

## Article

# Application and Evaluation of Stage–Storage–Discharge Methodology in Hydrological Study of the Southern Phosphate Mining Model Domain in Southwest Florida

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**Abstract:** This hydrological study investigated a combined rating methodology tested on a 14,090 km<sup>2</sup> area in Southwest Florida. The approach applied the Hydrological Simulation Program–Fortran (HSPF) over a 23-year period and was validated by 28 stream gauging stations. The regional hydrological complexity includes natural and agricultural areas, as well as extensive phosphate mining and urbanizing areas. This application is a novel and efficient methodology for generating stage–storage–discharge relationships using a geographic information system (GIS), empirical equations, and spreadsheets for 148,000 isolated and connected alluvial wetlands within the model domain. The validation metrics used to evaluate the applied methodology for populating the stage–storage–discharge relationship demonstrated the model effectiveness in simulating a range of hydrological events across various regions. For discharge prediction, the Nash–Sutcliffe efficiency values surpassed 0.7 at most stations, with an average of 0.67, and the average R squared was 0.74. This methodology, when applied, achieved a root-mean-square error of 4 m<sup>3</sup>/s for discharge prediction and 0.47 m for stage prediction. However, limitations emerged in simulating baseflow (low flows), highlighting the need for integrated modeling approaches to accurately capture groundwater–surface water interactions. The research provides an improved means for modeling regional water resources and lays the groundwork for enhanced hydrological modeling in watersheds with complex alluvial and isolated wetland systems.

**Keywords:** stage–storage–discharge; rating curve; streamflow; discharge rating curve; hydrological modeling; Southwest Florida; alluvial systems; isolated wetlands; surface water



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## 1. Introduction

The challenges of water resource management have become increasingly complex, heightened by intersecting factors such as climate change, rapid urbanization, and anticipated global population growth [1]. In the context of Florida, these challenges are augmented by large-scale phosphate mining. Approximately 4000 km<sup>2</sup> are in some phase of phosphate mining, permitting and preparation, active mining, or reclamation in the area [2]. Also, the state has experienced dramatic urban expansion since the mid-20th century, with approximately one thousand new residents arriving daily [3]. Such urban growth has had a significant impact on the state wetland ecosystems. Historically, wetlands covered nearly 50% of Florida's land area in the early 20th century [4]; however, extensive drainage and development have led to a reduction in this coverage to approximately 29% [4,5].

Effective management of water resources requires the judicious regulation of water use and hydrological flows, both to protect human life and property and to maximize the utility of available water assets [6]. While the area benefits from one of the most

extensive hydrologic gauging areas in the world, a pervasive challenge in hydrology is the scarcity of gauge stations and comprehensive surveyed data for wetlands in the area, resulting in significant uncertainties in understanding hydrologic behavior, especially in unmonitored basins [7]. To mitigate this, hydrological models have emerged as essential tools for informed decision-making [7]. These models offer simplified yet robust representations of complex hydrological processes and are crucial for predicting water levels and discharges [8]. Whether used for long-term, continuous simulations or specific, single-event analyses, hydrologic models yield invaluable insights into a myriad of impact factors [8]. These factors encompass climate variability, land-use alterations, mining activities, vulnerabilities to communities and properties, water resource conservation, and pressures related to groundwater extraction [9–12]. The application of such models provides decision-makers with the empirical evidence needed for developing effective water resource management strategies.

The Hydrological Simulation Program-FORTRAN (HSPF), a widely used, public-domain physical-based model, serves as a versatile tool for the continuous simulation of surface water hydrology, distinguished by its temporal adaptability [13]. The model can simulate hydrological behavior over time frames ranging from an hour to multiple decades [13]. To construct and calibrate a reasonably predictive model, HSPF necessitates several categories of input data. These encompass climate input data, specifically time-series data for precipitation and potential evapotranspiration (PET), as well as watershed characteristics such as topography, often represented by digital elevation models (DEMs) [13]. Other required information includes land use or land cover (LULC), soil types, and their hydraulic properties [13]. A schematic delineating the flow routing through the watershed is also essential, along with data on hydrological features such as wetlands, rivers, and lakes [13]. This data set should be augmented by stage–storage–discharge relationships, initial antecedent conditions, and groundwater information, including discharge and recharge rates [13]. A further refinement of the model calls for incorporating management and practice controls, such as lake release rules, rates and irrigation practices, for example from National Pollutant Discharge Elimination System (NPDES) data [13]. For calibration and validation, observed streamflow and stage data are essential, in conjunction with the model configuration and the defined segments or reaches used to simulate flow throughout the stream network [13].

West-Central (W-C) Florida is characterized by a coastal plain environment with low slopes, varying sandy superficial and shallow aquifers and a unique karst topography [3]. This distinctive geomorphological setting gives rise to a complex hydrology, with strong surface and groundwater interactions within watersheds and water bodies that are strongly influenced by a dynamic shallow water table [10,12]. The region aquifer system is particularly diverse, consisting of a shallow superficial aquifer and a poorly confined deeper Floridan aquifer. This latter formation displays significant variability: it is unconfined in the northern regions and becomes confined as it extends southward [3,10]. With an average thickness of approximately 600 m, the Floridan aquifer holds an astounding 19,000 km<sup>3</sup> of water resources but has limited utility due to surface water impacts and/or salinity intrusion [14]. This remarkable capacity is largely attributable to the high porosity and permeability of the limestone bedrock [10,15], which averages around 40% [16].

Florida is situated in a humid subtropical climate zone, characterized by distinct wet and dry seasons. The wet season extends from June to October and is primarily driven by short, intense convective thunderstorms originating from the Gulf of Mexico [11,12]. These mushroom-shaped convective storms account for approximately two-thirds of the region's annual rainfall and exhibit notable spatial variability [9,10]. Additionally, the early fall, most commonly around September, brings the potential for tropical cyclones during the hurricane season. These events occur at an approximate rate of 1.9 per year and contribute to about 10% of the annual rainfall [9]. In contrast, the dry season spans from November to May, featuring sporadic rainfall predominantly from passing cold fronts,

with less significant spatial variation [3,9,10,12]. The region receives an annual average of approximately 1321 mm (52 inches) of precipitation [9,10,12,17].

In hydrological modeling in these and other areas, precipitation and evapotranspiration (ET) control surface and groundwater hydrology [18]. Conventional rain gauge data sets are limited by spatial variability and data gaps, issues exacerbated during extreme weather events when gauges are susceptible to malfunction [9,19]. A recent study by Bowers [9] highlighted the advantages of using the Next Generation Weather Radar Gauge-Adjusted Radar (NEXRAD GAR) for the area. This high-resolution ( $2 \times 2$  km) data set is validated against standard rain gauge measurements and provides superior spatial representation of rainfall patterns [9]. Notably, NEXRAD GAR outperforms traditional rain gauges, particularly during the summer months when spatial variability in precipitation is most pronounced. Although NEXRAD GAR tends to slightly underestimate event intensity [9,20], its extensive spatial coverage ensures an improved capture of convective rainfall events. Complementary research by Bowers [9] and Hwang et al. [10] suggests that incorporating 15-min time-series precipitation data into HSPF models improves the accuracy of runoff simulations across diverse land uses.

Data for estimation of ET, which is strongly variable by land use and soil conditions, tend to be more sparse [12]. ET represents the combined water loss transfer to the atmosphere by surface-water evaporation and plant transpiration, and it is the second largest processes in the hydrological water budget for the area. An accurate quantification of ET's spatial and temporal variability is intrinsically challenging [21]. Meteorological variables influencing ET include solar radiation, temperature, relative humidity, wind speed, precipitation, cloud cover, and atmospheric pressure [22–24]. Soil-based or edaphic factors incorporate soil moisture, type, and temperature, while biotic variables involve plant species, leaf area index, vegetation density, root depth, phenological stage, and physiological stress [22–24]. Notably, studies by Bowers [9], Hwang et al. [10], and Ross et al. [12] indicate an annual ET contribution of approximately 39 inches to the overall water budget in W-C Florida. Extensive studies by Ross et al. [12], Zhang et al. [7], Zhang and Ross [11], and Zhang et al. [25] have focused on resolving ET rates by land use including natural, urban, and mining land-use categories.

The Florida Land Use and Cover Classification System (FLUCC) has 53 distinct land classifications [10]. For the purpose of hydrologic modeling with the HSPF, these categories need to be consolidated into several primary land-use classes based on the hydrologic behavior's similarity [10,12]. According to Bower's [9] study, estimated annual ET rates vary significantly across consolidated classes: urban impervious land registers at 15 inches, urban pervious land at 35 inches, low-slope range and scrub land at 32 inches, high-slope range and scrub land at 27 inches, flatwood forest at 38 inches, hardwood forest at 35 inches, irrigated row crop at 33 inches, and irrigated tree crop at 43 inches. Open water exhibits the highest ET rate at 55 inches per year [25].

In W-C Florida, hydrological models have been developed to assess various scales of hydrologic processes. These include the Integrated Hydrologic Model for North Tampa Bay (IHM-INTB) for regional-scale well-field pumping assessments [26], the Peace River Watershed Model for a watershed-level mining implications [7], and the Clay Settling Areas Model (CSAs) in Polk County, Florida for small-scale mine reclamation study [11]. These models employed HSPF and were calibrated and validated over varied timescales and spatial domains. The IHM-INTB, covering an area of 10,360 km<sup>2</sup> and 172 sub-basins, integrated surface water and groundwater simulations to analyze hydrological impacts under various pumping and rainfall scenarios. This model has been instrumental in understanding the interaction between surface and groundwater in a large moderately confined groundwater domain [12,26]. In this model, 344 hydrofeatures were modeled as RCHRES units, each of which required a defined stage–storage–discharge relationship, most of which were manually derived with limited calibration except at select gauge locations.

The hydrology of the Peace River Watershed, covering an area of 930 km<sup>2</sup>, was also modeled using HSPF [7]. This model was notable for its use of the Reach Reservoirs

module (RCHRES) to represent isolated wetlands, highlighting the complexity of capturing the interactions between wetlands, their ephemeral discharge, and the strong interaction with the shallow groundwater system in large and interconnected watersheds. In this model, around 249 hydrofeatures were modeled as RCHRES units, each of which required a defined stage–storage–discharge relationship but with an earlier attempt to parameterize the rating based on watershed and wetland characteristics, getting away from individual manual calibration.

