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Evaluation of precipitation products for enhancing hydrological model output: A Chemung River Watershed Case Study

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Abstract

Accurate and reliable hydrological model outputs in river catchments is greatly improved by the inclusion of high-quality precipitation data, especially in areas with limited or nonexistent precipitation data. Assessing the accuracy of precipitation data is essential for accurate modeling of hydrological processes in watersheds, which is vital for efficient water resource management. This study aims to assess the accuracy of the Soil and Water Assessment Tool (SWAT) in predicting stream discharge in the Chemung River watershed. The process used both in-situ measurements and gridded reanalysis precipitation data from the National Oceanic and Atmospheric Administration (NOAA) and the National Centers for Environmental Prediction (NCEP). The efficacy of these precipitation products in accurately simulating stream discharge in the study area was assessed by comparing the projected values with the actual stream discharge using the Nash-Sutcliffe Efficiency (NSE) method. The findings indicated that the discharge was underestimated by NOAA's data (NSE, 0.25), although the gridded data yielded diverse outcomes. Nevertheless, when the NOAA data was combined with the gridded data, the model's performance was significantly enhanced, leading to an NSE value of 0.38. This suggests a more accurate SWAT model. Findings from this study are significant for enhancing hydrological predictions and water resource management in regions with limited precipitation data, offering a practical approach to enhancing model accuracy where data quality is a constraint.

Keywords: Soil and water assessment tool (SWAT), Watershed modeling, Chemung River watershed, hydrological model, precipitation products

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1. Introduction

To support the development of ecologically sound water resource management strategies in response to the growing impacts of climate change and land use changes on watershed hydrological processes (e.g., Shigute et al., 2024; Usman et al., 2021), hydrological models have become essential tools. These models, be they physically based, empirical or conceptual, they can simulate complex hydrological processes related to quality and quantity of water as well as improve understanding of human related influence such as land use change on such processes (e.g., Shigute et al., 2022, 2024). Among these models, the Soil and Water Assessment Tool (SWAT, Arnold et al., 1998; Arnold and Fohrer, 2005) is a widely used hydrologic model to simulate runoff processes for predicting sediment and nutrient fluxes. The SWAT model requires precipitation data as a primary input for simulating complex hydrological processes (Arnold et al., 1998; Arnold and Fohrer, 2005; Zhang et al., 2023). However, different sources of precipitation data as well as interpolation and assimilation techniques involved in processing of precipitation data at varying spatio-temporal scales can affect accuracy of SWAT model simulations (Tan et al., 2021; Sexton et al., 2010; Qi et al., 2019).

A comprehensive evaluation of the sources of precipitation data for a given watershed is essential to assess SWAT model performance at the watershed scale (Muche et al., 2020; Tuo et al., 2016; Yang et al., 2014). Observed precipitation is not the only input data used in SWAT that may be adjusted in the calibration phase (Fukunaga et al., 2015; Van Liew et al., 2005; Moriasi et al., 2007). Other sources of precipitation data, such as reanalysis (i.e., data derived from a combination of gauged precipitation with other data sources), gridded data, radar estimates of precipitation, and satellite data, are often used in areas where direct measure of precipitation by rain gauge networks is not readily available. Yang et al. (2014) evaluated three sources of gridded data as compared to directly measured precipitation in two watersheds with different topographic characteristics. For the basin with significant topographic relief, gridded data failed to produce satisfactory results, whereas the basin with low relief found one source of gridded data to produce satisfactory results similar to gauged data. Similarly, Ashraf et al. (2011) investigated a watershed in SW New Mexico using a variety of spatially distributed precipitation data and gauged data. Although both data produced satisfactory results, gridded data both underestimated and overestimated precipitation without a perceptible pattern. Vu et al. (2012) showed that gridded data produce more satisfactory results than gauged data, however, these may be influenced by the spatial distribution of the gauging stations within proximity. Beyond the impact of poorly distributed gauging stations on hydrological modelling, the performance of some satellite-based precipitation products in some areas can be restricted due to the influence of topography (Aqnouy et al., 2024).

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The density and distribution of gauging stations can substantially influence performance of SWAT results. For example, spatially modeled data can produce better results in scenarios where a sub-catchment does not have a rain gauge within it, or when the gauge site is located near the margin of the basin (Masih et al., 2011). In data scarce basins, spatially distributed data using additional rain gauges outside the watershed or radar data (e.g., Tropical Rainfall Measuring Mission (TRMM)) can produce satisfactory results (Strauch et al., 2012). Tobin and Bennett (2009) evaluated rain gauge network, NEXRAD and Tropical rainfall Measuring Mission (TRMM) data to determine their usefulness in development of SWAT models in two watersheds in South Texas and Northern Mexico. Their results suggested that NEXRAD rainfall estimates provide a robust source of data, and rain gauge and TRMM data yield results with significant positive bias. Given similar results for the rain gauge and TRMM data, it suggests that the TRMM has the potential to provide quality data in areas with limited rain gauge networks. Tobin and Bennett (2012) further investigated satellite precipitation estimates, adjusted using NWS Multi-sensor Precipitation Estimates (MPE). The MPE integrates radar and rain gauge networks, and results show improved response of SWAT when using the MPE-adjusted satellite precipitation estimates for seven watersheds spread across the southern tier of the United States. More research is needed for a comprehensive assessment of hybrid models which use precipitation data integrated from multiple sources.

Techniques involved in integrating differently sourced precipitation data are critical for interpreting SWAT model simulations. Commonly used integration techniques include Bias Adjustment (BA), Simple Kriging with varying Local Means (SKlm), Kriging with External Drift (KED), Regression Kriging (RK), Nearest Neighborhood (NN), Inverse Distance Weighted (IDW), Simple Kriging (SK), Ordinary Kriging (OK), and Kriging with External Drift (KED). Xie et al. (2011) found that incorporating gauge rainfall measurements into Next Generation Weather Radar (NEXRAD) produce better results with the two Kriging-based methods (SKlm and RK). Zhang and Srinivasan (2009) showed that the spatial precipitation maps estimated by different interpolation methods have similar areal mean precipitation depth, but significantly different values of maximum precipitation, minimum precipitation, and coefficient of variation. Performance of these methods can vary from local to regional scale. Variation in either collection or spatio-temporal extents of precipitation data could affect the performance of the SWAT model. Critical evaluation of the performance of different methods at local or regional scale should be conducted to determine their effect on model performance.

