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Exploring the Potential of MIKE 11 NAM for Rainfall-Runoff Modeling Frameworks in Varied Environmental Settings – A comprehensive review

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ABSTRACT: *A Rainfall-Runoff (R-R) model serves as a mathematical framework elucidating the intricate relationship between rainfall and runoff within a watershed or catchment area. The process of converting rainfall into runoff across a catchment entails a highly intricate hydrological phenomenon characterized by nonlinearity, temporal variability, and spatial distribution. Over time, numerous models have been devised to simulate this phenomenon, tailored to address specific research objectives and varying complexities. These models span across categories such as empirical, black-box, conceptual, or physically-based distributed models, each uniquely suited to different problem domains. In essence, the overarching aim of these models is to effectively translate rainfall inputs into corresponding runoff outputs. Hydrological models, including Rainfall-Runoff (R-R) models, serve as simplified representations of complex real-world systems. Among the array of hydrologic models utilized for estimating runoff from precipitation, the MIKE 11 NAM model stands out as a widely acclaimed and accurate tool on a global scale. This model, characterized as deterministic and lumped, operates on a conceptual basis, relying on interconnected mathematical formulations to depict land phase dynamics within the hydrological cycle. In the context of this paper, an exploration of the diverse attributes of the NAM model is presented.*

Keywords: *Hydrologic Modeling, MIKE-NAM, Maximum Water Content, Nash-Sutcliffe Efficiency, Rainfall-Runoff Model*

INTRODUCTION

Water present in rivers and lakes is a direct and simple source for the industries, irrigation and domestic use which is obtained mainly from the rainfall; this rainfall reaches the water body through rainfall runoff process. Design of all water resources planning and management project require long term runoff data which is generally not available at the project sites. Hence runoff has to be predicted with the help of rainfall data. Transformation of rainfall into runoff over a catchment is a complex phenomenon as the process is highly non-linear, time varying and spatially distributed. With access to long-range data, tasks such as flood control, flood forecasting, and reservoir analysis can be efficiently conducted, enabling the establishment of predictive models. Through these models, it becomes feasible to forecast flow rates for extended periods ahead.

Hydrologic models serve as simplified representations of real-world systems, aiming to capture their essential dynamics. Among these models, the rainfall-runoff model stands out as a mathematical framework delineating the relationship between rainfall and runoff within a watershed or catchment area. It proves invaluable for predicting runoff volumes based onprecipitation inputs. Surface runoff is influenced by various factors including catchment size, length, slope, and time of concentration. Upon rainfall, water movement is dictated by soil conditions, topography, and moisture levels. Notably, infiltration plays a pivotal role in runoff computation within a watershed; higher infiltration on flat terrain leads to reduced runoff, while steep slopes typically result in increased runoff.

2.0 Classification of Hydrological Models

Essentially, hydrologic models are designed to simulate the diverse processes within the hydrologic cycle. These models vary in their spatial and temporal simulation capabilities, consequently yielding diverse outputs. Precipitation serves as the primary input for any rainfall-runoff model, with the model then predicting its fate considering various hydrologic cycle components such as interception, surface storage, and evapotranspiration. These predictions are contingent upon watershed parameters and are typically expressed as runoff. Most hydrologic models incorporate functions to distribute precipitation among these cycle components. The categorization of these models depends on the approach utilized in these distribution functions, leading to distinct classifications.

2.1 **Event based and Continuous Models**: Event-based models are employed to predict runoff resulting from individual storm events and are primarily utilized for design purposes, such as engineering culverts to accommodate specific storm frequencies (e.g., designing for a 100-year event). In contrast, continuous models are utilized to simulate flow patterns and other watershed functions across extended durations of time

2.2 **Conceptual and Physically based Models:**Conceptual models portray the watershed as a simplified system, employing flow parameters to represent physical relationships in a straightforward manner. Conversely, physically based models strive to replicate hydrological processes using fundamental physics-based equations, such as kinematic waves or diffusive wave equations.