For smaller-scale, more focused studies, models like the CSA model [11] was developed. An example study of a 20-year-old CSA in a Fort Meade, Florida mine provided insights into the hydrological behavior of reclaimed mined areas including pasture grasslands and clay settling areas (CSAs), common reclamation landforms, under varying hydro-meteorological stresses [11]. Such models form the basis of many of the land-use/soil type parameters used in this model application.

The development of stage–storage–discharge relationships within hydrological models has been more straightforward for smaller, less complex watersheds where good DEM data exist. However, for larger domains such as IHM-INTB and the Peace River Watershed model, this task becomes more challenging [27,28], requiring systematic parameterization and innovative methodology employing general and geographic information system (GIS) data to establish reliable and vast stage–storage–discharge relationships for these complex systems. This approach utilizes a GIS and DEMs to extract critical hydro-geospatial parameters and spreadsheet operations to prepare the many stage–storage–discharge relationships required for these expansive networks. This method marks a significant advancement and departure from manual calibration and instead systematically model the intricate stage–storage–discharge conditions of W-C Florida.

The principal objective of this study was to create a robust computational tool based on the Alshehri and Ross [27,28] framework for isolated and alluvial wetlands. Their prior research primarily focused on developing a methodology to accurately characterize the relationships between stage, storage, and discharge. This study aims to extend the application of that methodology by designing and implementing a computational tool. This tool was designed to accurately populate rating curve characteristics, thereby enhancing the modeling of hydrology within the specified study area. The tool effectiveness was evaluated by examining the ability to reproduce accurate hydrological stages and discharges within W-C Florida for a hydrologically diverse application. The method recommends parameter values for a reasonable and robust calibration in this and similar environments. This work represents a significant contribution to the hydrologic modeling community, providing benchmarks and strategies for similar hydrological models.

### *Study Area*

The southern phosphate mining model domain (SMD) is an expansive hydrological region in W-C Florida spanning 14,090 km<sup>2</sup>, strategically bounded by hydrological divides and distinct groundwater systems (Figure 1). The domain includes surface and groundwater flow divisions generally along Interstate-4 to the north, the Florida highlands' ridge divisions to the east, watershed and groundwater flow divisions of the Charlotte Harbor Estuary to the south, and the Gulf of Mexico to the west. This area encompasses several main watersheds, diverse counties, and crucial rivers, all intricately connected within the landscape. The area experiences an average annual rainfall of 1320 mm (52 inches) recorded between January 2000 and December 2023 [9]. The region is subject to considerable hydrological variability, further complicated by the prevalence of phosphate mining activities and rapid urbanization. To help understand the implications of these land-use changes on the hydrology of the principal river system, the Peace River, which is a tributary to a vital estuary of the region, Charlotte Harbor Estuary, an HSPF model was developed to simulate freshwater inflows from 2000 to 2023. This model utilized data from 28 stream gauging stations for calibration over the period 2000–2010 and subsequent validation from 2011 to 2023; please refer to Table 1 for more details about the study area. This compre-

hensive hydrologic modeling study, not the focus of this paper, was used as a test for the stage–storage–discharge methodology presented and assessed in this paper.

For background, the domain was subdivided into 165 sub-basins, each characterized by one of 53 hydrologically distinct land-cover/land-use (LU) types, as derived from the FLUCC database, with a total of 148,000 alluvial and isolated wetlands. These 53 LU types were further aggregated into 9 specialized pervious land elements (PERLNDs) in HSPF: high-slope and low-slope grassland, urban, flatwoods, hardwoods, several irrigated and unirrigated agricultural types, clay settling areas, active mining, and one impervious type (IMPLND) comprising the principal upland landforms of the region (Table 2). The hydrography of the region was characterized as one of four wetland features, lakes, isolated wetlands, connected ephemeral streams, and rivers, using unique HSPF RCHRESs elements. For the purpose of hydrological modeling, there was an assumption that each land-use element exhibited a similar hydrologic response to local meteorological drivers determined by the rainfall data set (Table 2). To accurately represent the spatial heterogeneity of climatic variables, a network of 66 NEXRAD GAR weather stations, derived from the Southwest Florida Water Management District's (SWFWMD) online database, and 13 reference ET stations, obtained from the Florida Automated Weather Network (FAWN) system, were strategically situated across the domain using Thiessen polygons and sub-basin delineations. Model parameters were further calibrated and assessed through the Parameter Estimation (PEST) software, version 17.5, created by Doherty and sourced from Brisbane, Australia, in accordance with established guidelines [29].



**Figure 1.** The southern phosphate mining model domain (SMD), Southwest Florida, United States.

**Table 1.** Hydrological and climatic characteristics of the southern phosphate mining model domain (SMD).

| Parameter                                       | Description                                    |
|-------------------------------------------------|------------------------------------------------|
| Hydrology type                                  | Coastal plain hydrology                        |
| Geographical area                               | 14,090 km <sup>2</sup>                         |
| Soil type                                       | Sandy soil                                     |
| Climate zone                                    | Humid subtropical                              |
| Wet season duration                             | June to October (about 2/3 of annual rainfall) |
| Dry season duration                             | November to May (about 1/3 of annual rainfall) |
| Average annual rainfall                         | ≈1320 mm (52 inches)                           |
| Potential evapotranspiration                    | ≈1320 mm (52 inches)                           |
| Groundwater environment                         | Shallow groundwater environment                |
| Total hydrography area                          | 383,248 km <sup>2</sup>                        |
| Number of wetlands                              | 148,000 wetlands                               |
| Number of USGS streamflow gauging stations      | 28                                             |
| Number of NEXRAD GAR stations                   | 66                                             |
| Number of reference evapotranspiration stations | 13                                             |

NEXRAD GAR is the Next Generation Weather Radar Gauge-Adjusted Radar.

**Table 2.** Distribution of hydrological response units (HRUs) in the SMD.

| Natural Landscape Features | Hydrological Response Unit (HRU) | Percentage   |
|----------------------------|----------------------------------|--------------|
| Uplands                    | Urban Impervious                 | 2.7%         |
|                            | Urban pervious                   | 13.1%        |
|                            | Low-slope grassland              | 25.8%        |
|                            | High-slope grassland             | 5.5%         |
|                            | Flatwoods                        | 5.1%         |
|                            | Hardwoods                        | 4.0%         |
|                            | Mining                           | 3.1%         |
|                            | Irrigated row crop               | 4.1%         |
|                            | Irrigated tree crop              | 9.5%         |
|                            | <b>Total uplands</b>             | <b>72.8%</b> |
| Hydrofeatures              | Wetlands                         | 6.9%         |
|                            | Streams                          | 16.7%        |
|                            | Rivers                           | 2.4%         |
|                            | Lakes                            | 1.2%         |
|                            | <b>Total hydrofeatures</b>       | <b>27.2%</b> |

Concerning model conceptualization, a total of 532 distinct hydrological features were identified, encompassing 165 wetlands, 165 streams, 37 lakes, and 165 rivers. The accurate simulation of each of these features necessitated and allowed the testing of the simplified parameter stage–storage–discharge relationship, the subject of this paper. In HSPF, stage–storage–discharge is provided and denoted as a function table (F-Table). Traditionally, F-Tables are generated by a limited GIS analysis, prismatic assumptions, and/or simple Manning-type (uniform flow) equations, in a simplistic spreadsheet-based calculation. The following approach provides a far more robust yet still relatively simple methodology to populate the stage–storage–discharge requirements of complex models such as the SMD example.

## 2. Methodology

The methodology advocated in this study involves straightforward analyses to create semi-automated F-Tables for RCHRES within the HSPF. In this example, hydrofeatures within the model were systematically categorized into wetlands, streams, lakes, and rivers based on their tendency to discharge. Lakes in the region generally discharge only in wet years, wetlands only for the middle to late wet season every year, ephemeral streams

discharge when there is a large runoff conditions but not throughout the year, and perennial rivers with persistent flow represent both runoff and groundwater baseflow.

The classification framework draws on the extensive research conducted by [27,28] and previous modeling experience by [7,12] as well as accepted knowledge of the area. The RCHRES module within HSPF was employed to simulate each categorized hydrofeature (wetlands, streams, lakes, and rivers). Each hydrofeature underwent individual simulation processes with unique rainfall and ET assignments as well as local known (permitted) surface water diversions, generating distinct User Control Input (UCI) files for each category. This granular approach allowed for a more detailed analysis and understanding of the individual and collective hydrological responses within the system.

Geographically isolated wetlands (GIWs) were delineated as wetland RCHRESs, characterized by their limited surface water connectivity, elevated invert levels, and unique groundwater ET extinction depths—the depth beyond which plants can no longer access water within the soil (the sum of the root zone depth and capillary zone depth). These wetlands typically exhibit visible water storage for only part of the year, estimated to last approximately 2/3 of the year (238 days [28]), and visibly dry beds during the dry season and rarely discharge but for a brief period each year.

Stream RCHRESs represent ephemeral alluvial (connected) wetlands, characterized by an incised invert that allows water flow for most runoff events, and may receive groundwater baseflow to support their ET demand but often do not discharge, which is indicative of these riparian wetlands. They represent essential conduits, linking all of the disparate aquatic systems. Lakes, within the RCHRES classification, are defined as perennial water bodies with continuous year-round water storage, which, in W-C Florida, are often regulated by outfall structures upon reaching their maximum storage capacity. Lakes in W-C Florida are primarily karst collapse relics, serving important deep groundwater recharge and storage functions but only discharging naturally to stream surface water features following infrequent multiyear El Niño–La Niña wet cycles, and most years do not appreciably discharge.

River RCHRESs were identified as principal routing elements within the watershed, functioning as primary conduits for the transfer of discharges from one basin to the subsequent one, exhibiting perennial and sometimes gauged flow downstream. These rivers are Strahler order 2 or higher in alluvial systems in W-C Florida, have their own identified drainage basins between confluences, and are all named and easily identified from GIS databases. The model routing scheme was developed based on the National Hydrography Dataset Plus High Resolution (NHDPlus HR) database obtained from the USGS.

In the simulation computational sequence, calculated upland (PERLND AND IMPLND) flows (runoff and baseflow) were portioned into wetland, stream, or lake RCHRESs as determined by the GIS. Wetland RCHRESs were modeled initially with outflows directed to stream RCHRESs or in some cases lake RCHRESs, also determined by a GIS analysis. Stream RCHRESs were then either routed to lakes and rivers, depending on the presence of lakes and their geographical/hydrological positioning. Stream and lake RCHRESs were directed to alluvial systems classified as river RCHRESs. In this manner, all water discharges (uplands and wetlands) from the entire basin would end up in subsequent downstream river RCHRESs and ultimately end up in the last river element for each basin. In all cases, routing features connecting multiple basins were considered in the river RCHRESs classification.

