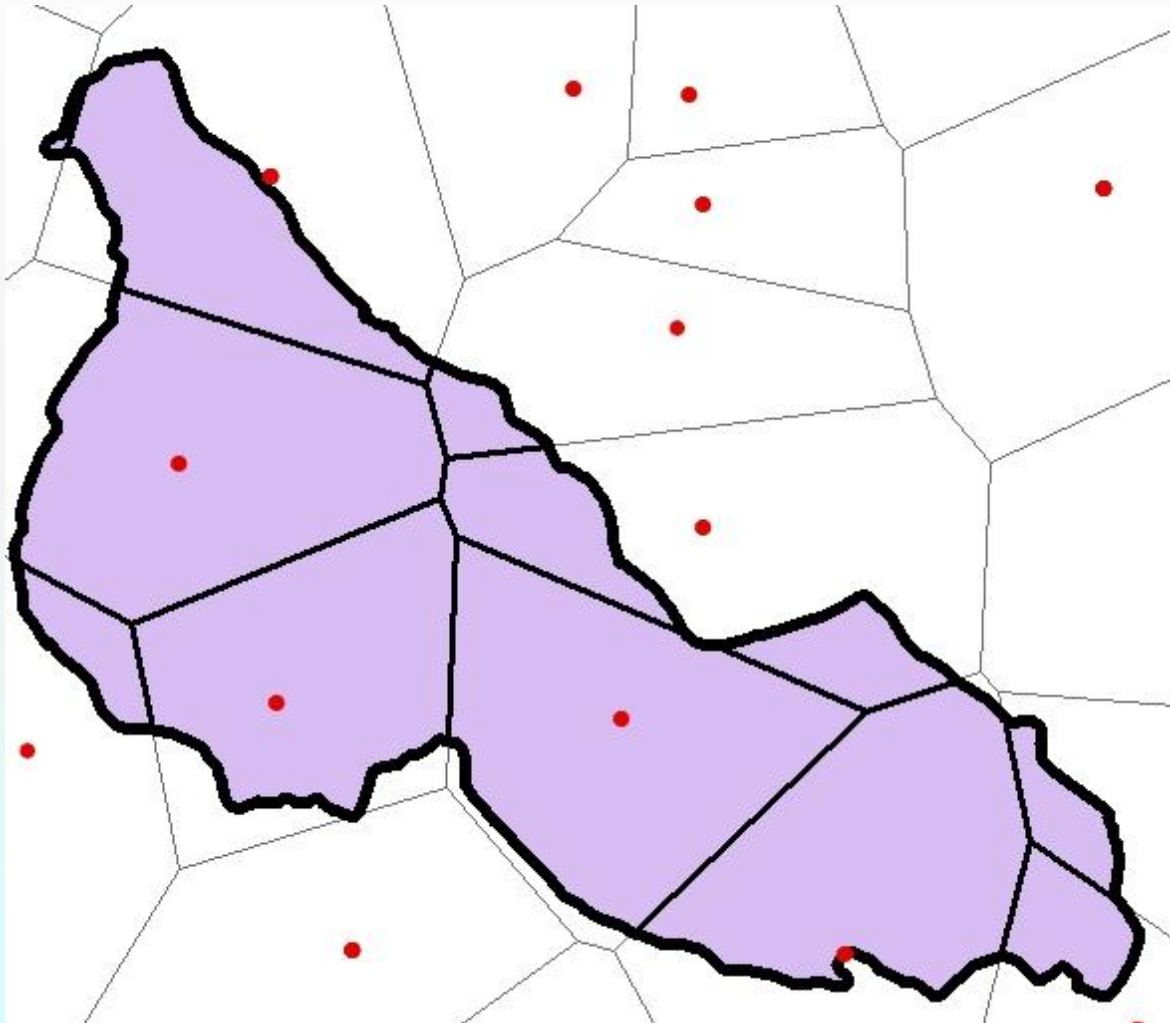
Characteristics Comparison

	Triangular Distribution	Socolofsky Method	Adjusted Socolofsky Method
Stochastic	N	Y	Y
Using existing hourly data	N	Y	Y
Conserve daily total	Y	N	Y
Conserve PDF	N	Y	Y
Multi events	N	Possible	Possible