This research aims to evaluate the performance of the Soil and Water Assessment Tool (SWAT) model in simulating stream discharge of the Chemung River watershed using different precipitation data sources, including rain gauges, gridded data, and a combination of both. The main objectives of this study are to (a) evaluate a SWAT model for the Chemung River catchment using ArcSWAT and analyze hydrologic response units (HRUs), (b) evaluate the model's ability to replicate observed in-stream conditions by using various precipitation datasets to assess its performance,

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(c) compare the SWAT model simulation results (for GR and NCDC) with actual discharge measured by the USGS at Chemung, using statistical methods such as the Nash-Sutcliffe method, 1-sample T-test, and 1-sample Sign test, and (d) identify an ideal precipitation product to enhance the SWAT model's performance in reproducing stream discharge in the Chemung River watershed. Additionally, provide recommendations for the selecting and integrating of precipitation data sources in hydrological modeling to improved accuracy and reliability in watershed management and flood control measures in the Chemung River watershed. Focusing our analysis on the Chemung River provides a level of granularity in modeling that enables a more accurate representation of the watershed's response to precipitation, which is critical for water resource management and planning. This contribution is particularly valuable as it directly informs the choice of data sources in future hydrological modeling efforts, leading to more precise water resource assessments and better-informed decision-making processes.

2.0 Materials and methods

2.1 Study Area

The Chemung River watershed (Fig. 1) located near the boundary between New York and Pennsylvania, has an estimated area of 6730 km² and serves as a significant tributary of the Susquehanna River. This watershed, which includes four significant sub watersheds (the Cohocton, Canisteo, Cowanesque, and Tioga Rivers), converges in close proximity to Corning, NY. It extends across Steuben and Chemung Counties in New York, as well as portions of five other New York counties and two counties in Pennsylvania. Additionally, a considerable portion of Tioga County is also encompassed within this watershed. Following the occurrence of Hurricane Agnes in 1979, the building of multiple small reservoirs of varying size was undertaken with the objective of controlling excessive water flows and reducing the occurrence of flooding. The study collected flow data from the USGS gauging station in Chemung, NY, which is situated approximately 16 km upstream from its confluence in Sayre, PA.

The Corning-Elmira, NY metropolitan region is the main urbanized hub within the Chemung River watershed, with a population of over 530,000. In comparison, smaller communities have populations of less than 5,000. According to USGS Streamstats (2016) data, forestry accounts for most of the land use (66%), with a tiny urban footprint (5.29% NLCD 2011 classes 21-24). The remaining land is primarily used for agriculture, including row crop farming, pasture lands, and dairy farming.

The topography of the area exhibits characteristic attributes commonly found in glaciated watersheds. These features include undulating to level highlands that contain steep-sided alluvial valleys, through which significant rivers traverse. The watershed exhibits a diversified physiography and land use pattern, as seen by the prevalence of

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forest cover on steep slopes adjacent to stream valleys, and the presence of agricultural operations on flatter hilltops and valleys.

The precipitation and snowmelt patterns in the Chemung River watershed are affected by climatological elements such as westerlies or prevailing wind patterns, as well as temperature fluctuations and evaporation rates. These factors are important in determining the hydrological dynamics of the region. Notwithstanding these inherent characteristics, the condition of hydro-meteorological monitoring within the watershed poses specific difficulties, such as potential biases stemming from divergent monitoring methodologies employed by different entities tasked with collecting rainfall and streamflow data. The significance of reliable data sources and monitoring procedures in the Chemung River watershed is highlighted by these complexities, as they are crucial for reliable hydrological modeling and effective management measures.

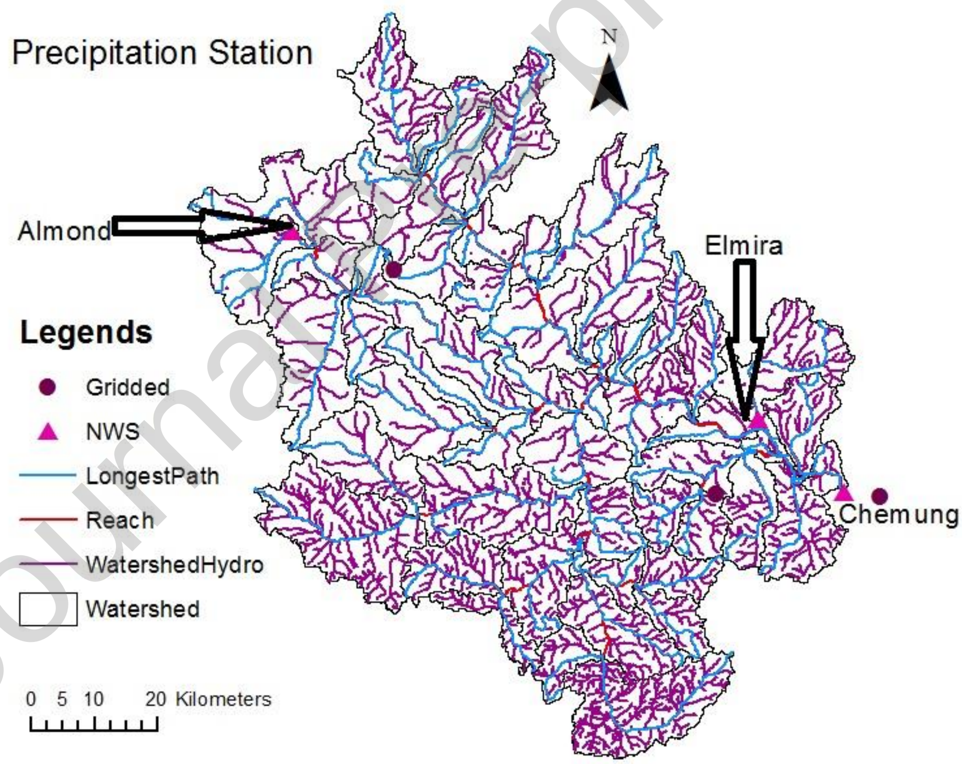

Fig. 1. Locations of precipitation stations in the studied watershed. The three National Weather Service (NWS) stations and locations for the gridded reanalysis rainfall data are also indicated. The grid points are the points where precipitation is calculated from observational data.