The hydrological behavior of the hydrofeatures described above was predominantly influenced by the size of their respective drainage areas. Given the impracticality of determining the drainage area for each wetland within a basin due to their abundance and distribution, the hydrologic response unit (HRU) method was employed. This method consolidates hydrofeatures of the same type within each basin, assuming a homogeneous response to climatic variables and ET.

To facilitate the assignment of drainage areas to these aggregated hydrofeatures, the spatially adaptive drainage area allocation (SADA) technique was implemented. SADA

proportionally distributes the total area of the basin among wetlands, streams, and lakes' RCHRES. This allocation is guided by a consideration of the spatial distribution and relative size of each hydrofeature, and user professional judgment. Notably, hydrofeatures that are centrally located and larger in size are apportioned a greater percentage of the drainage area. In contrast, those that are smaller or nearer the periphery of the basin are attributed a lesser percentage. This methodology effectively blends empirical evidence with user subjectivity to estimate the percentage uplands from the catchment. Perhaps improved GIS techniques will be developed to assist with this task in the future.

For river RCHRESs, the designated drainage area can be expansive, encompassing not only the local basin area that a reach falls in but also incorporating routed areas from any connected upstream basins that contribute to the streamflow. For example, the last river RCHRES for a named river system represents the surface drainage from the entire river basin.

## 2.1. Rivers and Streams' RCHRES

### 2.1.1. Discharge Rating Curve Characterization for Rivers and Streams' RCHRES

Alshehri and Ross [27] enhanced the non-dimensional model originally proposed by Mueses [30], to predict rating curve behaviors for ungauged river and stream sections. The enhanced methodology integrated GIS coverage, which included DEMs and accurately delineated watersheds, with empirical models that had demonstrated strong performance in estimating key variables for the revised Mueses model [27]. The cumulative drainage area ( $A_D$ ), the local longitudinal channel slope ( $S_C$ ), and channel width ( $W_C$ ) were employed to estimate stage–discharge relationships in alluvial environments. Alshehri and Ross [27] observed that on average, streams in W-C Florida typically experienced a break in rating behavior around or less than 10% of the time on long-term records. This break was considered associated with the transition to out-of-bank flows. Their analysis indicated the threshold distinguishing in-bank and out-of-bank conditions, and break in rating could be determined reliably by the flow depth that corresponded to the 10th-percentile daily exceedance flow ( $Q_{10}$ ).

Within this study, the practical aspects of the refined Mueses model, as developed by Alshehri and Ross [27], were applied to characterize the stage–discharge relationships of streams and rivers within the HSPF RCHRES module. The governing empirical equations for the refined Mueses model are as follows [27]:

For the in-bank behavior ( $Q \leq Q_{10}$ ):

$$m_1 = \frac{\log\left(\frac{Q_{50}}{Q_{10}}\right)}{\log\left(\frac{d_{50}}{d_{10}}\right)} \quad (1)$$

$$Q = Q_{10} \left( \frac{d}{d_{10}} \right)^{m_1} \quad (2)$$

For the out-of-bank behavior ( $Q > Q_{10}$ ):

$$m_2 = \frac{\log\left(\frac{Q_1}{Q_{10}}\right)}{\log\left(\frac{d_1}{d_{10}}\right)} \quad (3)$$

$$Q = Q_{10} \left( \frac{d}{d_{10}} \right)^{m_2} \quad (4)$$

where  $Q_{10}$  is the 10th-percentile daily exceedance ( $L^3/t$ ),  $d_{10}$  is the depth of  $Q_{10}$  (L),  $Q_{50}$  is the 50th-percentile daily exceedance discharge ( $L^3/t$ ),  $Q_1$  is the 1st-percentile daily exceedance discharge ( $L^3/t$ ), and  $d_{50}$  and  $d_1$  are the depths of  $Q_{50}$  and  $Q_1$  (L), respectively. The flow exponent,  $m_1$ , is the exponent for in-bank discharges, and  $m_2$  is the exponent for out-of-bank discharges.

Typical model application hinges on the accurate estimation of daily flows from runoff and groundwater from uplands, direct rainfall, ET, and evaporation stresses from wetlands and open water. The model then uses storage routing of all the hydrography elements using the derived stage–storage–discharge relationships of this methodology to predict downstream flows and all water depths of the hydrography (RCHRES) elements. Prior to creating the RCHRES stage–storage–discharge relationships, flows and stages at the index exceedance percentiles, including the 1st, 10th, and 50th percentiles must be derived from an advocated approach that integrates both gauge stations data and field observations from W-C Florida, which has led to the development of regression models adept at simulating stage–discharge relationships in W-C Florida and perhaps elsewhere [27], which are systematically detailed in Table 3.

**Table 3.** Empirical relations from Alshehri and Ross’s [27] investigation used to derive rating indexes in W-C Florida.

| Equations                                                                                | Description                                                                                                                                                                       |
|------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $\log(Q_{50}) = \alpha_{50} \cdot \log(A_D) - \beta_{50}$                                | $Q_{50}$ is the 50th-percentile daily exceedance ( $\text{m}^3/\text{s}$ ), $A_D$ is the drainage area ( $\text{km}^2$ ), $\alpha_{50} = 0.90$ , $\beta_{50} = 2.38$              |
| $\log(Q_{10}) = \alpha_{10} \cdot \log(A_D) - \beta_{10}$                                | $Q_{10}$ is the 10th-percentile daily exceedance ( $\text{m}^3/\text{s}$ ), $\alpha_{10} = 0.81$ , $\beta_{10} = 1.2$                                                             |
| $\log(Q_1) = \alpha_1 \cdot \log(A_D) - \beta_1$                                         | $Q_1$ is the 1st-percentile daily exceedance ( $\text{m}^3/\text{s}$ ), $\alpha_1 = 0.67$ , $\beta_1 = 0.32$                                                                      |
| $\log(A_{10}) = \kappa_{10} \cdot \log(A_D) - \iota_{10} \cdot \log(S_C^{0.5}) - x_{10}$ | $A_{10}$ is the cross-section area of $Q_{10}$ ( $\text{m}^2$ ), $S_C$ is the channel slope ( $\text{m}/\text{m}$ ), $\kappa_{10} = 0.69$ , $\iota_{10} = 2.38$ , $x_{10} = 1.62$ |
| $d_{h10} = \frac{A_{10}}{W_C}$                                                           | $d_{h10}$ is the hydraulic depth of $Q_{10}$ ( $\text{m}$ ), $W_C$ is the channel width ( $\text{m}$ )                                                                            |
| $\log(d_{10}) = \gamma_{10} \cdot \log(d_{h10}) + \epsilon_{10}$                         | $d_{10}$ is the depth of $Q_{10}$ ( $\text{m}$ ), $\gamma_{10} = 0.84$ , $\epsilon_{10} = 0.16$                                                                                   |
| $\log(d_{50}) = \gamma_{50} \cdot \log(d_{10}) - \epsilon_{50}$                          | $d_{50}$ is the depth of $Q_{50}$ ( $\text{m}$ ), $\gamma_{50} = 0.99$ , $\epsilon_{50} = 0.34$                                                                                   |
| $\log(d_1) = \gamma_1 \cdot \log(d_{10}) + \epsilon_1$                                   | $d_1$ is the depth of $Q_1$ ( $\text{m}$ ), $\gamma_1 = 0.86$ , $\epsilon_1 = 0.21$                                                                                               |

The robustness of these regression models is contingent upon accurate inputs of  $S_C$ ,  $W_C$ , and  $A_D$  for river and stream (RCHRES) categories from GIS. For river RCHRESs, the  $S_C$  and  $W_C$  parameters are reliably derived from DEMs [27]. However, estimating these parameters for stream RCHRESs presents a unique challenge due to their inherent variability. A stream designated as an interconnected stream system, and therefore a stream RCHRES, can contain dendritic creeks, ditches, swales, and improved channels within a reach segment. Consequently, the slope of a reach polygon was employed as a surrogate for  $S_C$  to account for the spatial variation and diverse typology of the stream RCHRES. In addition,  $W_C$  was determined through GIS transverse topography queries and subjective user interpretation as to top-of-bank width, acknowledging the diverse topographical/hydrologic profiles within the region.

#### 2.1.2. Characterization of Pool Storage for Streams and Rivers’ RCHRESs

Nilsson [31] developed a non-dimensional empirical model to reproduce the stage–storage relationships of isolated wetlands further advanced in Alshehri and Ross’s [27] model. The governing empirical equation for the model is as follows [31]:

$$V = \left( \frac{A_0 h_0}{n} \right) \cdot \left( \frac{h}{h_0} \right)^n \quad (5)$$

where  $h$  is the wetland pool depth (L),  $h_0$  is the maximum pool depth (L),  $A_0$  is the maximum wetland area corresponding to  $h_0$  ( $\text{L}^2$ ),  $V$  is the wetland volume corresponding to  $h$  ( $\text{L}^3$ ), and  $n$  is the dimensionless parameter to describe the wetland geometric shape.

To effectively utilize this model, essential data include a reference (ideally near full) wetland area ( $A_0$ ), the associated maximum depth ( $h_0$ ) at that level, and the shape parameter ( $n$ ). Wetland area and depth,  $A_0$  and  $h_0$ , can be derived from GIS coverage (e.g., areas from published National Wetlands inventory,  $h_0$  from cross-section profiles, or polygon assessments using high-resolution DEMs). However, determining the exponent,  $n$ , requires an analysis of high-resolution DEM or topographically derived storage at various depths

within each wetland, and thus a dedicated study examining storage behaviors within pools and in- and out-of-channel conditions in alluvial wetlands. Short of a detailed study to derive  $n$ , in any new application, user calibration of predictive simulation models can be used to derive effective  $n$ 's, comparing observed stages and flow timing at gauging stations or other observations once the event volumes are adequately reproduced by the model.

