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Integrated Hydrological Modeling to Analyze the Effects of Precipitation on Surface Water and Groundwater Hydrologic Processes in a Small Watershed

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Abstract: The main objective of this study is to evaluate the performance of the integrated hydrological model, MIKE SHE in a small watershed to analyze the effect of two different precipitation sources on model outputs (groundwater elevation and surface water flows). The model was calibrated and validated with observed groundwater elevations and surface water flows measured at the United States Geological Survey (USGS) gage stations in the basin. The model calibration performance for surface water flows (R = 0.80, MAE= 0.20 m^3/s, BIAS = -0.14 m^3/s, NSE = 0.59) and groundwater elevations (R = 0.74, MAE = 0.45 m, BIAS = 0.08 m, NSE = 0.35) showed that the model was able to predict hydrological processes based on forcing variables in a small watershed. The analysis did not show the model with precipitation at the nearer (NOAA-Edwardsville) gauge station has better performance than the farther gauge station (NOAA-St. Louis). The quantitative analyses for the most sensitive model output variable suggested that precipitation uncertainties had noticeable impacts on surface water flows (0.81% to 11.19%), than groundwater elevations (0.06% to 0.07%), with an average of 6.71% and 0.66%, respectively. Our results showed noticeable differences in simulated surface water flows in spring (12.9%) and winter (36%) seasons compared to summer (11.4%) and fall (4.6%) as a result of difference (6% to 18%) in precipitation, which indicated that uncertainties in precipitation impact simulated surface water flows in a small watershed vary with different seasons. Our analyses have shown that precipitation affects the simulated hydrological processes and care should be taken while selecting input datasets (i.e., precipitation) for better hydrological model performance, specifically for surface water flows.

Keywords: integrated hydrological modeling; groundwater; surface water; MIKE SHE; precipitation sources; watershed

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1. Introduction

Water-resources management has been a challenging task for water managers, hydrologists, and ecologists to fulfill various demands such as energy, agricultural, industrial, municipal, flood control, and ecological processes, etc. [1]. For example, water-resource management has a direct negative impact on the riverine ecosystem, and therefore, ecosystem restoration has focused on restoring ecological flows [2–4].

Hydrological models (e.g., SWAT, DRAINMOD, HEC-HMS, etc.) have been used to simulate hydrological responses. However, some of these models do not consider direct interaction with groundwater [5,6]. Stand-alone groundwater models (e.g., MODFLOW) have been used in past studies to simulate groundwater-flow processes [7]. The integrated hydrological (surface and groundwater) model MIKE SHE has been successfully tested in watersheds with different characteristics in the USA [8] and around the world [5,9]. One of the major advantages of MIKE SHE is that it considers a dynamic interaction between groundwater and surface water flows in streams and rivers. The advantages of integrated models are highlighted by various recent studies [9–13]. Since MIKE SHE is a spatially distributed model (grid-based), it can incorporate spatial variability of physical and meteorological parameters [8] compared to lumped models such as, for example, SWAT [14] and HEC-HMS [6].

Hydrological modeling requires meteorological data such as precipitation, wind speed, atmospheric temperature, and solar radiation to simulate surface water flow, sediment transport, and water quality [15]. An accurate spatial and temporal representation of precipitation is crucial to predict hydrological responses and water balance within a watershed since it is the most significant model input parameter [16–18]. Therefore, both the spatial and temporal variation of precipitation is very important for better hydrological model performance and watershed management [19,20]. Rainfall data measured at gauge stations may not be able to capture accurate spatial variability [21,22]. To lower the effects of such variation on runoff volume and timing, spatially distributed rainfall data sources can be used [23]. Meanwhile, continuous monitoring of precipitation and other meteorological parameters such as wind speed, temperature, solar radiation, and stream runoff is also crucial to analyze the watershed water balance [24]. Therefore, hydrological monitoring is important to understand the real effect of precipitation on hydrologic responses, including groundwater [24–26].

Past studies used different precipitation sources (point and spatially distributed), e.g., gauges, radar, satellite, etc. [27–31]. A gauge station is a major source of precipitation data for hydrological analysis [32] and yields better results using multiple rain gauge stations within the watershed [33]. A study showed that poorly distributed rain gauge stations impact model results [34], forcing to recalibrate the model with different precipitation sources [28,35]. National Oceanic and Atmospheric Administration (NOAA) provide the best rainfall data measurement; however, they are not error-free [36]. Site-specific rainfall data distribution can cause an error in the hydrological model results [37]. Radar-based and Climate Forecast System Reanalysis (CFSR) rainfall data have received increasing attention for hydrologic analyses because of the large area coverage [31,35,38,39].

Over the last couple of decades, various studies have been designed to determine the effect of precipitation on hydrologic responses. The impacts vary significantly depending on the type of precipitation, hydrologic models, and watershed characteristics [15,16,21,28,31,33,35,40–45]. For example, the sensitivity of spatial precipitation distribution to the surface-runoff response depends on the model scale [42,46]. Lopes [47] showed that spatial distribution of precipitation had significant effects on the runoff mechanism, irrespective of scales in the Walnut Gulch watershed, Arizona. Moreover, Guo et al. [48] found better calibration results with a fine spatial resolution of precipitation data. Previous studies showed that the hydrological model performance was better with CFSR data, compared to traditionally observed weather data [43]. Another study showed that PRISM-based (Parameter-elevation Relationships on Independent Slopes Model) precipitation provides a better streamflow prediction than CFSR and gauge data within a watershed [35]. Furthermore, they found better results with NCDC (National Climatic Data Center) gauge data than for the CFSR, due to the close proximity of NCDC stations to the watershed boundary. Uncertainties in rainfall result in parametric uncertainty in a distributed hydrological model and simulated flows [39]. A study showed that the errors due to model parameters are similar or even higher than the errors due to rainfall uncertainties [49]. The simulated surface water flow is not only affected by the change in precipitation, but also by evapotranspiration and groundwater contribution [50–53]. These studies indicated that uncertainties in the hydrological model simulated flows due to change in precipitation spatially and temporally (i.e., months and seasons).

Besides surface water flows, groundwater systems are influenced by change in precipitation because they are typically recharged from the ground surface. For example, autumn and winter precipitation has a noticeable impact on groundwater level than in spring and summer seasons, where air temperature is driving groundwater fluctuations [50]. Increased precipitation results in elevated groundwater elevations in some areas, whereas lowered in other areas [52]. Another study concluded that groundwater storage changes do not reflect the long-term trend in precipitation, but the change is due to alteration of evapotranspiration, and reduction in snowmelt [51]. Studies have shown mixed results for correlations between precipitation and groundwater elevations [50–52].

