



Application of GPM IMERG satellite-based precipitation products for flood runoff simulation in a dam watershed

*1st NARBO Webinar
Challenges of “New Normal” river basin management:
The pandemic is not over yet, the flood control must go on*

Younghyun Cho
K-water Research Institute, K-water (Korea Water Resources Corporation)
December 17, 2021 yhcho@kwater.or.kr

Introduction

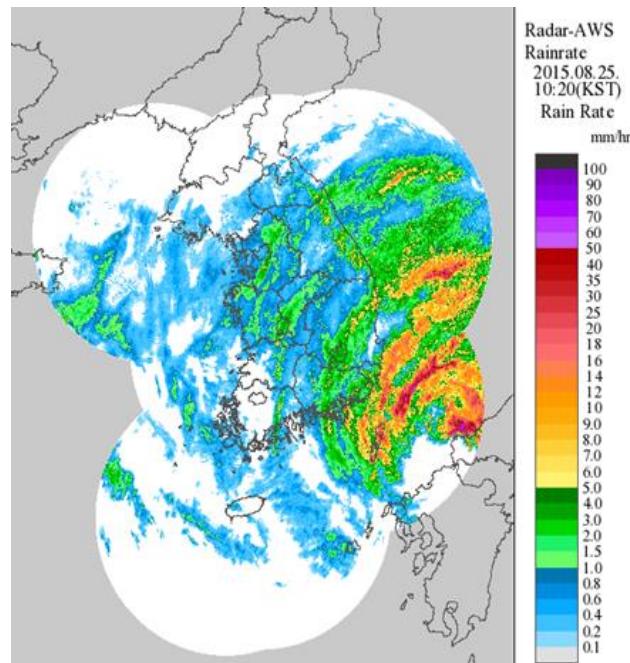
Background

- Since most of South Korea is consisted of mountainous areas (about 65%), the spatial distribution of precipitation during rainfall storm event is highly variable.
- Especially, in the dam watershed, which is a typical mountainous terrain, the shape and pattern of rainfall and the resulting changes in the outflow show complicated characteristics.
- Therefore, it is often unlikely to use the areal rainfall, which is estimated by averaged method (e.g. Thiessen polygon) with gauge observations, for flood runoff analysis and the introduction of the radar-based spatially distributed rainfall is required for hydrological simulation.

Introduction

RAR (Radar-AWS Rainrates)

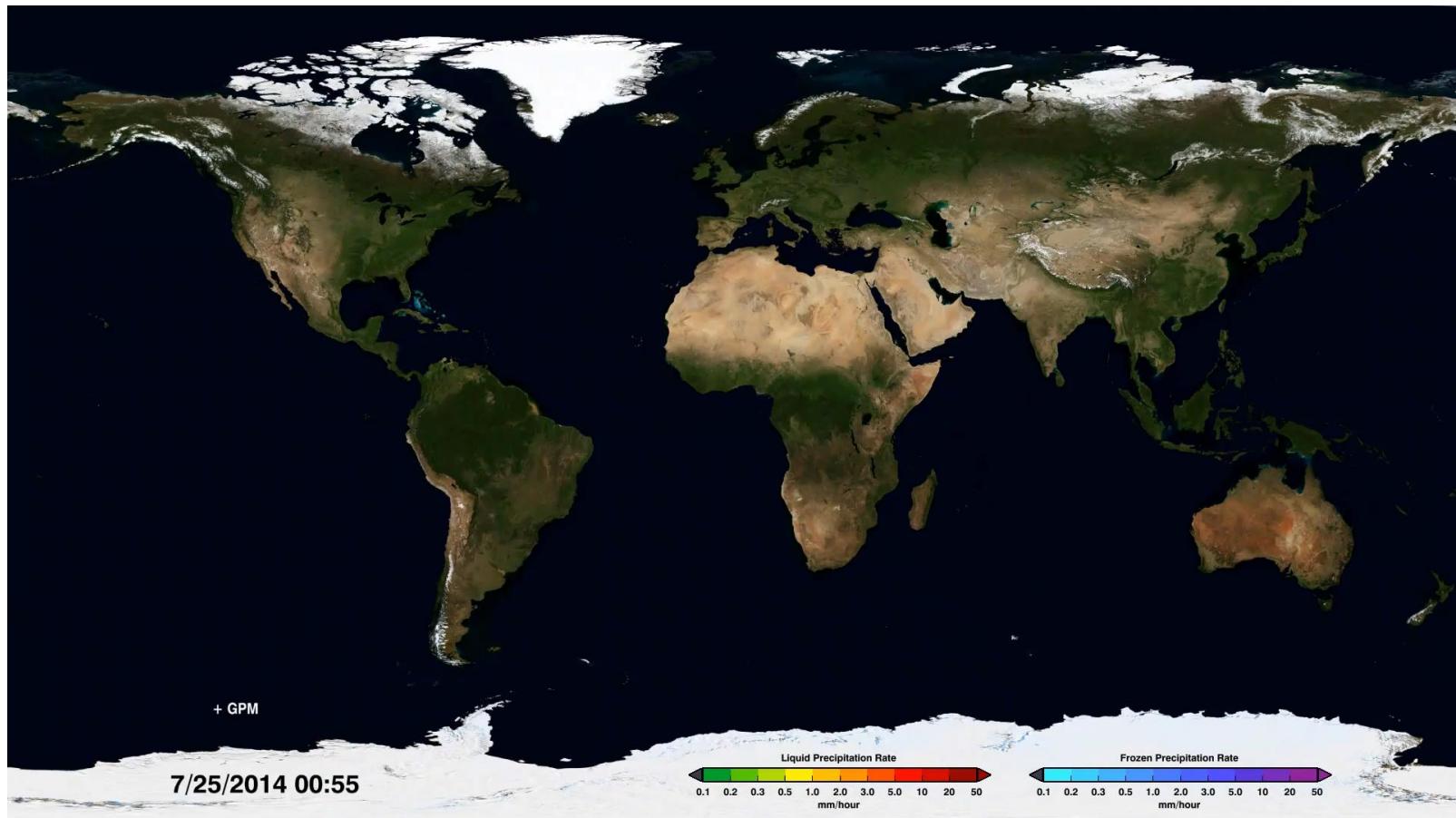
- Quantitative precipitation estimations (QPEs) using the real time **Z-R relationship** based on radar reflectivity (Z) and rain gauge observations (R)
- KMA (Korea Meteorological Administration) has continuously improved the "Radar-AWS Rainrates (RAR)" data production technology to provide more **accurate radar-based precipitation estimations**, showing considerable accuracy compared to the ground observations.



*Latest version: RAR ver. 2.0 (2015. 9)

GPM IMERG

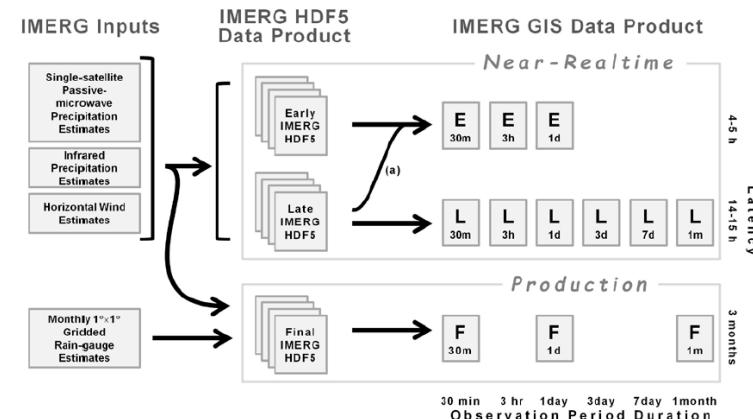
IMERG (Integrated Multi-satellitE Retrievals for GPM)



GPM IMERG

Data specifications

- Spatial resolution: $0.1^\circ \times 0.1^\circ$ (roughly [10 x 10 km](#)), from $60^\circ\text{N} - 60^\circ\text{S}$
- Temporal resolution: [half-hourly](#), [daily](#), and [monthly](#) (final only), value-added products at 3 hours, 1, 3, and 7 days are also available
- Map system: WGS84 (GCS, default)
- Multiple runs accommodate different user requirements for latency and accuracy
 - "Early" – 4~5 hours (flash flooding)
 - "Late" – 14~15 hours (crop irrigation)
 - "Final" – 3 months ([research data](#))



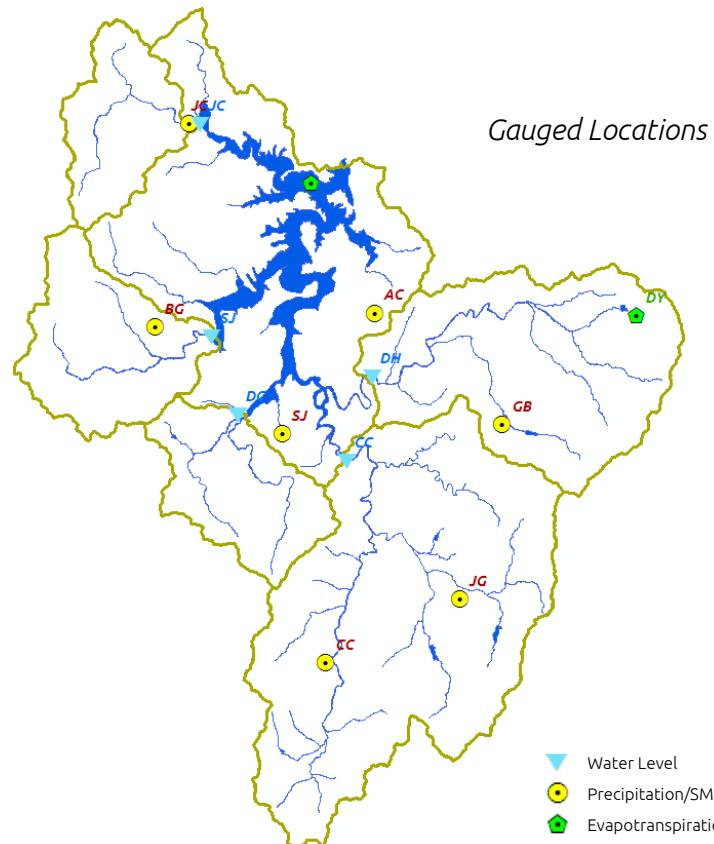
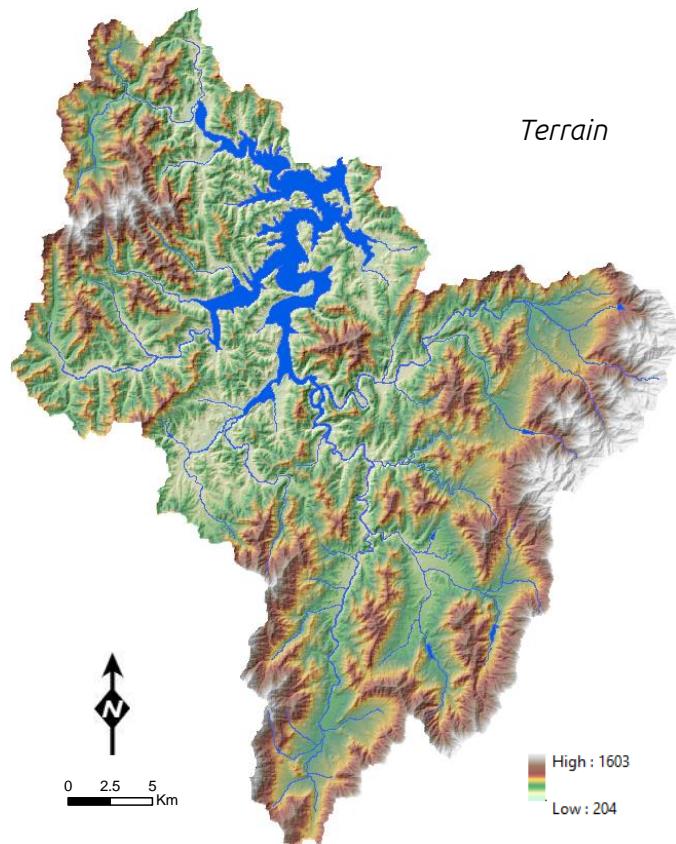
GPM IMERG

GPM_3IMERGHH (V06)