For this application, a study was conducted to establish range and mean behaviors of the (Nilsson) shape parameter within the channel-bank ( $n_1$ ) and the out-of-bank ( $n_2$ ) conditions. As per the findings of Alshehri and Ross [27], when the depth is less than or equal to the  $d_{10}$ , the primary pool storage in the alluvial wetland is within channel, with possible limited unconnected pool storage in bowls within the wetland. Only channel storage may be visible. To estimate  $n_1$ , cross-sectional areas associated with  $Q_{10}$  ( $A_{10}$ ) from 86 USGS streamflow gauge stations in W-C Florida were acquired. Subsequently,  $A_{10}$  was converted to  $V_0$ , using GIS-derived channel thalweg lengths, and  $n_1$  values for each channel were derived from (Equation (5)).

Given the limited studies on higher pool storage behavior with alluvial wetlands, estimating the storage behavior of the out-of-bank bowl of alluvial wetlands became more challenging. To address out-of-bank storage conditions, model results from numerous flood studies using the Advanced Interconnected Channels and Ponds Routing (AdICPR) model [32] were utilized with DEMs to establish the stage-storage,  $n_2$ , parameter for a representative sample of alluvial wetlands. The scope of this analysis included 150 alluvial wetlands, highlighting the diversity of  $n_2$  and perhaps identifying useful indices to help with the prediction of this parameter in a broader setting.

The governing empirical equations for stream and river RCHRESs were conceptualized as follows: for within channel storage behavior ( $h \leq d_{10}$ ),

$$V_1 = \left( \frac{A_0 \cdot d_{10}}{n_1} \right) \cdot \left( \frac{h}{d_{10}} \right)^{n_1}; \quad (6)$$

for out-of-channel storage behavior ( $h > d_{10}$ ),

$$V = V_1 + \left( \frac{A_0 \cdot (h_0 - d_{10})}{n_2} \right) \cdot \left( \frac{h - d_{10}}{(h_0 - d_{10})} \right)^{n_2} \quad (7)$$

where  $V_1$  is the channel storage ( $L^3$ ),  $n_1$  is the dimensionless shape parameter for within channel storage behavior, and  $n_2$  is the dimensionless shape parameter for floodplain wetland storage (out-of-bank storage).

## 2.2. Wetlands and Lakes' RCHRESs

### Discharge Rating Curves for Wetlands' RCHRES

In a separate study conducted by Alshehri and Ross [28], Mueses's [30] model underwent refinement to more accurately replicate the stage-discharge relationship of geographically isolated wetlands (GIWs), wetlands that conditionally connect or rarely discharge to downstream alluvial wetlands. In this application, wetlands identified through a GIS corridor analysis as GIWs were modeled as wetland RCHRESs. Thus, the model application accounted for the observed and important behavior of these complex systems in the contribution of stream high-flow conditions, particularly their limitations in discharging during the dry season and the conditions required for a commencement of discharge during the wet season.

For wetland RECRES, instead of normalizing the model by  $Q_{10}$  and  $d_{10}$ , which often yields zero values for these features, the refined model employed a normalization by the 100-year discharge and depth ( $Q_{100}$  and  $d_{100}$ ) conditions; the governing empirical equation was as follows [28]:

$$Q = Q_{100} \cdot \left( \frac{d}{d_{100}} \right)^m \quad (8)$$

where  $Q$  is the model discharges ( $L^3/s$ ),  $Q_{100}$  is the 100 yr discharge ( $L^3/s$ ),  $d$  is the flow depth above the invert ( $L$ ), and  $d_{100}$  is the depth of the flow associated with the  $Q_{100}$  ( $L$ ).  $Q_{100}$  data do not generally exist for the vast number of GIWs that exist in a model domain, but they can be readily derived from 100 yr flood plain studies for select wetlands aimed at quantifying the 100 yr flood stages.

To establish the stage–discharge relationship for wetland RCHRESs, specific parameters of  $m$ ,  $d_{100}$ , and  $Q_{100}$  had to be derived. Alshehri and Ross [28] explored these variables and developed an empirical equation to estimate  $Q_{100}$  by utilizing  $A_D$  and the total area of cumulative wetlands ( $A_W$ ) as predictors. The quality of the regression model for  $Q_{100}$  was assessed using R-squared  $R^2$ , and an analysis revealed that the  $R^2$  value for estimating  $Q_{100}$  stood at 0.82 [28]. This empirical model was deemed suitable for environments similar to the coastal plains of W-C Florida. However, when it is applied in different environments, it might necessitate some adjustments. Also, it was discovered that for  $d_{100}$ , which represents the depth at which there is a 1% chance of exceedance in any given year, there is minimal variation across GIWs in W-C Florida, and an average depth could be employed. Hence, an average value of 0.43 m for  $d_{100}$  was derived from studying 35 characteristic wetlands in the area and this value was assigned to derive stage–discharge relationship for wetland RCHRESs. In addition, an investigation into a representative  $m$  for GIW systems revealed that an average value of 2.45 effectively represented the typical discharge behavior of GIWs when treated as unified (multiple GIWs in each wetland RCHRES) hydrological feature. This value, however, may be unique for this study area and should be considered subject to calibration within this domain and others, with a possible range extending from 1.8 to 3.1 physically to accommodate site-specific conditions. Alshehri and Ross [28] determined that the optimal approach for estimating the invert elevation of GIWs involved first establishing the mean elevation of the land within a 4.5 m buffer zone around the wetlands. Their study compared GIS-derived inverts to actual surveyed inverts and found the mean of the buffer was much better than the minimum as was first expected. Subsequently, they recommended employing a specific area-weighted averaging method to estimate a representative invert elevation for the DEMs readily available for the study area. The empirical equation for  $Q_{100}$  as advocated by Alshehri and Ross [28] was:

$$\log(Q_{100}) = g_1 \cdot \log(A_D) - g_2 \cdot \log(A_W) + g_3 \quad (9)$$

where  $Q_{100}$  was previously defined,  $A_D$  is the drainage area ( $\text{km}^2$ ),  $A_W$  is the cumulative wetland area ( $\text{km}^2$ ), and empirical coefficients of  $g_1$ ,  $g_2$ , and  $g_3$  were found to be 1.49, 0.57, and 0.54, respectively, by studying flood-plain modeling results for GIWs.

### 2.3. Discharge Rating Curves for Lakes' RCHRES

Lakes in W-C Florida are generally karst collapse features with historically little or no surface water drainage, instead typically draining vertically to deep groundwater recharge [9,33]. However, with urbanization of the surrounding basins and flood management, drainage connection has been implemented in the form of ditching and control structures, such as weir systems, which facilitate discharge during intense events such as hurricanes, a common occurrence in the region. Generally, these structures begin to release water as the lakes approach their maximum capacity or limiting stage. To characterize the discharge rating curves for these systems, the standard broad-crested weir equation was employed. The length of the weir was estimated using GIS imagery maps or published information, allowing for the calculation of  $Q$  using the empirical weir equation as follows:

$$Q = 1.77 \cdot W \cdot H^{1.5} \quad (10)$$

where 1.77 is the weir constant, which includes the weir coefficient assumed to be 0.6 ( $\text{m}^{0.5}/\text{s}$ ),  $W$  is the weir width estimated from GIS (m) or published values, and  $H$  is the flow depth above the derived or published invert elevation (m). The unfortunate condition is that many of these lake control structures have adjustable and sometimes

locally constructed and operated structures. Many are often adjusted in extreme events to serve resident desires to manage levels with no record of their settings. This is one identified problem for prediction and modeling extreme flows in the region.

### 2.3.1. Storage Rating Curves for Wetlands and Lakes' RCHRESs

In characterizing the storage rating curves for wetland and lake RCHRESs, the methodology first proposed by Nilsson [31] and later adapted by Alshehri and Ross [27] was employed. The recent study by Alshehri and Ross [27] specifically investigated the storage behavior and depth of GIWs within W-C Florida, otherwise applying the model developed by Nilsson [31]. The recent research by Alshehri and Ross [27] yielded a useful discovery: the average  $n$  value, a parameter indicating the storage capacity of GIWs, was 2.47 with relatively little variability. Furthermore, Alshehri and Ross [27] pinpointed the operational range for  $n$ , in general lying between 1.54 and 3.4. The representative value (2.5) found may be unique to the area but was also advocated by Nilsson [31] for wetlands outside of the study area. Nilsson [31] included 17 lakes in their study as well as wetlands outside of Florida and determined the mean shape parameter,  $n$ , to be 2.5.

The maximum depth was estimated from available studies and published bathymetry for the lakes when accessible; otherwise, a value was inferred based on surrounding lakes with available depth data. The lake areas were estimated from GIS coverage.

### 2.3.2. Stage–Storage within Soils

During the dry season, when the beds of most of these hydrofeatures become visible, it is necessary to enable the model to account for ET from soil storage. The research on soil storage was carried out by Alshehri and Ross [28] following earlier field studies by Ross et al. [12] and Zhang et al. [7] leading to the creation of a linear model aimed at quantifying the available storage within soil media. The main assumption of the model is the amount of water available for ET within the soil can be determined as the difference between saturation soil moisture content ( $\theta_s$ ) and wilting point soil moisture content ( $\theta_{w.p}$ ), over the root zone (ET extinction zone) of the wetland. The ET extinction depth, the water table depth below which it ceases to support wetland ET, is dependent on soil type and wetland root zone properties according to Ross et al. [12]. Soil ET occurs up to the extinction point, which is determined by the root zone depth, capillary zone dimension, and saturation and wilting point moisture contents. To derive these soil storage relationships, hydrofeatures were superimposed onto soil-type coverage, associating soil types with soil characterization data, which included capillary zone, saturation, and wilting point (suction head thresholds) data. With wetland root zone dimensions previously derived for the region [34], the available storage within the soil media was calculated using a simple governing empirical equation of the form [27]:

$$V_{MaxSoil} = A_0 \cdot \xi_X (\theta_s - \theta_{w.p}) \quad (11)$$

where  $V_{MaxSoil}$  is the full soil storage ( $L^3$ ),  $A_0$  is the wetland area ( $L^2$ ),  $\xi_X$  is the extinction depth, which is the sum of the capillary zone depth and root zone depth ( $L$ ),  $\theta_s$  is the saturation soil moisture content ( $L/L$ ), and  $\theta_{w.p}$  is the wilting point soil moisture content which is the soil moisture content at which a plant no longer can extract water from soil ( $L/L$ ).

