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Hydrological Modeling of Large River Basin Using Soil Moisture Accounting Model and Monte Carlo Simulation

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Abstract: This description outlines a Geographic Information System (GIS)-based rainfall-runoff model that simulates the flow of water in a river basin. The model operates on a daily time step and consists of four non-linear storage components: interception, soil moisture, channel, and groundwater. It employs (SCS) Unit Hydrograph model to determine unit hydrograph ordinates. The model replicates the movement and storage of water in various parts of the basin, including vegetation, the soil surface, the soil profile, and groundwater layers. To address uncertainty, a Monte Carlo simulation feature is integrated into the model. This feature generates required number of sample sets with random parameter values. The model is run for all these realizations during a calibration period, and performance metrics like NSE are calculated for each calibration yearTo assess prediction uncertainty, model parameter weights are computed by normalizing the corresponding likelihood values. These weights sum up to one and represent the probabilistic distribution of predicted variables, illustrating the impact of structural and parameter errors on model predictions. A sensitivity analysis reveals that the Muskingum constants K and X have the greatest influence on model performance, while parameters θGW, θSW, θfc, and θpc have a minimal effect on the model's performance.

Keywords:SMA model ,Monte Carlo Simulation, Optimization , Uncertainty analysis ,Sensitivity Analysis

I. INTRODUCTION

In recent decades, there has been a notable increase in the application of hydrological models, coupling them with Geographic Information Systems (GIS) and advanced simulation techniques[1][2][3][4].V. Sheikh et al. [5]emphasized the crucial role of soil moisture content in the root zone as a primary driver in governing hydrological processes near the land surface. Their research reveals into how precipitation is distributed into infiltration, runoff, storage in the root zone, and percolation into deeper groundwater storage. A comprehensive evaluation of how multiple variables such as rainfall, land use, and climate impact the response of a catchment area. They employed a distributed-parameter, physical-process watershed model to simulate flood peaks, volume, soil water equations, sediments, and groundwater recharge. Their study introduced the Soil Moisture Accounting concept with a static infiltration component to conceptualize the activation of soil moisture, which involves satisfying soil moisture deficits before runoff activation[6]. James Charalambous et al. [7]applied the URBS hydrological model in combination with Monte Carlo simulation to examine rainfall-runoff processes within a catchment. Their significant finding

demonstrated that Monte Carlo simulation techniques are effectively applicable to large catchment areas, highlighting the practicality of this approach in real-world applications. Adeyemi Emman Aladejare et al. [8]presented a

probabilistic approach that involves utilizing Monte Carlo Simulation (MCS) for purposes related to design optimization and sensitivity analysis. This method optimizes specific design parameters or objectives while accounting for probabilistic variables and uncertainties. Following single-objective optimizations, they performed sensitivity analysis using stochastic activity networks (SANs) within the field of operations research. Peter L. Bonate[9]introduced a simulation approach that integrates mathematical modeling with the incorporation of stochastic or random variability. This class of simulation methodology aims to provide a more comprehensive understanding of complex systems subject to uncertainty.

II SOIL MOISTURE ACCOUNTING MODEL

A   Input Data

Ideally, the process begins by defining a watershed through the utilization of Geographic Information System (GIS) software, which takes as input a high-resolution digital elevation model (DEM) with a spatial resolution of 30 meters by 30 meters, obtained from the Shuttle Radar Topography Mission (SRTM) accessible through the USGS Earth Explorer.[10][11][12] Topographical datasets are then derived using this DEM. Over a span of seventeen years, data spanning from 2001 to 2017 was meticulously collected for the Wainganga River Basin. Precipitation datasets, in particular, were extracted from the Indian Meteorological Department (IMD) in Pune, with a spatial resolution of 0.25

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meters by 0.25 meters. Furthermore, data on potential evaporation was sourced from the Copernicus Climate Change Data Store. To complete the information set, observed stream flow data for a specific outlet within the watershed was procured from the India Water Resources and Information System (WRIS). Additionally, the observed dataset was converted into units of millimeters per day.

B   Model description

i. storage capacity model

In the current scenario, the pivotal factors influencing the quantity of water that vegetation can intercept include the rainfall on the same day and the prevailing rate of evaporation. Within this context, we designate the upper limit of storage capacity for interception as "CEP_{max}."

Section I
If,

$PET_n > CEP_{max}$;

Then, $EVP_{max} = CEP_{max}$

And if $PET_n < CEP_{max}$;

Then, $EVP_{max} = PET_n$ (1)

The preceding segment endeavors to estimate potential evaporation by considering the interception storage, assuming it's at maximum capacity, and then transfers the outcomes to Section II of the model.

Section II
If, $0 \leq intstore_{n-1} \leq CEP_{max}$ and,
Case (1)
If, $rainfall_n \leq (CEP_{max} - intstore_{n-1})$
Then, $intcept_n = rainfall$
$evp_n = min((intstore_{n-1} + rainfall_n), EVP_{max})$ (2)
Case(2)
If, $rainfall_n \geq (CEP_{max} - intstore_{n-1})$
Then,
$intercept_n = (CEP_{max} - interstore_{n-1})$
$evp_n = EVP_{max}$

Taking into consideration the current day's rainfall, the maximum capacity of the interception store for that day, as well as the previous day's interception storage, this section thoroughly calculates the actual evaporation value.