- File name: 3B-HHR.MS.MRG.3IMERG.\$YYYY\$MM\$DD-S\$HH\$MM\$NN-E\$HH\$MM\$NN.\$MMMM.V06B.HDF5.nc4
- Spatial resolution: $0.1^\circ \times 0.1^\circ$ (roughly [10 x 10 km](#)), from $90^\circ\text{N} - 90^\circ\text{S}$ ($60^\circ\text{N} - 60^\circ\text{S}$ full)
- Temporal resolution: [half-hourly](#) (final run, 3.5 months latency)
- Version 6 of IMERG was released in April 2019; the first version to cover the approximately 20-year period from [June 2000 to the present](#) (TRMM and GPM era)
- Data access: <https://disc.gsfc.nasa.gov/>

Study Area

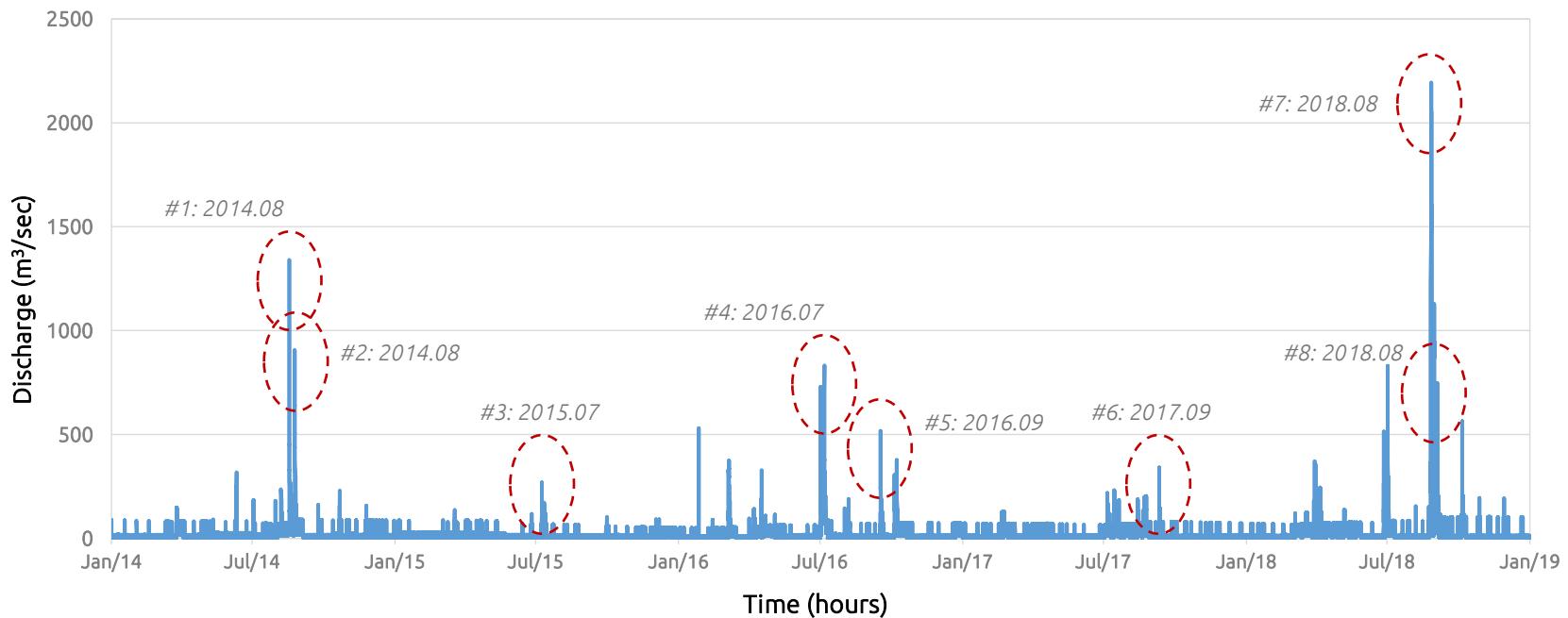
Yongdam dam watershed



Storm Events

Storm event selection

- 8 storm events (hourly) from 2014 to 2018



Storm Events

Independent single event (2014 to 2018, **hourly**)

Storm Events (#: Period)	Precipitation Total (mm)													
	Gauged data								Radar-based data			Satellite-based data		
	GB	JG	CC	SJ	BG	JC	AC	Areal average	Min.	Max.	Areal average	Min.	Max.	Areal average
1: 2014.08.17. 13:00~08.20. 12:00	97	114	128	100	121	100	101	108.3	64.8	146.9	88.7	96.5	174.2	134.4
2: 2014.08.24. 01:00~08.28. 24:00	90	71	64	106	57	87	101	82.2	37.4	100.1	58.9	80.9	113.2	99.5
3: 2015.07.08. 13:00~07.11. 12:00	51	37	47	77	59	61	69	57.3	16.8	65.3	38.1	9.2	81.2	39.0
4: 2016.07.01. 13:00~07.03. 12:00	119	128	153	125	101	124	115	122.9	12.3	183.5	96.9	116.7	152.3	138.9
5: 2016.09.16. 13:00~09.19. 24:00	147	129	158	148	134	145	162	146.1	15.3	145.2	101.1	91.6	121.3	102.0
6: 2017.09.10. 01:00~09.12. 24:00	69	77	78	73	73	57	78	71.8	5.1	77.8	50.6	32.2	56.1	42.1
7: 2018.08.25. 13:00~08.30. 12:00	245	286	331	316	288	269	285	286.3	22.7	305.9	198.6	128.4	218.9	189.4
8: 2018.08.30. 13:00~09.02. 12:00	84	110	98	84	69	100	61	86.0	4.8	113.3	56.7	50.2	110.7	71.0

*SCS CN method does not account for infiltration recovery during intervals of no rain

IMERG Data Processing

Procedure

<Data Processing>

IMERG Conversion &
Geo-referencing in ArcGIS

- netCDF4 to ASCII
- *Projection: WGS84 to SHG grid (ITRF2000)

<Program>

*Python script
in ArcGIS (ArcPy)
<developed>*



HEC-DSS file Generation

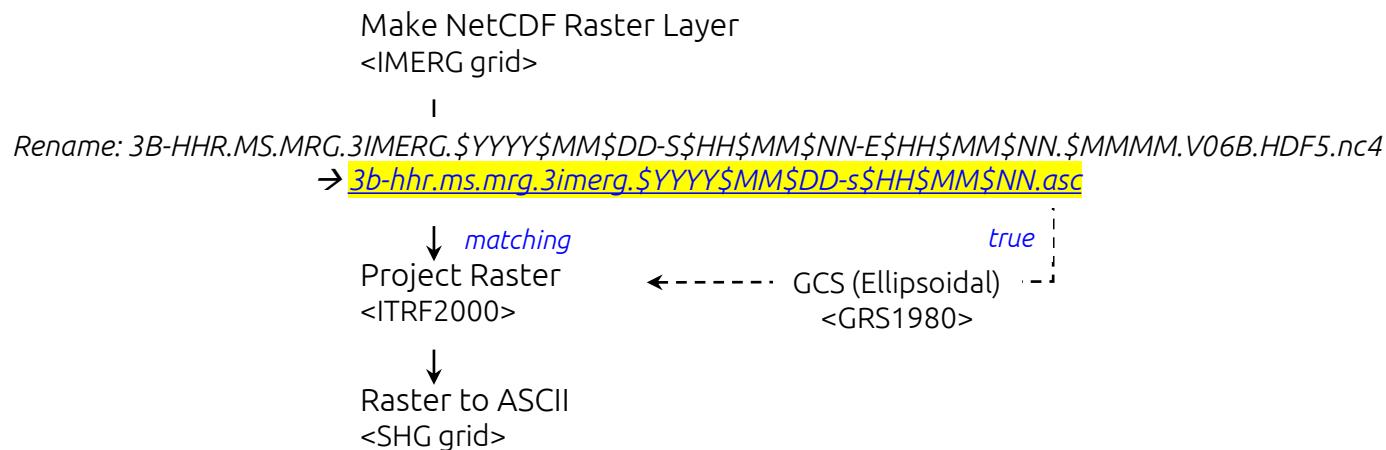
- ASCII to DSS grid

*HEC-GridUtil
<asc2dssGrid.exe>*

IMERG Data Processing

IMERG Conversion & Geo-referencing in ArcGIS

- IMERG (netCDF4 file); need to [convert](#) to [ASCII file](#) for practical uses
 - *Projection: WGS84 to SHG (ITRF2000) grid
- Python script
 - [*nc4toasc.py*](#) ([ArcPy](#) module for using multiple [geoprocessing tools](#))



IMERG Data Processing

HEC-DSS file generation

- ASCII to DSS grid
- HEC-GridUtil
 - *asc2dssGrid.exe* (bridges the gap between raster GIS and grids in DSS)

*ASCII file (3b-hhr.ms.mrg.3imerg.\$YYYY\$MM\$DD-s\$HH\$MM\$NN.asc) – header info.

Name	Description
NCOLS	Number of grid columns (integer)
NROWS	Number of grid rows (integer)
Rename: 3b-hhr.ms.mrg.3imerg.\$YYYY\$MM\$DD-s\$HH\$MM\$NN.asc → <u>IMERG.\$YYYY\$MM\$DD\$HH\$MM.dss</u>	
YLLCORNER	Lower-left Y coordinate (real)
CELLSIZE	Cell size (real); width of a square cell
NODATA_VALUE	Value to indicate a null cell, where a value is either missing or has been removed (default: -9999)

Hydrologic Modeling

HEC-HMS

Model Development

- HEC-GeoHMS (with Arc Hydro Tools)

**Basin Model, Grid Cell file generation*

- HEC-HMS

HEC-GridUtil

**Clark Unit Hydrograph Transform / ModClark Transform* ←----- .dss grid file



Event Simulation

- Performance test → Calibration/Validation

**Combining observed data*



Results Evaluation

- Comparison with gauged and radar/satellite-based rainfall simulation results

Hydrologic Modeling

HEC-HMS

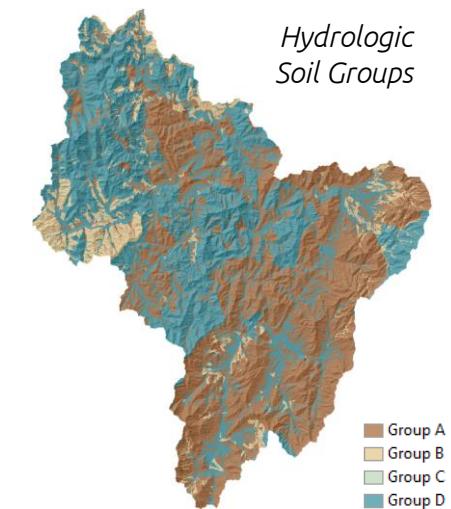
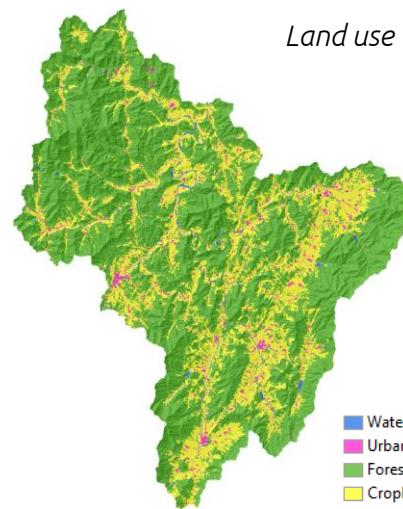
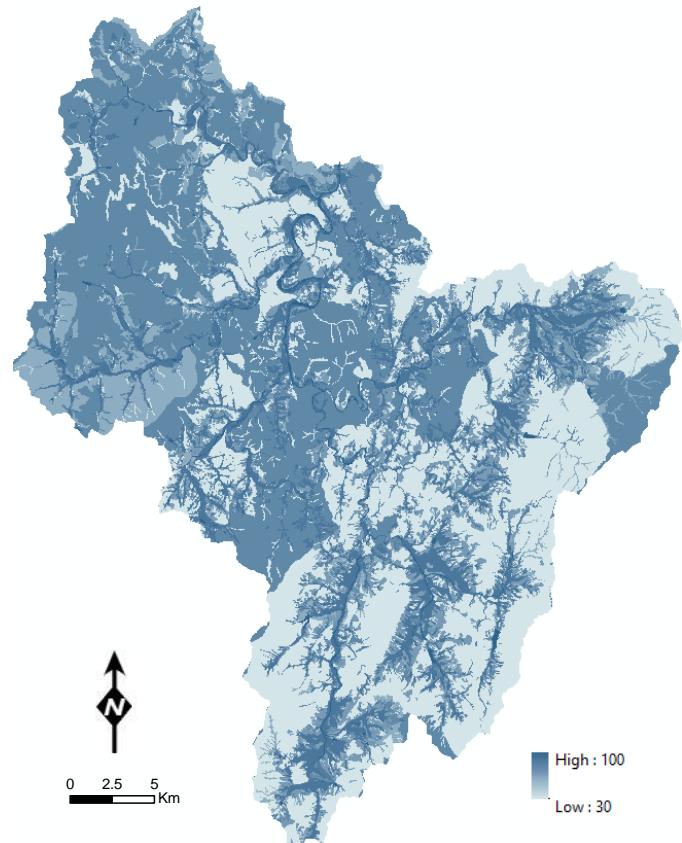
- Calculation methods