Design



Observed Hourly Precipitation

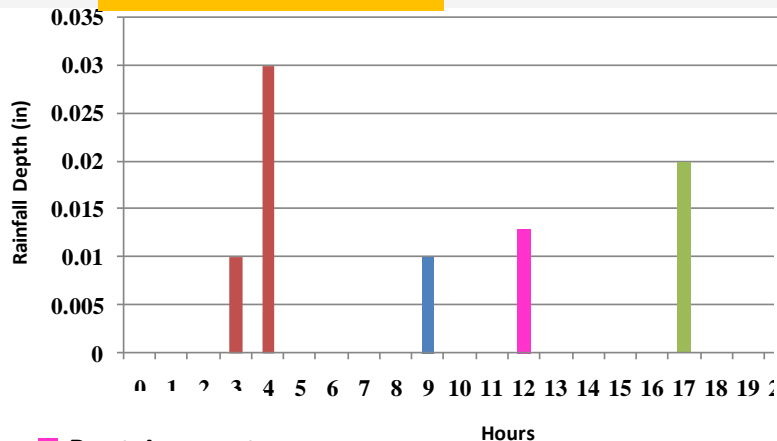


- ◆ **Virtual station: area weighted mean of stations whose Thiessen polygons fall into the watershed**

Disaggregated Precipitation

- ◆ Triangular Distribution
- ◆ **Ten** simulations for each Socolofsky method and Adjusted Socolofsky method *using precipitation from the virtual station as the existing rainfall event database*