Section III
$intstore_n = intstore_{n-1} + intcept_n - evp_n$ (3)

In Section III, the simulation focuses on the evolution of the interception store over time, taking into account factors such as precipitation, evaporation, and the state of the interception store.

ii. Net Rainfall

Net rainfall is the term used to describe the actual precipitation that reaches the ground, factoring in the losses incurred due to interception.

$rainnet_n = (rainfall_n - intcep_n)*canopy + rainfall*(1-canopy)$ (4)

Where, $rainnet_n$ = Net rainfall (mm), on nth day;
canopy = Basin Covered vegetation(%)

iii. SCS Unit Hydrograph Model

The model under consideration incorporates a parametric-based Unit Hydrograph (UH) Model. The UH model from the Soil Conservation Service (SCS) employs a dimensionless unit hydrograph to forecast the runoff reaction of a watershed in response to a rainfall event[13][14]. It describes the discharge, denoted as Ut, at any given moment as a proportion to the peak discharge, denoted as Up, for that specific moment, which is a fraction of Tp, the time it takes to reach the UH peak. The equation is expressed as follows:

$$UH_{Depth} = C \frac{A}{T_p}$$ (5)

C = Conversion Constant (2.08 in SI),
A = area of catchment

In a unit hydrograph, the time at which the peak, or the time of the rising flow, occurs is intricately connected to the duration of the excess precipitation unit. More precisely, it corresponds to the duration required for the excess precipitation to traverse the watershed and attain its maximum runoff response. This linkage plays a pivotal role in hydrological modeling and is frequently represented as a fraction of the excess precipitation duration.

$$T_p = \frac{t_r}{2} + t_{lag}$$ (6)
$$t_{lag} = 0.6*t_c$$ (7)

Where,
T_p = Time of Peak,
t_r = Duration of Excess precipitation,
t_{lag} = Lag time,
T_c = Time of Concentration

By utilizing equations (5) and (6), one can employ a dimensionless version of the unit hydrograph to compute the complete unit hydrograph for a particular rainfall event. This implies that the hydrograph takes on a triangular configuration. It's worth noting that 37.5% of the total runoff volume transpires prior to reaching the time when the peak discharge (Tp) occurs, while the remaining 62.5% of the volume transpires after Tp.

$$T_b = \frac{1}{0.375} T_p = 2.67 T_p$$ (8)

Tb = Entire 100% Volume of runoff

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iv Infiltration Model

Once the canopy interception storage is saturated with precipitation, any surplus water is then accessible for seepage into the soil. The model calculates the potential volume of evaporation and infiltration through the following process.

$$infil = Infil_{max} * (1 - \frac{szwc}{\theta fc}) \qquad (9)$$

Where,
Infil = potential evaporation infiltration volume
MaxSoil Infil= maximum infiltration rate
szwc= volume in the soil storage at the beginning of the time step
θfc= maximum volume of the soil storage

The actual infiltration volume during a specific time interval, denoted as ActInfil, is determined by taking the minimum of two factors: Pinfil and the available water volume for infiltration, which is represented by rainnet.

v. Actual Evapotranspiration

Part [1]
EVP from interception model by Equ 1 $\qquad (10)$

Part [2]
Case(1)
if, $\theta SW \leq \theta SW_n < \theta fc$

EVP from equation (2)

$$uzet_n = (pet_n - evp_n) * [\frac{(\theta SW_n - SW)}{\theta fc}]^{(1 - \frac{(\theta SW_n - \theta SW)}{\theta fc})}$$

$$lzetn = (pet_n - evp_n - uzet_n)^{e - (L+1)} \qquad (11)$$

Case (2)
if, $\theta fc \leq \theta SW_n$
EVP (from equation (2))

$$uzet_n = (pet_n - evp_n) \qquad (12)$$
$$lzet_n = (pet_n - evp_n - uzet_n) * e^{-LZC}$$

Part [3]
$$aet_n = evp_n + uzet_n + lzet_n \qquad (13)$$

Where,
Aet=Actual evapotranspiration (mm),
$uzet_n$= Upper soil zone evapotranspiration (mm),
$lzet_n$= Ground water store evapotranspiration
LZC=Constant governing evapotranspiration from lower zone (parameter).

vi. Soil Moisture storage

Applying a mass balance equation at every time step is a fundamental and widely used method. The equation used to adjust soil moisture content is as follows

$$\theta SW_n = \theta SW_{n-1} + rainet_n(1 - UH_{Depth}) - uzet_{n-1} - pflow_{n-1} - drain_{n-1} - szro_{n-1} \qquad (14)$$

$$\theta SW1_n = \theta SW_{n-1} - uzet_{n-1} - pflow_{n-1} - drain_{n-1} - szro_{n-1} \qquad (15)$$

