CHAPTER II

REVIEW OF LITERATURE

Wetlands play a crucial role as ecosystems, supporting life on earth by providing diverse habitats and essential ecological services (Menon *et al.*,2023). One such internationally significant wetland is the *Vembanad Kol* Wetland in Kerala, known for its unique natural wetland type (Mitsch and Gosselink, 2000). The northern part of this wetland, known as *kole land* experiences most fertile soil due to nutrient rich alluvium which gets deposited from rivers (Johnkutty and Venugopal, 1993). Despite their ecological significance, *kole lands* requires quantifying floodwater accumulation as well as canal storage which is essential for effective flood prediction and water resource management. The exit for all water present in north *kole* land is through Enamakkal and Idiyanchira regulators but there is lack operation policies. In this chapter some of the research works conducted in this field to estimate the surface volume, inflow estimation, seepage analysis and simulation-based optimizations models and software are discussed.

2.1 ESTIMATION OF SURFACE VOLUME OF RESERVOIR

Kole lands act as small reservoir where knowing capacities is crucial in water resource assessment. Hence principle of calculation of volume contained in the reservoir is used for calculation of runoff volume accumulation in *kole* lands. A more precise approach for estimating reservoir capacity involves delineating the area enclosed by contours at suitable intervals. By calculating the volume between two consecutive contours and these volumes were summed up to determine the overall capacity of the reservoir (Lawrence and Cascio, 2004).

Many methods available for estimating the volume of a reservoir, categorized into direct and indirect approaches. Direct methods include the Mid-Area Method and the Prismoidal Method. The Mid-Area Method assumes that the areas contained within successive contours represent cross-sections, with the distance between the contours corresponding to the contour interval. The Prismoidal Method, on the other hand, assumes that the volume enclosed by two contour intervals represents as a prism. Indirect methods involve estimating surface areas from topographical maps or satellite images. These surface areas are then used to establish a power relationship between the surface area and the reservoir's capacity, which is subsequently used to estimate the total capacity. Indirect methods are generally less labour-intensive and quicker compared to direct methods (Sawunyama, 2005)

Assaf *et al.* (2021) used geographic information systems (GIS) to measure and analyze the amount of water stored in small reservoirs. In this study, the Natural Difference water Index (NDWI) is used to detect the surface area as the base to estimate small reservoir storage capacities. The model equation created by this study provided a tool to know the amount of water available per day in the small reservoirs during the dry season.

Khojiakbar *et al.* (2019) used Remote Sensing and Geoinformation Technologies for calculating the area and volume of a water reservoir. The study was conducted at Tashtepa water reservoir, which is proposed for construction in the Tashkent region. The Tashtepa reservoir area was analyzed using the Google Earth program, where the alignment for dam construction was identified, and the data was saved in KML (Keyhole Markup Language) format. The alignment and digital elevation model (DEM) of the reservoir area were then uploaded into Global Mapper, a geographic information system (GIS) software. Contours were generated within the DEM, and the longitudinal profile of the alignment along the dams was defined. Using this information, the surface area and volume of the water reservoir were calculated for each contour level. The results were used to create curve lines depicting the relationship between contour and contour area

Irvem (2020) suggested water storage capacity can be estimated using a Digital Elevation Model (DEM), which can be generated from a digitized topographic map of basin. In this study, the Buyuk Karacay Dam, located in Hatay province, Turkey, was selected as a case study. The water storage volume for the Buyuk Karacay Dam was estimated using the DEM within a GIS environment. The procedures for calculating storage volume were described, considering the crest elevation of the virtual dam and the surrounding topography. Maps of the stream network, stream order, and flooded areas were generated using DEM in ILWIS 3.6

software. DEMs with pixel sizes of 10, 20, 30, 40, and 50 m were used to calculate storage volume based on a dam crest elevation of 347 m above Mean Sea Level (MSL). The estimated volumes were then compared to assess the impact of pixel size on volume prediction, with results from a survey method conducted after the construction of the Buyuk Karacay Dam. The findings indicated that a 10-meter pixel size provided the most accurate volume estimation. Using this pixel size, the dam reservoir's storage capacity was estimated to be 59.38 ha-m^3, which closely matched the survey method's result of 57.25 ha-m^3.