It is apparent that researchers found the mixed performance of the hydrological model specifically for surface water, based on different precipitation sources (e.g., gauge stations, CFSR, NEXRAD, etc.) and their proximity to the watershed. However, the performance of an integrated hydrological model based on the precipitation measured at different gauge stations (e.g., NOAA), for predicting groundwater elevations and surface water flows in a small watershed is lacking. It is unclear if groundwater elevations or surface water flows are the most sensitive to precipitation. Furthermore, the knowledge about how uncertainties of precipitation input in the hydrological model impact simulated surface water flows in different seasons lacking.

This study is focused on changes in groundwater elevations and surface water flows due to differences in measured precipitation at NOAA-St. Louis and NOAA-Edwardsville gauges in a small watershed using integrated hydrological model MIKE SHE. Specifically, we used calibrated model with CFSR based meteorological and precipitation data to quantify, i. Most sensitive variable (i.e., groundwater elevations or surface water flows). ii. Seasonal variations of difference in surface water flows with respect to change in precipitation.

2. Materials and Methods

2.1. Study Area

A small watershed (298 km^2) (hereafter Canteen-Cahokia Watershed) within the Canteen-Cahokia Watershed (HUC-10) is considered for this study, which is located about 16 km northeast of downtown city of St. Louis, Missouri, and drains into the Mississippi River (Figure 1). The watershed comprises 30% agricultural field, mostly plain land with mild slopes.

2.2. Integrated Hydrological Modeling—MIKE SHE

Integrated hydrological models dynamically couple surface water and groundwater flow processes at a wide range of spatial scales [28,54]. This study used an integrated hydrologic modeling system (200 m $\times$ 200 m grid size), MIKE SHE to simulate groundwater and surface water flows (DHI) [55]. The diffusive wave approximation method was used to simulate the overland flow in the horizontal direction, whereas Richard's equation simulates the unsaturated flow along the vertical direction. Water movement in SZ (saturated zone) was simulated using the Boussinesq equation [56]. Kristensen and Jensen's method was applied to describe the evapotranspiration, considering interception from the canopy, evaporation from the soil, and plants transpiration [57].

MIKE Hydro River is a one-dimensional (1D) river modeling software (Version 2019) based on the dynamic wave approximation of the Saint Venant equation [58]. The coupling of MIKE SHE and MIKE Hydro River allows an interaction between surface water hydrodynamics and groundwater flow regimes [59,60]. The Saint Venant diffusive wave approximation method was used to predict the overland flow. Manning's number (inverse of manning's roughness), initial water depth, and detention storage parameters were considered for the simulation of overland flows. The channel network alignment for the model was digitized along the perineal streams in the watershed (Figure 1). The cross-section geometry along the channels was extracted from a one-meter resolution LiDAR DEM.

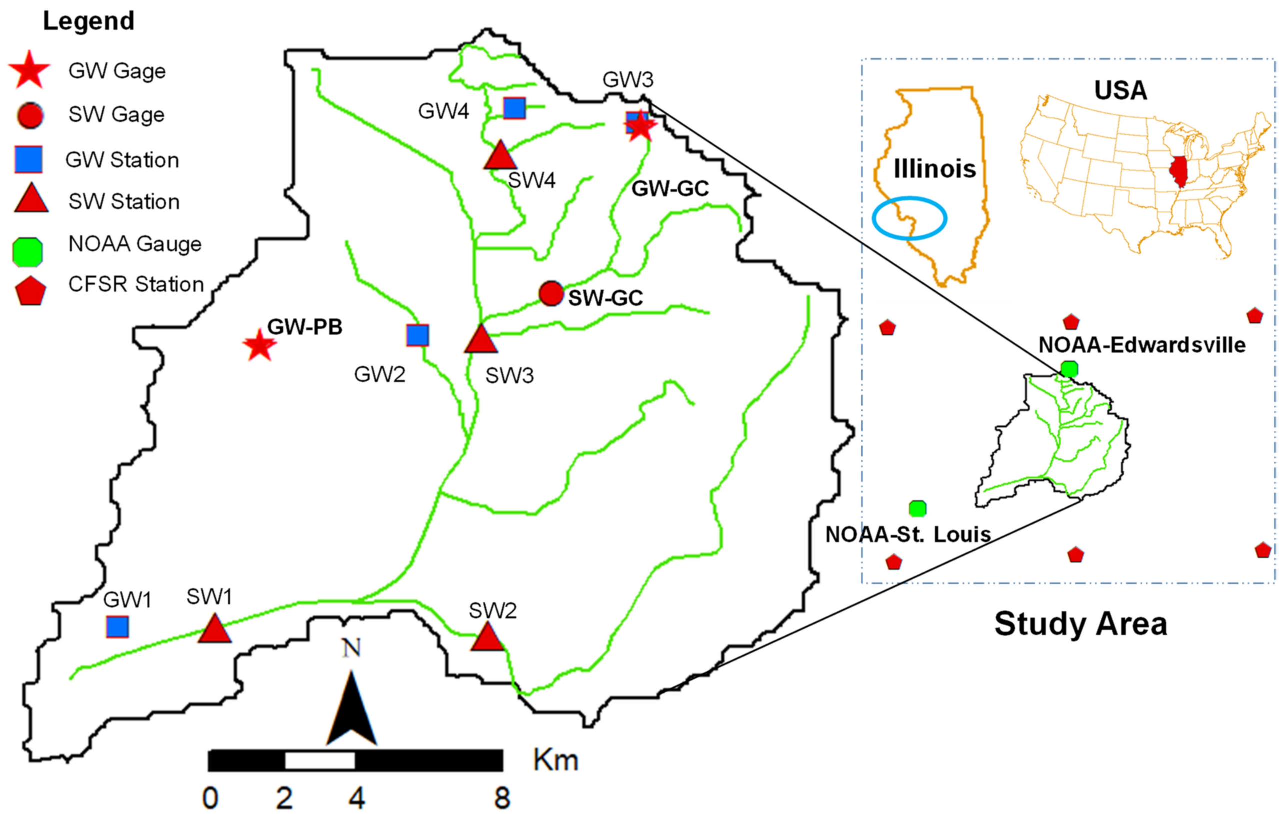

Figure 1. Location of Canteen-Cahokia watershed showing National Oceanic and Atmospheric Administration (NOAA) precipitation gauges, Climate Forecast System Reanalysis (CFSR) stations, and USGS groundwater (GW-GC: USGS Groundwater Station# 384656089582001 at Glen Carbon, Illinois) and surface water gauge stations (SW-GC: USGS surface water flow station# 05588720 at Glen Carbon, Illinois). SW = surface water, GW = groundwater, GC = Glen Carbon, PB = Pontoon Beach.

2.3. Input Data

The topography of the watershed was represented by a high-resolution (10 m × 10 m) Digital Elevation Model (DEM). Meteorological data, including on precipitation (discrete), were based on global weather data CFSR for SWAT (https://globalweather.tamu.edu/) and NOAA (https://www.ncdc.noaa.gov/cdo-web/). CFSR data are prepared from data-assimilation techniques utilizing conventional meteorological gauge observations, satellite irradiances, and advanced atmospheric, oceanic, and surface-modeling components at ~38 km resolution [61].