2.2 Data sources and preprocessing

Precipitation data was obtained from three general sources. Climatic data from USGS was obtained within the ArcSWAT model. Gridded data (GR) was obtained from the U.S. National Oceanographic and Atmospheric Administration's (NOAA) National Center for Environmental Prediction (NCEP). The NCEP supplies a seamless grid of digital data. Gauged data was obtained from the National Centers for Environmental Information's National Climate Data Center (NCDC). The statistical summary of climate-based USGS, GR, and NCEP data are provided in Figs. S1-3. The statistical summary of combination from NCDC and GR difference data is provided in Supplementary Fig. S3 and of combination from NCDC and GR average data in Supplementary Fig. S4.

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2.2.1. Climate Based USGS Data

SWAT provides an option for using climatological averages of daily precipitation. The data spans a 30-year or longer period of time to produce the averages. Three different sets of data were used and model results for all were found to be unacceptable with NS values ranging from -1.90 to -2.49.

2.2.2. Gridded Data

The GR was obtained from the NCEP North American Regional Reanalysis database (Mesinger et al., 2006). Reanalysis data uses observational networks worldwide to generate climatic information for a wide array of variables over set grid spacing. Within North America, GR data is calculated eight times per day, and the database supplies daily and monthly averages. The grid resolution is approximately 32 km. Some of the limitations to these data are observational constraints and a changing mix of input data that may create considerable variability in the modeled results. The locations of precipitation stations in the watershed are shown in Fig. S6.

2.2.3. NCDC Data

SWAT input files were modified to use data from the three National Weather Service (NWS) rain gauges within the watershed. These data were obtained from the NOAA NCDC database using the Climate Data Online (CDO) search tool (https://www.ncei.noaa.gov/cdo-web/). Apart from rainfall, our analyses used data from the CDO repository including, temperature, relative humidity, solar radiation, and wind speed all measured and available on daily time scales.

2.2.4. NCDC and Gridded difference Data

To better refine the model results, the data obtained from the NCDC for three stations in the watershed was averaged with the corresponding GR data to create new values for the three sites. Note that the GR data locations are not identical to the rain gauge locations. The corresponding pairs were spatially averaged as well, but with no significant change in model results.

2.2.5. NCDC and Gridded Average

As previously mentioned, it is observed that NCDC underestimates stream discharge while the GR data appears to be similar to the observed stream discharge on average but has a much larger range. To better refine the model results, the data obtained from the NCDC for three stations in the watershed was averaged with the corresponding GR data to create new values for the three sites. Note that the GR data locations are not identical to the rain gauge locations. The corresponding pairs were spatially averaged as well, but with no significant change in model results.

2.3 Analysis methods

The SWAT model (Arnold et al., 1998; Arnold and Fohrer, 2005), developed and supported since 1990s, is used to simulate hydrology and water-quality in watersheds of various sizes, ranging from small catchments to large river basin scales. In SWAT, a watershed is divided into hydrologic response units (HRU) as indicated in the supplementary information. The model calculates hydrologic and physical parameters for each HRU. The framework for this study is summarized in Fig. 2 and Figs. S1-S3 summarize the SWAT model setup using ArcSWAT (Section 2.3.1) and HRU analysis with land use, soil and slope data as inputs.

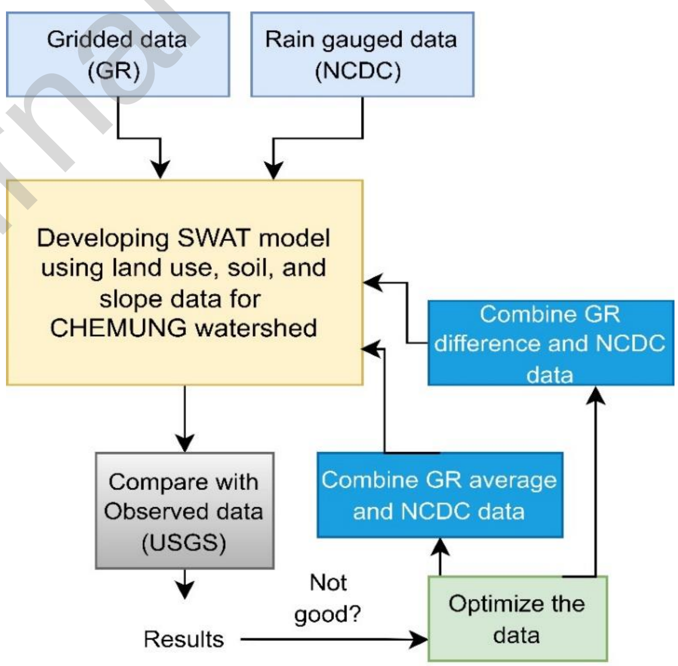

Fig. 2. Framework for the study. Two major precipitation products (gridded reanalysis and NCDC gauged data) are used as input to the SWAT model and outputs are evaluated using a range of statistical metrics, including the NSE.

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2.3.1 Development of SWAT model for Chemung River catchment

After setting up the project in ArcSWAT, the watershed was delineated using the Digital Elevation Model (DEM) for the designated study region. The next step involves the creation of flow direction and flow accumulation grids. The essential stream area threshold is determined by considering the size of the watershed and characteristics specified by the user. Choose the location of the watershed outlet and define the boundaries of the watershed accordingly. The essential characteristics for each sub-basin encompassed within the watershed was then computed. The steps used have been summarized in Fig. S1. After this process, the STATSGO soil data was prepared by importing and processing of soil raster data. ArcSWAT tools can be used to define land use, soil, and slope parameters for HRU analysis. Generate Hydrologic Response Units (HRUs) by utilizing predetermined threshold values for land use, soil composition, and slope characteristics (Fig. S2). Furthermore, the meteorological input tables for SWAT should be generated, encompassing several parameters such as rainfall data, temperature, relative humidity, solar radiation, and wind speed. Utilize the Write Input Tables option to generate additional input files and tables necessary for SWAT simulation (Fig. S3).