2.3 **Lumped and Distributed Models:** Lumped models treat the entire watershed as a single entity, with each model parameter representing an average value across the entire area, leading to potentially less accurate outputs. On the other hand, distributed models divide the watershed into smaller sub-basins or hydrological units (grids), each characterized by distinct values of model parameters. Consequently, distributed models account for spatial variability within the watershed, resulting in more precise outcomes compared to lumped models.

LITERATURE REVIEW

Fleming (1975) assessed the reliability of the MIKE 11 NAM model by employing the Root Mean Square Error (RMSE) method, which quantifies the absolute error between observed and simulated flows. As the RMSE values approach zero, they indicate a closer alignment between observed and simulated flows.

SupiahShamsudin et al. (2002) conducted a study on the Layangriver employing the MIKE 11 NAM model, yielding satisfactory and reliable outcomes. The peak flow recorded in 1992 stood at 20.94m^3/s. Through calibration and validation, the model produced an Efficiency Index of 0.75 and a Root Mean Square Error value of 0.08. Additionally, it was noted that enhancing the availability of automatic rainfall stations could lead to improved estimations of runoff discharge.

Faith Keskin et al. (2007) conducted a study in the Yuvacik Dam basin, Turkey, employing the MIKE 11 NAM model to simulate runoff, utilizing both rainfall and snowmelt as inputs. The primary objective was to provide water to the Izmit municipality while also managing downstream floods resulting from runoff. Through calibration and validation, it was determined that the model effectively replicated observed inflow starting times, peaks, and time bases, with a coefficient of determination exceeding 0.7 in the majority of events.

Doulgeris et al. (2010) conducted a study in the Strymonas River catchment, employing the MIKE 11 NAM model. The model's parameters were calibrated initially using an auto-calibration method, followed by a trial and error approach. It was determined that the model effectively predicted river discharge to a satisfactory degree.

Nguyen et al. (2010) conducted a study in the Ben Hai river basin, aiming to integrate auto-calibration with the trial and error approach within the MIKE 11 NAM model. The study concluded that the alignment of hydrograph shape and total flow volume between simulation and observation suggests consistency in the model parameters.

Galkate et al. (2011) conducted a study at the Rahatgarh site within the Bina basin, Madhya Pradesh, utilizing the MIKE 11 NAM model. The study involved the development, calibration, and validation of the model using streamflow data from the Rahatgarh site. The coefficient of determination values for calibration and validation stood at 0.796 and 0.609, respectively, indicating a strong correlation between observed and simulated flow values concerning rate, timing, and volume & shape of hydrograph. Additionally, the model's performance was assessed using the Nash-Sutcliffe Efficiency Index (EI) and Sum of Square of Error (SSE), with an efficiency index of 81%, indicating its suitability for extended time periods within the Bina basin.

Odiyo et al. (2012) conducted a study on the Latonyanda River Quaternary catchment employing the MIKE 11 NAM model. The study found a strong correlation between observed and simulated runoff flow within the LRQ catchment, albeit with some discrepancies. Notably, peak events were under-predicted, and a few instances of low flows were observed. Additionally, occasional over-predictions were attributed to illegal irrigation abstractions, which reduced the observed values.

Hafezparast et al. (2013) conducted a study in the Sarsoo River basin, employing the MIKE 11 NAM model with an auto-calibration approach. Calibration of the model utilized streamflow data and subsequent validation spanned three years. The study concluded that the relationship between observed and simulated flow values exhibited a notably strong correlation, with a coefficient of determination reaching 0.74.

Abu El-Nasr et al. (2013) conducted a study in the Jeker Catchment, Belgium, utilizing two distinct methods: MIKE 11 NAM and MIKE SHE. The study's conclusion indicated that the MIKE NAM model outperformed MIKE SHE both during calibration and validation periods.

S.I.I. Amir et al. (2013) conducted a study in the Fitzroy basin, Australia, employing the MIKE 11 NAM model with an auto-calibration approach for model parameters across multiple sub-catchments. Calibration and validation of the model were carried out, with results effectively represented through hydrographs. The model's reliability was assessed using the efficiency index (EI), ranging between 0.849 and 0.961, and the index of agreement (IA), ranging between 0.821 and 0.951.