The meteorological data used for model calibration and validation were based on CFSR and includes precipitation (mm/day), maximum and minimum temperature (°C), solar radiation (MJ/m^2/d), wind speed (m/s), and average relative humidity (%). The reference evapotranspiration (ET_0) was calculated based on the Penman-Monteith method (Zotarelli et al. 2010) using an Excel program [62]. Estimated ET_0 (mm/day) was based on the assumption of evapotranspiration from reference vegetation considering canopy resistance, aerodynamic resistance, and soil heat flux intensity.

Nine major land use types were considered in our study, which collectively comprised more than 90% of the total area (i.e., land, bare soil, deciduous forest, evergreen forest, cultivated crops, hay/pasture, woody wetlands, open water, and herbaceous wetlands). Although there were 128 STATSGO soil types present in the watershed, only ten major soil types were considered by merging similar soil types (i.e., silty clay loam, silt loam, silty clay, sandy loam, urban land, water, clay loam, silt, loam, and sand) [63]. To estimate groundwater flow through the unsaturated soil zone, water retention and hydraulic conductivity of soil were considered, which is based on the Van Genuchten method [13,64,65].

The study area has limited measured surface water flows and groundwater availability for model calibration and validation. Daily averaged surface water data are available from May 2000 to October 2011 for SW-GC (USGS surface water gage station# 05588720) located at the Judy Branch Creek in the city of Glen Carbon, IL (watershed area 21.3 km^2). Two USGS gage stations, GW-GC (USGS Groundwater Station# 384656089582001) and GW-PB (USGS Groundwater Station# 384352090054102) located at the city of Glen Carbon and Pontoon Beach, IL, respectively were used to calibrate and validate the groundwater model.

2.4. Sensitivity Analysis

The sensitivity analyses of model parameters were performed using the Autocalibration Function of MIKE SHE [DHI, 55]. The most sensitive parameters for groundwater and surface water hydrology reported by various previous studies are hydraulic conductivity, specific yield, initial potential head of aquifer, soil bypass coefficient, manning's roughness, evapotranspiration parameters, leakage coefficient, and detention storage [9,11,13,66].

The hydraulic conductivity and bypass constant (which refers to the fraction of rainfall infiltrates into the soil before water starts to appear as overland/channel flow) were found sensitive for both groundwater and surface water similar in another study [8]. Other surface water sensitive parameters were overland and channel manning's number M (i.e., the inverse of roughness coefficient), detention storage, ET coefficients (C_2 and C_3), groundwater initial potential head, and groundwater leakage coefficients. The groundwater and surface water sensitive parameters were similar to other studies for lowland watersheds using the MIKE SHE model [5,8,13,67,68].

2.5. Model Calibration Parameters Optimization

The calibration of MIKE SHE and MIKE Hydro River models are performed simultaneously as the change of a parameter in one model can affect another model's results [58]. Groundwater elevation and surface water flow from April 2005 to March 2009 were used for the calibration process, whereas from April 2009 to September 2011 for the validation. However, additional 2 years were added as a model warm-up period before the calibration and validation periods to avoid the errors because of model instabilities. Final optimized model parameter values are those which yield the best error statistics.

Autocalibration was performed against daily groundwater elevations at GW-GC and surface water flows at SW-GC stations. During the calibration processes, the program changes different groundwater (e.g., hydraulic conductivity, specific yield, initial potential, soil bypass coefficient) and surface water (e.g., manning's number M (i.e., the inverse of roughness coefficient) for both overland and river channel, and detention storage) parameters and calculate error statistics. The final optimized parameters were within the ranges reported in other studies using MIKE SHE (Table 1) [5,14,33,58,69–71].

2.6. Model Performance Analysis

To test the best fit of a model, the most commonly used statistical performance indicators, Coefficient of Correlation (R), Nash-Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), and Bias (BIAS) were estimated in this study [72]. Simulated and measured daily groundwater elevations and surface water flows were compared during the calibration and validation processes to analyze model performance. The R shows the fraction of deviation between modeled and observed data [73], and ranges from 0 to 1, with 0 being the least favored and 1 being the most favored. The NSE describes the predictive power of a hydrological model. The higher the value is, the better representation of model parameters. NSE values less than 0 occur when the observed mean is a better predictor than the model [73]. BIAS measures the average tendency (of the simulated values larger or smaller than their observed ones [71]. The MAE measures an average mean discrepancy between two datasets and is a more natural way of error measurement [74].

Table 1. Final Optimized Calibrated Parameters for Surface water and Groundwater.

Model	Parameters	Initial	Range	Calibrated
MIKE SHE	Overland and Unsaturated Zone			
	Manning's M	17	10–40	26.80
	Detention Storage (mm)	2	0–10	5.08
	Bypass Constant	0.26	0.15–0.9	0.27
	Saturated Zone			
	Horizontal Hydraulic Conductivity (10^{-6} m/s)	5.6	0.0056–566	96.80
	Vertical Hydraulic Conductivity (10^{-6} m/s)	0.56	56.6	9.68
	Specific Yield	0.2	0.2–0.4	0.20
	Initial Potential (−m)	5	1–10	6.32
	ET Parameters (Kristensen And Jensen)			
	Canopy Interception (mm)	0.05	0.05–0.4	0.07
	C1	0.2	0.05–0.4	0.34
	C2	0.2	0.05–0.4	0.06
	C3 (mm/day)	20	5–40	6.95
	A_{root} (/m)	0.3	0.05–0.4	0.31
MIKE Hydro	River and Lakes			
	Manning's M	36	10–40	18.45
	Leakage Coefficient (10^{-6})	5.6	0.0056–566	2.30

We further analyzed the model performance by comparing simulated groundwater elevations and surface water flows based on precipitation measured at two NOAA gauge stations and CFSR. All three models have the same calibrated parameters and input datasets except precipitation. We simulated groundwater elevations and surface water flows using models with three different precipitation sources, a. NOAA-Edwardsville, b. NOAA-St. Louis, and c. CFSR. We analyzed differences in model outputs due to precipitation measured at each NOAA gauge station and CFSR. The analysis informs whether NOAA-Edwardsville or NOAA-St. Louis model performs better (groundwater elevations and surface water flows) with reference to the CFSR model.

The NOAA gauge stations are located at the city of Edwardsville, IL (hereafter NOAA-Edwardsville) and St. Louis, MO (hereafter NOAA-St. Louis). The NOAA-Edwardsville gauge station is located close (less than 1 km) to the watershed boundary, whereas the NOAA-St. Louis is about 6.5 km far away. R and MAE were estimated using simulated groundwater elevations and surface water flows (April 2005–January 2007) at four different random stations (locations) (Figure 1).