Hydrologic Element	Calculation Type	Methods	
		Gauged data simulation	Radar/Satellite-based data simulation
Subbasin	Ruoff-volume	SCS curve number (CN)	Gridded SCS CN
	Direct-runoff (Transform)	Clark Unit Hydrograph	Modified Clark Method (ModClark)
	Baseflow		Recession
Reach	Routing		Muskingum
Precipitation		Gage Weights (Thiessen polygon)	Gridded Precipitation (RAR, IMERG)
Discharge		Time-series data	Time-series data

*Simulation run: consists of basin model, meteorological model, and control specification

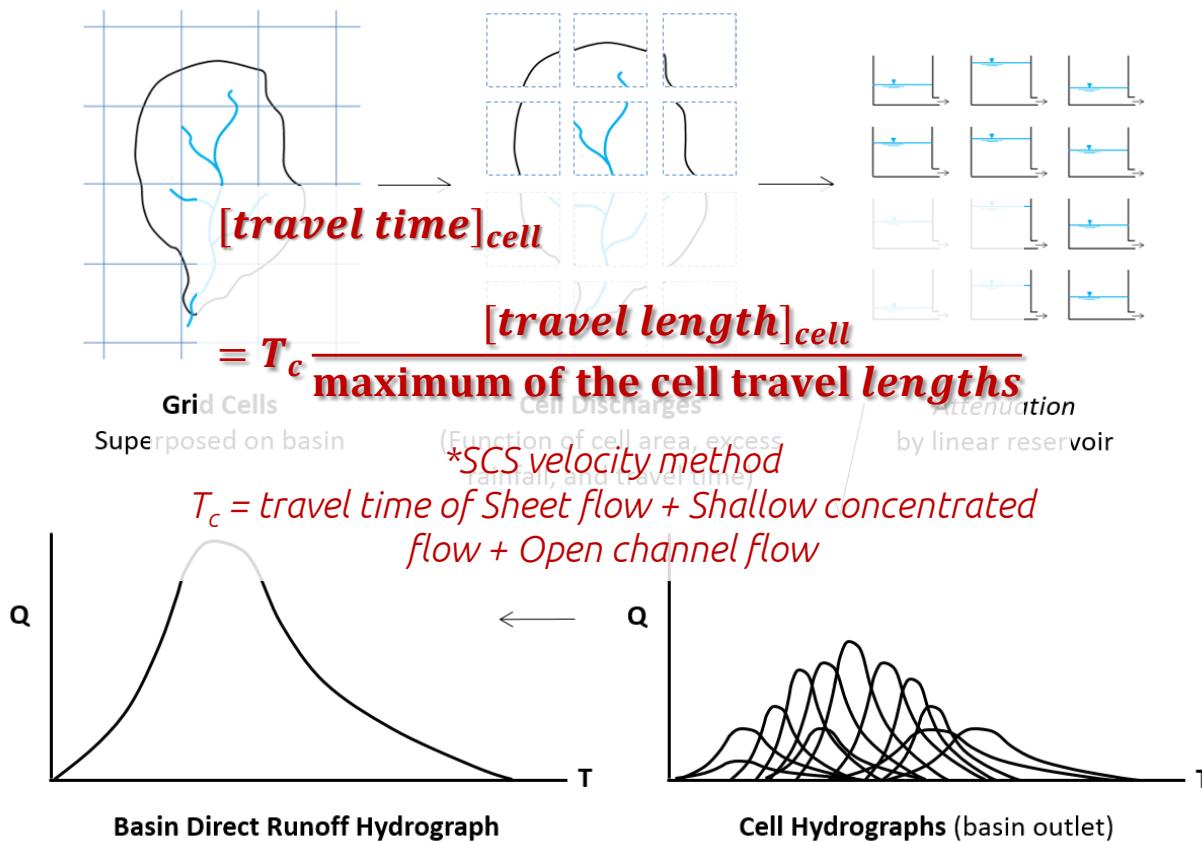
Hydrologic Modeling

SCS Curve Number



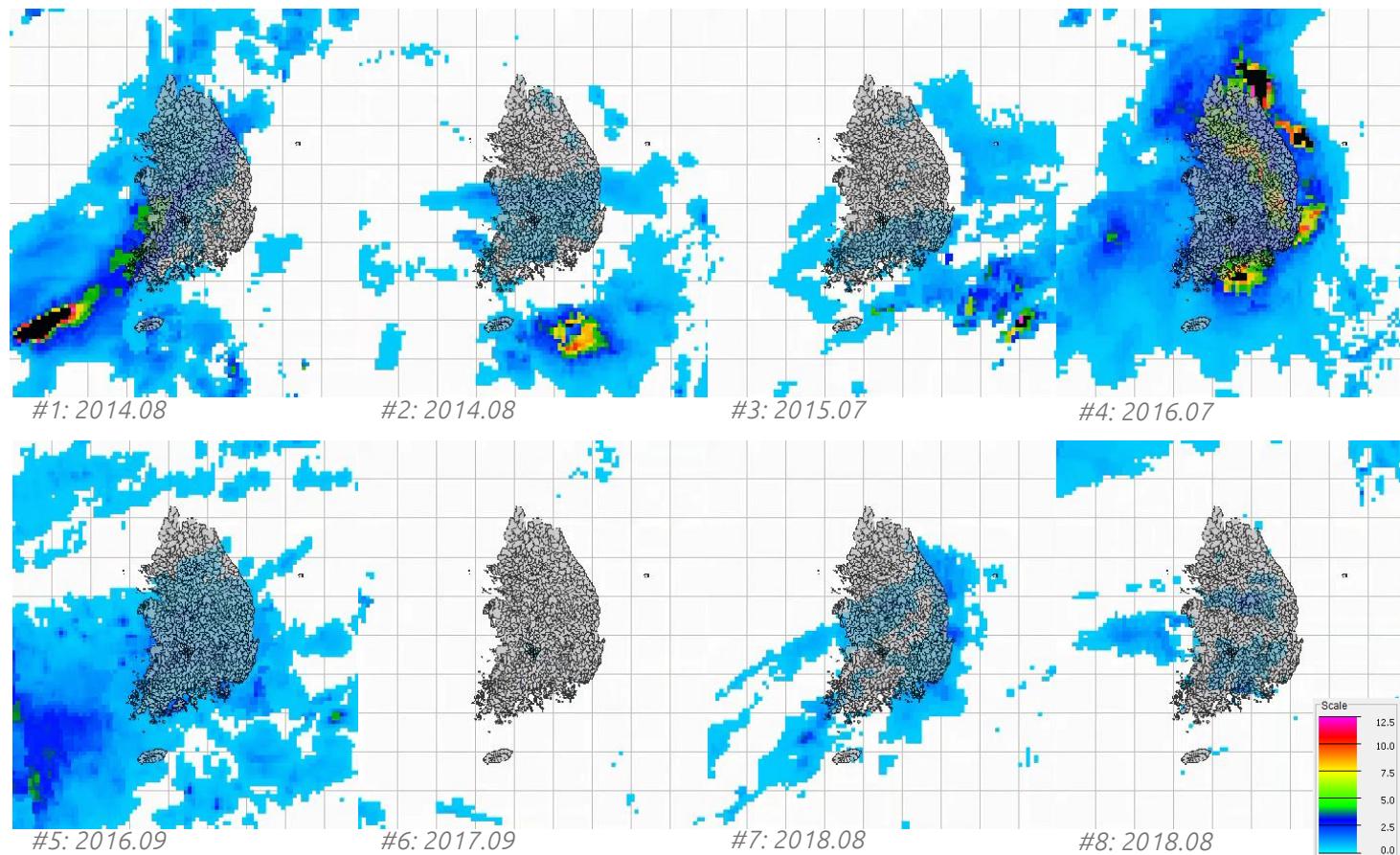
Hydrologic Modeling

ModClark



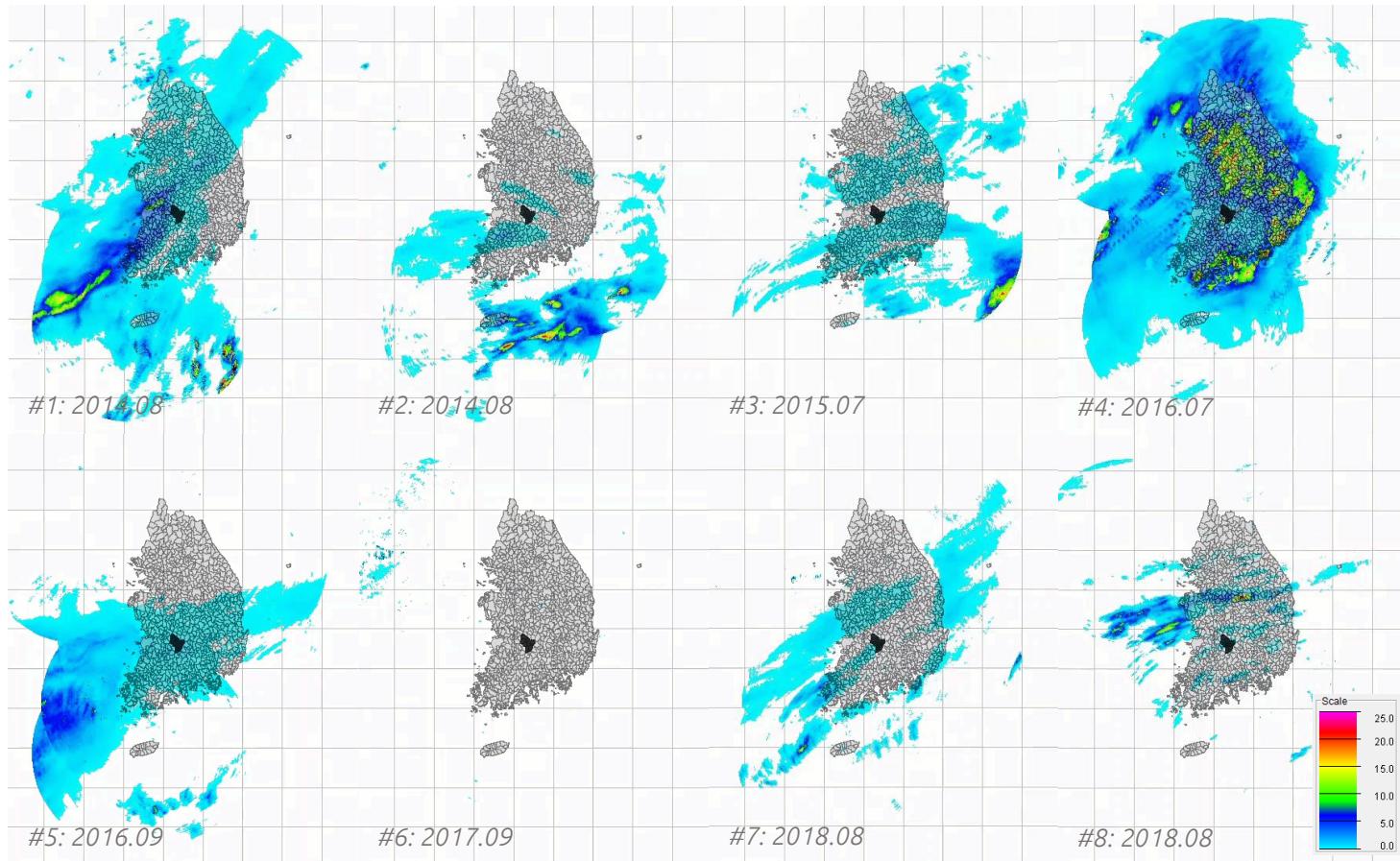
IMERG QPEs

Spatiotemporal representation (2014 to 2018, **sub-hourly**)