Where,
θSW_n = soil zone water content (mm),
θSW_{1n} = Previous day soil zone water content after losses (mm),
θSW_{n-1}=Previous day soil zone water content (mm),
$uzet_{n-1}$ is the previous day evapotranspiration from upper soil zone in mm,
$pflow_{n-1}$ = Macropore flow in mm,
$drain_{n-1}$ = Drainage in mm,
$szro_{n-1}$ = Interflow in mm.2.5.7 Interflow

Interflow pertains to the lateral flow of water beneath the soil surface, above the groundwater table but below the ground level. This phenomenon typically occurs when the soil reaches a state of saturation, preventing further water infiltration. In the model, interflow is permissible as long as the soil moisture content remains above the field capacity threshold.

$$szro = MaxSoil\ Infil \left(\frac{szwc}{\theta pc}\right) \left(1 - \frac{gzwc}{GZWCmax}\right) \qquad (16)$$

vi Base Flow
Excess water that permeates the soil beyond its field capacity serves as a recharge source for the groundwater reservoir or aquifer. When the soil's moisture content reaches the field capacity, any surplus water that infiltrates into the soil contributes to the recharge of the groundwater.
Mathematically, the determination of base flow is as follows:

$$\theta GW = Maxsoilper * \left(\frac{\theta GW}{\theta GW\ max}\right) * \left(1 - \frac{\theta GW_n}{\theta GW_{max}}\right) \qquad (17)$$

The groundwater storage receives input from the drainage of the upper soil layer and releases output primarily in the form of base flow and lower zone evapotranspiration. To update the groundwater store on a daily basis, the following equation is applied:

$$\theta GW_n = \theta GW_{n-1} + drain_n - lzet_{n-1} - gwro_{n-1} - infilz \qquad (18)$$

Where $gwro_n$ is the ground water runoff in mm, θGW_n is the ground water store in mm

vii Muskingum Model
SMA model is linked with the Muskingum model calculates the discharge at the outlet of the basin, the. The Muskingum model, in a comprehensive manner, utilizes finite difference approximation to establish a solution for the continuity equation governing the flow routing.

$$\left(\frac{I_{t-1} + I_t}{2}\right) - \left(\frac{O_{t-1} + O_t}{2}\right) = \left(\frac{S_t - S_{t-1}}{\Delta t}\right) \qquad (19)$$

In the modeling of catchment areas, particularly during flood events, storage volumes in river reaches are described using the concepts of prism storage and wedge storage. These concepts help estimate the total storage capacity and its

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variation under different flow conditions. Consequently, the Muskingum model defines storage as follows:

$S_t = KO_t + KX(I_t - O_t)$

(20)

$= KO_t + KXI_t - KXO_t$

$= K[XI_t + (1-X)O_t]$

S_t = Storage, K = Travel Time, X = diamensionless weight ($0 \leq X \leq 0.5$)

From above weighted discharge is represented by $[XI_t + (1-X)O_t]$. Substituting equation 26 into equation 27 and the result values at time t is:

$$O_t = \left(\frac{\Delta t - 2KX}{2K(1-X)+\Delta t}\right) * I_t + \left(\frac{\Delta t + 2KX}{2K(1-X)+\Delta t}\right) * I_{t-1} + \left(\frac{2K(1-K)-\Delta t}{2K(1-X)+\Delta t}\right) O_{t-1} \quad (21)$$

The equation mentioned above is utilized in the model to compute the discharge values of a hydrograph, taking into account time-stepped rainfall, the initial condition (where $O_t = 0$), and the Muskingum parameters K and X.

III. METHODOLOGY

A   Monte Carlo Simulation

Monte Carlo simulation is a computational technique that was developed in the 1940s.[15][16] It depends on statistical sampling methods to derive probabilistic estimates for mathematical equations or models. These simulations generate probabilistic approximations for how a system behaves and are carried out using computers[17][18][19]. To gauge a system or model's behavior under uncertain conditions, a substantial amount of iterations or trials are executed. Monte Carlo simulation relies on statistical sampling techniques, often involving the generation of random numbers, to embody uncertainty in input parameters or variables. These randomly sampled values serve as inputs for the model or equation. They produce distributions that depict potential outcomes, enabling an evaluation of the spectrum of possible results along with their respective probabilities.[20][21]

B   Hydrological Modelling

An updated modeling framework has been incorporated into a basic rainfall-runoff model, combining the loss method and Muskingum routing for hydrological modeling alongside Monte Carlo simulation. In this setup, the rainfall output is determined by simulating model input and parameters. During each model run, a unique set of input and model parameter values is chosen. [22]These values are selected randomly from their associated distributions, signifying that they are not fixed but are drawn from probability distributions. This introduces an element of randomness into the model runs.

i. Performance indicator

NSE (Nash-Sutcliffe Efficiency) stands as a widely acknowledged and frequently employed metric for evaluating hydrological models. Its purpose is to evaluate the quality of fit by measuring the agreement between simulated values (S) and observed values (O) of a hydrological variable, typically stream flow.

$$NSE = 1 - \frac{\Sigma Q_{i,s} - Q_{i,o})^2}{\Sigma(Q_{i,o} - Q_o)^2} \quad [22]$$

NSE = Nash Sutcliff efficiency
$Q_{i,s}$ =is the ith simulated discharge
$Q_{i,o}$ =is the ith observed discharge