2.7. Effect of Precipitation Sources on Groundwater and Surface Water Flows

2.7.1. Sensitive Variable (i.e., Groundwater Elevations or Surface Water Flows)

We quantified the most sensitive variable (i.e., groundwater elevations or surface water flows) due to the effects of two precipitation sources (i.e., NOAA-St. Louis Vs NOAA-Edwardsville) by estimating R and MAE. The MAEs were normalized with respect to the NOAA-Edwardsville simulated average groundwater elevations or surface water flows at four random stations (Figure 1) and presented in percentages (%). Furthermore, weighted (by surface water flows or groundwater elevations) averages of MAE and R were calculated for comparison. The variable with higher MAE (%) and lower R are defined as the most sensitive.

2.7.2. Seasonal Variations of Difference in Surface Water Flow with Respect to Change in Precipitation

We analyzed the relationships between the difference in simulated surface water flows (%) with respect to difference in precipitation measured at NOAA-Edwardsville and NOAA-St. Louis gauges considering overall and seasonal datasets. Differences (%) in precipitation and surface water flows were calculated relative to the NOAA-Edwardsville gauge precipitation. For the category "All", we considered entire datasets from April 2005 to January 2007. For "Season", datasets were classified into four seasons, Spring (March, April, and May), Summer (June, July, and August), Fall (September, October, and November), and Winter (December, January, and February). Later, we calculated weighted-average surface water flows based on four different random stations for comparison (Figure 1). The analysis will yield if there is a correlation between differences in precipitation and simulated surface water flows considering entire datasets and four seasons.

3. Results

3.1. Model Performance

3.1.1. Model Calibration and Validation

R, MAE, BIAS, and NSE between simulated and measured groundwater elevations at the GW-GC gage station were 0.74, 0.45 m, 0.08 m, and 0.35, respectively (Figure 2 and Table 2). The average positive BIAS of 0.08 m showed that MIKE SHE underpredicted groundwater elevations during the calibration period (Table 2). The R, MAE, BIAS, and NSE were 0.74, 0.39 m, −0.24 m, and 0.14, respectively for groundwater elevations during the model validation period at the GW-GC gage station. The overall model performance trend during the validation period was similar to the calibration for groundwater elevations, except for BIAS and NSE (Table 2). The BIAS (−0.24 m) was negative for the validation period, which showed overprediction by model, opposite to the outcome from the model calibration (Figure 2b and Table 2).

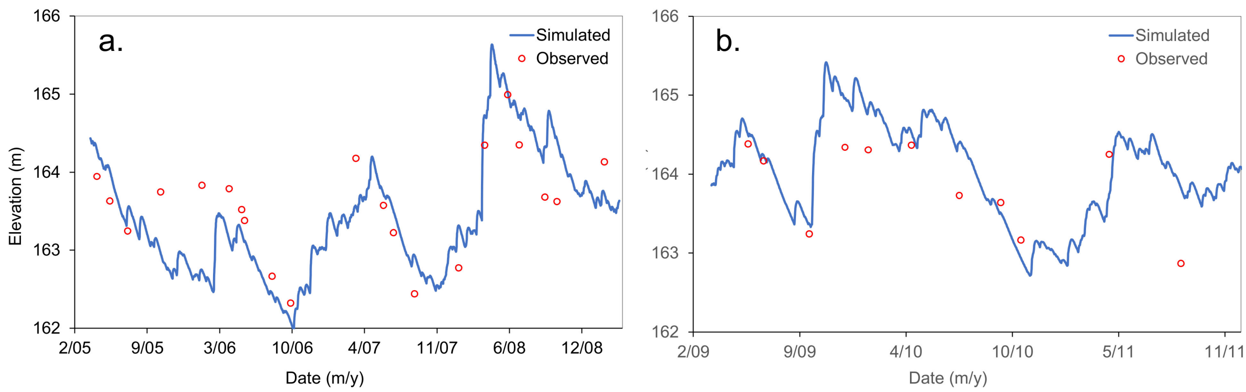

Figure 2. Measured and simulated daily groundwater elevations for (**a**) Calibration and (**b**) Validation periods at GW-GC gage station (USGS Groundwater Station# 384656089582001 at the city of Glen Carbon, IL).

Table 2. Model performance statistics for the model calibration and validation. GW, SW, and GC stand for Groundwater, surface water, and Glen Carbon, respectively.

Parameters	Calibration		Validation	
	GW-GC	SW-GC	GW-GC	SW-GC
R	0.74	0.80	0.74	0.65
MAE (m, m^3/s)	0.45	0.20	0.39	0.22
SD *	0.65	0.44	0.53	0.57
BIAS (m, m^3/s)	0.08	−0.14	−0.24	−0.02
NSE	0.35	0.59	0.14	0.42

* Standard deviation of measurement.

The R, MAE, BIAS, and NSE for the observed and measured surface water at the SW-GC gage station were 0.80, 0.20 m^3/s, −0.14 m^3/s, and 0.51, respectively (Figure 3a and Table 2). Unlike for groundwater, negative BIAS (−0.14 m^3/s) showed that MIKE SHE overpredicted surface water flow during the calibration period. The surface water flow prediction during the validation period at the SW-GC gage station was R, 0.65, 0.22 m^3/s, -0.02 m^3/s, and 0.42 for MAE, BIAS, and NSE, respectively (Figure 3b and Table 2).