Satish et al. (2015) conducted a study in the Ujjain Basin, a part of the Shipra Basin in Madhya Pradesh, focusing on water availability for Ujjain city, particularly for the KhumbMela scheduled for 2016. They developed a rainfall-runoff model using MIKE 11 software for the entire Shipra basin and incorporated the Narmada-Shipra link for the year 1992. Dependable flow volumes were calculated for various probabilities. Following the addition of the Narmada-Shipra link, the river maintained a minimum flow of 1.72m^3/s throughout the non-monsoon period. The highest flow recorded was 9.21m^3/s at a 70% probability, while at 100% probability, it reduced to 0.02m^3/s

Neerav Agrawal et al. (2016) discusses Rainfall-Runoff (R-R) models, which describe the relationship between rainfall and runoff in a watershed. These models are essential for understanding complex hydrological processes. They are categorized into empirical, black-box, conceptual, or physically-based distributed models based on their complexity and purpose. R-R models simplify real-world systems and are used to calculate runoff from rainfall. The MIKE 11

NAM model is highlighted as one of the most accurate R-R models, being deterministic and conceptual. The paragraph mentions a paper discussing various features of the NAM model.

Julian R. Thompson et al (2017)describe the simulation of thirty UK Climate Projections 2009 (UKCP09) scenarios using a MIKE SHE/MIKE 11 model for a restored floodplain in eastern England. The simulations reveal uncertainty in the direction of annual precipitation changes, with extreme changes ranging from -27% to +30%. Wetter winters and drier summers are expected, alongside an increase in potential evapotranspiration for most scenarios. Mean discharge is projected to decline, with reductions of 11-17% in the central probability range. High and low flows are expected to decrease, along with a reduction in the frequency of bank full discharge exceedance. Winter high floodplain water tables are predicted to decline in duration, while summer water tables are projected to be lower by at least 0.11 m and 0.18 m for the 2050s and 2080s, respectively. Additionally, flood extent is anticipated to decrease in most scenarios, and drier conditions may induce ecological responses, impacting floodplain vegetation.

Jayapadma et al. (2018) discusses the utilization of computer-based catchment models for water resources planning and management, focusing on the MIKE 11NAM lumped conceptual rainfall-runoff model. It emphasizes the challenges of data availability for physically based distributed models. The study evaluates the model's performance in simulating hydrological parameters of the Gin River basin in Sri Lanka using locally available and public domain data. Despite the basin's susceptibility to flooding, the model's simulated runoff shows good agreement with observed discharge, as indicated by favorable Nash-Sutcliffe efficiency and volume ratio values. Additionally, the simulated base flow aligns well with the basin's hydrological behavior.

Noymanee et al. (2019) discusses urban flooding in Thailand and the need for accurate real-time flood water level forecasts. It introduces a study aiming to improve flood prediction using hydrological modeling combined with five machine learning techniques: linear regression, neural network regression, Bayesian linear regression, and boosted decision tree regression. The MIKE 11 hydrologic forecasting model is utilized for testing. Training data from 2012-2016 are used to develop the models, which are then tested on 2017 data to evaluate error reduction in runoff forecasting.

Sajadi bami Yasamin et al. (2020) the challenges in selecting appropriate hydrological rainfall-runoff (R-R) models for catchment simulation and highlights the importance of understanding each model's advantages and limitations. It describes a specific study evaluating the performance of the MIKE11 NAM lumped conceptual hydrological rainfall-runoff model in simulating daily flow rates in the Gonbad catchment. The model was calibrated and validated using flow rate data from three hydrometric stations in the catchment. Evaluation metrics such as Percent Bias (PBIAS) and Nash-Sutcliffe Efficiency (NSE) were utilized, with satisfactory results obtained for both calibration and validation periods. The MIKE 11 NAM model demonstrated capability in simulating daily mean flow rates and mean flow volumes in the studied catchment.

Huu Duy Nguyen et al. (2021) The study addresses flood risk in spatial planning amidst climate change and urbanization, aiming to develop strategies for mitigating future urban flood risk. It combines land use change and hydraulic models to predict future flood risk under various scenarios. Using satellite imagery, land cover maps for 1995, 2019, and a projected 2040 were created, and flood risk was assessed through hydrodynamic modeling and the Analytic Hierarchy Process method. While urbanization increases flood risk, reductions in poverty rates decrease the area exposed to high and very high risks. The study's methodology highlights the importance of satellite imagery and data continuity in decision-making for planning.