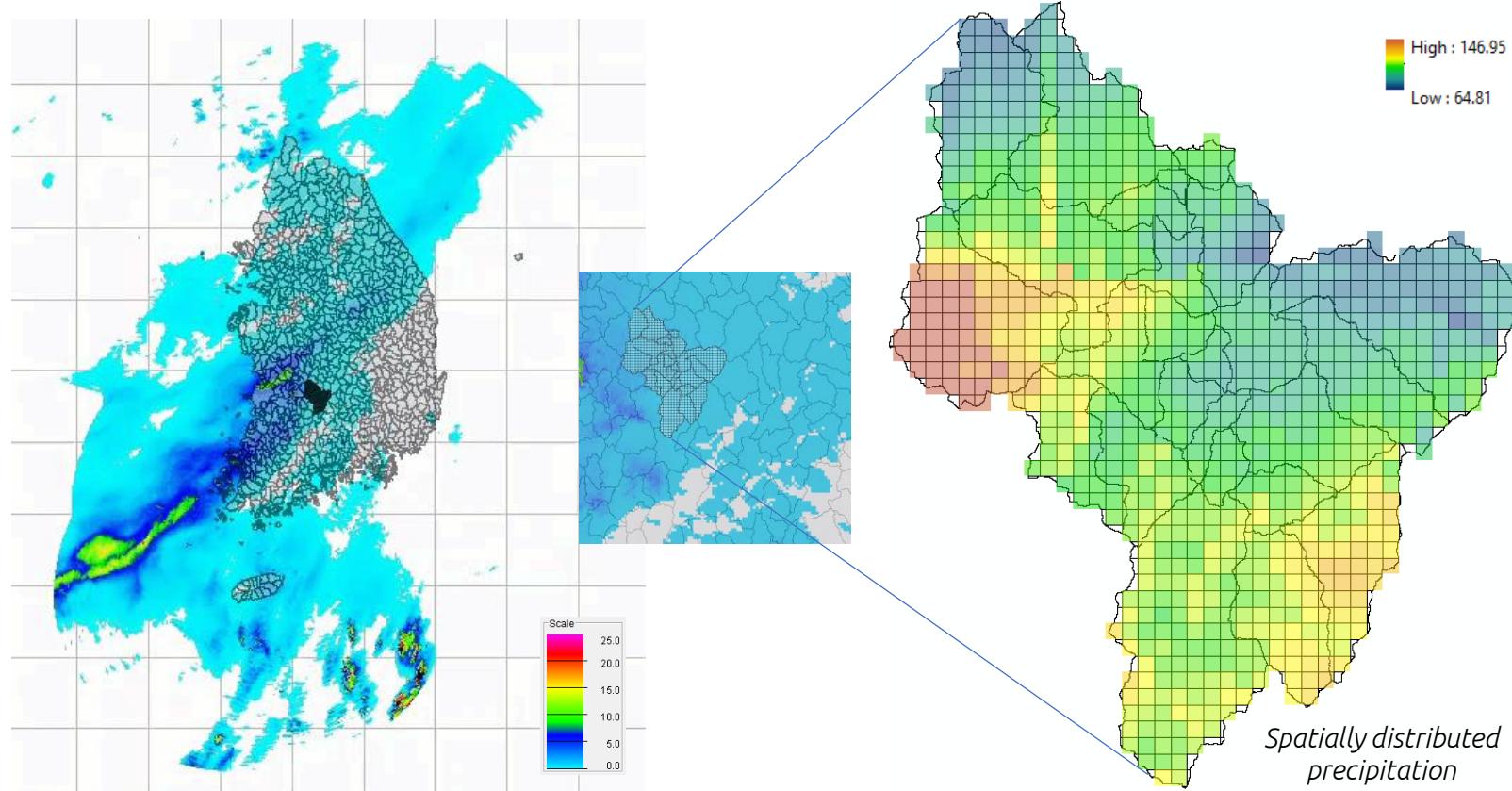
RAR QPEs

Spatiotemporal representation (2014 to 2018, **hourly**)



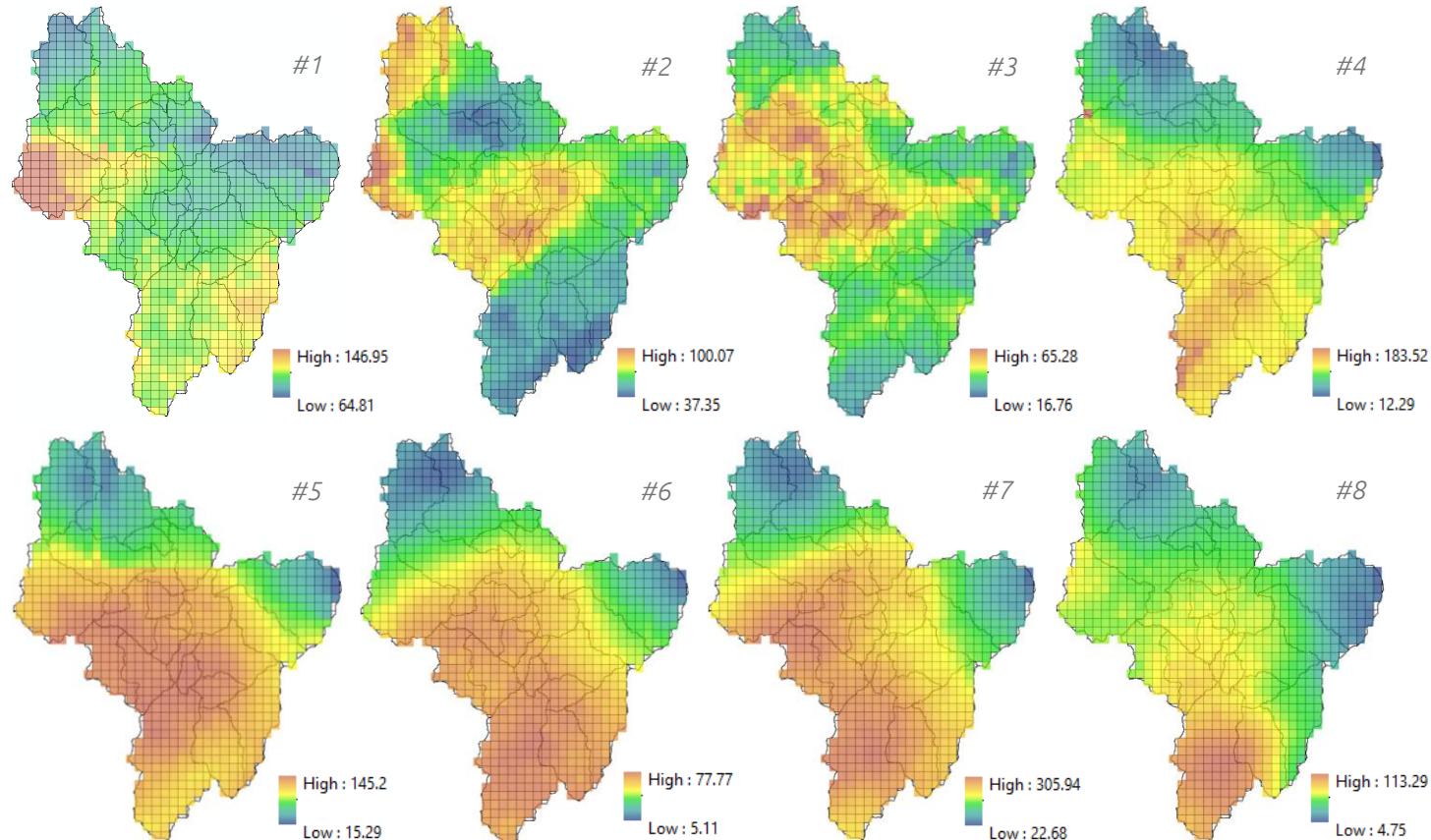
RAR QPEs

Spatiotemporal representation – storm event (#1)



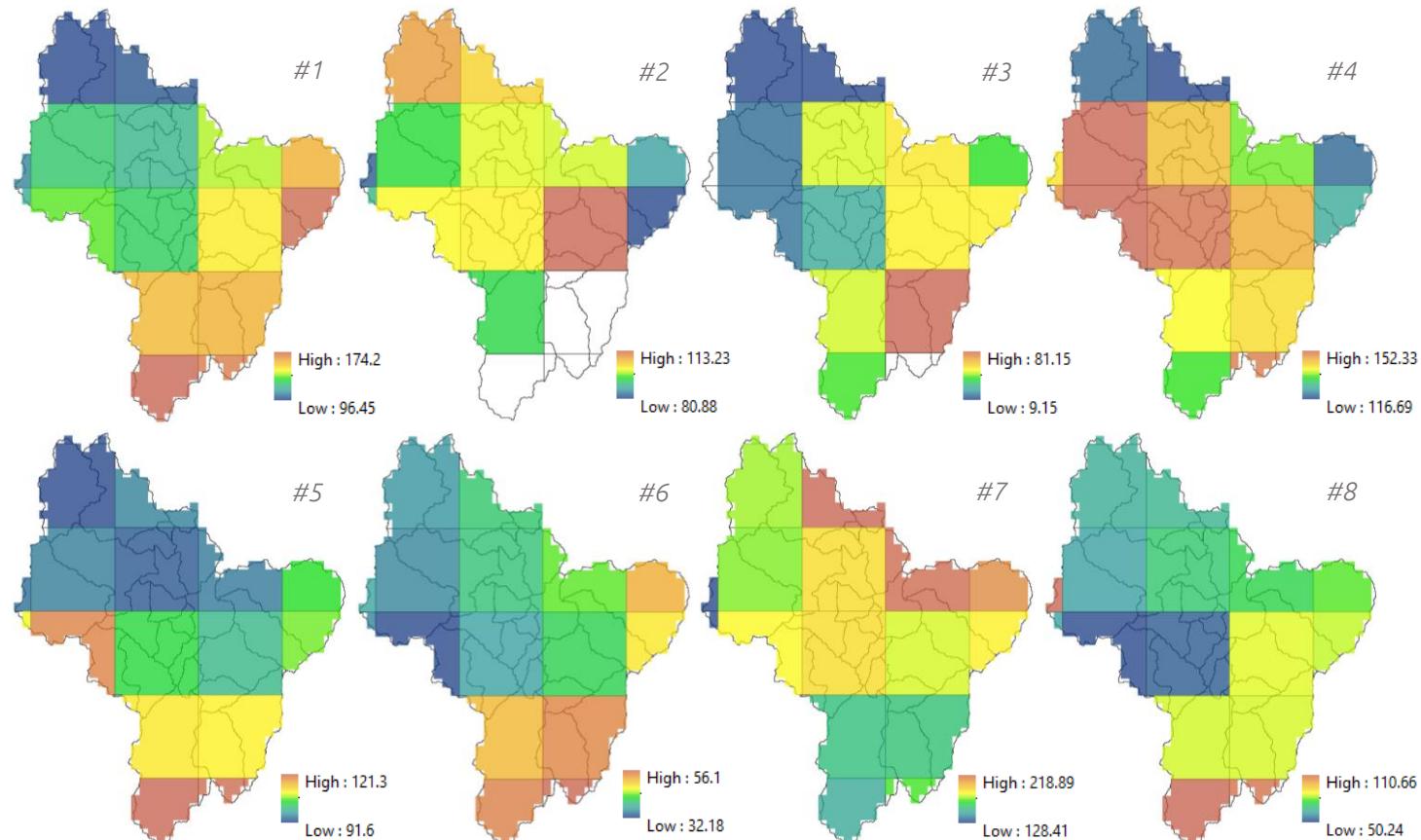
RAR QPEs

Spatial variability



IMERG QPEs

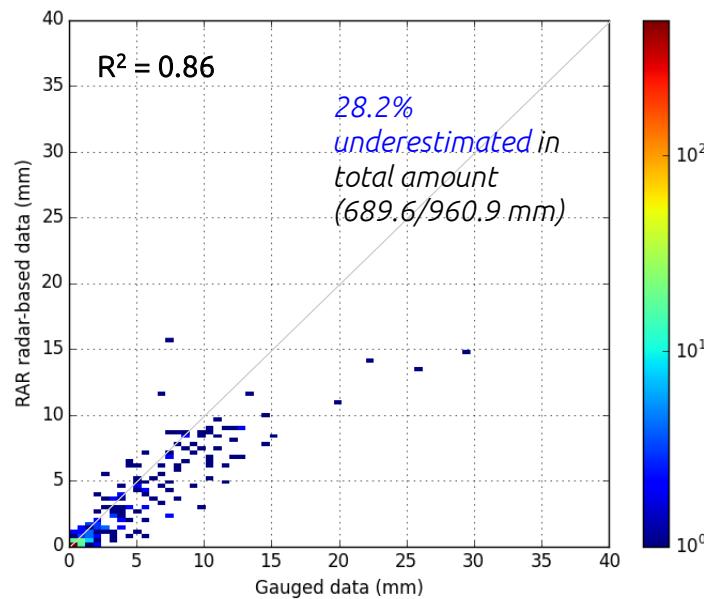
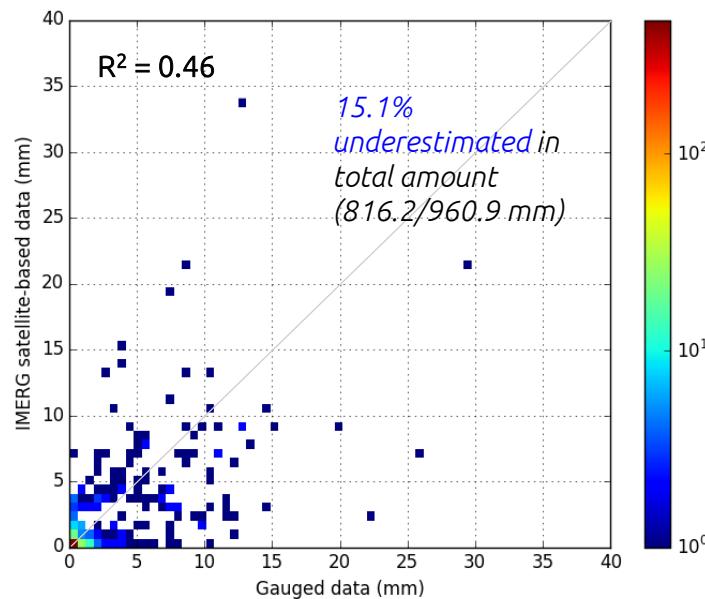
Spatial variability