Sum of Squared Errors (SSE)

SSE (Sum of Squared Errors) is determined by adding together the squares of the discrepancies between model predictions and observed values.

$$SSE = \sum_{i=1}^{n} (Q_{i,s} - Q_{i,o})^2 \quad [23]$$

Sum of Squared Log Errors (SLE)

SSLE (Sum of Squared Logarithmic Errors) represents a modified version of SSE in which both observed and predicted values undergo a natural logarithm transformation before the squared differences are computed.

$$SLE = \sum_{i=1}^{n} \{\log(Q_{i,s}) - \log(Q_{i,o})\}^2 \quad [24]$$

Sum of Absolute Errors (SAE):

SAE (Sum of Absolute Errors) is determined by adding together the absolute values of the disparities between model predictions and observed values.

$$SAE = \sum_{i=1}^{n} |(Q_{i,s} - Q_{i,o})| \quad [25]$$

ii. Model Calibration

Model calibration involves the process of adjusting the parameters or configurations of a mathematical or computational model to align its predictions or simulations as closely as possible with observed data.[23][24] In the context of predicting the propagation of flow through a river reach, while considering the time it takes for water to travel downstream, the Muskingum-Cunge routing, also known as the Muskingum method, is employed. The model calibration phase spans from 2001 to 2010, followed by a validation phase from 2011 to 2017.

The steps in model calibration are as follows:
1. Commence by establishing an objective function or fitness function, which quantifies the degree of fit between model predictions and observed data.
2. Specify the input parameters for the model (θGW, θSW, K,

Table no 1   Optimized Parameter Set

Sr. No	Parameter	Description	Optimum Value	Lower	Upper
1	θGW	Ground zone water content	455	445	465
2	θSW	Soil zone water content	88	78	98
3	θfc	Field capacity	232	222	242
4	θpc	Pore capacity	361	351	371
5	k	Muskingum constant	3.12	1	5
6	x	Muskingum constant	0.13	0.1	0.5

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X, θfc, θqc).

3. Define the range and probability distribution for each input parameter, as indicated in Table 1

4. Input each set of parameter values into the model and execute simulations. Generate a set of ten thousand sample parameter sets with random values.

5. Calculate performance indices (NSE, SSE, SLE, SAE) after running the model for each calibrated year, noting the parameter set with the maximum efficiency.

6. Obtain the optimal parameter set by computing the average value that represents the highest efficiency over the calibration period.

7. Ultimately, as illustrated in Table 2, model efficiencies are computed for both the calibration and validation periods.

C   *Quantifying the Uncertainty*

Monte Carlo Variability characterizes the inherent fluctuations and disparities in data or results that naturally unfold over time. Uncertainty materializes when there is a dearth of information or understanding about forthcoming events or their outcomes [25][26]It's crucial to recognize

that both variability and uncertainty are integral aspects of any hydrological process. Even when armed with a substantial reservoir of historical performance data and advanced forecasting techniques, the future remains fundamentally unpredictable. In the realm of uncertainty analysis, the common practice of employing Monte Carlo Simulation (MCS) produces outcomes presented as Cumulative Density Functions (CDFs), histograms, and confidence intervals. CDFs serve as visual representations of the probability distribution of a variable. CDFs represent the individual model runs with various parameter values randomly selected for each run. They depict the cumulative probability of the variable assuming values less than or equal to a specific threshold. CDFs serve as valuable tools for comprehending the overall distribution shape and evaluating the likelihood of specific outcomes. On the other hand, confidence intervals offer a range of values within which a particular statistic or parameter is projected to be located with a specified level of confidence. In the context of uncertainty analysis, you can determine confidence intervals (e.g., 95% and 5% intervals) surrounding the target outcome by utilizing the results derived from the MCS. These intervals serve as an indicator of the

Table 2   Calibration and Validation period efficiency

YEAR	PARAMETER						CALIBRATION PERIOD EFFICIENCY									
	θGW	θSW	θfc	θpc	k	x	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
2001	461	98	235	364	3.08	0.126	0.96	0.94	0.95	0.96	0.94	0.96	0.94	0.95	0.96	0.97
2002	465	99	239	364	2.7	0.13	0.95	0.94	0.95	0.94	0.94	0.95	0.94	0.94	0.96	0.98
2003	458	91	233	368	2.8	0.13	0.96	0.94	0.95	0.95	0.94	0.95	0.94	0.95	0.96	0.98
2004	457	98	226	355	3.86	0.137	0.95	0.92	0.93	0.97	0.92	0.95	0.96	0.96	0.94	0.97
2005	450	88	239	364	2.9	0.127	0.96	0.94	0.95	0.95	0.94	0.95	0.94	0.95	0.96	0.98
2006	459	88	236	355	3.24	0.13	0.96	0.93	0.95	0.96	0.94	0.96	0.94	0.96	0.96	0.98
2007	467	100	222	367	2.87	1.3	0.96	0.94	0.95	0.95	0.94	0.95	0.94	0.95	0.96	0.98
2008	460	84	232	361	3.76	0.14	0.95	0.92	0.93	0.97	0.92	0.95	0.92	0.97	0.94	0.97
2009	460	95	229	361	2.86	0.125	0.96	0.94	0.95	0.95	0.94	0.95	0.94	0.94	0.96	0.97
2010	455	88	233	353	3.09	0.135	0.96	0.94	0.95	0.96	0.94	0.96	0.94	0.96	0.96	0.98
Avg	459	93	232	361	3.12	0.13	0.96	0.94	0.95	0.96	0.94	0.95	0.94	0.95	0.96	0.98