Abera Shigute Nannawo et al. (2022) The study focuses on predicting streamflow in the Bilate basin, Ethiopia, despite limited hydrometric data, using MLR-based regionalization and the MIKE11-NAM hydrological model. Data from 1995 to 2020 were used for modeling, with distinct periods for warm-up, calibration, and validation. Decreasing rainfall, particularly in spring and summer, is noted, leading to an expected decrease in streamflow during dry months. The model's performance, assessed through R2 values and water balance error, yielded satisfactory results during calibration and validation. The basin's flow is mainly contributed by streams from the northern, northwest, and southwest highlands, with the MIKE11-NAM model proving advantageous in rugged terrains with limited data availability from gauging stations.

Nhu Y Nguyen et al. (2023) The study examines future streamflow in the Nam Ou Basin, a sub-catchment of the Mekong Basin, using CMIP6 climate scenarios. Employing the MIKE-NAM model and observed data, it forecasts increased river discharges under climate change, with varying magnitudes across scenarios. The wet season is projected to start earlier, with wet season flows increasing and dry season flows decreasing. Annual peak discharge is also expected to rise. These findings underscore the importance of disaster risk mitigation, particularly in the context of climate change, for the Nam Ou Basin and similar regions within the Mekong Basin.

Huu Duy Nguyen et al. (2024) The study addresses flood prediction's importance for local decision-making and focuses on resolving the extrapolation problem in flood depth prediction. It integrates machine learning (XGBoost, Extra-Trees, CatBoost, and LightGBM) with hydraulic modeling under MIKE FLOOD. Results indicate that the hydraulic model effectively provides flood depth data for machine learning. XGBoost performs best in addressing the extrapolation problem, followed by Extra-Trees, CatBoost, and LightGBM. Floods in Quang Binh province ranged from 0 to 3.2 meters, with high flood depths concentrated along and downstream of major rivers like Gianh and Nhat Le–Kien Giang.

Types of Rainfall-Runoff Models

The rainfall runoff models are mainly divided into three categories: black box, conceptual and physically based models.

4.1 **Black Box Models:**Black box models, also referred to as metric or empirical models, derive variable parameters and model structure based on time series data. They rely solely on available data and do not consider catchment behavior, earning them the designation of black box models. In these models, the catchment is viewed as a single unit where rainfall serves as the input and runoff as the output.

4.2 **Conceptual Models:** Conceptual models, also known as grey box or parametric models, are structured around storages such as reservoirs, replenished through hydrological processes like rainfall, runoff, infiltration, and evapotranspiration. These models determine various parameters through a calibration approach using time series data of rainfall and runoff. They typically view the catchment as a homogeneous single unit.

4.3 **Physical based Models:** Physically based models, often termed mechanistic models, rely directly on the hydrological processes at play and utilize spatial discretization or similar hydrologically-based units to generate streamflow. These models spatially discretize the catchment into smaller units based on homogeneous hydrological properties.

The transformation of precipitation into runoff within a catchment represents a nonlinear, time-varying, spatially distributed, and complex hydrological process. Various models exist for estimating runoff from given rainfall inputs, each chosen based on the specific objectives of the modeling endeavor. Below, we outline some of the widely utilized rainfall-runoff models.

MIKE 11-NAM

MIKE 11 NAM software was developed by Danish Hydraulic Institute (DHI), Denmark. It is a one dimensional modeling tool which was formulated in 1972 particularly for the water resources planning and management applications. It is specifically meant for imitation of river flows, irrigation systems and channels. The quality analysis of rivers & channels, and sediment transport studies can also be performed through different modules of MIKE 11 software. MIKE 11 uses the Nedbor Afrstromnings Model (NAM) to establish the rainfall-runoff calculation.