IMERG QPEs

Validation (scatter density plot)

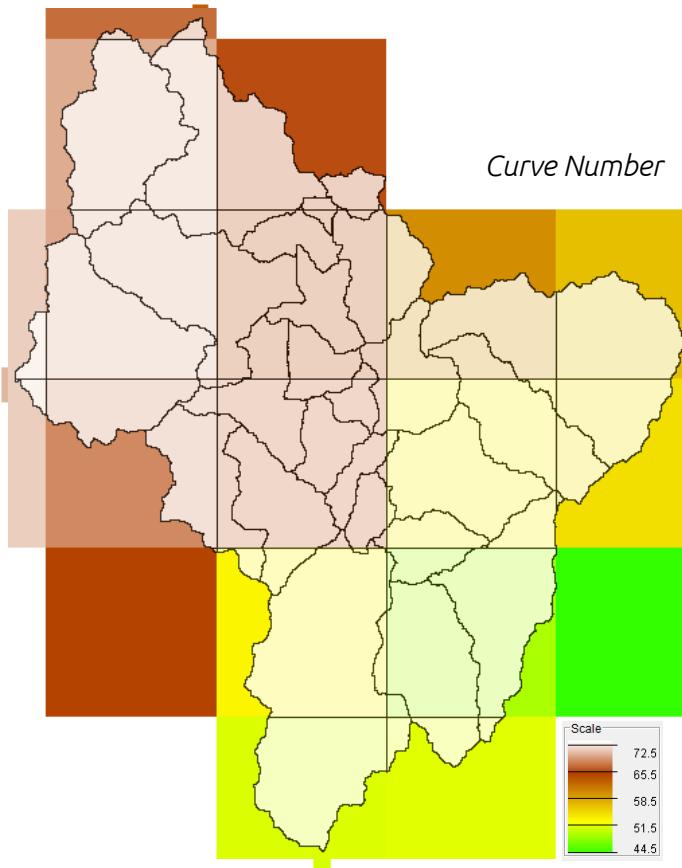
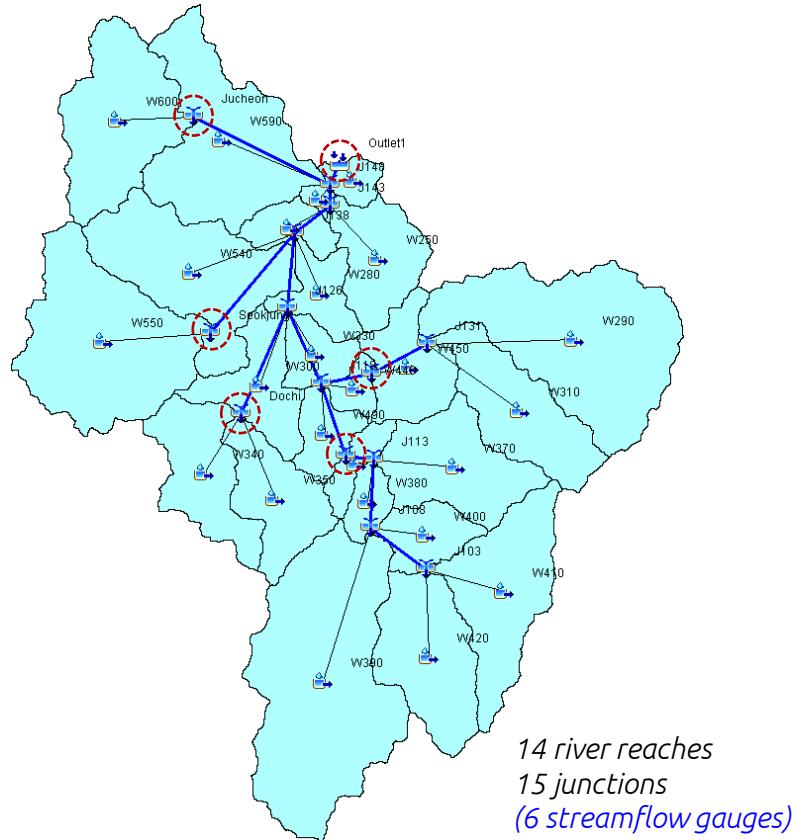
- Correlation (R^2)
 - Areal average for satellite/radar-based and gauged data: **0.46/0.86**
 - **Underestimated** trends in larger values of IMERG/RAR QPEs



Model Development

Basin model

*Stream network definition: 3% threshold of watershed area



Model Calibration

Parameters

- Initial values

Hydrologic Element	Process	Initial parameter values	
		Gauged data simulation	Radar/Satellite-based data simulation
Subbasin	Loss	SCS CN <ul style="list-style-type: none">- Curve Number: <i>determined</i>- Initial abstraction (mm): 0- Impervious(%): 0	Gridded SCS CN <ul style="list-style-type: none">- Curve Number Grid: <i>determined</i>- Ratio: 0.05- Factor: 1.0
	Transform	Clark UH / ModClark <ul style="list-style-type: none">- Time of concentration (HR): <i>determined</i>- Storage coefficient (HR): 2.0	
	Baseflow	Recession <ul style="list-style-type: none">- Initial discharge (m^3/s): <i>observed</i>- Recession constant: 0.2- Ratio to peak: 0.4	
Reach	Routing	Muskingum <ul style="list-style-type: none">- Muskingum K (HR): 0.25- Muskingum X: 0.25- Number of subreaches: 1	

Model Calibration

Parameters

- Calibrated parameters

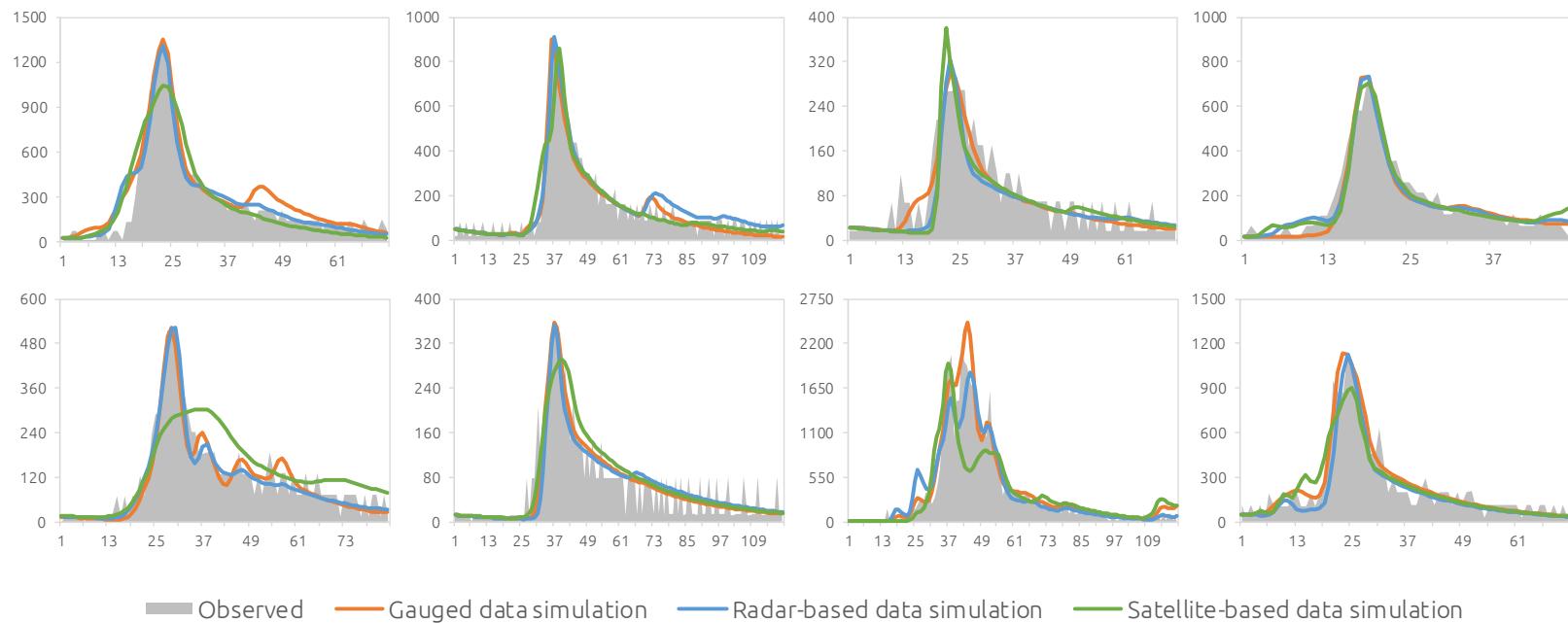
Storm Events (#)	Gauged data simulation						Radar-based data simulation						Satellite-based data simulation					
	Loss		Transform		Routing		Loss		Transform		Routing		Loss		Transform		Routing	
	I_a	$Im.$	T_c	R	K	X	$Ra.$	$Fa.$	T_c	R	K	X	$Ra.$	$Fa.$	T_c	R	K	X
1	-	✓	-	-	-	-	-	✓	-	✓	-	-	-	✓	-	✓	-	-
2	-	✓	-	✓	✓	-	-	✓	-	✓	-	-	-	✓	✓	-	✓	-
3	-	✓	✓	✓	✓	-	✓	✓	-	-	-	-	-	✓	✓	-	✓	-
4	✓	-	✓	-	✓	-	✓	✓	-	-	✓	-	-	✓	-	-	-	-
5	✓	-	✓	-	✓	-	✓	-	-	-	-	-	-	✓	-	✓	✓	-
6	-	✓	✓	✓	✓	-	✓	✓	✓	✓	-	-	-	✓	-	✓	✓	-
7	-	✓	-	✓	-	-	✓	✓	-	-	-	-	-	✓	-	-	-	-
8	-	✓	-	✓	✓	-	✓	✓	-	✓	✓	-	✓	✓	-	✓	✓	-

*No changes for CN & N. of subreaches; Baseflow parameter values are the same for both model simulations