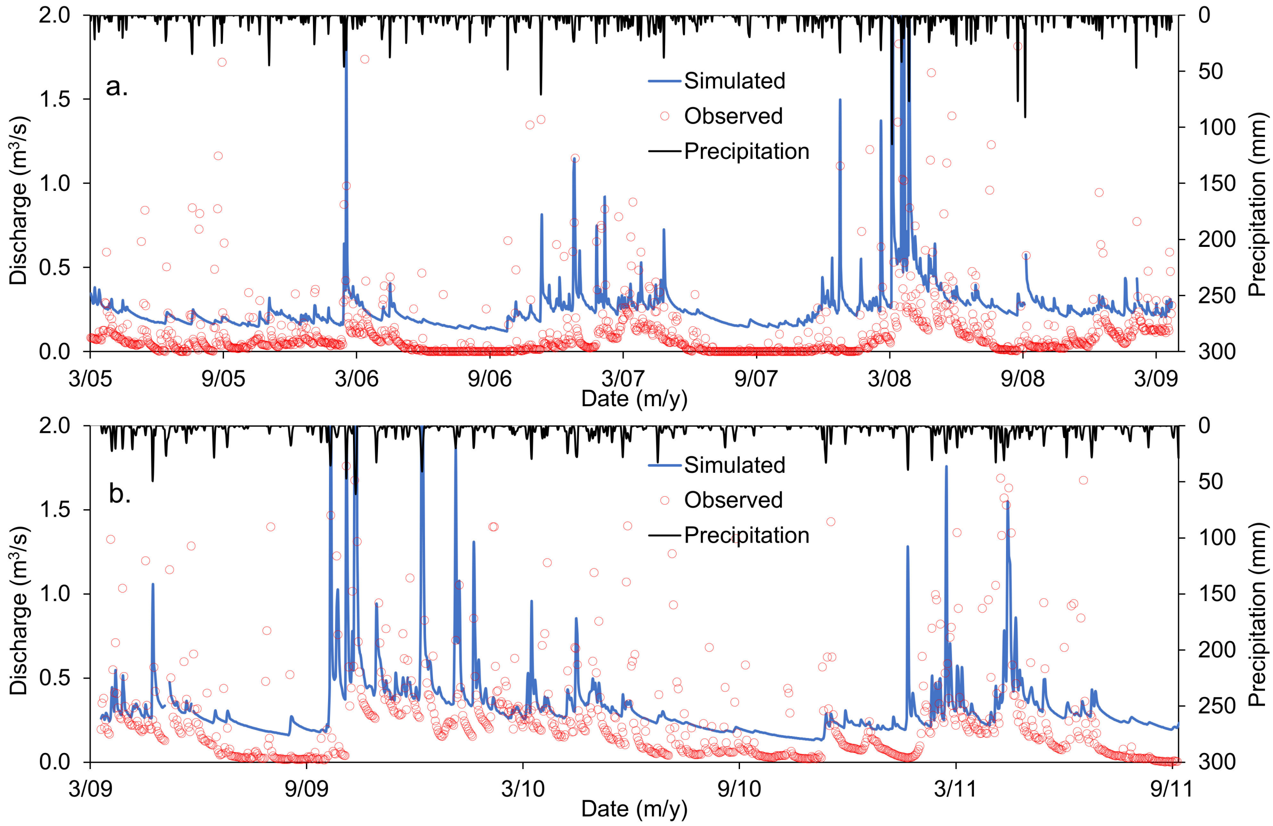

Figure 3. Measured and simulated daily surface flow hydrograph at SW-GC gage (USGS surface water station# 05588720 at the city of Glen Carbon, IL) and CFSR precipitation depths for (**a**) Calibration and (**b**) Validation.

3.1.2. NOAA-Edwardsville Vs NOAA-St. Louis

The weighted average MAEs for groundwater elevations were 0.09 m (0.07 m to 0.11 m) and 0.15 m (0.03 to 0.21 m) for NOAA-Edwardsville and NOAA-St. Louis models, respectively at all four GW stations. The values reported in parenthesis are a range. Similarly, weighted average R were 0.78 (0.73 to 0.82) and 0.65 (0.58 to 0.70) for NOAA-Edwardsville and NOAA-St. Louis precipitation models, respectively (Table 3). The results showed that the NOAA-Edwardsville model performed better (values close to the CFSR model) than for NOAA-St. Louis considering average R and MAE.

The weighted average MAE for surface water flows for the NOAA-Edwardsville and NOAA-St. Louis models were 0.78 m^3/s (0.02 to 1.02 m^3/s) and 0.68 m^3/s (0.02 to 0.91 m^3/s), respectively (Table 3). Similarly, weighted average R were 0.64 (0.62 to 0.66) and 0.41 (0.34 to 0.46) for the NOAA-Edwardsville and NOAA-St. Louis models, respectively. The results showed NOAA-St. Louis model performed better (close to the CFSR model) than for the NOAA-Edwardsville considering average MAE, whereas the trend was opposite for R.

Table 3. Difference in model performance statistics between NOAA-Edwardsville Vs CFSR and NOAA-St. Louis Vs CFSR precipitation models for groundwater elevations and surface water flows at four random stations.

	Parameters	GW1	GW2	GW3	GW4	Average
Groundwater Elevation						
NOAA-Edwardsville	R	0.80	0.73	0.78	0.82	0.78
	MAE (m)	0.09	0.09	0.11	0.07	0.09
NOAA-St. Louis	R	0.70	0.63	0.58	0.68	0.65
	MAE (m)	0.03	0.10	0.23	0.21	0.15
Surface Water						
	Parameters	SW1	SW2	SW3	SW4	Average
NOAA-Edwardsville	R	0.66	0.62	0.63	0.64	0.64
	MAE (m^3/s)	1.02	0.38	0.02	0.03	0.78
NOAA-St. Louis	R	0.46	0.38	0.34	0.45	0.41
	MAE (m^3/s)	0.91	0.31	0.02	0.02	0.68

3.2. Effect of Precipitation on Groundwater and Surface Water Flows

3.2.1. Sensitive Variable (i.e., Groundwater Elevations or Surface Water Flows)

The weighted average MAE (considering all four stations) for simulated groundwater elevations and surface water flows were 0.07% (0.06% to 0.08%) and 6.71% (0.81% to 11.19%) for NOAA-Edwardsville and NOAA-St. Louis models, respectively (Table 4). Similarly, the average R were 0.78 (0.73 to 0.82) and 0.66 (0.63 to 0.72) for simulated groundwater elevations and surface water flows, respectively (Table 4). Therefore, differences were higher for surface water flows considering both MAE and R. Nevertheless, differences in daily average groundwater and surface water flow between NOAA-Edwardsville and NOAA-St. Louis models vary at each station (Figures 4 and 5). For example, the difference in surface water flows varied from −18% to 10% at station 1, whereas −4% to 1% at station 4 (Figure 5). Negative values indicated higher surface water flows or groundwater elevations for the NOAA-Edwardsville model.

Table 4. MAE (%) and R between NOAA-Edwardsville Vs NOAA-St. Louis models for groundwater elevations and surface water flows at four random stations. The difference MAE (%) is calculated relative to the NOAA-Edwardsville model.

	Parameters	**GW/SW1**	**GW/SW2**	**GW/SW3**	**GW/SW4**	**Average**
Groundwater	R	0.80	0.73	0.78	0.82	0.78
	MAE (m)	0.07	0.06	0.08	0.06	0.07
Surface Water	R	0.72	0.64	0.65	0.63	0.66
	MAE (m^3/s)	5.22	9.61	0.81	11.19	6.71

3.2.2. Seasonal Variations of Difference in Surface Water Flow with Respect to Change in Precipitation

Considering all (April 2005 to April 2007) datasets, the difference in precipitation between NOAA-Edwardsville and NOAA-St. Louis gauge was 12.6%, whereas the difference in surface water flows was 19% (Figure 6). Seasonal differences in precipitation varied between 6% (summer) to 18% (winter), which resulted in the difference in surface water flow between 4.6% (fall) to 36% (winter) (Figure 6). The difference in surface water flows was relatively lower in fall (4.6%) and summer (11.4%) compared to spring (12.9%) and winter (36%). The highest difference for surface water flows was in the winter (36%) between NOAA-Edwardsville and NOAA-St. Louis models.