2.3.2 Combining data approach

a) **Difference calculation**: We determined the difference between the NCDC and GR data for precipitation occurrences that align with each other to rectify the biases detected in the individual datasets.

b) **Averaging**: We determined spatial average of three NCDC stations with corresponding GR grid points and created a new dataset for balancing the underestimation by NCDC and the overestimation by GR.

2.3.3 Evaluating performance of SWAT model on different precipitation data

Both datasets were assessed for their individual performance in the SWAT model. After then, the integrated datasets (both the difference and averaged data) were then input into the SWAT model. The model was run using these individual and integrated datasets, and the outputs were compared to the observed discharge data from USGS. Thus, results of model simulations are broken down by the type or source of precipitation input. Results of model runs for stream discharge for the two-year calibration period are compared with actual discharge measured by the USGS at Chemung, NY. The performance of the SWAT model using the individual and integrated datasets was evaluated using the Nash-Sutcliffe Efficiency (NSE) method (Ougahi and Mahmood, 2022), which measures the predictive power of the model. Additionally, R-squared values were calculated to assess the correlation between observed and simulated discharge.

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3. Results

3.1 SWAT model

The data distribution and boxplots for different data sources used in this study such as USGS, NCDC, GR, combination of GR difference and NCDC, and combination of GR average and NCDC data are depicted in Figs. 3 and 4, respectively and discussed in the sub-sections that follow. In the histogram distribution, lower rainfall values are more common across all three datasets, with a positive skew showing some instances of higher rainfall values. The general pattern seems closely aligned in the three datasets in terms of their distribution (Figs. 3a). To understand the consistency and variability between the two datasets, the relationship between GR and NCDC datasets in terms of differences and averages are evaluated (Figs. 3b and c). The differences histogram shows that most values are near zero, indicating similarity. The averages histogram shows a positive skew, indicating that while lower rainfall values are common, higher values also occur, contributing to the average. This information can be useful for understanding the consistency and variability between the two datasets in hydrological analysis.

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3.1.1. SWAT model using GR data

Our model simulation using GR data for three nodes within the watershed produce an unfavorable outcome. Compared to the USGS measured discharge data, the average daily discharge for the SWAT simulation was similar, 3550 ft^3 sec-1 versus 3415 ft^3 sec-1, respectively. Maximum values, however, were substantially higher for the SWAT model results with a maximum daily discharge estimate of 60,688 ft^3 sec-1 versus 52,000 ft^3 sec-1 for the observed USGS data. The minimum discharge values for the measured discharge and simulated discharge were 165 ft^3 sec-1 and 79.5 ft^3 sec-1, respectively, ignoring the simulated values of zero on the first day of the run. These data suggest that the SWAT simulation tends to overestimate discharge for large precipitation events. We attribute it to the tendency of GR data to overestimate precipitation, particularly during significant precipitation events, as demonstrated in our SWAT model simulations. This leads to an overestimation of stream discharge. Nevertheless, re-analysis may result in variability due to changing the combination of input data sources and observational limitations, which can lead to inconsistency.

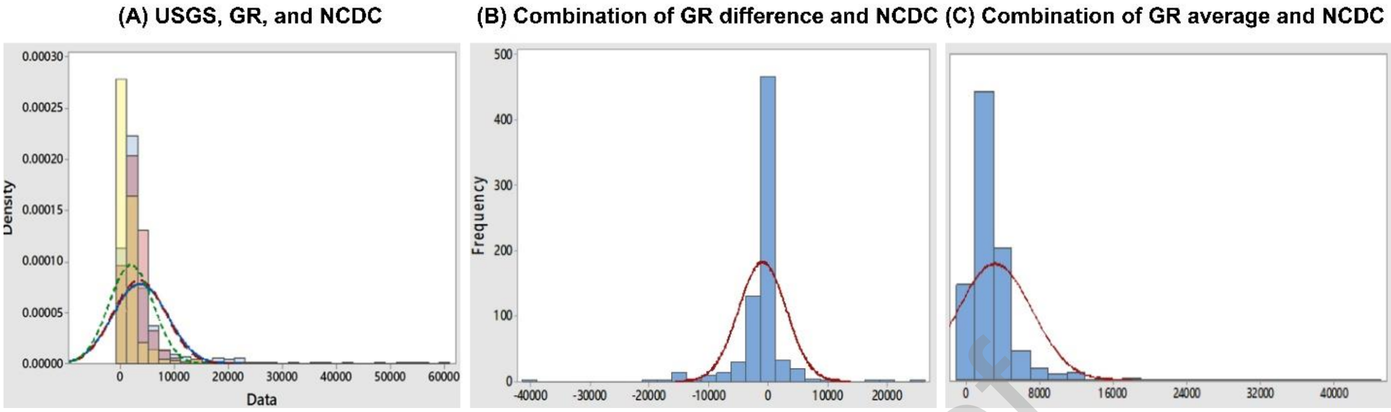

Fig. 3. Histogram plots showing data distribution of USGS, GR and NCDC data (A), combination of GR difference and NCDC data (B), and combination of GR average and NCDC data (C).