Liu *et al.* (2020) used surface volume in ArcGIS to understand the terrain of a reservoir. The surface volume tool in ArcGIS calculates the volume between the topographic map and a reference plane, which could be used to develop the elevation and volume relationship curve. Additionally, using the surface volume tool in ArcGIS, they developed both the original and updated elevation-volume curves of the reservoir. By calculating the difference between these curves, the amount of silting and its distribution within the reservoir was determined. The results indicated that the total sedimentation volume in the reservoir was 4.3 Mm^3, with the majority of the sedimentation occurred in areas with elevations below 50 m and above 60 m.

Mehmood *et al.* (2014) conducted experiment to analyses the submergence of the dam using GIS. The study was conducted in Par-Tapi-Narmada River Link Project, Gujarat State. The methodology involved Generation of Digital Elevation Model (DEM), generation of contours of 5m interval using CARTOSAT DEM data and computation of submergence under various land use classes. The contours of different FRL of 144, 149, 154, 159 and 164 m were generated and superimposed on IRS LISS-IV image and extent of submergence was delineated

Fernández *et al.* (2022) conducted study on ideal placement of reservoirs using GIS. The study involved automated ArcGIS Pro model that work with various DEM resolutions to calculate volume / surface area ratio using surface volume tool. In the first case study, a new reservoir could store 30.7 m^3 of water m^{-2}, compared to the current 9 m^3/m^2 stored in the nearby existing reservoir. This could reduce the flooded area from 25.4 km^2 to just 6.7 km^2. The methodology presented in this study enabled the selection of optimal sites where reservoirs can be built with a smaller water surface area.

Hossain *et al.* (2018) conducted study on extraction of DEM for Saint Martin Island, Bangladesh. They stated that various methods and data sources for digital elevation modelling (DEM) are well established, but traditional high-resolution data often lack easy public access. Although DEM from sources like SRTM (90-m and 30-m) and Global ASTER (30 m) are available for free, their resolution is sometimes insufficient for large-scale, small-area studies.

Bakiev and Khasanov (2021) conducted a study for determining area and volume of the reservoir. Contours were generated for each DEM and then compared with the contours from a topographic map. The results indicated that the contours from the SRTM and ALOS PALSAR DEMs closely matched those on the topographic map, whereas the contours from the ASTER GDEM showed less alignment. 120 contours were were generated from topographic map and DEMs. The highest capacity obtained from 117m (sea level) was 2132243697 m^3 and corresponding area was 214.47 km^2.

Hagos *et al.* (2022) identified dam site using GIS for Chemoga watershed, Ethiopia. The surface volume sub tool in the 3D analyst tool in the ArcMap platform is used to determine the reservoir's 2D, 3D surface area and volume, as well as the cross section (height and width) of the proposed dam. The height of the dams varies between 8 and 64 m based on the cross-section along the dam axis, while the width ranges from 173 to 875 m. The maximum storage capacity of the reservoirs differs according to the surrounding topographic conditions, ranging from 1.68 to 31.48 Mm^3. Additionally, the 2D surface area of the reservoirs spans from 3.19 to 231.8 ha across the six proposed dams.

2.2 ESTIMATION OF INFLOW TO THE RESERVOIR/ REGULATOR

Rainfall-runoff modelling is crucial for understanding and managing water inflow to *kole* lands and the functioning of regulators in the canal system. By estimating the runoff, how much water will be available for irrigation, flood control and overall water resource management can be assessed.

2.2.1 Rainfall-Runoff Models

According to Shoemaker *et al.* (2005), "model" refers to a collection of equations or algorithms that simulate the behaviour of the physical system. Additionally, it can be used to describe the various computer software programmes that automate the computes of a set of equations or a combination of equations that form a system.

Since the computer revolution, hydrological modelling has made a huge leap forward, which gives birth to a new branch of hydrology, called digital or numerical hydrology (Singh, 2018). The integration of several hydrologic cycle components and the simulation of the entire watershed were made possible by the hydrological modellers' ability to handle a vast amount of data.

The advancement of GIS and remote sensing technology has had an impact on the development of watershed modelling. Hydrologists now have more capabilities because to GIS development, including the ability to handle and study large databases that characterise variability in soil surface properties and to better display model results (Daniel *et al.,* 2011).

Previous literature evaluations have provided several ways for categorising hydrological models based on a wide range of characteristics (Devia *et al.,* 2015). The rainfall-runoff models have been divided into various classes by the hydrological modellers. Deterministic and stochastic models based on the spatial variability, whereas lumped and distributed models depending on the model parameters as a function of space and time.