Simulation 1



Rest Amount

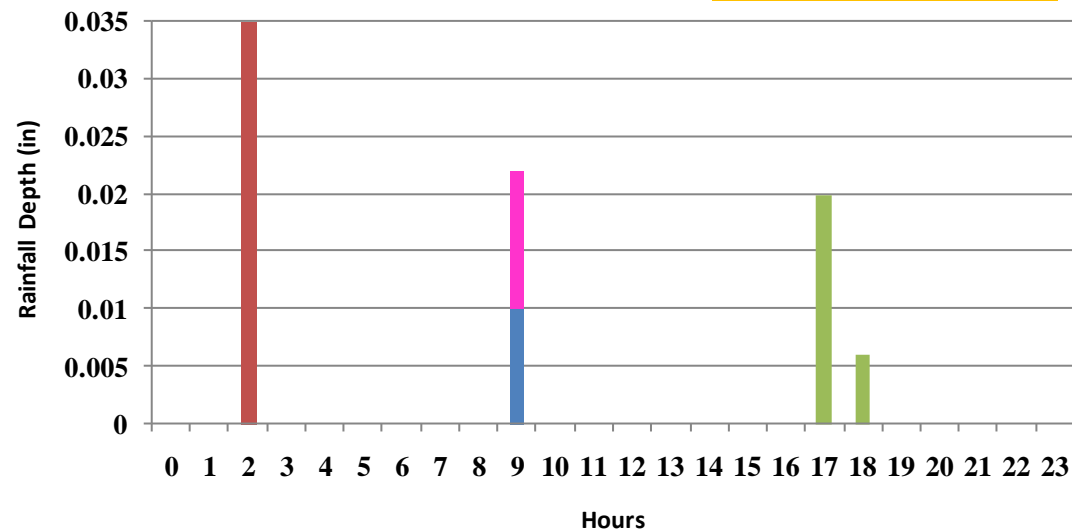
Event3

Event2

Event1



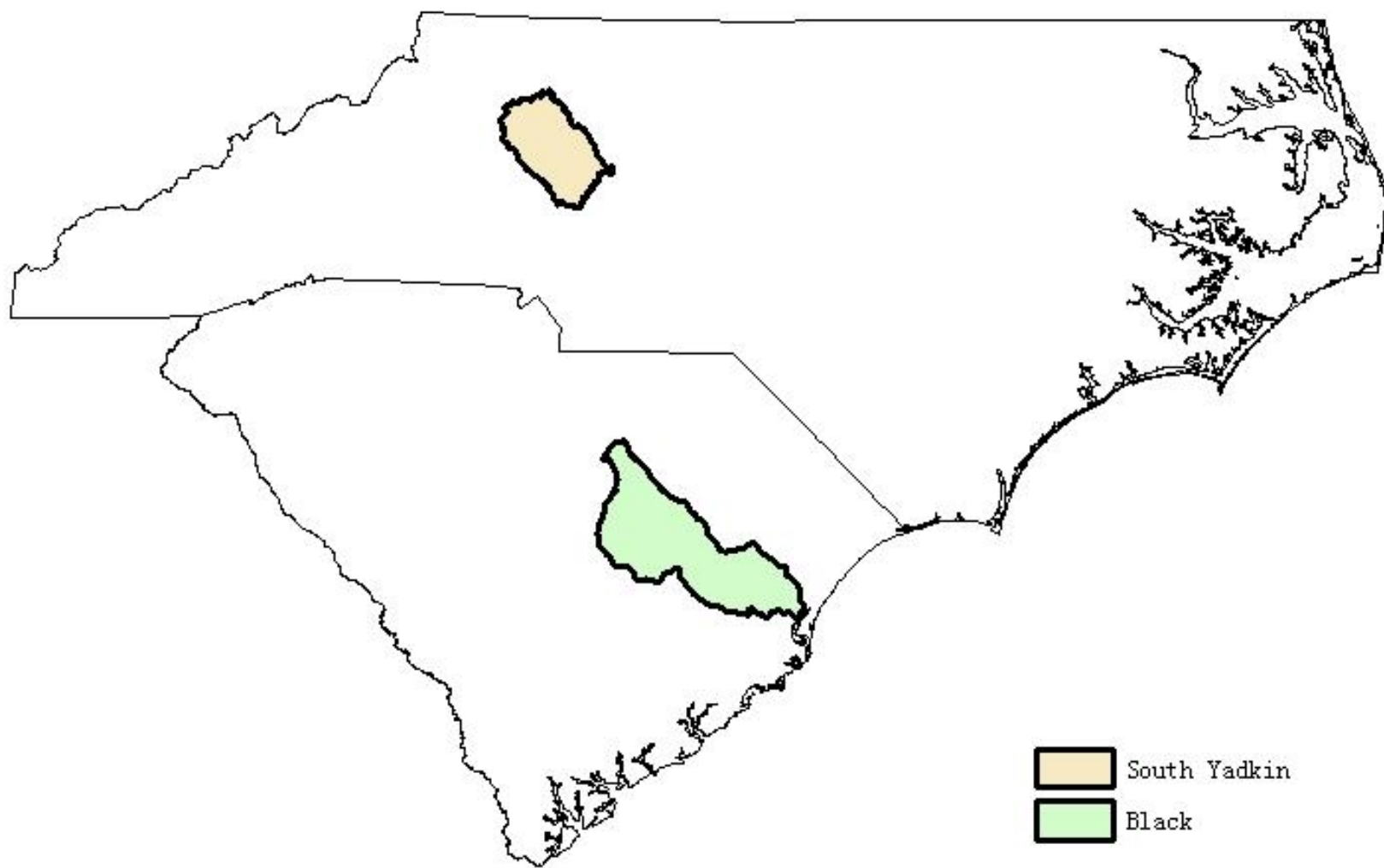
Simulation 2



Comparisons

- ◆ Four types of hourly precipitation time series
 - ◆ Precipitation from the virtual station (a combination of observed hourly precipitation)
 - ◆ Triangular distribution
 - ◆ Socolofsky Method (ten simulations)
 - ◆ Adjusted Socolofsky Method (ten simulations)
- ◆ The simulated stream flows VS. the observed stream flows in the **verification** time period

Study Area



Model performance evaluation

◆ Indices

- ◆ index of agreement (d) (higher, better)
- ◆ mean absolute error (MAE) (lower, better)
- ◆ **Nash-Sutcliffe efficiency (NS) (closer to 1, better)**
- ◆ percent bias (p-bias) (lower, better)
- ◆ root mean squared error (RMSE) (lower, better)
- ◆ **Willmott Index (dr) (Willmott et al. 2011) (closer to 1, better)**

Nash-Sutcliffe efficiency (NS)

- ◆ range from $-\infty$ to 1
- ◆ $NS = 1$: a perfect match
- ◆ $NS = 0$: the model predictions are as accurate as the mean of the observed data
- ◆ $NS < 0$: the observed mean is a better predictor than the model

$$NS = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$$

Nash and Sutcliffe (1970)

where: P_i is
predicted value, O_i is
observed value, \bar{O} is
the observed mean

Willmott Index

- Measures ratio of **mean absolute error of modeled vs. observations** to **mean absolute error of observations relative to observed mean**