YEAR	PARAMETER						VALIDATION PERIOD EFFICIENCY						
1)	θGW	θSW	θfc	θpc	k	x	2011	2012	2013	2014	2015	2016	2017
2001	461	98	235	364	3.08	0.126	0.96	0.96	0.94	0.91	0.92	0.97	0.96
2002	465	99	239	364	2.7	0.13	0.96	0.95	0.94	0.91	0.93	0.98	0.95
2003	458	91	233	368	2.8	0.13	0.96	0.96	0.95	0.92	0.93	0.98	0.95
2004	457	98	226	355	3.86	0.137	0.97	0.99	0.96	0.91	0.92	0.97	0.96
2005	450	88	239	364	2.9	0.127	0.96	0.96	0.94	0.91	0.93	0.98	0.96
2006	459	88	236	355	3.24	0.13	0.96	0.97	0.95	0.91	0.93	0.98	0.97
2007	467	100	222	367	2.87	1.3	0.96	0.96	0.95	0.92	0.93	0.98	0.96
2008	460	84	232	361	3.76	0.14	0.97	0.99	0.97	0.91	0.92	0.97	0.96
2009	460	95	229	361	2.86	0.125	0.95	0.95	0.94	0.91	0.92	0.97	0.96
2010	455	88	233	353	3.09	0.135	0.97	0.98	0.96	0.92	0.93	0.98	0.96
Avg	459	93	232	361	3.12	0.13	0.96	0.97	0.95	0.91	0.93	0.98	0.96

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precision and reliability of the estimate.

D   Sensitivity

Sensitivity analysis plays a crucial role in pinpointing the input variables that wield the most substantial influence on project outcomes [27]The objective of sensitivity analysis is to gain insights into how changes in individual parameters affect the predictions or results generated by the model. Through a methodical process of adjusting each parameter while holding the others constant, you can determine which parameters exert the greatest impact on the model's output and which ones have a comparatively minor effect[28]. This knowledge is invaluable for comprehending the model's behaviour, identifying pivotal parameters, and concentrating efforts on minimizing uncertainty in those critical variables[29][30].