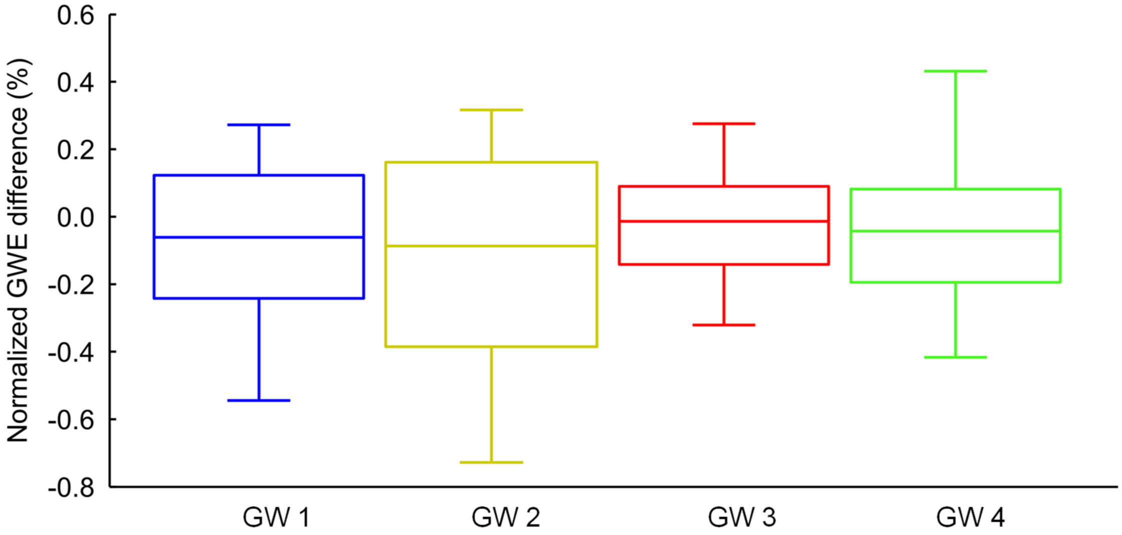

Figure 4. Distribution of difference (%) in simulated daily groundwater elevations at four different stations for NOAA-Edwardsville and NOAA-St. Louis models.

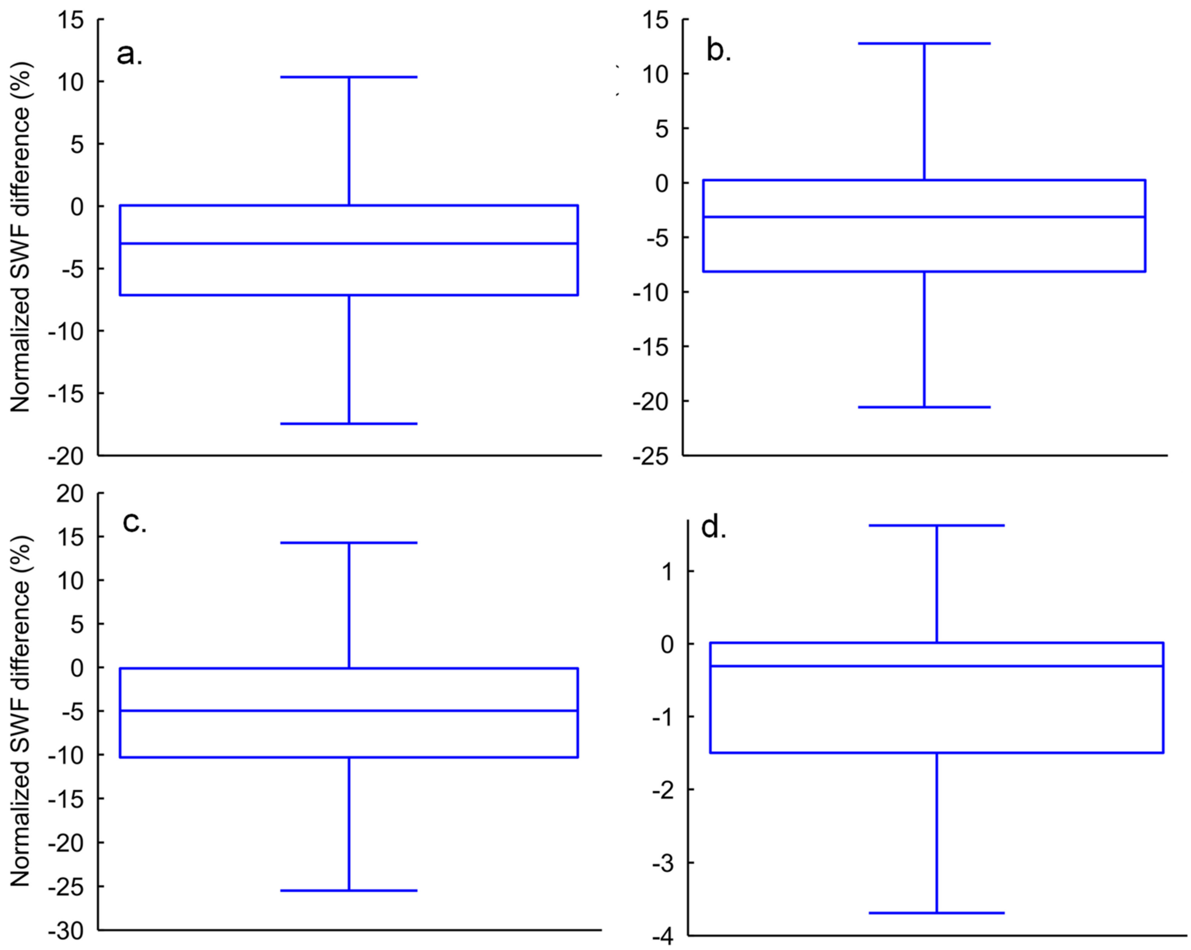

Figure 5. Distribution of difference in simulated daily surface water flows at four different stations from NOAA-Edwardsville and NOAA-St. Louis models. (**a**) Station 1; (**b**) Station 2; (**c**) Station 3; (**d**) Station 4.

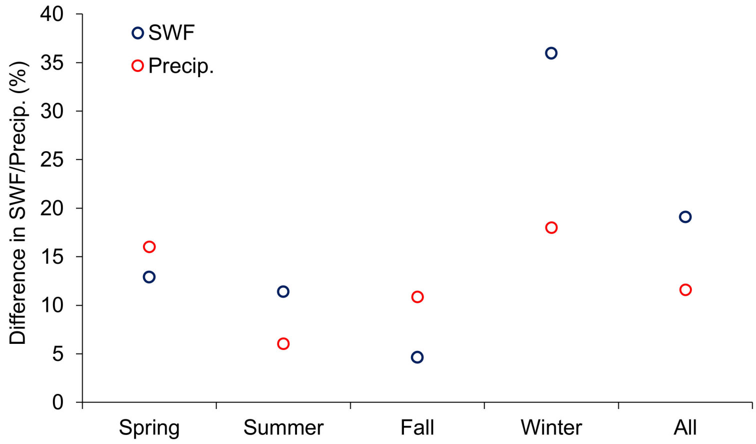

Figure 6. Difference in precipitation (Precip.) and surface water flows (SWF) considering all (April 2005 to January 2007) and seasonal datasets based on NOAA-Edwardsville and NOAA-St. Louis models.