The NAM model serves as a conceptual framework aimed at simulating rainfall runoff. This model categorizes the flow into overland flow (surface flow), interflow (subsurface flow), and base flow. It operates through a series of interconnected mathematical statements that depict the dynamics of the land phase within the hydrological cycle. The simulation within the NAM model revolves around four distinct yet interconnected storage components: surface storage, groundwater storage, root zone storage, and snow storage. Furthermore, the NAM model integrates additional depletions through irrigation and groundwater pumping modules. The inclusion of snow storage is contingent upon its significant contribution to runoff. Among the primary storages, the upper zone storage accounts for vegetation, depressions, and near-surface (cultivated) soil. The lower zone storage encompasses the root zone and the primary soil horizons, while groundwater storage represents water-bearing rocks. The combination of overland flow, interflow originating from the upper zone, and base flow originating from groundwater undergoes further routing and aggregation to yield the overall model flow at the basin outlet.

4.4 Description of MIKE 11 NAM

The NAM model can be configured with various model parameters, but by default, it automatically considers only nine parameters, which include surface zone storage, root zone storage, and groundwater storage. During the calibration process, these parameters are adjusted to establish the most accurate relationship between simulated and observed discharges. A minimum of three years of data is necessary for the model to generate reliable results. The nine default parameters of NAM are as follows:

4.4.1 **Maximum water content in surface Storage (U_{max}):** This parameter signifies the total water content within interception storage (such as vegetation and depression storage) and storage within the upper layers of soil.

4.4.2 **Maximum water content in root zone storage (L_{max}):** This parameter denotes the maximum moisture content within the soil in the root zone, which is accessible for transpiration by vegetation.

4.4.3 **Overland flow runoff coefficient (CQOF):** This parameter dictates how excess rainfall is partitioned between overland flow and infiltration.

4.4.4 **Time constant for routing interflow (CKIF) :**This parameter determines the amount of interflow which decreases with larger time constants.

4.4.5 **Time constants for routing overland flow (CK, CK):** These two parameters shape the peaks of hydrographs. Routing occurs through two linear reservoirs connected in series, each with distinct time constants measured in hours. Sharp, high peaks are associated with shorter time durations, and conversely.

4.4.6 **Root zone threshold value for overland flow (TOF):** This parameter establishes the relative threshold of moisture content in the root zone, beyond which overland flow initiates. Its impact is particularly noticeable during the rainy season, where an increase in its value delays the onset of runoff.

4.4.7 **Root zone threshold value for interflow (TIF):** This parameter determines the relative value of the moisture content in root zone above which interflow is generated.

4.4.8 **Time constant for routing base flow (CKBF):** This parameter can be determined from the hydrograph recession in dry periods. In rare cases, the shape of the measured recession changes to a slower recession after some time. To simulate this, a second groundwater reservoir may be required.

4.4.9 **Root zone threshold value for groundwater recharge (TG):**This parameter dictates the significance of moisture content in the root zone, beyond which groundwater recharge occurs. Elevating this parameter diminishes the replenishment of groundwater storage.