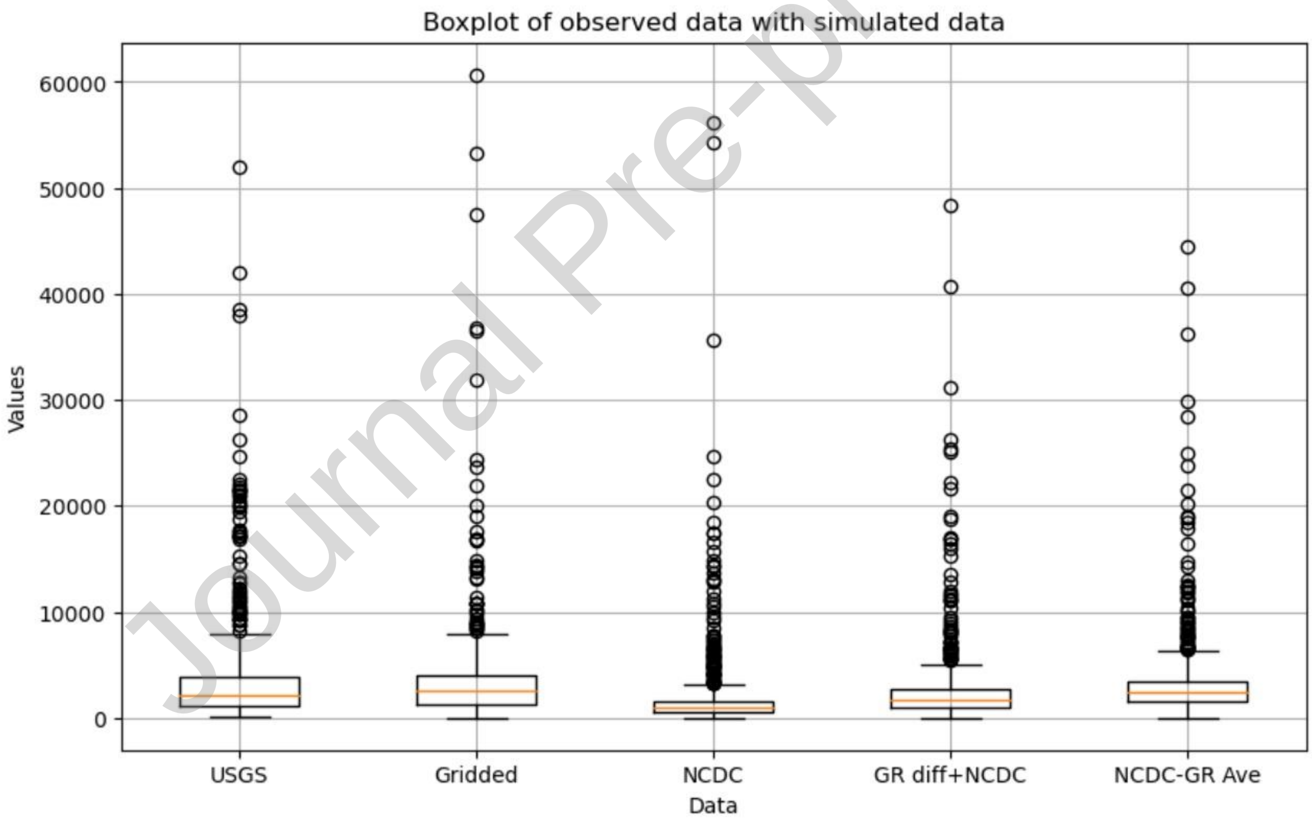

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Fig. 4. Boxplots of stream discharge ($ft^3\ sec^{-1}$) showing summary of observed (USGS) and simulated (GR, NCDC, combination of GR difference and NCDC, and combination of GR average and NCDC) model results for the four SWAT models.

3.1.2. SWAT model using NCDC data

The resultant model simulation results using NCDC data for three rain gauges in the watershed produce a more favorable outcome than the previously discussed data sources. Compared to the USGS measured discharge data, the

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average daily discharge for the SWAT simulation was lower, 3550 ft^3 sec^{-1} versus 1891 ft^3 sec^{-1}, respectively. Maximum and minimum values were comparable. Maximum discharge values for the measured discharge and simulated discharge were 52000 ft^3 sec^{-1} and 56106 ft^3 sec^{-1}, respectively. The minimum discharge values for the measured discharge and simulated discharge were 165 ft^3 sec^{-1} and 53 ft^3 sec^{-1}, respectively, ignoring the simulated values of zero on the first two days of the run. These data suggest that the SWAT simulation tends to underestimate discharge for this set of precipitation input. Although the NCDC data tends to underestimate the stream discharge, as we have shown in our SWAT model simulations, this underestimation could be caused by the limited geographical coverage and gaps in the observational network. Nevertheless, the geographical coverage of the NCDC data is restricted to the specific areas where the rain gauges are located, which may not provide an accurate representation of the entire watershed.

3.1.3. SWAT model using combination of NCDC and GR difference data

The model simulation results using NCDC data for three rain gauges and the three GR data points, a total of 6 sites, in the watershed produce a favorable outcome. Compared to the USGS measured discharge data, the average daily discharge for the SWAT simulation was lower, 3550 ft^3 sec^{-1} versus 2572 ft^3 sec^{-1}, respectively. Maximum and minimum values were comparable. Maximum discharge values for the measured discharge and simulated discharge were 52,000 ft^3 sec^{-1} and 48,397 ft^3 sec^{-1}, respectively. The minimum discharge values for the measured discharge and simulated discharge were 165 ft^3 sec^{-1} and 53 ft^3 sec^{-1}, respectively, ignoring the simulated values of zero on the first day of the run. These data suggest that the SWAT simulation is again underestimating discharge with this set of precipitation inputs.

3.1.4. SWAT model using combination of NCDC and GR average data

The resultant model simulation results using NCDC data for three rain gauges in the watershed produce a more favorable outcome than the previously discussed data sources. Compared to the USGS measured discharge data, the average daily discharge for the SWAT simulation was lower, 3550 ft^3 sec^{-1} versus 1891 ft^3 sec^{-1}, respectively. Maximum and minimum values were comparable. Maximum discharge values for the measured discharge and simulated discharge were 52000 ft^3 sec^{-1} and 56106 ft^3 sec^{-1}, respectively. The minimum discharge values for the measured discharge and simulated discharge were 165 ft^3 sec^{-1} and 53 ft^3 sec^{-1}, respectively, ignoring the simulated values of zero on the first two days of the run. These data suggest that the SWAT simulation tends to underestimate discharge for this set of precipitation input. The goal of the combined NCDC and GR Data is to counteract the biases found in the individual datasets by combining the wide coverage of GR data with the point-specific accuracy of NCDC data. Although the combined datasets exhibit enhanced performance measures (such as NSE and R-squared values), the

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process of integration may introduce more complexity and possible sources of inaccuracy. The combined datasets still demonstrate some level of underestimating of stream discharge, especially during specific seasons, suggesting the need for further improvement.