Model Performance

Comparison

- Graphical results



*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Comparison

- Statistical results

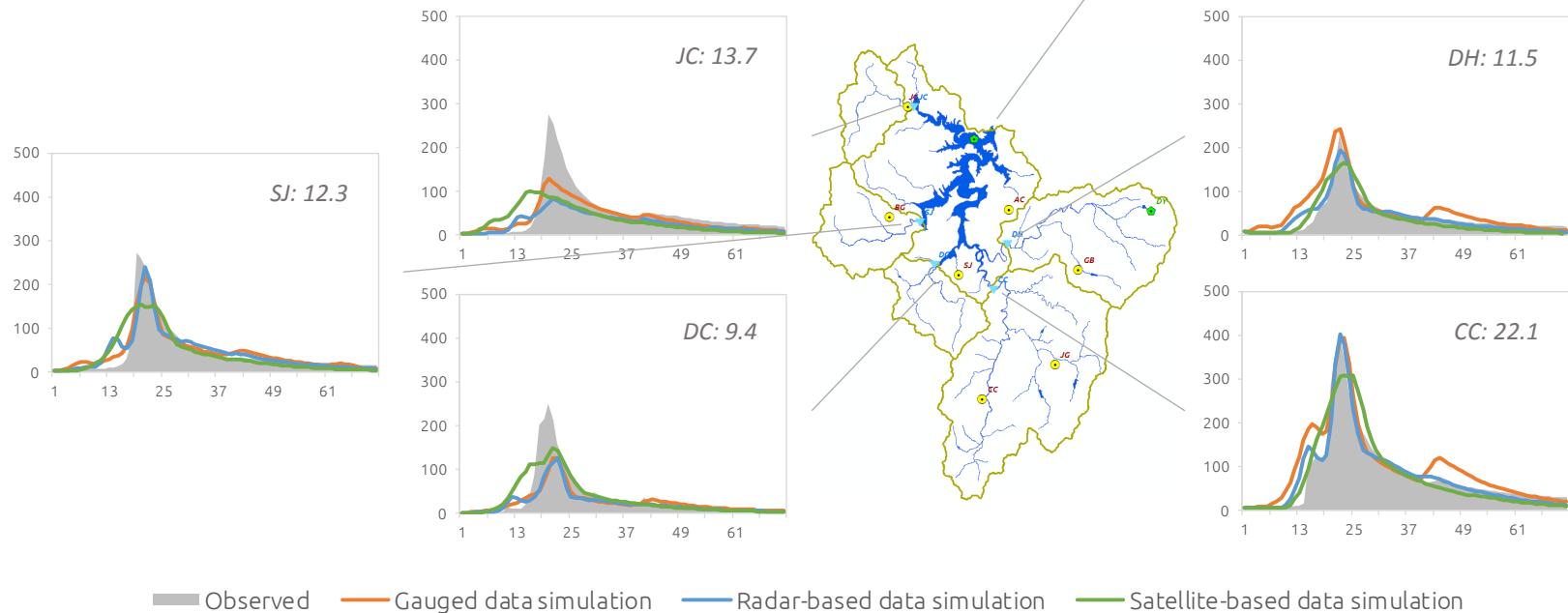
Storm Events (#)	Gauged data simulation			Radar-based data simulation			Satellite-based data simulation		
	E_{NS}	R^2	PBIAS(%)	E_{NS}	R^2	PBIAS(%)	E_{NS}	R^2	PBIAS(%)
1	0.914	0.937	16.97	0.914	0.914	4.01	0.878	0.878	-1.20
2	0.941	0.945	-5.61	0.919	0.925	9.54	0.842	0.843	-3.14
3	0.844	0.853	-9.05	0.716	0.752	-18.06	0.663	0.697	-13.90
4	0.920	0.928	-7.35	0.921	0.920	-2.57	0.906	0.905	-0.99
5	0.893	0.902	-6.69	0.912	0.921	-7.28	0.611	0.629	14.35
6	0.800	0.812	0.38	0.763	0.765	-0.63	0.773	0.790	9.05
7	0.930	0.948	11.87	0.895	0.896	-0.18	0.670	0.673	-7.34
8	0.921	0.925	1.43	0.865	0.891	-17.64	0.861	0.878	-7.19
Avg.	<u>0.895</u>	<u>0.906</u>	<u>7.42</u>	<u>0.863</u>	<u>0.873</u>	<u>7.49</u>	<u>0.776</u>	<u>0.787</u>	<u>7.15</u>

* E_{NS} and R^2 arithmetic mean; PBIAS arithmetic mean of absolute value

Model Performance

Sub-basin comparison

- Graphical results – storm event (#1)

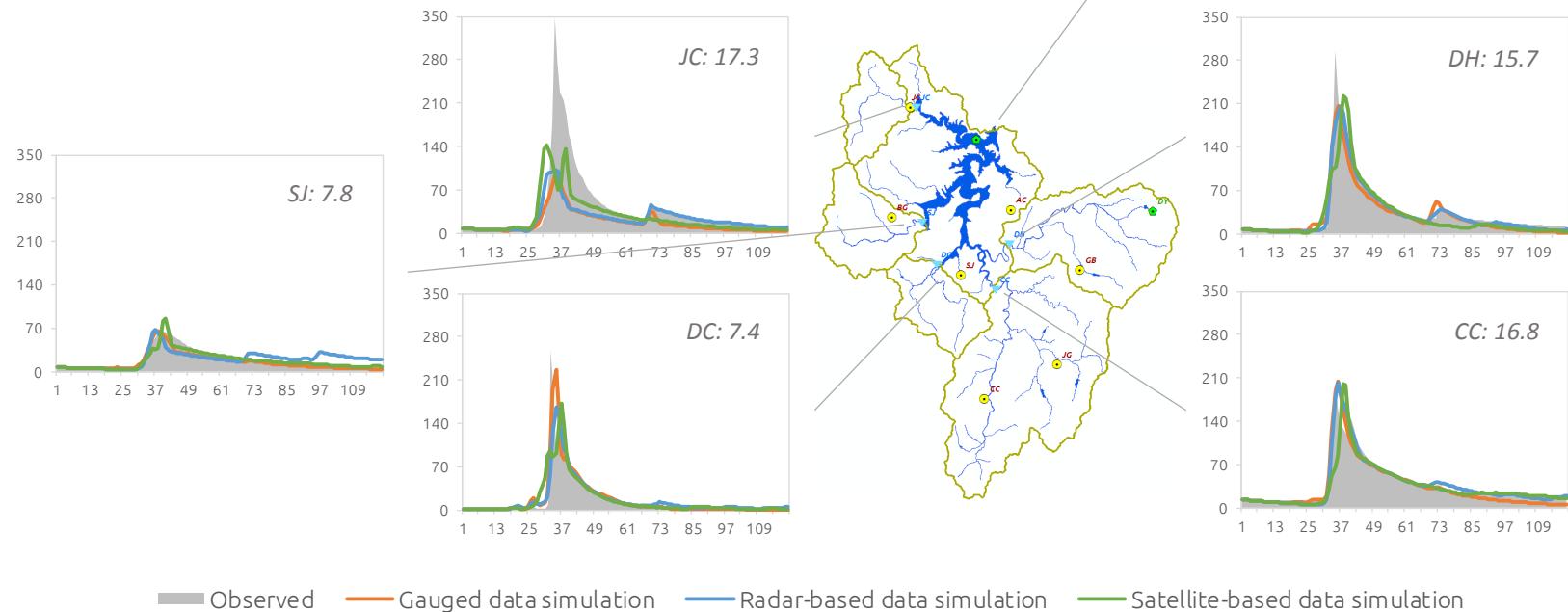


*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Graphical results – storm event (#2)

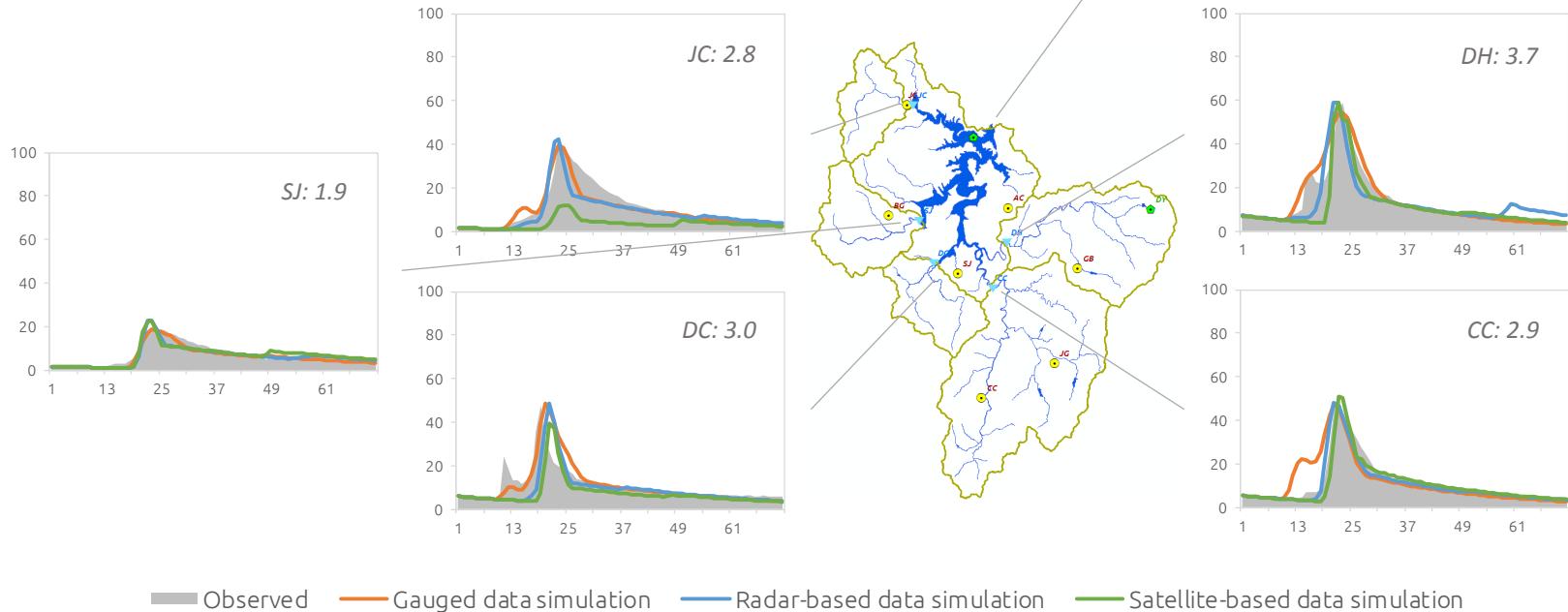


*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Graphical results – storm event (#3)

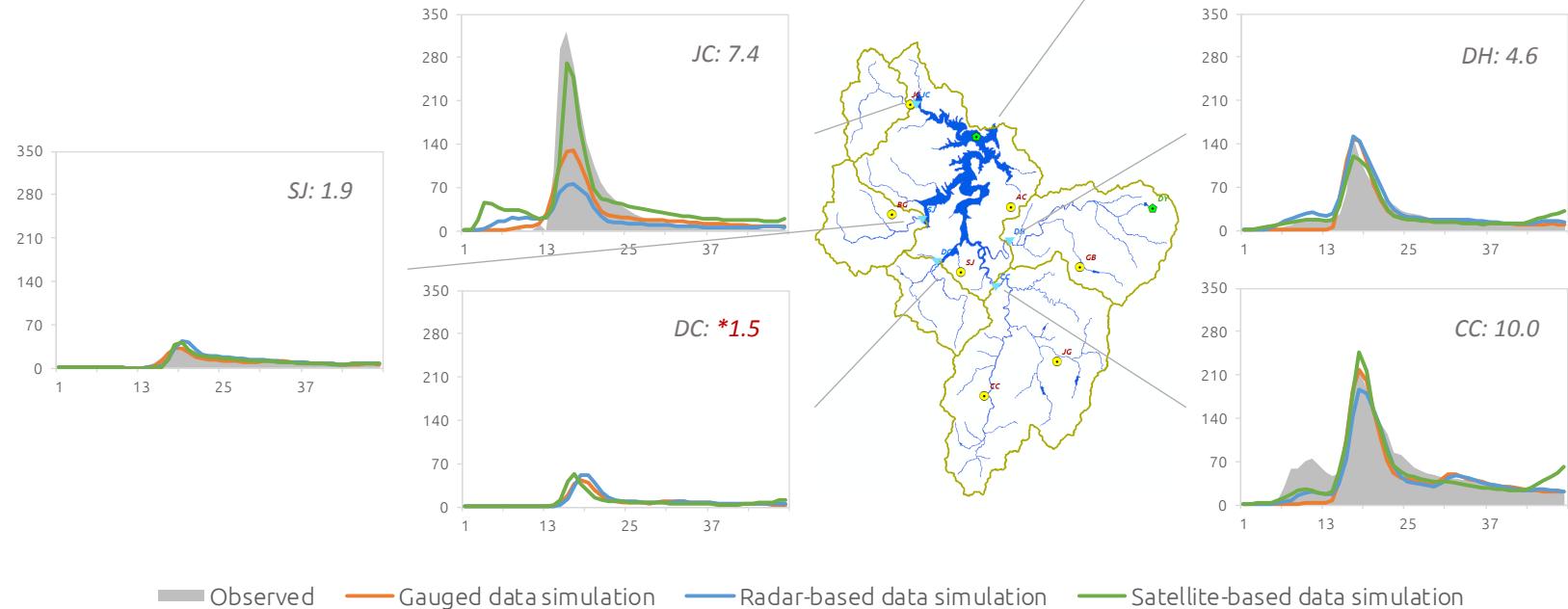


*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Graphical results – storm event (#4)