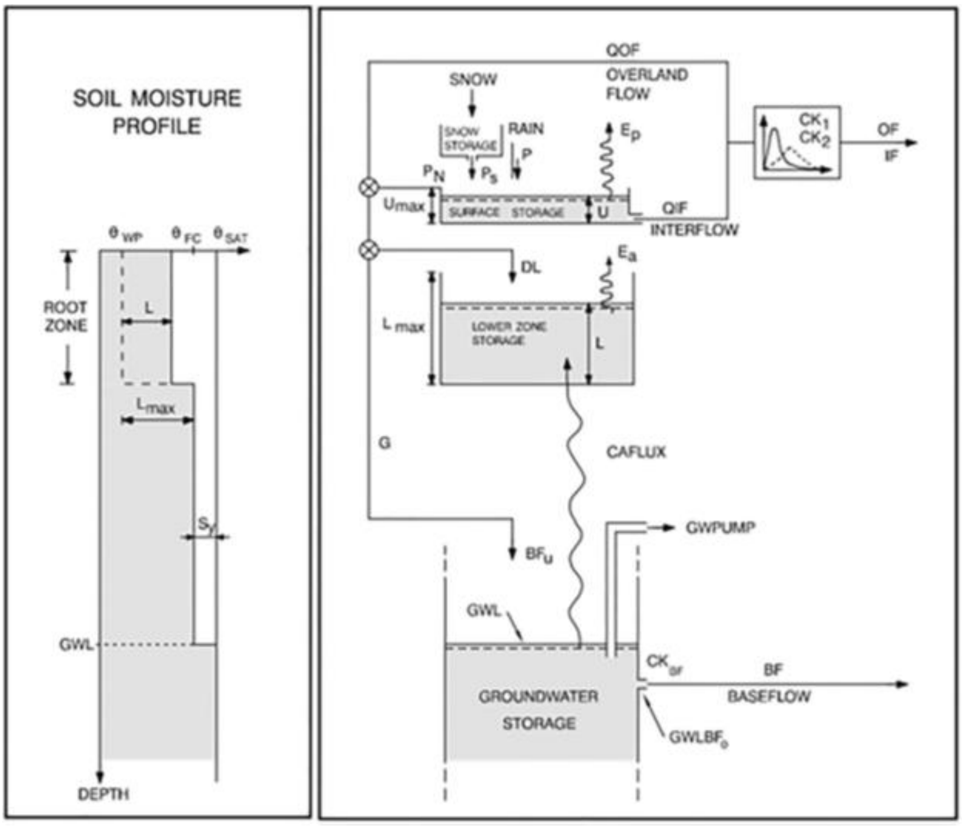

Fig.1Structure of NAM Model

The default ranges for these 9 parameters are given below:

Table 1 Parameters Range Values of NAM Model

Parameter	Lower Bound	Upper bound	Units
Umax	10	20	mm
Lmax	100	300	mm
CQOF	0.1	1.0	-
CKIF	200	1000	hours
CK1, CK2	10	50	hours
TOF	0	0.99	-
TIF	0	0.99	-
CKBF	1000	4000	hours
TG	0	0.99	-

4.5 Basic Modeling Components

The elements of NAM model representing the various phases of hydrological cycle are represented mathematically by the following functions:

5.2.1Evaporation: The initial fulfilment of evaporation demands (Ea) occurs at the potential rate from the surface capacity. If the moisture content (U) in the surface capacity falls below these demands (U <Ep), the deficit is assumed to be withdrawn by root activityfrom the lower zone capacity at an actual rate (Ea). Ea is corresponding to the potential evapotranspiration and fluctuates directly with the relative soil dampness content as.

$$E_a + \left\{ \frac{L}{U + \frac{L}{L_{max}}(E - U)} \right\} (U \geq E) \text{ otherwise}$$

5.2.2 Net rainfall and infiltration: Net rainfall P_N is not clearly defined by the MIKE 11 NAM but appears to be given by mathematical equation as below:

$$P_N = \max\left(0, P - E_a - QIF - (U_{max} - U)\right)$$

This leaves infiltration to the lower zone capacity will be defined as

a. $I = P_n - QOF$

5.2.3 Overland flow: At the point when the surface storage spills, i.e. at the point when U >U_{max}, the overabundance water P_n offers rises to overland stream and also to infiltration. QOF indicates the part of P_n that adds to overland flow. It is thought to be corresponding to P_n and to differ directly with the relative soil dampness content, L/L_{max}, of the lower zone storage. It only happens when the saturated fraction of the lower zone exceeds threshold

$$QOF = \left\{ CQOF\ P_n \left[\frac{L/L_{max} - TOF}{1 - TOF} \right] \right\} L/L_{max} \geq TOF \quad 0 \quad \text{otherwise}$$

5.2.4 Interflow: The proportion of interflow, denoted as QIF, is believed to be contingent upon U and is expected to correlate directly with the relative moisture content of the lower zone storage. It materializes only when a critical saturation fraction of the lower zone surpasses the threshold value. However, this interflow must be constrained to ensure sufficient water availability to maintain the upper zone storage.

$$QIF = \left\{ CQIF \left[\frac{L/L_{max} - TIF}{1 - TIF} \right] \right\} L/L_{max} \geq TIF \quad \text{otherwise}$$

5.2.5 Interflow and overland flow routing: The interflow is directed through two straight reservoirs in arrangement with the same time consistent CK12. The overland stream routing is also based on the linear reservoir idea but with a variable time consistent. To hold a linear response for nearly surface flows and a kinematic response for above surface flows at higher discharges, the time constants will be modified as

$$CK = \begin{cases} CK_{12} & \\ CK_{12} \left[\frac{OF}{OF_{min}} \right]^{-\beta} & OF \leq OF_{min} \quad \text{otherwise} \end{cases}$$

Where OF is the overland flow (mm/hour) and OF_{min} is the upper limit for linear routing (=0.4 mm/hour) and β=0.4.