3.2 SWAT model performance evaluation on different precipitation data

Performance evaluation from different sources of SWAT model such as GR, NCDC data, the concatenation of NCDC and GR difference data, and concatenation of NCDC and GR average data is done.

3.2.1. SWAT model results on Gridded data

The comparison of actual discharge (USGS) versus simulated discharge (GR) produces a slope with an X coefficient of 0.42 and an R^2 value of 0.19 (Fig. 5a). The slope of the regression suggests that SWAT should underestimate discharge, but the scatter in the data with some very large discrepancies between model and observed data, especially at lower observed discharges, creates the similarity in the overall average daily discharge. The correlation test produces a Pearson correlation coefficient of 0.437 and is found to be significant at 95% with a p value of less than 0.001. Model performance evaluated by the NS method returns a value of -0.08.

Differences between USGS and GR discharge are shown in Fig. 5b. Differences are seen throughout the 2-year period, with the exception of a period from approximately May 2005 to October 2005 (for 165 days), but no discernable pattern is otherwise apparent. The calculated difference ranges from -40,040 ft^3 sec-1 to 54508 ft^3 sec-1 with an average of -134 ft^3 sec-1. This shows that while overall the model results show very close comparison to observed data on average, the range of values is large resulting in the slightly negative NS value.

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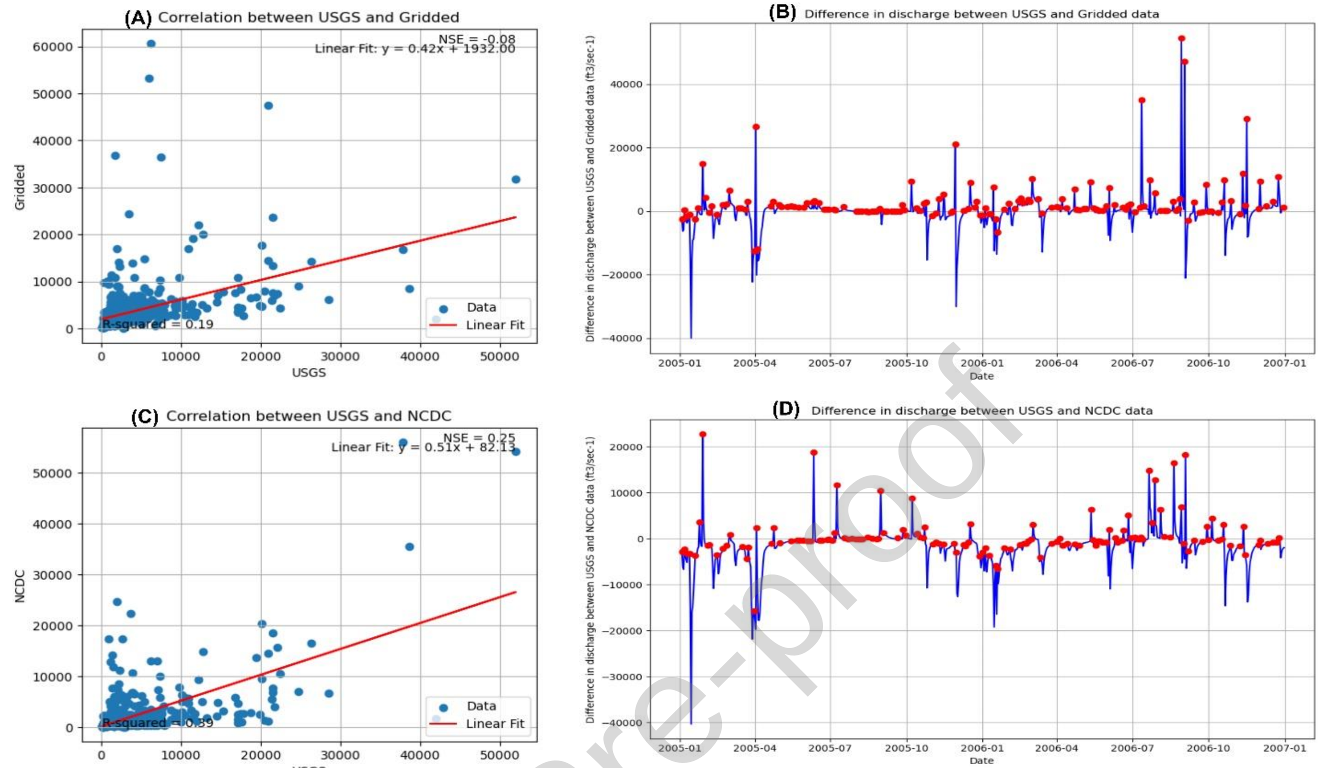

Fig. 5. Correlations of USGS and GR data (A), Discharge difference between GR and USGS data (B), Correlations of USGS and NCDC data (C), and Discharge difference between NCDC and USGS data (D).

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3.2.2. SWAT model results on NCDC data

Comparison of actual discharge (USGS) versus simulated discharge (NCDC) produces a slope with a X coefficient of slightly higher than 0.50 and an R^2 value of 0.39 (Fig. 6c). The slope of the regression line supports the previous supposition that for this model run, SWAT tends to underestimate discharge. The correlation test produces a Pearson correlation coefficient of 0.628 and is found to be significant at 95% with a p value of less than 0.001. Model performance evaluated by the Nash Sutcliffe method returns a value of 0.25.