III RESULTS AND DISCUSSIONS

Dotty plots, often referred to as scatter plots, are visual representations in which individual data points are depicted as dots on a two-dimensional grid. In the provided Graph 1, the horizontal x-axis signifies the parameter values, while the vertical y-axis represents a certain metric assessing the performance or results of the objective function. In the context of each dot on the plot, it corresponds to a single realization from the Monte Carlo simulation, and its position on the chart is determined by the parameter values and the corresponding value of the objective function for that particular realization. Parameters that exert a substantial influence on the likelihood measures or variables are assigned higher rankings, whereas those with a lesser impact receive lower rankings, as depicted in Graph 2. On the contrary, when the cumulative distributions of parameter values are closely grouped in the plot, it signifies that the likelihood measure or variable is not significantly affected by that specific parameter. Changes in the parameter yield minimal impact on the outcomes, and the parameter may not be a critical driver of variability within the model. Graphs 3 and 4 illustrate the simulated discharge histogram and the cumulative distribution, which provides information about sample quartiles.
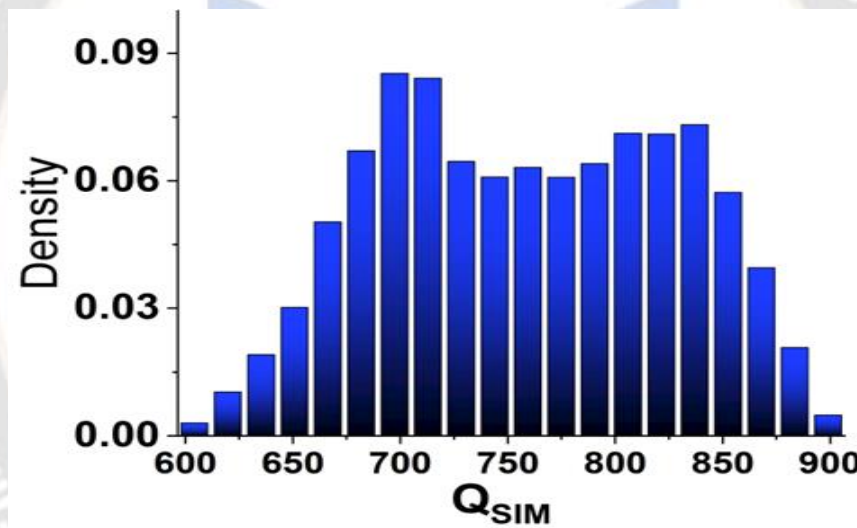
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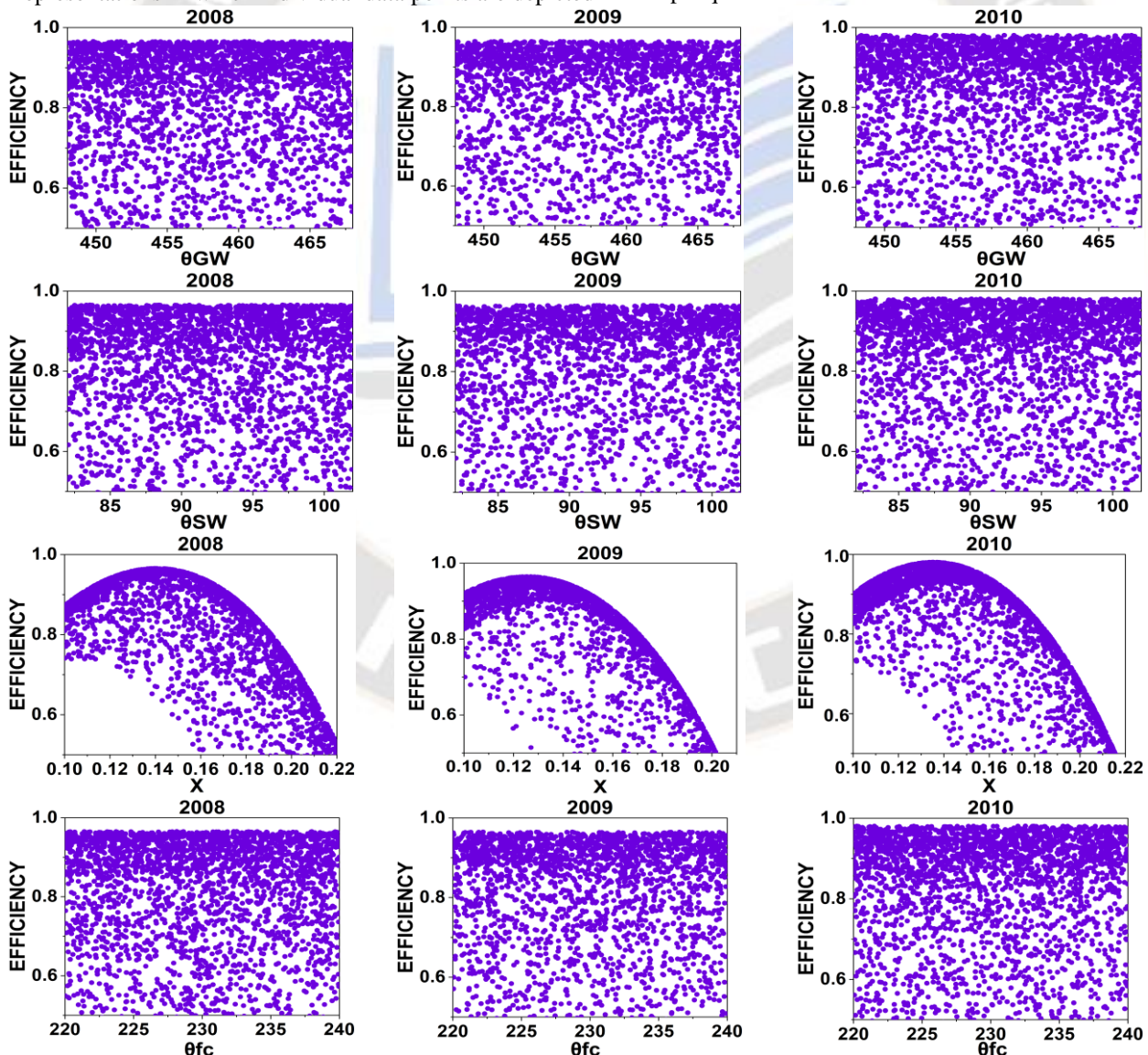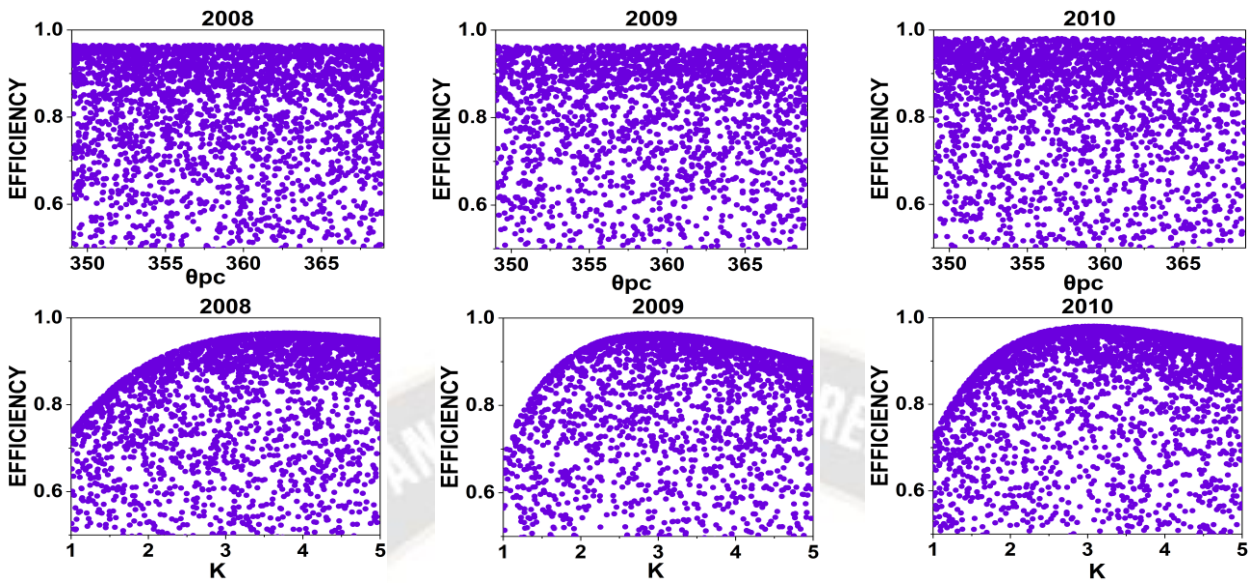
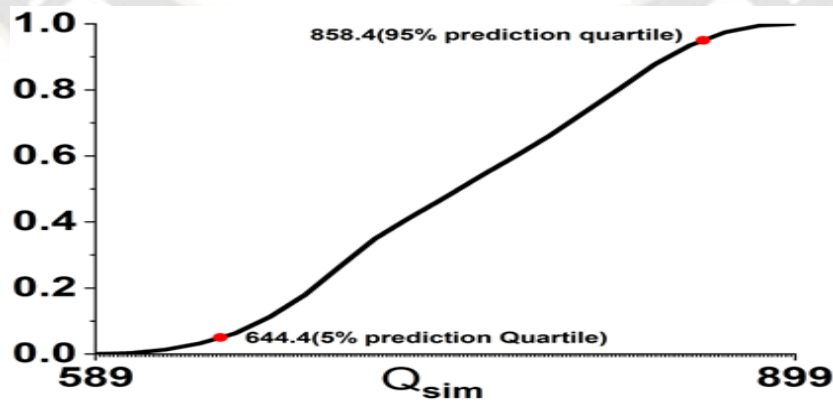*Graph 1 Monte Carlo simulation Dotty plots*