4. Discussion

4.1. Model Performance

We estimated the model performance statistical indicators R, MAE, BIAS, and NSE to analyze model performance against measured groundwater elevations and surface water flows at USGS gauge stations (Figure 1) [75,76]. We observed mixed model performance based on different statistical model performance indicators. The model performed satisfactorily considering MAE, where the values were generally less than half of SD (standard deviation) of observed flows [76] (Table 2). The model performance was comparable to past studies considering statistical model performance indicators [77,78]. The model performance was similar during calibration and validation periods (Table 2). In general, the model overpredicted baseflow during non-rainfall events for both calibration and validation periods (Figure 3). Nonetheless, based on the criteria suggested by prior researchers for model performance interpretation, the model performance for a small watershed is deemed satisfactory [67,75,76].

The model performances were analyzed by removing the days when the measured precipitation at CFSR and NOAA-Edwardsville gauge stations differed considerably during calibration and validation periods. Based on our judgement, precipitation measurements had uncertainties (either in CFSR or NOAA-Edwardsville gauges) during those days. We removed 34 (2.3%) and 12 (1.3%) data points out of 1461 and 913, respectively during the calibration and validation processes. Therefore, care should be taken while interpreting the model performance. It is a common practice to remove poorly performing datasets during hydrological model results analyses, however, it may change statistics and data distribution (e.g., mean, SD and range) [79–82].

Furthermore, we calculated the correlation between the measured precipitation (CFSR) and surface water flows at a USGS SW-GC gauge station (April 2005 to March 2012), which was relatively low (R = 0.53) (Figure 7a). The differences were evident during high precipitation and flow events. The lack of good correlations between measured surface flows and precipitations as well extreme events may cause poor model performance.

This study used CFSR based precipitation for model calibration, which was interpolated on a 38 km grid [35]. Various studies have shown that spatially distributed rainfall at a fine resolution is required for small scales analyses [40,83]. For example, 2 km grid rainfall was suggested by Bell and Moore [41] to model a small watershed (i.e., 132 km^2 in size).

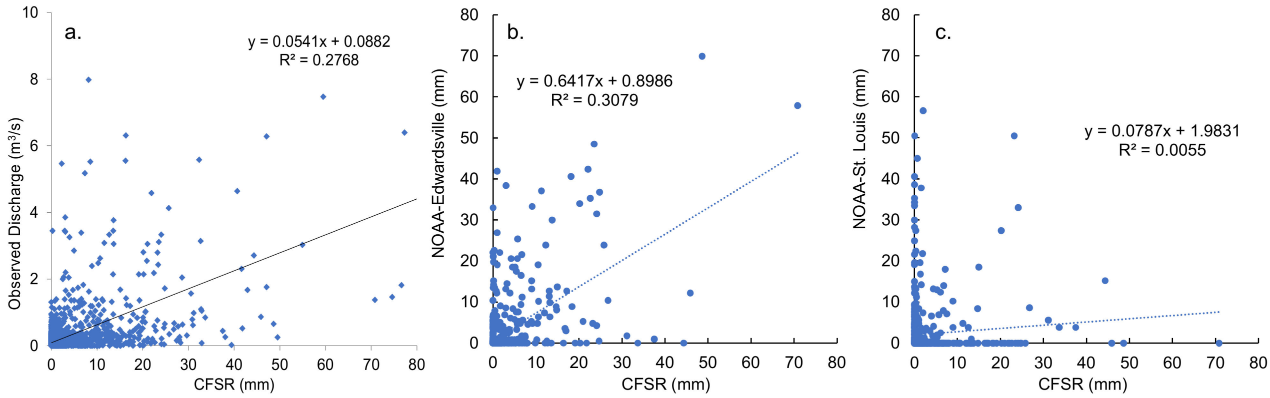

Figure 7. Correlations between (**a**) CFSR based precipitation and surface water flow (USGS gauge station at Glen Carbon), (**b**) CFSR and NOAA-Edwardsville precipitation, and (**c**) CFSR and NOAA-St. Louis precipitation.

A small watershed may have a steep flow slope (flow change faster), high flow variations, and flashy hydrographs compared to a moderate and large watershed that may cause unsatisfactory model performance [46]. Runoff estimation improves as the watershed size increases, despite low rainfall resolution data [40,84]. Cunha, Mandapaka, Krajewski, Mantilla and Bradley [31] investigated the impact of the radar-rainfall error on hydrological model simulated flood magnitude and concluded that uncertainties in simulated peak flow decrease considerably with larger watersheds. Furthermore, as the watershed area increases, the peak flow differences at outlets were practically negligible. The measured surface water flows at the USGS gauge station were comparatively variable (flashy) than measured precipitation in this study, which is a typical trend for a small watershed (Figures 3 and 7a). Furthermore, another study showed that the calibration performance of the model was distinct for two different precipitation datasets (gauge station and NEXRAD). The NEXRAD data performed better than the gauge station for a small watershed [28]. Therefore, we speculated that the model performance was affected by a small drainage area (21.3 km^2 at the USGS gauge station) and limited observed data (single gauge station for groundwater and surface water measurements) availability in this study. The GW-GC station had 20 and 11 groundwater elevations measurements during the calibration and validation periods, respectively. Additionally, GW-PB (Figure 1) has only a total of seven data points, which were used to further verify the model performance for groundwater elevation predictions [85].

The time step and the grid size used in the model can affect the model performances [86–88]. A daily time step was used in this study, but Zhang, Wang, Sun, McNulty, Zhang, Li, Zhang, Klaghofer and Strauss [67] suggested that the daily (24 hours) time step may not be sufficient to capture a quick response of precipitation on surface runoff in overland flow dominant watersheds. The model was not able to predict highly variable surface water flows at the USGS gauge station as a result of rainfall. Specifically, during high events, peak flows occur within a few hours (less than 24 hours model time step) in the Canteen-Cahokia watershed, which comprises low stream lengths and channels [89].

Evapotranspiration (ET) had significant effects on groundwater and surface water flows [90]. A total of nine different land-use types (developed land, cultivated crops, bare soil, deciduous forest, evergreen forest, hay/pasture, woody wetlands, open water, and herbaceous wetlands) were considered in the analysis. An inaccurate representation of land-use impacts surface runoff, soil moisture, and groundwater recharge spatially and temporally in a distributed hydrological model [9,65,91,92]. Furthermore, because of lack of sufficient vegetation parameters (i.e., LAI and RD), temporal vegetation distribution was assumed to be constant and such a generalization can impact the model performance [93].