Devia *et al.* (2015) stated that the deterministic model will produce the same results for a single set of input value inputs. In case of stochastic models, which can produce a variety of output values from a single set of inputs. The watershed is treated as a single entity in lumped models, sometimes known as "global models," which ignore regional heterogeneity. As a result, the resulting outputs fail to consider the spatial variability of processes, inputs, boundary conditions, and geometric system properties (Singh, 2002). A distributed model, by contrast, makes predictions by breaking the entire watershed into smaller parts (such as square cells or triangulated irregular networks) to allow the spatial variation of the parameters, inputs, and outputs (Moradkhani and Sorooshian, 2008). It has been proposed to combine the benefits of both kinds of spatial representation using semi-distributed models. As a result, these models can accurately depict a watershed's key characteristics while requiring less data and spending lower computation cost to run than distributed models (Orellana *et al.,* 2008).

Rainfall-runoff models are classified by time scale into two types: continuous simulation models and event-based models. Continuous simulation models use a time series of rainfall data that may include multiple storm events, while event-based models focus on a single rainfall storm event. Based on spatial scale, models are categorized by catchment size: small catchments (up to 100 km^2), medium-sized catchments (100-1000 km^2), and large catchments (over 1000 km^2).

Hydrological models can be divided into three groups based on the physical processes they simulate: empirical, conceptual, and physically-based models. These processes are described by the model algorithms, and the model is data-dependent (Saavedra and Mannaerts, 2005).

Experimental data or observable input-output interactions are used to build empirical (black box) models, which do not explicitly describe the behaviour brought on by certain processes. The stationary assumption, which holds that underlying conditions do not change during the simulation period, is the restriction on using empirical models at the watershed level (Kandel *et al.,* 2004). Conceptual models (grey box) sit between empirical models and physically-based models; they typically take physical laws into consideration but do so in a highly simplified manner. Physically-based, also called process-based (white box) models, are described in terms of critical governing laws associated with the hydrological cycle, and they have a logical structure similar to the real system being modelled.The following table shows the main characteristics of the three models.

Table 2.1 Rainfall-Runoff Models Comparison Based on Process Description (Singh, 2018)

Empirical model	Conceptual model	Physically-based model
Data based or metric or black-box model	Parametric or grey box model	Mechanistic or white box model
Involve mathematical equations, derive value from available time series	Based on modelling of reservoirs and include semi-empirical equations with a physical basis	Based on spatial distribution, Evaluation of parameters describing physical characteristics
Little consideration of features and processes of the system	Parameters are derived from field data and calibration.	Require data about the initial state of model and morphology of catchment
High predictive power, low explanatory depth	Simple and can be easily implemented in computer code	Complex model. Require human expertise and computation capability
Cannot be generated to other catchments	Require large hydrological and meteorological data	Suffer from scale-related problems
ANN, unit hydrograph	HBV model, TOPMODEL	MIKE-SHE model, SWAT

The SWAT model was successful in getting approval for its use in a variety of global climates and situations. The model is widely used to research a variety of topics, including hydrological modelling, erosion, climate change, and water quality at different spatial and temporal scales across Asia, Africa, and Europe (Tuppad *et al.*, 2011).

Soil & Water Assessment Tool (SWAT) is a river basin scale model developed to quantify the impact of land management practices in large, complex watersheds. The objective of SWAT is to forecast the long-term response in substantial basins and it is continuous-time model. In the early 1990s, SWAT's first version was developed (Engel *et al.,*1993). The SWAT model is comprehensive model that requires a lot of background information such as initial subbasin topographic parameters, land use, and soil type. Hydrologic Response Units (HRU) are created in a SWAT model based on the type of soil and landuse. During simulations, the same HRU is assumed to be homogeneous in hydrologic response to land cover change.

The quantity and quality of runoff from a watershed are largely determined by precipitation and the land and water management practices within the area. Estimating runoff is essential for various purposes, such as conserving water for irrigation or drinking, enhancing groundwater recharge, reducing peak flow to prevent flooding, and controlling erosion (Jain *et al.*, 2010).

Studies conducted in river basins and watersheds globally have demonstrated that the SWAT model is an effective tool for estimating runoff and assessing soil erosion, aiding in the efficient planning and management of water resources (Shen *et al.*, 2009; Tibebe and Bewket, 2010; Wenjie *et al.*, 2011).