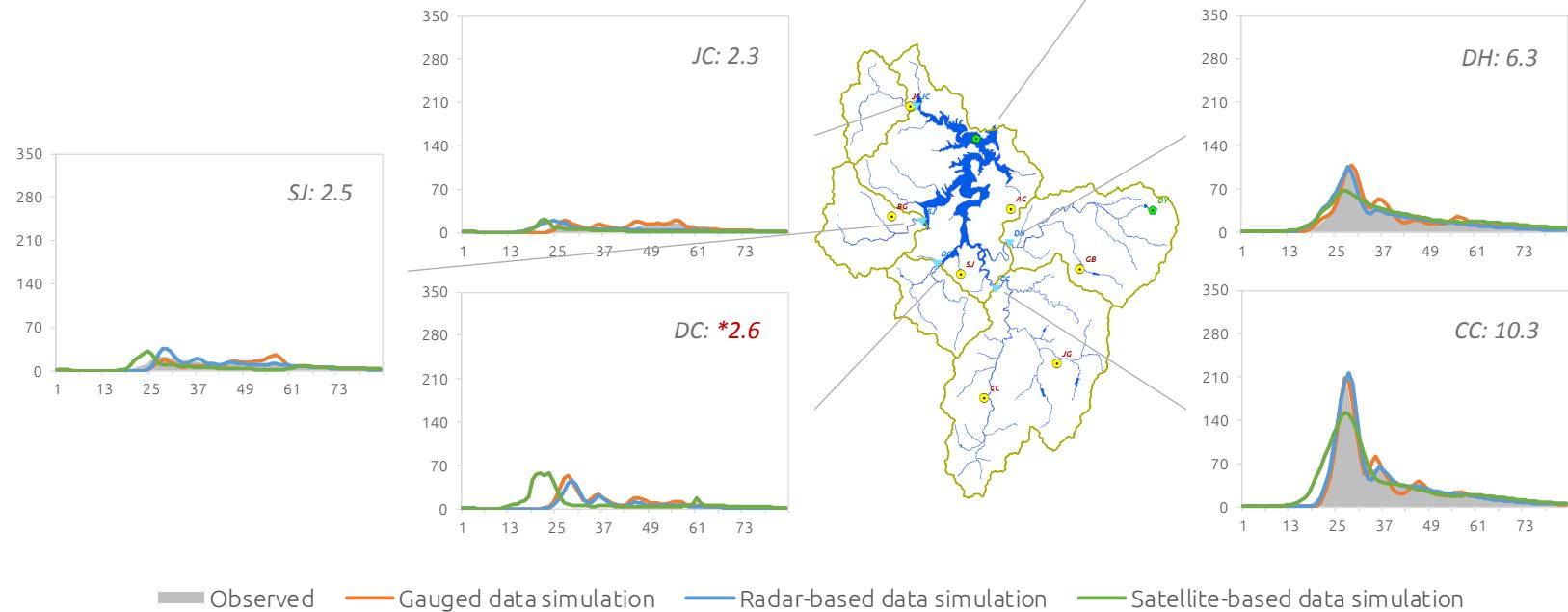


*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Graphical results – storm event (#5)

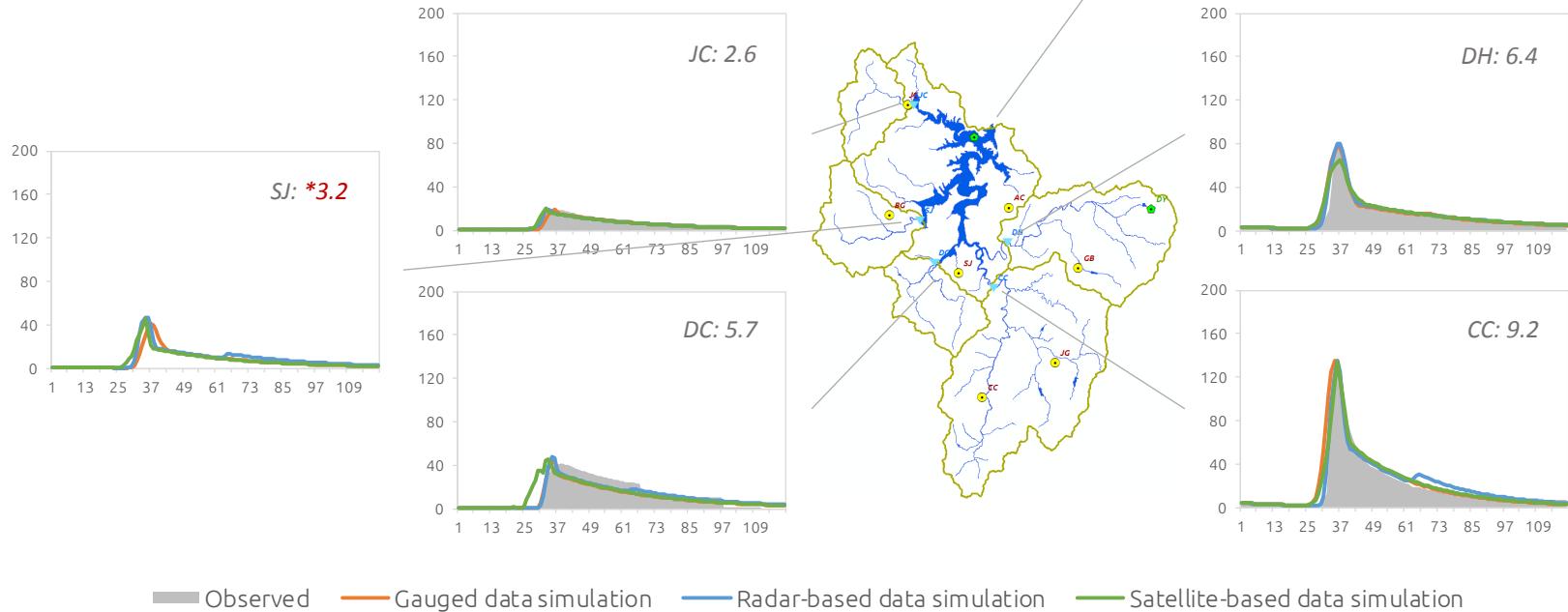


*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Graphical results – storm event (#6)

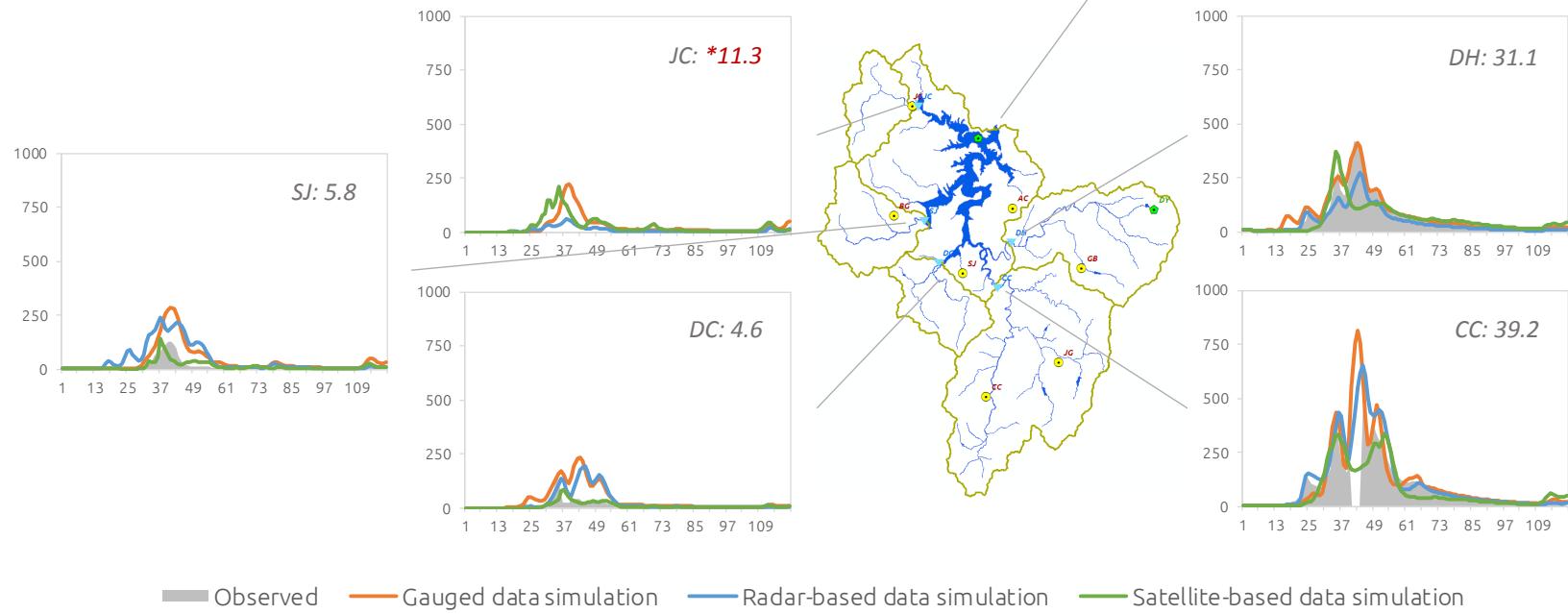


*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Graphical results – storm event (#7)

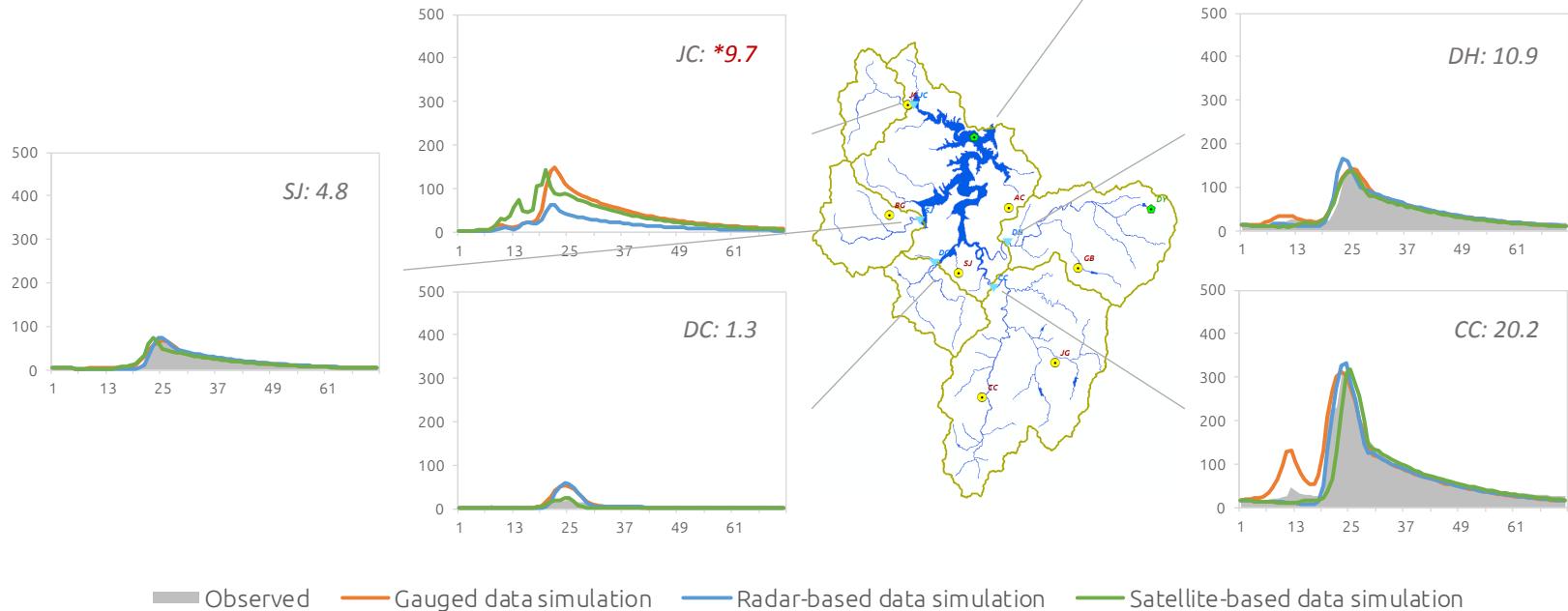


*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Graphical results – storm event (#8)