- $d_r=1$: perfect agreement
- $d_r=0.5$: sum of error magnitudes is half perfect model deviation and observed deviation magnitudes
- $d_r=-0.5$: sum of error magnitudes is twice perfect model deviation and observed deviation magnitudes
- $d_r=-1$: model-estimated deviations about observed mean are poor estimates of observed deviation **OR** means little observed variability

$$d_r = \begin{cases} 1 - \frac{\sum_{i=1}^n |P_i - O_i|}{c \sum_{i=1}^n |O_i - \bar{O}|}, & \text{when} \\ \sum_{i=1}^n |P_i - O_i| \leq c \sum_{i=1}^n |O_i - \bar{O}| \\ \frac{c \sum_{i=1}^n |O_i - \bar{O}|}{\sum_{i=1}^n |P_i - O_i|} - 1, & \text{when} \\ \sum_{i=1}^n |P_i - O_i| > c \sum_{i=1}^n |O_i - \bar{O}| \end{cases}$$

Willmott et al. (2011)

where: P_i is predicted value, O_i is observed value, \bar{O} is the observed mean, and $c=2$

Results

- ◆ **Socolofsky (S) and Adjusted Socolofsky (AS) VS. Virtual station (V)**



	d	MAE	NS	p-bias	RMSE	dr
V	0.89	83.10	0.64	-15.47	186.8	0.67
S1	0.86	87.60	0.57	-15.48	204.7	0.66
S2	0.79	93.66	0.40	-18.10	241.3	0.63
S3	0.86	86.43	0.58	-10.27	202.2	0.66
S4	0.84	83.09	0.51	-8.91	218.3	0.67
S5	0.81	82.70	0.48	-11.40	225.4	0.68
S6	0.78	105.15	0.30	-26.64	260.2	0.59
S7	0.76	92.13	0.32	-10.23	256.5	0.64
S8	0.78	100.31	0.35	-25.47	251.9	0.61
S9	0.81	93.72	0.42	-15.36	236.6	0.63
S10	0.86	87.46	0.58	-17.88	201.8	0.66

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AS2	0.84	86.53	0.54	-13.47	210.2	0.66
AS3	0.82	87.20	0.48	-13.74	224.1	0.66
AS4	0.82	91.19	0.47	-14.45	227.3	0.64
AS5	0.86	83.31	0.59	-12.86	199.3	0.67
AS6	0.85	84.10	0.56	-12.73	206.5	0.67
AS7	0.86	84.76	0.59	-13.32	200.0	0.67
AS8	0.82	88.52	0.47	-13.76	227.0	0.65
AS9	0.83	90.31	0.49	-14.35	222.5	0.65
AS10	0.83	85.77	0.51	-13.18	217.4	0.66

Socolofsky (S) and Adjusted Socolofsky (AS) produced **similar** statistics to precipitation from the virtual station (V)

	d	MAE	NS	p-bias	RMSE	dr
V	0.89	83.10	0.64	-15.47	186.8	0.67
S1	0.86	87.60	0.57	-15.48	204.7	0.66
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AS3	0.82	87.20	0.48	-13.74	224.1	0.66
AS4	0.82	91.19	0.47	-14.45	227.3	0.64
AS5	0.86	83.31	0.59	-12.86	199.3	0.67
AS6	0.85	84.10	0.56	-12.73	206.5	0.67
AS7	0.86	84.76	0.59	-13.32	200.0	0.67
AS8	0.82	88.52	0.47	-13.76	227.0	0.65
AS9	0.83	90.31	0.49	-14.35	222.5	0.65
AS10	0.83	85.77	0.51	-13.18	217.4	0.66

Socolofsky (S) varied **more** than Adjusted Socolofsky (AS) because it does not conserve the depth of daily rainfall

Results

◆ Triangular (T) VS. Virtual station (V) South Yadkin NC (V is better)

	d	MAE	NS	p-bias	RMSE	dr
V	0.89	83.10	0.64	-15.47	186.82	0.67
T	0.86	92.99	0.51	-15.66	219.06	0.64

Black basin SC (T is better)

	d	MAE	NS	p-bias	RMSE	dr
V	0.89	387.22	0.69	-18.73	656.1	0.75
T	0.91	332.88	0.75	-9.14	586.3	0.79

Conclusion

- ◆ **The adjusted Socolofsky method**
 - ◆ **most robust in terms of performance when compared to the model verification run using the observed hourly precipitation as input**
 - ◆ **a useful means of disaggregating the daily precipitation from GCMs under different scenarios**
- ◆ **comparisons in more watersheds to test the robustness and consistency of these methods**