2.2.1.1 Overview of SWAT model

In order to forecast the effects of land management methods on water, sediment, and agricultural chemical yields in large complex watersheds with a diversity of soils, land use, and management circumstances, Arnold *et al.* (1998) developed SWAT on behalf of the US Department of Agriculture (USDA) (Neitsch *et al.,* 2011).

Based on topography, watershed is divided into a number of sub-basins. Then, each sub-basin is conceptually further divided into a number of Hydrologic Response Units (HRUs), each of which has a distinct combination of soil, land use, and slope (Worqlul *et al.,* 2018).

1. Model processes

According to Neitsch *et al.* (2011), the modelling of hydrology or the hydrologic cycle in SWAT is divided into two phases:

The watershed's sub-basins' water, sediment, and nutrient fluxes to the main channel are determined by the land phase, while the watershed's water flow, tributaries, and outlet are determined by the routing phase.

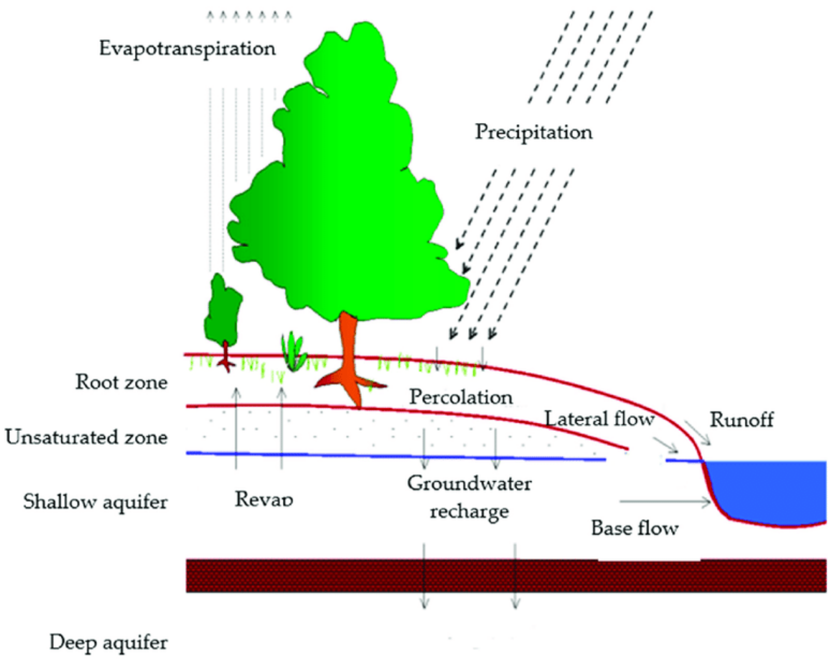

Fig. 2.1 Schematic representation of the hydrologic cycle in SWAT model

The SWAT document provides comprehensive details about these two phases (Neitsch *et al.,* 2011). The following sentences give a basic overview of these phases:

Land Phase of the Hydrologic Cycle

The water balance equation given below provides an estimate of the hydrological cycle in the model (Neitsch *et al.*, 2011):

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})$$

Where SW_t is the soil water content, t is the time in days, and R_{day}, Q_{surf}, E_a, W_{seep} and $Q_{gw}$are, respectively, daily amounts of precipitation, surface runoff, evapotranspiration, water entering the vadose zone from the soil profile, and return flow (all units are in mm).

SWAT includes two techniques for calculating surface runoff: (i) The Soil Conservation Service (SCS) Curve Number (CN) method (Neitsch *et al.,* 2011). This method is only available at a daily time step, daily and a sub-hourly time step and (ii) the Green and Ampt infiltration method (Green and Ampt, 1911; Neitsch *et al.,* 2011) can be used. Storage routing algorithms combined with crack-flow model are used to predict the percolation across each soil layer.

Using three methods—Priestley-Taylor (Priestley and Taylor, 1972), Penman-Monteith (Monteith, 1965), and Hargreaves—the projected evapotranspiration (PET) is calculated in SWAT (Hargreaves and Samani, 1985). The number of inputs required varies amongst the three PET methods offered in SWAT. Solar radiation, air temperature, relative humidity, and wind speed are necessary for the Penman-Monteith approach. The only difference between the Priestley-Taylor and the Hargreaves methods is that the Priestley-Taylor method just needs to know the air temperature.