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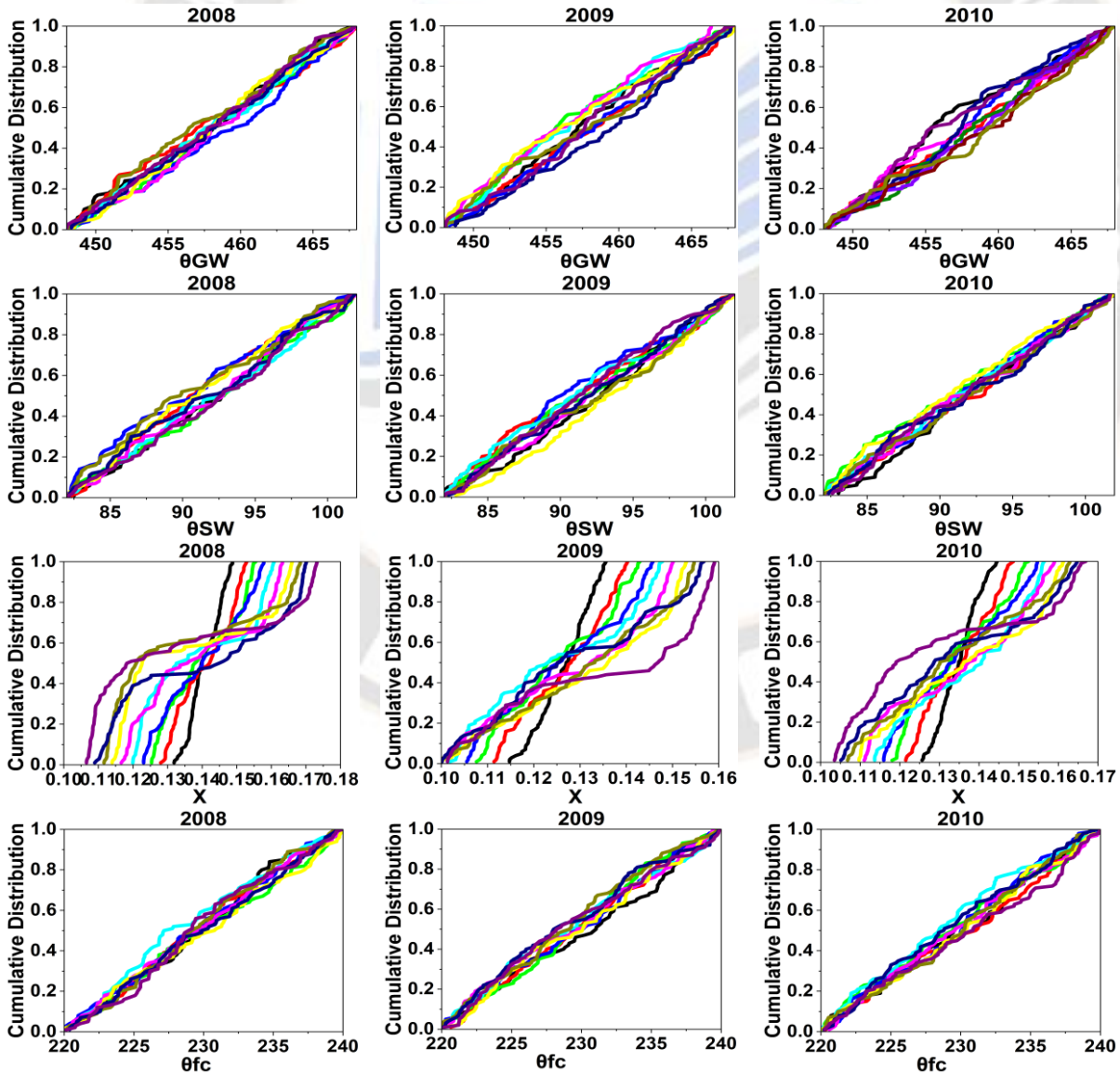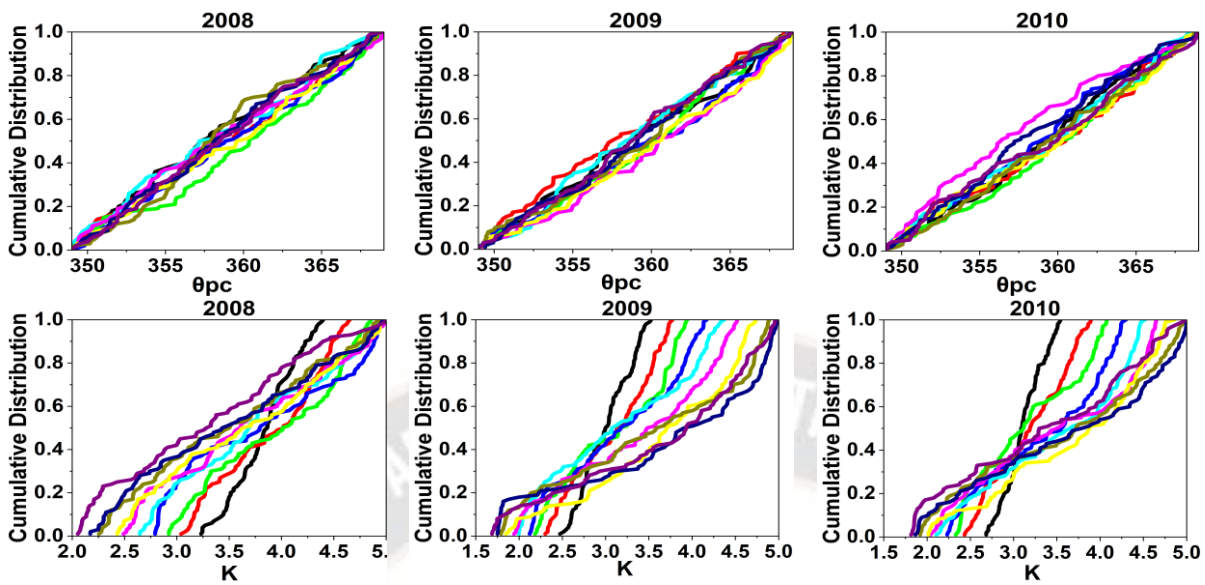
Graph 2 Sensitivity plots