*X-axis represents simulation time (hours) and Y-axis represents discharge (m^3/sec)

Model Performance

Sub-basin comparison

- Statistical results (E_{NS})

Storm Events (#)	Gauged data simulation					Radar-based data simulation					Satellite-based data simulation				
	CC	DH	DC	SJ	JC	CC	DH	DC	SJ	JC	CC	DH	DC	SJ	JC
1	0.81	0.55	0.61	0.88	0.68	0.93	0.90	0.60	0.80	0.35	0.88	0.82	0.73	0.69	0.27
2	0.92	0.92	0.71	0.88	0.38	0.93	0.92	0.66	0.48	0.40	0.71	0.70	0.65	0.89	0.44
3	0.66	0.93	0.51	0.92	0.85	0.93	0.73	0.15	0.80	0.74	0.89	0.75	-0.10	0.74	-0.14
4	0.74	0.81	*-	0.86	0.60	0.81	0.85	*-	0.76	0.31	0.83	0.89	*-	0.77	0.79
5	0.95	0.95	*-	0.08	*0.65	0.96	0.90	*-	0.61	*-0.42	0.91	0.85	*-	-0.28	*-1.18
6	0.86	0.91	0.82	*	0.94	0.96	0.95	0.86	*	0.86	0.95	0.90	0.61	*	0.79
7	*-0.74	0.95	*-4.58	*-2.02	*	*-0.03	0.79	*-2.89	*-3.09	*	*0.64	0.49	*0.40	*0.57	*
8	0.85	0.94	*-1.19	0.97	*	0.94	0.83	*-1.46	0.96	*	0.74	0.94	*0.60	0.86	*
Avg.	0.83	0.87	0.66	0.77	0.69	0.92	0.86	0.57	0.74	0.53	0.84	0.79	0.47	0.61	0.43

*Observation (streamflow) error

Conclusions

Summary

- A set of programs for IMERG data processing were developed to conduct hydrologic simulation using HEC-HMS with 8 storm events.
- HEC-HMS basin models were developed with subbasins and grid cells.
- IMERG data shows poor spatial variability and underestimated trends in larger values for validation against gauged observations ($R^2 0.46$).
 - Need to extensive calibrations for loss & transform parameters in HEC-HMS
- IMERG data is possibly used as a precipitation input for flood runoff simulation in data-sparse regions due to the reasonable model performance ($E_{NS} 0.78$, $R^2 0.78$, and $PBIAS 7.2\%$) under extensive calibration
 - Radar-based QPEs clearly captured the event (others completely missed it)

Further Study

Distributed-Clark

HYDROLOGICAL SCIENCES JOURNAL
https://doi.org/10.1002/hys.1667 | 101–104



JANUARY 2017

CHO AND ENGEL

A spatially distributed Clark's unit hydrograph based hybrid hydrologic model (Distributed-Clark)

Younghyun Cho^{1,2}, Bernard A. Engel¹ and Venkatesh M. Merwade³

¹Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, Indiana, USA; ²Hydroinformatics Center, Korea Water Resources Corporation, Gwacheon, Republic of Korea; ³Lyles School of Civil Eng, West Lafayette, Indiana, USA

ABSTRACT
A hybrid hydrologic model (Distributed-Clark), which is a lumped conceptual and distributed feature model, was developed based on the combined concept of Clark's unit hydrograph and its spatial decomposition methods, incorporating refined spatially variable flow dynamics to implement hydrologic simulations using spatially distributed runoff flow. In Distributed-Clark, the Soil Conservation Service (SCS) rainfall-runoff method is utilized to estimate conditional unit-based runoff depth and a set of gauged unit hydrographs is used for runoff routing to obtain a direct runoff flow hydrograph. Case studies (four watersheds in the central part of the USA) using spatially distributed (Thiessen polygon-based) rainfall data of storm events were used to evaluate the model performance. Results demonstrate a relatively good fit to observed streamflow, with a Nash-Sutcliffe efficiency (E_{NS}) of 0.62 and percent bias (R^*) of 1.6%, as well as a better fit in comparison with outputs of spatially averaged rainfall data simulations for two models including HEC-HMS.

1 Introduction

Various datasets needed for hydrological modelling, including topography, land cover, soil and rainfall, can now be obtained in gridded form. Similarly, the use of geographic information systems (GIS) software to manage, interpret and prepare spatial data for hydrological modelling is providing a lot of opportunities as well as challenges for hydrological modellers. In addition, exponential increases in computer capabilities have largely removed historical barriers that restricted the development of complex distributed or semi-distributed watershed models. However, the application of these models has made it difficult to evaluate their simulated results given the extraordinary number of parameters involved and the issues related to model calibration, including uncertainty in parameter values and computing time required for their estimation. Thus, calibration and validation of (semi-) distributed hydrological models to estimate streamflow hydrographs using spatially distributed data have become major tasks despite the availability of high computing power (Vieux 2004, Shrestha and Rode 2008, Zhang et al. 2009, Rouholahnejad et al. 2012, Ha et al. 2018). Hence, to reduce the possible uncertainty of selecting reasonable model parameter values and to avoid time-consuming

model calibration, a watershed model needs to be simple, but that can support state-of-the-art hydrology is needed. The study, therefore, uses GIS-based hydrological modelling parameters for spatially distributed simulation through in-depth research that uses GIS-based spatially distributed methods to derive unit hydrographs. Then, a spatially distributed graph-based hydrologic model is presented.

This paper provides a review of the different differences of the proposed model in Section 2, and a each modelling component of model development in Section 3. Model application and the study area, data evaluation target, Section 5 evaluate model performance for the purpose making comparisons of spatially distributed (Thiessen polygon rainfall data, and a summary are provided in Section 6.

NEXRAD Quantitative Precipitation Estimations for Hydrologic Simulation Using a Hybrid Hydrologic Model

YOUNGHYUN CHO

Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, Indiana, USA

BERNARD A. ENGEL

Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, Indiana, USA

(Manuscript received 7 January 2016, in final form 10 September 2016)

ABSTRACT

A hybrid hydrologic model (lumped conceptual and distributed feature model) introduced to perform hydrologic simulations using spatially distributed NEXRAD precipitation estimations (QPEs). In Distributed-Clark, spatially distributed excess rainfall data and spatially distributed unit hydrographs are utilized to calculate a direct runoff flow hydrograph. This simple modeling parameters reduces calibration complexity relative to physically based models by only focusing on integrated flow estimation at watershed outlets. Case quality of NEXRAD stage IV QPEs for hydrologic simulation compared to NEXRAD data validation against rain gauge observations and performance evaluation results are reported for the spatially distributed stage IV and spatial data for four study watersheds. The results show significant differences between gauged and gauged rainfall amounts, with NEXRAD data overestimated by 7.5% and 9.91% by 15.0% and 11.4% accompanied by spatial variability. These differences affect hydrologic applications. Rainfall-runoff flow simulations using spatially distributed QPEs demonstrate relatively good fit [direct runoff: Nash-Sutcliffe efficiency (E_{NS}) determination $R^2 = 0.89$, and percent bias (PBAS) = 3.92%; streamflow: $E_{NS} \cdot PBAS = 1.87\%$] against observed flow as well as better fit (R^2 of 3.7% and R^* of runoff than spatially averaged gauged rainfall for the same model calibration a provided estimates of flow volumes and peak rates that can be underestimated in hydrospace.

1. Introduction

Precipitation is one of the primary inputs for hydrological modeling and related fields of work. As a grand effort to enhance precipitation estimation procedures, the National Weather Service (NWS) deployed a nationwide network of Weather Surveillance Radar-1988 Doppler (WSR-88D) radars (over 160) under the Next Generation Weather Radar (NEXRAD) program during the 1990s (Hudlow and Smith 1989; Crum and Albany 1993; Fulton et al. 1998). In the data processing steps of Precipitation Processing System (PPS), which is

one of the radar products hourly digital precipitation array (DP-8RD reflectivity data, precipitation data, limited gauge data and satellite multisensor precipitation NWS River Forecast C products (regional MPE stage II data with additional gauge data (S et al. 1998). In late 2001, Environmental Protection Agency's "NCEP stage I" (OPE) products

Received: 2 April 2017 | Accepted: 26 January 2018

DOI: 10.1002/hys.1667



WILEY

RESEARCH ARTICLE

Spatially distributed long-term hydrologic simulation using a continuous SCS CN method-based hybrid hydrologic model

Younghyun Cho^{1,2} | Bernard A. Engel¹

¹Department of Agricultural and Biological Engineering, Purdue University, 225 South University Street, West Lafayette, IN 47907-2093, USA

²Hydroinformatics Cooperation Center, K-water (Korea Water Resources Corporation), 11 Gyojaekwon-Ro, Gwacheon 13981, Republic of Korea

Correspondence:
Bernard A. Engel, Department of Agricultural and Biological Engineering, Purdue University, 225 South University Street, West Lafayette, IN 47907-2093, USA.
Email: engel@purdue.edu

Abstract

A continuous Soil Conservation Service (SCS) curve number (CN) method that considers time-varied SCS CN values was developed based on the original SCS CN method with a revised soil moisture accounting approach to estimate run-off depth for long-term discontinuous storm events. The method was applied to spatially distributed long-term hydrologic simulation of rainfall-runoff flow with an underlying assumption for its spatial variability using a geographic information systems-based spatially distributed Clark's unit hydrograph method (Distributed-Clark; hybrid hydrologic model), which is a simple few parameter run-off routing method for input of spatiotemporally varied run-off depth, incorporating conditional unit hydrograph adoption for different run-off precipitation depth-based direct run-off flow convolution. Case studies of spatially distributed long-term (total of 6 years) hydrologic simulation for four river basins using daily NEXRAD quantitative precipitation estimations demonstrate overall performances of Nash-Sutcliffe efficiency (E_{NS}) 0.62, coefficient of determination (R^2) 0.64, and percent bias 0.33% in direct run-off and $E_{NS} = 0.72$, $R^2 = 0.72$, and percent bias 0.15% in total streamflow for model result comparison against observed streamflow. These results show better fit (improvement in E_{NS} of 42.0% and R^2 of 33.3% for total streamflow) than the same model using spatially averaged gauged rainfall. Incorporation of logic for conditional initial abstraction in a continuous SCS CN method, which can accommodate initial loss amounts based on previous rainfall, slightly enhances model simulation performance; both E_{NS} and R^2 increased by 1.4% for total streamflow in a 4-year calibration period. A continuous SCS CN method-based hybrid hydrologic model presented in this study, however, is potentially significant to improved implementation of long-term hydrologic applications for spatially distributed rainfall-runoff generation and routing, as a relatively simple hydrologic modelling approach for the use of more reliable gridded types of quantitative precipitation estimations.

Keywords

continuous SCS CN method, GIS, hybrid hydrologic model, NEXRAD QPEs, spatially distributed long-term rainfall-runoff flow estimation

1 | INTRODUCTION

The Soil Conservation Service (SCS) run-off curve number (CN) method that was developed in the 1950s by the SCS (now NRCS, Natural Resources Conservation Service) (SCS, 1957, 1972; USDA NRCS, 2010) is a popular, ubiquitous, and enduring means of estimating storm run-off from rainfall events (Hjelmfelt, Ward, Woodward, & Van Mullem, 2009). This method of rainfall excess estimation from rainfall depth is widely used in applied hydrology. Hjelmfelt (1980) and Ponce and Hawkins (1996) indicate that its advantages of convenience, simplicity,

and responsiveness to readily identified catchment properties (soil type, land use/treatment, surface condition, antecedent condition, etc.) are the grounds to maintain its popularity. Furthermore, geographic information systems (GIS), introduced in the 1990s, also enables this method to be easily adopted in hydrologic models, particularly for its parametric data (soil, land use, etc.) processing.

However, this method has a limitation when applied to long-term storm hydrologic application because it originated as an empirical, event-based procedure for flood hydrology (Goren & Moore, 2005) and does not contain an expression for time (Woodward, Hawkins,

Corresponding author e-mail: Bernard A. Engel, engel@purdue.edu
© Supplementary data can be viewed here

© 2018 WILEY

Corresponding author e-mail: Bernard A. Engel, engel@purdue.edu
DOI: 10.1175/JHM-D-16-0013.1

© 2017 American Meteorological Society

904 | Copyright © 2018 John Wiley & Sons, Ltd.

wileyonlinelibrary.com/journal/hys

Hydrological Processes, 2018;32:904–922

Thanks for listening!