The only distinguishing factor in the behavior of soil storage among wetland, stream, lake, and river RCHRESs is the extinction depth. Essentially, the extinction depth varies for each hydrofeature type to account for the capacity of roots and capillary rise to extract water for ET. For wetland RCHRESs, as established by the study conducted by Shah [34], the extinction depth varies but can be approximated as 2 m generally for the area. In contrast, stream and river RCHRESs exhibit extinction depths generally below 2 m. This ostensibly results from the fact that alluvial wetlands generally drain and are fed by superficial lateral groundwater flow (baseflow), and therefore feature shallower root systems, but it certainly depends on the particular setting. In some instances, these stream and river channels are

simply incised into the upland landscape and may entirely lack alluvial vegetation and have limited in-bank and out-of-bank bowl storage capacity. Based on model calibration and field observations [12], an extinction depth of 1.2 m was selected for all alluvial (stream and river) wetlands.

Regarding lake RCHRESs, since lakes rarely go completely dry in the study domain, they are insensitive to the value of soil storage parameters and magnitudes derived. Therefore, the value for extinction depth,  $\zeta_X$ , selected, which was based on the capillary zone dimension only, was 0.6 m for all lake soils. This choice considered the possibility that some lakes may experience periods of extreme dryness during exceptional drought conditions, but that condition was not present nor measurements available to test during the 23-year simulation period.

### 2.3.3. The Semi-Automated Spreadsheets Generator for F-Tables

A spreadsheet was developed with three distinct tabs dedicated to each RCHRES type: wetlands, streams, lakes, and rivers. An additional tab, titled “Area Analysis”, was created from GIS analyses to allocate the cumulative drainage and wetland areas among these hydrofeatures and to aggregate the area of each to populate the F-Tables for all the RCHRESs using the proposed method.

The “Area Analysis” tab incorporated results derived from watershed delineation processes. This tab detailed the individual basin areas along with their total drainage areas and specified the extent of each hydrofeature type, which included wetlands, streams, lakes, and rivers. Through the application of the GIS analysis and the SADA method, the tabulated data facilitated the distribution of the basin areas among wetlands, streams, and lakes, assigning each a proportional percentage of the total area. Conversely, for rivers, the assigned drainage area comprised the entire basin in addition to all tributary basins. As a result, for each hydrofeature category, there was a quantified  $A_D$  and hydrofeature area ( $A_0$ ).

The first tab for each hydrofeature served as the calibration section and featured adjustable knobs (for example empirical coefficients  $m$  and  $n$ ) for fine-tuning the F-table during calibration. It also contained essential parameters required for the F-table creation, including hydrofeature identification numbers, watershed characteristics, hydrofeature hydrological information (type, root zone, etc.), discharge parameters, as well as soil, channel, and pool storage parameters. The second tab was dedicated to populating the F-Table, covering the range from 0 storage to above the top of the wetlands, above the ever-expected water levels for the simulation. The primary function of this tab was to integrate soil moisture storage, pool storage in topographical depressions, and channel storage, as well as to account for both in-bank and overbank flow discharges at each stage. The integration of soil storage, pool storage, and discharge models within the table was conducted by referencing the invert elevations. It also played a crucial role in determining the resolution of the F-Table, which defines the increments from zero to the maximum. The third tab served the purpose of formatting the F-Table in the model input (User Control Input, UCI) format, making the F-Tables ready for use within the model.

### 2.3.4. Model Validation and Water Budget Analysis

The hydrology of the SMD model domain was simulated using HSPF (v14) over a 23-year period, from 1 January 2000 to 31 December 2022, a period including both extreme drought and wet conditions. This comprehensive simulation generated outputs including average monthly water levels, discharge rates, and cumulative monthly discharges. These outputs were compared against observed data obtained from 28 USGS gauge stations in the model domain. To assess the model predictive accuracy, a standard suite of evaluation metrics were employed:  $R^2$ , root-mean-square error (RMSE), mean error (ME), Nash–Sutcliffe efficiency (NSE), and flow exceedance percentiles ranging from the 90th to the 0.01st. Furthermore, the model was analyzed for its water budget by landform and catchments, as well as all appreciable fluxes and storage types for landforms and wetlands for each watershed

and each stream gauge area. This analysis was important for ensuring the constraints on the model (e.g., meeting ET targets) were met, as well as ensuring the most comprehensive validation and accuracy in simulating hydrological processes. Among other metrics, the relative error (RE) and mean error (ME) served as key metrics to understand the error magnitudes of prediction and assessment of the hydrological model for the SMD analyses and intended investigations.

## 2.4. Results and Discussion

### 2.4.1. Nilsson's [31] Shape Parameter for Alluvial Systems, $n_1$ and $n_2$

The assessment of channel and pool storage behavior in alluvial systems in Southwest Florida yielded insight into the suitability and accuracy of the proposed stage–storage–discharge. The study also identified a range of  $n_1$  values from 1 to 2.57 for alluvial wetland segments. A statistical analysis revealed an average  $n_1$  value of 1.56, with a median of 1.51, and a standard deviation of 0.39, signifying low variability as the median and average values were closely aligned. These values were quite lower than typical mean values (2.5) derived for GIWs and nonalluvial wetlands.

The parameter  $n_1$  denotes the cross-sectional shape (concave and only slightly non-linear nature) of channels. The physical interpretation of  $n$  was explained in Nilsson [31] as follows:  $n = 2$  indicates a shape akin to a triangular or conic prism,  $n = 1$  corresponds to a rectangular prism (seawall-type constant wetland area),  $1 < n < 2$  is a concave section, and  $n > 2$  is a convex section, which is similar to the bottom of a margarita glass, typical of isolated karst collapse wetlands in the study area.

Furthermore, a broad spectrum of  $n_2$  values was observed in the study of alluvial wetland hydrology, ranging from 1 to 3.95, signifying a high variability in the flood plain. This range underscored the diverse and hard-to-predict storage behavior of the out-of-bank regions of these wetlands compared to  $n_1$ . An average  $n_2$  value of 1.74, coupled with a standard deviation of 0.78, illustrated both the poorer central tendency and the higher variability within this data set compared to  $n_1$ . The derived value of 1.74 for the  $n_2$  indicated a tendency towards a more non-linear (more conic) cross-sectional configuration that increased surface area variability in the shape. However, some of the extreme values might be impacted by anthropogenic activities. Therefore,  $\pm 0.78$  of the mean could be used as a range for the calibration of  $n_2$ .

### 2.4.2. Model Validation

Hydrological models are approximations that serve a multitude of purposes, notably helping to understand a system and simulating water levels and discharges from which alternatives can be evaluated. If the alternatives are to be evaluated at the extremes (e.g., 100 yr flood studies) then the model performance should be evaluated for the extremes (low flow or highest flow). If the interest is in the more common flows and levels, then metrics should be assessed in a more common range (e.g., 90% to 10% exceedance flows and levels). Understanding this is vital for effective resource management, model results assessment and ultimately ecosystem protection. In this study, simulated water levels and discharges were compared and evaluated against observed data using the following metrics:  $R^2$ , NSE, RMSE, ME, and scatter plots for a variety of indices.

The NSE is particularly valuable in hydrologic modeling, offering a measure of a model's predictive power. Its heightened sensitivity to extreme discharge events, which include both peak- and low-flow conditions, highlights the model performance under varying hydrological extremes. This range is essential for evaluating the model effectiveness in various contexts, including its ability to capture groundwater contributions, sensitivity to dryer ET dominated periods or high-flow flood-dominated out-of-bank conditions.

A common  $R^2$  analysis provides insight into how well the model explains the variance in the observed data, offering a general perspective on model performance. To delve deeper into the model average performance, the  $Q_{50}$  percentile was analyzed. Additionally, the model behavior during varying hydrological conditions (dry, wet, and extreme) was

evaluated using the  $Q_{90}$ ,  $Q_{10}$ ,  $Q_1$ , and  $Q_{0.01}$  percentiles. This examination aimed to assess the model accuracy in predicting percentile exceedance discharges in comparison with observed data.

Lastly, the evaluation of RMSE, ME, and RE for both discharges and water levels helped in identifying the model limitations and the inherent uncertainties in simulating these parameters. Understanding these aspects is necessary for comprehending the extent of deviation from observed values and, consequently, the reliability and expected error of the model prediction.

When the model performance was assessed using NSE against data from available USGS gauging stations, the analysis revealed a range of performance across the stations: approximately 70% of the stations exhibited an NSE value of 0.7 or higher, and about 25% demonstrated NSE values of 0.8 or above. The average NSE across all stations was 0.67, the standard deviation was 0.13, with maximum and minimum NSE values being 0.84 and 0.38, respectively. Notably, all NSE values were above zero, indicating the model's effectiveness in estimating discharges, particularly for extreme- and low-flow events. This is significant given the NSE's heightened sensitivity to such events, and its relatively lower sensitivity to average flow conditions, see Figure 2b.

Considering the expansive nature of the studied area, which includes literally thousands of wetlands within the hundreds of watersheds modeled, a substantial percentage of wetland and water bodies (27.2%), active mining and CSAs, and the pronounced interaction between surface water and groundwater in the region, an average NSE of approximately 0.7 is considered indicative of strong model performance. This assessment is especially relevant given the model's intended purpose of evaluating the general water balance and streamflow prediction in the region. However, it is worth noting that for applications such as flood protection, these NSE values might not be sufficient, see Figure 2b, as the most extreme performance,  $Q_{0.01}$ , was considered poor.

However, the methodology employed in this study is particularly noteworthy for its efficiency, parameter reduction, and accuracy. The model was developed without conducting extensive surveying or bathymetric studies, relying instead on GIS-based data. Simple coefficients were estimated then adjusted slightly as calibration knobs. Despite these limitations, the model demonstrated reasonable performance for a robust and long hydrological period. This underscores the effectiveness of the approach in handling complex basins and regional model domains.

The model performance, evaluated using  $R^2$  values, demonstrated an average of 0.74, a standard deviation of 0.1, a maximum of 0.84, and a minimum of 0.54. This indicated that the model successfully predicted 74% of the hydrological variance. Notably, about 46% of the  $R^2$  values equaled or exceeded 0.8, and 89% were at or above 0.7, underscoring a strong model performance. These  $R^2$  values provide insights into the model's general behavior and its capability to predict hydrological trends. In general, the model was able to capture a large portion of the variability in the observed behaviors, see Figure 2a.