Differences between USGS and NCDC are summarized in Fig. 6d. While no strong season pattern exists, the simulated results seem more apt to underestimate discharge during cold seasons, possibly indicating a weakness in the simulations ability to handle snowmelt. The calculated difference ranges from 22715 ft^3 sec^{-1} to -40331 ft^3 sec^{-1} with an average of -1695 ft^3 sec^{-1}. This further confirms that this model run underestimates discharge.

3.2.3. SWAT model results on combination from NCDC and Gridded difference Data

Comparison of actual discharge (USGS) versus simulated discharge (combination of NCDC and GR difference) produces a slope with a X coefficient of approximately 0.5 and an R^2 value of 0.40. The slope of the regression line supports the previous supposition that for this model run, SWAT tends to underestimate discharge. The correlation test produces a Pearson correlation coefficient of 0.635 and is found to be significant at 95% with a p value of less than 0.001. Model performance evaluated by the NS method returns a value of 0.35 (Fig. 6a).

Differences between USGS and combination of NCDC and GR difference discharge are shown in Fig. 6b. With the exception of a few days in the early part of the model run and a couple more around September 2006, variation is relatively small as is shown in the NS value. The calculated difference ranges from 25,025 ft^3 sec^{-1} to -40,252 ft^3 sec^{-1} with an average of -978 ft^3 sec^{-1}. This supports the contention that this model run underestimates discharge.

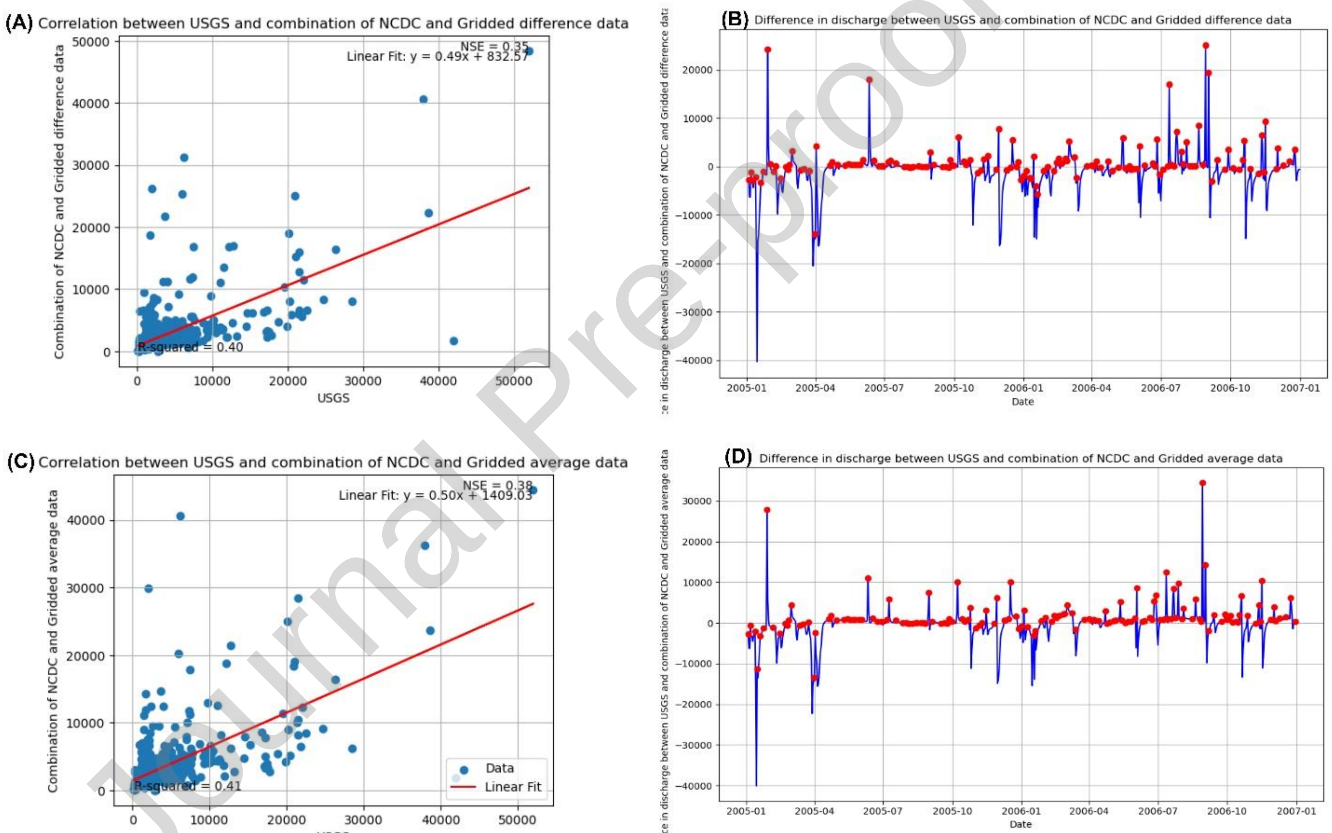

Fig. 6. Correlation of discharge using USGS and combination of GR and NCDC from 6 stations (A), discharge difference between USGS and combination of NCDC and GR difference data (B), correlation of discharge using USGS and combination of NCDC and GR averaged precipitation (C), and Discharge Difference between USGS and combination of NCDC and GR Average (D).

3.2.4. SWAT model results on combination from NCDC and Gridded Average data

Comparison of actual discharge (USGS) versus simulated discharge (combination of NCDC and GR average) produces a slope with a X coefficient of 0.5 and an R^2 value of 0.41 (Fig. 6c). The slope of the regression line supports the previous supposition that for this model run, SWAT tends to underestimate discharge. The correlation test produces a Pearson correlation coefficient of 0.628 and is found to be significant at 95% with a p value of less than 0.001.

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Model performance evaluated by the Nash Sutcliffe method returns a value of 0.38. Differences between USGS and combination of NCDC and GR average discharge are shown in Fig. 6d. While no strong season pattern exists, the simulated results seem more apt to underestimate discharge during cold seasons, possibly indicating a weakness in the simulations ability to handle snowmelt. The calculated difference ranges from 22715 ft^3 sec^{-1} to -40331 ft^3 sec^{-1} with an average of -1695 ft^3 sec^{-1}. This further confirms that this model run underestimates discharge.