Graph 3 Qsimulates vs Density

Graph 4 Qsimulates vs cumulative density

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IV CONCLUSION

The Soil Moisture Accounting model, when combined with GIS techniques, demonstrates a strong alignment with observed and simulated stream flow. When integrated with the Monte Carlo algorithm, it reveals that the model employed in this study adheres to the principles of equifinality and non-uniqueness. In essence, this implies that when fitting the model to real-world data, there are numerous sets of model parameters that can be used, and each of these parameter sets can yield a satisfactory match with the observed data. This practical insight suggests that the system being modeled is intricate, and there exists inherent uncertainty in determining the "correct" model parameters, as multiple sets of parameters can yield comparable results. The optimum parameter values, which lead to favorable model performance, closely resemble previously identified optima. A sensitivity analysis underscores that the Muskingum constants K and X exert a significant influence on the model's performance, while the parameters θGW, θSW, K, X, θfc, and θqc have a relatively minor impact on the model's functionality. In the realm of uncertainty analysis, one can determine confidence intervals (e.g., 95% and 5% intervals) surrounding the outcome of interest by utilizing the results from the Monte Carlo Simulation. These intervals serve as a measure of the precision and reliability of the estimate. The model has shown promise in its initial application, indicating its effectiveness in some aspect, potentially in its ability to model or analyze a specific system or process.

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. DECLARATIONS

Author contribution. Author 1 has collected input and analyzed,developed formulas and software model.Calibration and validation was dne.After running model results were plotted for efficiency, sensitivity ,uncertainty while author 2 look into GIS part ,graphs and checked result.

FUNDING STATEMENT.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ADDITIONAL INFORMATION

SME MODEL prepared is applied for Copyrights.

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