Regarding the discharge predictions, the average RMSE was  $4.08 \text{ m}^3/\text{s}$ , with a maximum of  $25.49 \text{ m}^3/\text{s}$  and a minimum of  $0.79 \text{ m}^3/\text{s}$ . This RMSE range suggested that the model could effectively represent the complex hydrology of the SMD within an average error margin of  $4.08 \text{ m}^3/\text{s}$ . Given the extreme weather events impacting the region and the extensive water bodies, an average RMSE of  $4.08 \text{ m}^3/\text{s}$  is considered good for the intended purpose. The model exhibited no bias, with an ME averaging  $-0.01 \text{ m}^3/\text{s}$ , indicating no systemic error across all stations. Maximum and minimum MEs were  $0.47 \text{ m}^3/\text{s}$  and  $-0.84 \text{ m}^3/\text{s}$ , respectively (see Figure 2c,d).

In terms of water level predictions, the model achieved an average RMSE of 0.47 m, a standard deviation of 0.15 m, a maximum of 0.72 m, and a minimum of 0.12 m, indicating a high level of accuracy for water level prediction. The average ME was 0.008 m, indicating no significant systemic error, with a maximum ME of 0.46 m and a minimum of  $-0.3 \text{ m}$ , see Figures 2e,f and 3.

The calibration period for the model spanned 10 years, with a subsequent validation over 13 years. Considering the lengthy simulation period of 23 years, the model performance was further validated. Additionally, the model capably captured the varying flows and levels observed in W-C Florida, including La Niña (wet years) and El Niño (dry years) patterns. The region exposure to numerous major hurricanes, including approximately 79 tropical or subtropical cyclones (e.g., 4 experienced in 2014) during the study period, further underscores the model's robustness in simulating the complex hydrologic variability of the domain.

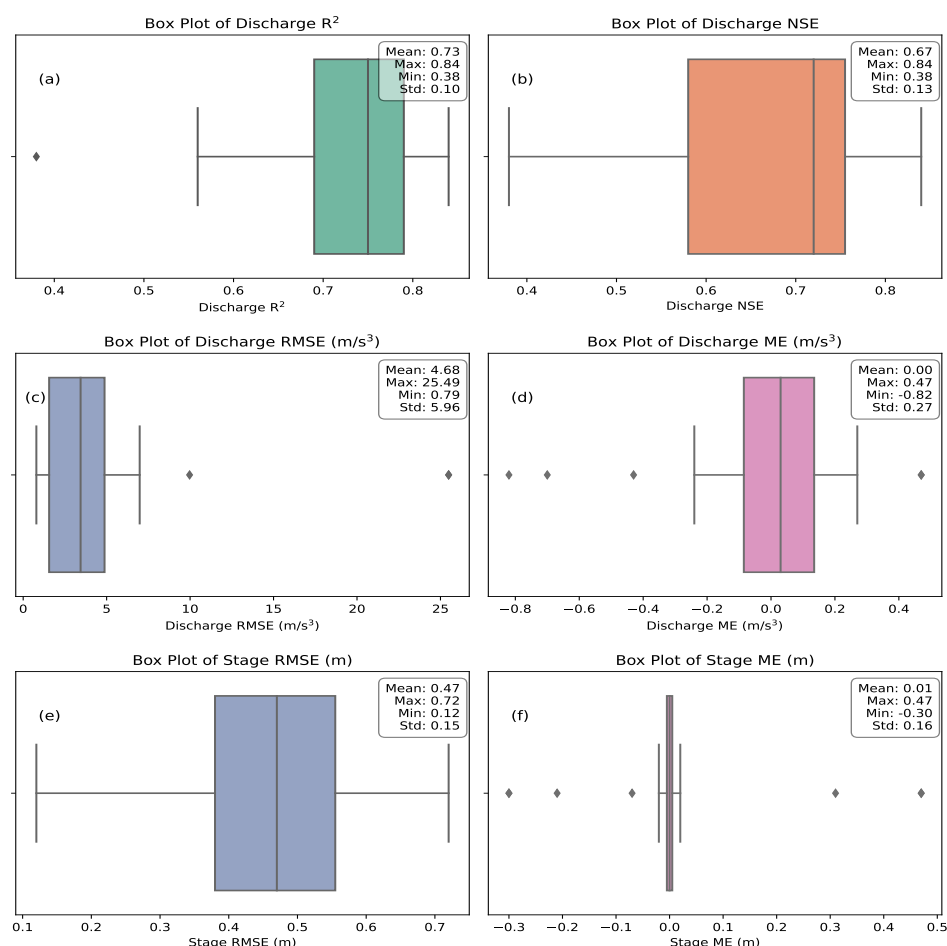


**Figure 2.** Comparison of model predictions and observed discharge and stage data, with (a) a box plot of  $R^2$  for discharge data, (b) a box plot of the Nash–Sutcliffe efficiency (NSE) for discharge data, (c) a box plot of the root-mean-square error (RMSE) for discharge data, (d) a box plot of the mean error (ME) for discharge data, (e) a box plot of the RMSE for stage data, and (f) a box plot of the ME for stage data. Diamond points represent data points that reside beyond the whiskers. These whiskers extend to the maximum data point within 1.5 times the interquartile range from both the first and third quartiles. These limits are used to categorize extreme values that deviate from the most common range of the data.

To discern why the model exhibited varying performance across different stations, an in-depth comparison of the best and poorest performing stations relative to observed hydrographs was conducted, focusing on discharge pulses and cumulative discharges. Additionally, the behavior at locations where the model performed poorly was investigated to help understand the model limitations.

For the stations with good model performance, Figure 4a,b, the model streamflow predictions (represented by a red line) closely aligned with the observed streamflow (blue line) in both cases. This alignment indicated the model effectively captured streamflow

variability. Furthermore, during peak flow events, the model generally replicated the timing and magnitude of these events with only slightly more variability. In terms of cumulative streamflow, there was a noteworthy congruence between the cumulative modeled (dotted red line) and observed streamflows (dotted blue line), suggesting consistent model performance over time.

In locations where the model performance was poor, as illustrated in Figure 5a,b, notable discrepancies between modeled and observed streamflows were evident. The model particularly struggled to accurately capture peak-flow events, often overestimating, or underestimating them. This inaccuracy could stem from incorrect model parameters, inadequate representation of physical processes, or issues related to data quality.

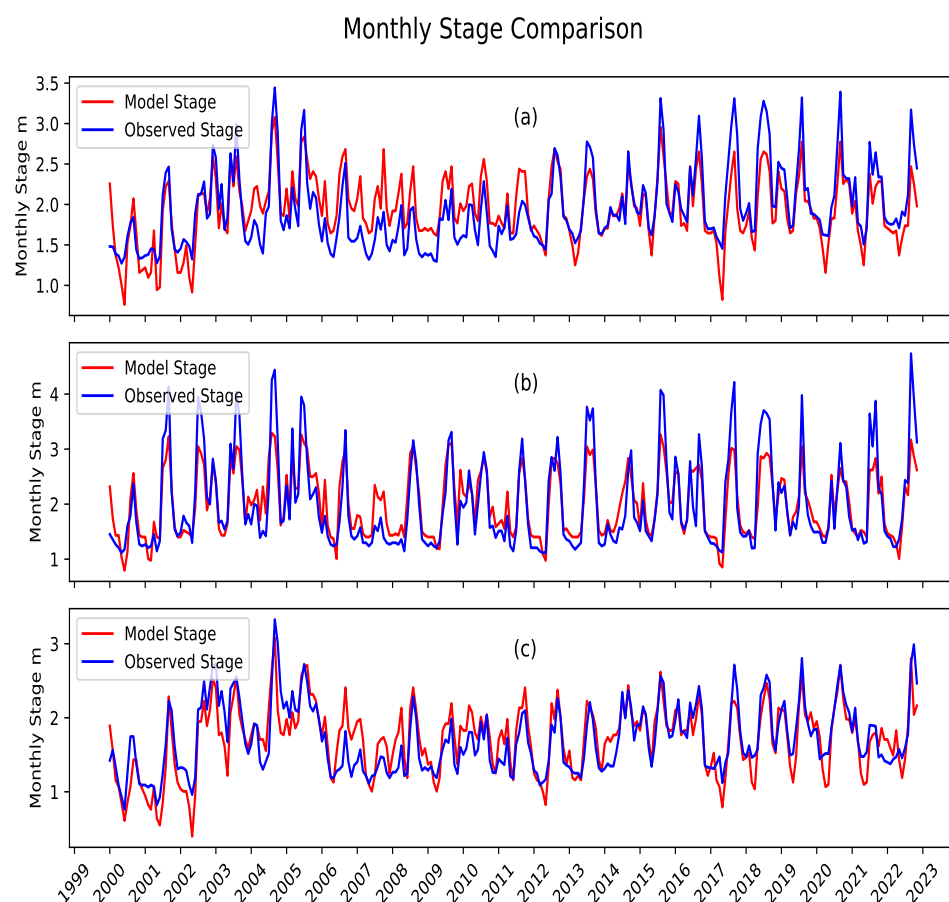


**Figure 3.** Comparison of model predictions and observed stage data for three different locations: (a) North Prong Alafia River at Keysville, (b) Horse Creek near Arcadia, (c) Peace River at Bartow.

Regarding cumulative streamflow, the divergence between cumulative modeled and observed streamflows over time suggests that these discrepancies have the potential to compound, bearing significant implications for long-term water resource planning and management. This may be attributable to complex hydrological processes not captured by the model due to its inherent limitations or incorrect parameterization. Departures in model and observations for cumulative flows are not considered significant if the deviation is nearly instantaneous, and then the cumulative becomes more or less mirrored offsets. This deviation suggests the model or data set failed during an event or short period, perhaps from rainfall mischaracterization or unknown anthropogenic activity. However, departures in cumulative performance that grow in time suggest the model is misrepresentative of low-flow baseflow or higher-flow runoff periods and is an indication of poorer calibration and predictive capability. Regions with poor model performance might exhibit more hetero-

geneous physical characteristics or greater human interference, such as water withdrawals or larger land-use changes (e.g., mining), which are not adequately represented in the model. Additionally, the interaction between groundwater and surface water, a critical aspect in W-C Florida, might be poorly represented in these regions, thus affecting the model's low-flow accuracy.

Given the high interaction between groundwater and surface water in the W-C Florida environment, a baseflow separation procedure [35] was applied to both modeled results and observed discharges. Then, a comparison of this estimated baseflow and separated runoff through scatter plots and  $R^2$  analysis was performed to evaluate the model's effectiveness in simulating groundwater and runoff dominated contributions. The slope (indicative of bias) and  $R^2$  values for baseflow and streamflow were analyzed to gauge model performance.