4. Discussion and conclusion

The use of hydrologic models such as SWAT rely on high quality precipitation data as it is the most important input parameter. Given that sources of precipitation data may vary by location, it is important to determine the best source of data for a particular watershed. In this study, it was found that data from rain gauges within the watershed were the best individual source of precipitation data. Although numerous gauges were available within and adjacent to the watershed, it was found, similar to Hernandez et al. (2000) that a small number, in this case, three, did the best job when used in the SWAT model, as determined by the Nash-Sutcliffe method. The three gauges used were close to the center axis of the watershed, analogous to results found by Masih et al. (2011).

Other studies have found that gridded reanalysis data is superior to rain gauge networks (e.g., Strauch et al., 2012). In some of these cases, rain gauges are not readily available within the watershed, or only near the margins. Here we found that gridded reanalysis data did a poor job of matching observed stream discharge. While it is difficult to determine the exact reasons for the failure of the gridded data, it is possible that the location, spatial distribution, and physiographic features of the primary stations used to produce the reanalysis data do not allow for an accurate representation of the local area of the watershed. Such features, including topography have been identified as important sources of large uncertainties in satellite-based precipitation (e.g., Aqnouy et al., 2024) and forcing parameters (e.g., gauged rainfall) for reanalysis and model-based soil moisture products (Agutu et al., 2021). However, gridded precipitation products like APHRODITE (Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation) perform better than other precipitation products in simulating observed discharge over complex terrains (Usman et al., 2022). This product, which is based on a dense network of rain-gauge data across Asia, including mountainous areas in the Middle East, highlights the importance of regional precipitation products for hydrological model simulations.

Although rain gauge data was found to produce better model results than gridded data, it was noted that the rain gauge data produced results that underestimated the observed stream discharge. Gridded data, while not producing

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acceptable results, more closely matched the mean annual discharge, but with a large amount of variability. Tobin and Bennett (2009, 2012) showed that using an integrated data set that combines sources of data, a more robust model result may be obtained. For the Chemung watershed, it was found that a combination of data also produces more favorable results. Best results were obtained by producing an average precipitation value using rain gauge measurements and the closest grid point. While this increased the variability range of the model results as compared to just the rain gauge network data model results, it had the effect of reducing the stream discharge underestimation. Figure 5 shows a boxplot of the four different SWAT model results compared to the observed stream discharge data. These indicates that the averaged rain gauge and gridded data precipitation input (NCDC-Gridded Ave) has the closest mean discharge and a similar distribution of high flow events. This is likely the reason for it producing the best model results as evaluated using the NS value. These results suggest that the source of precipitation data should be systematically evaluated to determine the best source or sources of data. This was also suggested by Yan et al. (2014), and Usman et al., (2022) work, which investigated the potential of ten different rainfall products to predict streamflow in topographically complex catchments using a hydrological model, reinforces the need for such evaluations.

Our findings suggest that a combination of NCDC and GR data would provide more accurate SWAT outcome at catchment scale. In addition, the use of advanced data fusion techniques and the integration of high-resolution satellite precipitation data can enhance the accuracy of model inputs. It is essential to regularly calibrate and validate models using observed discharge data in to consider regional and temporal differences. We recommend use of multi-objective calibration techniques and incorporating ensemble modeling to more effectively capture the spectrum of potential outcomes and minimize uncertainty. We expect our findings would support improved application of hydrological models in watershed management, with a goal of enhancing model predictability and enabling better-informed decision-making.

The limitations of this study include the use of climate-based USGS data, which may not capture short-term variability and extreme precipitation events, and the GR data, which may introduce variability and inconsistencies. The NCDC data, which captures local precipitation events with high accuracy, may also underestimate stream discharge due to its limited spatial coverage and gaps in the observational network. Despite its robustness and widespread use, the SWAT model has inherent limitations that can affect the accuracy of our results. The model's assumptions and parameterizations may not completely capture the complex patterns of the watershed, especially when dealing with changing climatic circumstances. The model partitions the watershed into HRUs, presumably oversimplifying the spatial heterogeneity within the watershed. Moreover, the effectiveness of the model is greatly influenced by the excellence and clarity of the input data, as well as the calibration and validation procedures. These factors may contribute to disparities between the observed and simulated discharge, which can impact the accuracy of our

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findings. Additionally, there may be additional errors in the model simulations due to the way SWAT incorporates land use changes, soil moisture dynamics, and snowmelt processes.

The model simulations are subject to the propagation of uncertainties and biases in the input data, such as measurement errors, temporal and spatial coverage restrictions, and variability in data quality. These factors might have an impact on the accuracy of the results. The biases in the precipitation data, whether due to underestimation or overestimation, have a direct impact on the projected stream discharge. For example, the combination of NCDC and GR data, which is intended to address discrepancies in individual datasets, brings in further complexity and possible sources of inaccuracy. Although there have been advances in the combined datasets, the integrated technique still tends to underestimate stream discharge to some extent, especially during specific seasons. To address these uncertainties and biases, it is necessary to conduct an extensive sensitivity analysis and maybe employ additional data sources or advanced data assimilation techniques to improve the accuracy and reliability of the model.

Future research should incorporate high-resolution satellite precipitation data, such as that obtained from the Global Precipitation Measurement mission, and ground-based radar data to enhance the precision of spatial and temporal measurements. Advanced data fusion techniques can help reduce biases that may exist in individual datasets. Furthermore, improving the parameterization and calibration processes of the SWAT model, integrating more advanced snowmelt and soil moisture modules, and implementing multi-objective calibration methodologies can strengthen the model's reliability. Uncertainties can be further decreased by utilizing machine learning for bias correction and downscaling, as well as ensemble modeling. These measures will improve the accuracy and reliability of hydrological models and provide more accurate information for watershed management in different climatic situations.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Highlights

- Evaluation of SWAT model in simulating discharge of the Chemung River watershed.
- Combination of two rainfall products improved SWAT model simulation of discharge.
- The continued evaluation of rainfall data for hydrologic simulation is reinforced.

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