Despite some uncertainties in the model, we deemed that the model performance is acceptable to analyze the effects of precipitation on groundwater and surface water flows in a small watershed. Although the calibrated model (with CFSR precipitation) had certain uncertainties in model parameters, it was consistent across all three models. Therefore, the model should not noticeably distort the outcome when comparing the effects of different types of precipitation on hydrological processes.

Precipitation has the most critical influence on hydrological processes [28,39]; therefore, quality data is warranted for better model performance. The lack of finer spatial resolution of precipitation, and a high level of sensitivity of precipitation on a smaller spatial scale watershed influences the performance of the hydrological model [28]. Despite NOAA gauge network and radar-based precipitation being available for larger areas and different temporal resolutions (e.g., daily), uncertainties remained, which effect simulated hydrological processes [31,39]. Therefore, our results showed the importance of spatially and temporally varied high-resolution precipitation and surface water flow measurements for better model performance in small watersheds specifically to simulate surface water flows. The model performance is also affected by uncertainties in other datasets such as meteorological, land-use, soil type, topography, observed surface water flows and groundwater elevations, and scale (size) of the watershed [16,30,49].

Nonetheless, each of the models can be calibrated using NOAA meteorological and precipitation data. In that case, the effects of precipitation on groundwater elevations and surface water flows may have been different [35]. However, there is a fundamental issue with calibrating the model with different datasets and comparing the results. For example, calibrations using the two data sources may result in different model parameterizations, although having the same watershed characteristics. This may cause parameters overly influential in model results, which is also known as an equifinality [15,39].

We did not find a consistent pattern that the nearer gauge (i.e., NOAA-Edwardsville) station precipitation model performance is better (close to the CFSR model) than the farther gauge (i. e., NOAA-St. Louis) considering different statistical model performance indicators (MAE and R) for groundwater elevations and surface water flows at individual random stations (Table 3). However, Radcliffe and Mukundan [35], found better results from the model that has precipitation measured at a nearer gauge station than for the farther one.

CFSR Vs NOAA-Edwardsville (R = 0.31) measured precipitation had a higher correlation than for CFSR Vs NOAA-St. Louis (0.005) (Figure 7b,c). Our results showed a similar pattern (NOAA-Edwardsville performing better) for simulated groundwater elevations and surface water considering R (Table 3). However, NOAA-St. Louis model had a lower average MAE than for the NOAA-Edwardsville, despite NOAA-Edwardsville average precipitation being closer to the CFSR. The average $\pm$ SD (standard deviation) precipitation (April 2005 to January 2007) at CFSR, NOAA-Edwardsville, and NOAA-St. Louis gauge stations were 2.43 $\pm$ 6.34 mm, 2.46 $\pm$ 7.33 mm, and 2.17 $\pm$ 6.72 mm, respectively. Nevertheless, we just considered two gauge stations located around the watershed, but need to analyze results based on multiple gauges farther apart spatially before drawing any concrete conclusion regarding the model performance based on spatial distances of gauge stations.

4.2. Effects of Precipitation on Groundwater and Surface Water

An analysis of the most sensitive variable (groundwater elevation or surface water flow) showed that the effect of precipitation is more considerable in surface water flows (0.81% to 11.19%), than groundwater elevations (0.06% to 0.08%) (Table 4). Effects vary noticeably considering individual stations and daily average flows and groundwater elevations (Figures 4 and 5). Although past studies have shown contradicting results regarding the relationship between precipitation and groundwater elevations [50–52], our results showed minimal (0.06% to 0.08%) effects of precipitation on simulated groundwater elevations. Our results are consistent with Gardner and Heilweil [94], where they concluded groundwater elevations respond slowly to precipitation.

Our study did not show a systematic change in surface water flows as a result of the difference in precipitation (Figure 6) but they were season-specific. We found the lowest difference in surface water flows in summer and fall seasons, which might be due to a higher evapotranspiration rate resulting in lower flows in rivers [95]. Evapotranspiration increases with higher atmospheric temperature and impacts surface runoff balance in river systems. The difference in surface water flow change depends on precipitation, atmospheric temperature, evapotranspiration as well as groundwater contributions [50–53], which support our results. Surface water flows changes were relatively less in summer and fall seasons despite higher differences in precipitation (Figure 6) because of higher evapotranspiration from the system [95]. Decreasing trends in baseflow within the US Midwest are attributed to increasing temperatures and evapotranspiration during the summer months [53].

4.3. Study Application

Our study has shown that care should be taken while selecting input datasets (e.g., precipitation) for hydrological model development and forecasting hydrological processes [16,39]. Many important factors should be considered before selecting precipitation data sources for simulating groundwater elevations and surface water flows, for example, the spatial and temporal scale of the model, rain gauge data availability, watershed area, input data quality, and model structure and spatial discretization [28]. Based on our results, the effects of precipitation uncertainties on simulated surface water flows vary season by season because of changing atmospheric temperature and evapotranspiration processes [95]. Our results suggested that high temporal and spatial resolution input data and the data used for model calibration (groundwater elevation and surface water flows) would improve hydrological model performance to simulate surface water flows than for groundwater elevations. The results emphasized the importance of the accurate input datasets (e.g., precipitation) for reliable model predictions [39,48]. The model developed in this study can be used to simulate hydrological processes in the future for the Canteen–Cahokia watershed to analyze impacts on future climate change and land cover changes due to urbanization on the hydrological process (groundwater elevations and surface water flows), and subsequent impacts on ecosystems (aquatic and riparian) and urban flooding [96,97]. This study is focused on a small watershed; therefore, further studies are required to transfer the findings to other watersheds in different geographic regions and large watersheds.

5. Conclusions

A spatially distributed MIKE SHE integrated hydrological model was calibrated and validated with daily averaged measured groundwater elevations and surface water flows. The calibrated model was used to analyze the effects of different precipitation on simulated hydrologic processes (i.e., groundwater elevations and surface water flows). The MIKE SHE model was able to predict surface water flows and groundwater elevations with reasonable accuracy at daily time steps for a small watershed. The study did not conclusively show that the model based on precipitation measured at nearer gauge (NOAA-Edwardsville) performs better than the model based on farther gauge (NOAA-St. Louis) precipitation.

The analyses for the most sensitive model output variable showed that differences in precipitation had noticeable (0.81% to 11.19%) effect on simulated surface water flows, whereas it had minimal (0.06% to 0.08%) effects on groundwater elevations. We found greater differences in simulated surface water flows in spring (12.9%) and winter (36%) compared to summer (11.4%) and fall (4.6%) due to difference in precipitations (6% to 18%) measured at NOAA-Edwardsville and NOAA-St. Louis gauges. The study showed that uncertainties in precipitation on simulated surface water flows vary with the season in a small watershed.

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