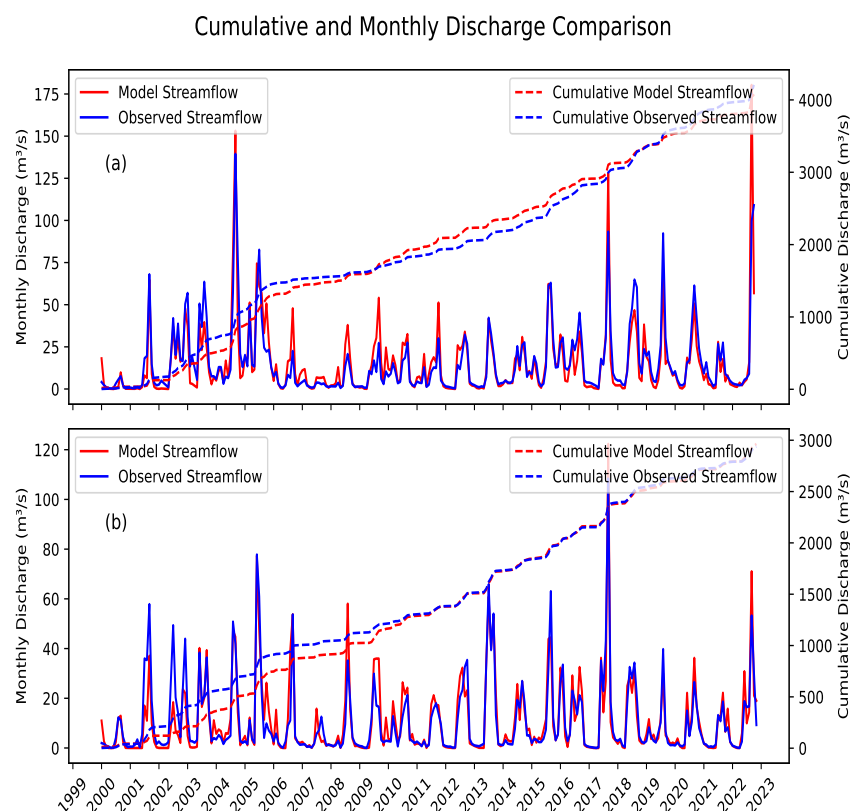


**Figure 4.** Comparison of modeled and observed discharge hydrographs at two locations (a,b) with good performance according to NSE and  $R^2$  results. The solid red line represents the modeled discharges, while the solid blue line represents the observed discharges. The dotted red line illustrates the cumulative modeled discharges, and the dotted blue line depicts the cumulative observed discharges throughout the simulation period.

The results indicated that the contribution of baseflow to total discharges at good-performance locations was limited compared to poor-performance locations. For good-performance locations, the average observed baseflow contribution was 5.6 cm/year, while the modeled baseflow averaged 4.5 cm/year. In contrast, in poor-performance locations, the observed baseflow was approximately 9.4 cm/year, while the modeled baseflow was about 2.8 cm/year. These findings suggest that in locations with suboptimal performance, there was a higher groundwater contribution to the total discharges, and the model generally did a poorer job at predicting baseflow in these areas.

Figure 6 presents a comparative analysis between the modeled and observed behaviors for streamflow and baseflow. While the model generally did well in simulating streamflow,

it demonstrated marked deficiencies in replicating baseflow at locations with poor model performance (Figure 6e,g).

The  $R^2$  values for streamflow were satisfactory across all locations ( $R^2 > 0.76$ ). However, baseflow performance, as depicted in Figure 6a,c, was notably better in locations where the overall model performance was good. Conversely, in Figure 6e,g, the model performance in simulating baseflow was suboptimal, adversely affecting the total discharge simulations and resulting in poor performance at these locations. This suggests that while the proposed method is effective in predicting runoff dominated streamflow across all locations, limitations in baseflow simulation, potentially due to inaccuracies in groundwater discharge representation, led to compromised performance in certain areas.

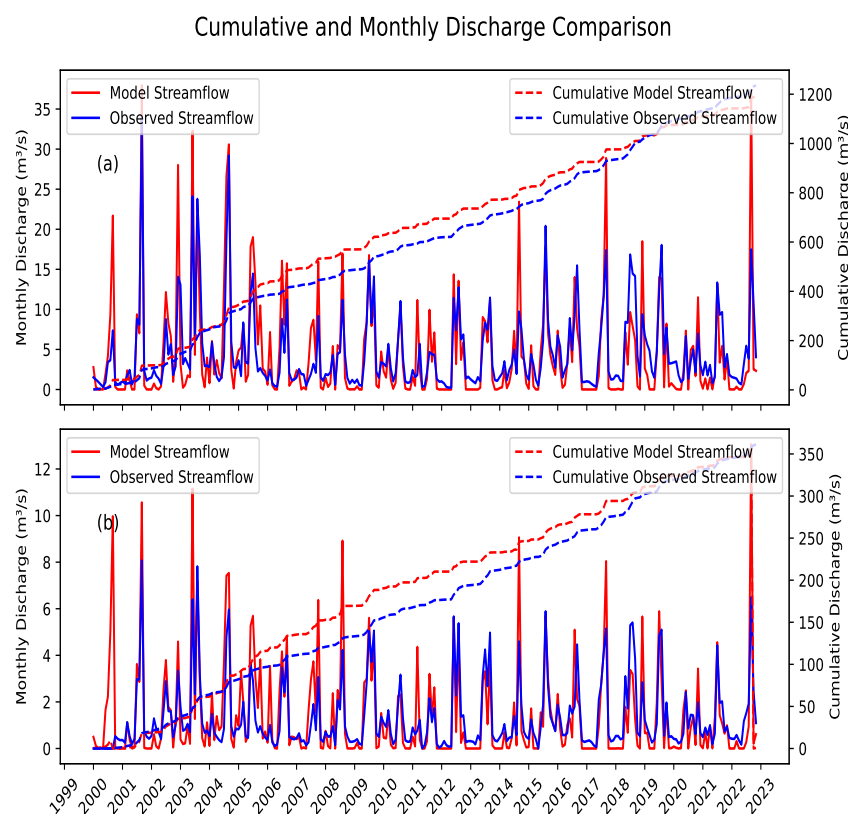


**Figure 5.** Comparison of modeled and observed discharge hydrographs at two locations (a,b) with poorer model performance according to NSE and  $R^2$  results. The solid red line represents the modeled discharges, while the solid blue line represents the observed discharges. The dotted red line illustrates the cumulative modeled discharges, and the dotted blue line depicts the cumulative observed discharges throughout the simulation period.

The model performance across various flow percentiles (0.01, 1, 10, 50, 90) was visually assessed through scatter plots compared to observed values, providing insights into the model behavior from extreme- to low-flow conditions. For an ideal model performance, predictions would align closely with the 45-degree reference line in these plots, indicating both accuracy and a lack of bias.

The slope values obtained for these percentiles ( $Q_{0.01}$ : 1.61,  $Q_1$ : 0.87,  $Q_{10}$ : 0.90,  $Q_{50}$ : 1.00,  $Q_{90}$ : 0.32) indicated a robust performance for ( $Q_1$ ,  $Q_{10}$ ,  $Q_{50}$ ), with a near-perfect slope of 1.00. In addition, the  $R^2$  values for ( $Q_1$ ,  $Q_{10}$ ,  $Q_{50}$ ) were nearly one. However, the model predictions for extreme flow events ( $Q_{0.01}$ ,  $Q_{90}$ ) deviated from the expected 1:1 slope, pointing to less accurate performance in these ranges. Such discrepancies could be due to the system's inherent complexity, including the interplay between groundwater and

surface water, as well as the noted reliability of observed data for both low and extreme high flows.

In addition, the limitations of the model in predicting peak stages and discharges (Figures 3–5 and 7) can be attributed to the complexities of human interventions and the non-linear dynamics of hydrological responses during extreme events. For high flows exceeding  $Q_{0.01}$ , the model performance suffered due to its inability to account for emergency management actions such as lake draining and dam operations, which are critical during extreme weather events. These human interventions introduced variables not currently simulated by the model, thereby impacting its performance during these critical periods. Notably, the model exhibited satisfactory performance for flows between  $Q_{90}$  and  $Q_{0.01}$ , where such interventions have less influence. The model's strengths are in water resource management, while its limitations make it less suitable for flood management (predicting extreme events). See Figure 7 for more details about the model performance.