5.2.6 Ground water recharge: The amount of infiltrating water, denoted as G, replenishing the groundwater capacity, relies on the soil moisture content within the root zone capacity. This is linked to the infiltration entering the lower zone, occurring when the saturated fraction surpasses the threshold value.

$$G = \left\{ I \left[\frac{L/L_{max} - TG}{1 - TG} \right] L/L_{max} > TG \quad otherwise \right.$$

5.2.7 Ground water storage and base flow: The groundwater capacity allows the water as base flow in two ways. The simple one is that it uses a linear reservoir concept such that base flow is

$$q_g = \{CKBFS_g S_g > 0 \quad otherwise$$

The second one directs to use the concept of a shallow reservoir typical of depression catchments with little topographic variations and have possibility for water logging. In this case base flow is directly related to water table depth above the maximum drawdown of groundwater zone and is given by

$$q_g = \{C K_{BF} S_y \left(D^g_{max} - D_g\right) D^g_{max} \geq D_g \quad otherwise$$

Where

S_g = water in groundwater storage above zero reference (negative values are possible)

D_g = depth of water table below zero datum

D^g_{max} = depth of water table attaining a maximum value

5.2.8 Capillary flux: Water can ascend from the groundwater to the lower zone storage through capillary action. The capillary flux, denoted as C, correlates with the square root of the deficit in the lower zone and inversely with the drawdown in the groundwater reservoir.

$$C = \left(1 - \frac{L}{L_{max}}\right)\left(\frac{D_g}{D_g^1}\right)$$

If C has units of mm/day then the parameter α is given by

i. α = 1.50 + 0.45 D_g^1

Where D_g^1 is the depth of the groundwater table at which the capillary flux is 1 mm/day when L=0

NAM model requires various input data which includes the parameters to define the catchment, model parameters, initial conditions, hydro-meteorological data and stream flow data.

The fundamental meteorological data required include precipitation, potential evapotranspiration, and temperature. Utilizing these inputs, the model generates output in the form of catchment runoff, contributions from subsurface flow to the channel, and details regarding other aspects of the land phase of the hydrological cycle, such as soil moisture content and groundwater recharge. Both input and output data for the model are in a time series format. The NAM model has been applied to various catchments worldwide, encompassing diverse hydrological regimes and climatic conditions. It has been observed that the model can effectively predict river discharge, demonstrating a noteworthy agreement between observed and simulated flow values concerning rate, timing, volume, and shape of the hydrograph.

CONCLUSIONS

Rainfall-runoff modeling constitutes a crucial aspect of water resources planning and management projects. Numerous well-established models exist for such modeling purposes. The NAM model is one such tool capable of accurately predicting basin runoff when appropriately calibrated. The model's efficiency improves with the length of the input time series data used for calibration. Once developed, the NAM model serves to estimate dependable flows for a basin and forecast flood flows, providing essential inputs for water resources management at the basin level.

The conclusion of the paper encapsulates a comprehensive exploration of the NAM modeling approach for rainfall-runoff estimation across diverse geographical regions. Through a meticulous analysis of 20 pertinent literature reviews, the paper delineates various methodologies employed by different authors worldwide. The MIKE-NAM model, elucidated with its nine key parameters encompassing surface and root zone storage, runoff coefficients, and routing constants, forms the cornerstone of the study. A visual representation of the NAM model's structure enhances understanding, while a detailed table showcases the range of values utilized for calibration and validation of model parameters. Additionally, fundamental components of the NAM model such as evaporation, infiltration, overland flow, interflow, and groundwater dynamics are expounded upon, along with their associated formulas. By synthesizing these insights, the paper not only contributes to the advancement of hydrological modeling techniques but also offers valuable insights for future research endeavors in this domain.

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