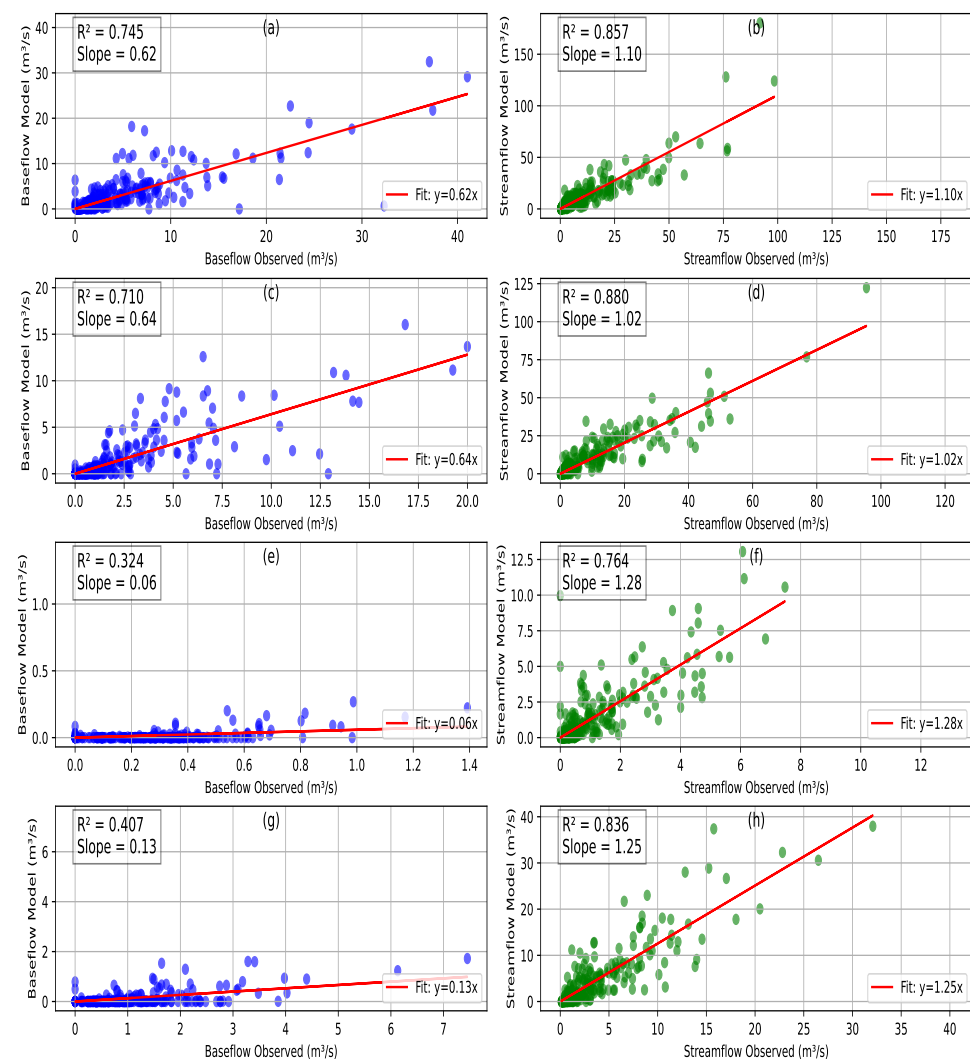


**Figure 6.** Scatter plots comparing predicted and observed baseflows and streamflows. Baseflow was separated from streamflow using an approach by Perry [35]. Graphs (a,c) display the baseflow comparisons at locations where the model performed well, (b,d) present the streamflow comparisons at locations where the model performed well, (e,g) illustrate the baseflow comparisons at locations where the model performance was poor, and (f,h) depict the streamflow comparisons at locations where the model performance was poor.

The analysis of discharges from a water budget perspective revealed that the model predicted streamflow values ranging from 59.61 cm/year to 15.83 cm/year, with an average

of 32.9 cm/year. In comparison, observed streamflow data ranged from 59.96 cm/year to 15.49 cm/year, averaging 33.23 cm/year. The ME and relative error were  $-0.33$  cm/yr and  $-0.6$  %/yr, respectively, see Figure 8.

The model application described in this study primarily aimed to test the stage–storage–discharge methodology and approach, particularly assessing the uncertainty in populating the F-Table. The model predicted the flow from the hydrologic behavior, and the rating simply determined the timing and magnitude of the resulting flow and stage. Results indicated that the model was generally capable of reproducing water levels and discharges across various conditions, from typical to extreme events. However, its predictions for minimum flow conditions highlighted some model limitations, not necessarily limitations with the F-tables or stage–storage–discharge methodology but likely with the groundwater flow prediction. The exception could be in the highest flow (0.01%) conditions. Poor model performance could be associated with inadequate high-flow rating, or it could be from inadequate runoff prediction. This is particularly evident in the context of the regional hydrology, where the water table interacts extensively with streams and wetlands, especially during dry seasons, likely adequately captured by the model.

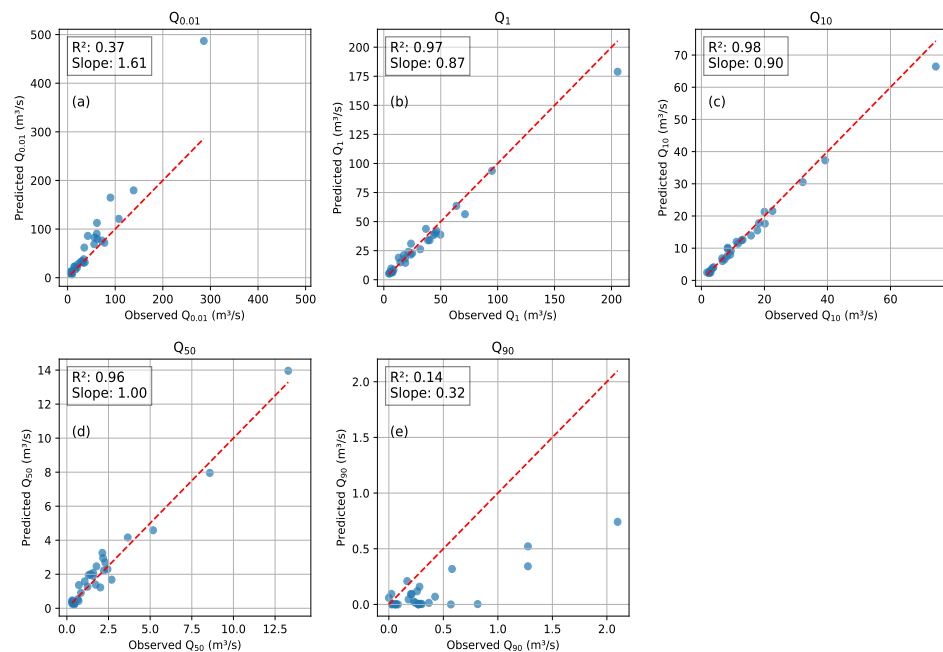


**Figure 7.** Comparison of observed and predicted discharge values for different quantiles ( $\text{m}^3/\text{s}$ ), (a)  $Q_{0.01}$ , (b)  $Q_1$ , (c)  $Q_{10}$ , (d)  $Q_{50}$ , (e)  $Q_{90}$ .

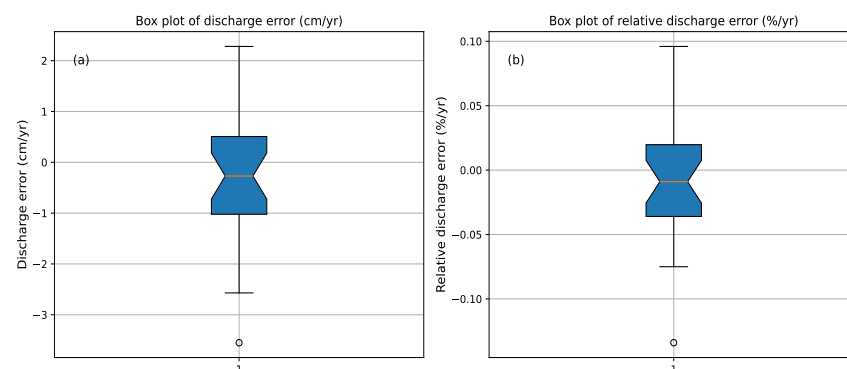


**Figure 8.** Box plots of (a) discharge error as a water budget per year, and (b) the relative discharge error per year.

In this application, HSPF showed proficiency in simulating surface water dynamics. Nonetheless, challenges in scenarios where streams receive significant groundwater discharges are evident. This limitation underscores the necessity for an integrated hydrologic model [26] and better physical groundwater prediction.

### 2.5. Conclusions

This study sought to test a new combined procedure to populate vast stage–storage–discharge rating requirements for larger regional modeling containing many isolated and alluvial wetlands, stream, and lake hydrography elements. These complex hydrologic networks are typical of larger regional models in coastal plain settings [3]. The model application was a complex 14,090 km<sup>2</sup> basin, the Peace River watershed in West-Central Florida, utilizing a widely used and tested hydrologic model (HSPF) previously applied for the region. The model predicted runoff, ET, groundwater recharge, and groundwater contributions to streamflow (baseflow) for a period spanning 23 years (2000–2022). The study developed a novel and computationally efficient approach to generate F-Tables (stage–storage–discharge rating) that better represented the attenuation and flow conveyance behavior of the surface storage’s rich environment. The study area included literally thousands of wetland polygons that greatly attenuated the runoff accumulation and transmittal downstream. The model performance was tested against 28 long-term streamflow gauging station records in the study area. The model yielded overall very reasonable errors in streamflow predictions (mean error  $\approx 0$  and RMSE = 4 m<sup>3</sup>/s) and stage prediction (mean error  $\approx 0$  and RMSE = 0.47 m). Furthermore, the model demonstrated robustness, capturing most of the observations except some of the more extreme (wet and dry) conditions. Some of the extreme behaviors included responses to a period of record drought condition (2000–2001) and several extreme wet periods following unusual successive multiple major hurricanes (2004, 2014).

To enhance the model applicability across the entire spectrum of discharges, detailed consideration must be given to human interventions and their inclusion within the model. Furthermore, integrating a groundwater model with the existing surface water model could yield a more comprehensive understanding of the interactions between groundwater and surface water systems, thereby improving predictions of low-flow conditions. Also, the depth of the water level is a critical determinant of storage capacity. Assuming that the water level depth at the outlet (for stream RCHRESs) dictates storage for the entire alluvial connected wetland reach, the system tends to overestimate the capacity within upstream segments. This overestimation is particularly significant where these segments are of a lower order than the outlet. These stream RCHRESs are typically first- or second-order streams, with a wide variability in stages over the reach. Establishing a better correlation between the depth at the outlet and upstream depths could therefore refine the representation of storage. Such an adjustment would likely lead to more accurate predictions of stages and discharges, especially for extreme events.

The model implementation of the Nilsson [31] storage shape parameters and Mueses [30] discharge relations provided valuable insight into the storage and discharge behavior of alluvial and isolated wetland systems and their role in the late season discharge behavior of streamflow. Model validation metrics, including R<sup>2</sup>, NSE, RMSE, and ME, indicated a strong performance in predicting water levels and discharges, with the majority of stations exhibiting NSE values above 0.7. This performance is indicative of the model’s ability to simulate not only typical hydrological conditions but also most extreme events effectively.

However, the study also identified limitations in the model’s ability to simulate baseflow accurately, particularly in areas with higher groundwater contributions. This limitation emphasizes the need for further research and potential integration of more physically based groundwater modeling techniques similar to what is being applied elsewhere (e.g., Geurink and Bass [26]), better capturing the interactions between groundwater and surface water in these systems. The technique demonstrated here should be applicable in any environment, not just coastal plain settings, where stage–storage–discharge rating conditions must be

developed for stream and wetland hydrography where limited survey or DEM data are available. Even where high-resolution DEM and stream cross sections are available, the equations and parameterization of this technique can be fitted and are shown to be useful to develop suitable equations to interpret the data and implement a model. Alshehri and Ross [27,28] showed that the stage–storage–discharge parameters were highly accurate in representing high-resolution topographic and bathymetric data in measured wetlands and stream sections.

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