Routing Phase of the Hydrologic Cycle

The Hydrological Model command 's structure is used to direct the loadings of water, sediment, and nutrients to the main channel through the network of streams in the watershed (Williams and Hann, 1972). According to Neitsch *et al.* (2011), there are four distinct parts to the routing procedure in the main channel: flood routing, sediment routing, nutrient routing, channel pesticide routing.

2.2.2.2 Improving the Predictive Accuracy of The Model

Before going for simulations, hydrologic models must go through calibration in order to increase their predicted accuracy. If calibrated correctly, the SWAT model can be effectively utilised to support water management policy (Abdelhamid *et al.,* 2011). All model inputs may not be available to the desired precision, and this emphasizes the need of model calibration. The models must also be validated with an independent set of observed data to model prediction and to improve predictive accuracy. The term validation is used to explain the method of analysing the performance of simulation and/or forecasting of models (Daniel *et al., 2011*).

Sensitivity Analysis

Before going to the actual calibration and validation procedure in SWAT, it is crucial to identify the most sensitive parameters for a watershed or sub-watershed. On the basis of sensitivity analysis or expert judgement, the user chooses which variables to change. Sensitivity analysis is the process of estimating how quickly the output of a model will change in response to changes in the model's inputs. The most sensitive parameters and the level of precision needed for calibration must be determined. Sensitivity analysis enables the identification and ranking of parameters that significantly affect a set of desired model outputs (Saltelli *et al.,* 2000).

The two primary methods of sensitivity analysis are local, which involves altering values one at a time, and global, which involves allowing all parameter values to change (Van Griensven *et al.*, 2006). The outcomes of the two analyses, however, can vary. The importance of one parameter is frequently influenced by the value of other related parameters; hence, the problem with one-at-a-time analysis is that the correct values of other parameters that are fixed are never known.

The global sensitivity analysis, all parameters are allowed to vary by certain percentage or are simultaneously changed, allowing investigation of parameter interactions and their impacts on model outputs. The global sensitivity analysis has the drawback of requiring a large number of simulations. However, both techniques are important steps in the calibration of the model since they provide insight on the sensitivity of the parameters. In various climatic conditions, the modelled stream flow may also show varying sensitivity of parameters (Cibin *et al.,* 2010).

Calibration and Validation

Calibrating process is the second phase. By better parameterizing a model to a specific set of local conditions, calibration attempts to lower the prediction uncertainty. When calibrating a model, values for the input parameters are carefully chosen (within their respective uncertainty bounds) and the model's output is compared to the observed data under the same assumptions.

The validation of the relevant component (streamflow, sediment yields, etc.) is the last step. Model validation is the process of proving that a particular site-specific model is capable of producing simulations that are "sufficiently accurate," though the exact definition of "sufficiently accurate" can vary depending on the project's objectives. Running a model with parameters that were established during the calibration procedure and comparing the predictions to actual observed data that was not used in the calibration constitutes validation. A good model calibration and validation should typically include:

1. Observed data that include wet, average, and dry years

2. Multiple evaluation techniques

3. Calibrating all constituents to be evaluated; and

4. Verification that other important model outputs are reasonable.

To ascertain whether the model has been calibrated and validated properly, graphical and statistical methods are typically used along with kind of objective statistical criteria.

When performing SWAT calibration, the input parameters must be restricted to a realistic range. Identification of crucial parameters and parameter accuracy are important for calibration. In other words, before calibrating a SWAT model, modelers must choose which parameters to include based on their prior experience or the findings of a sensitivity analysis. The impact of HRUs on the model calibration process was examined in few researches. the majority of studies concentrate on streamflow predictions for watersheds between 20 and 18,000 km^2 (Gassman *et al.,* 2007). The SWAT CUP is the most popular software used for calibration. GLUE , SUFI-2 (Abbaspour *et al.,* 2017), and ParaSol are now supported by the software (Van Griensven *et al.,* 2006).

SUFI-2 is a Bayesian framework-based algorithm widely used for surface runoff calibration. after determining the objective function and parameter range, the algorithm provides a parameter set using Latin hypercube sampling, and the resulting 95% prediction interval of each parameter is calculated. When calculating a model's uncertainty, two things are considered: The P-factor is is the percentage of observed data enveloped in 95% prediction uncertainty (PPU), which is determined at the 2.5% and 97.5% levels of the cumulative distribution of output variables. The r-factor is calculated by dividing the average thickness of the 95PPU band by the standard deviation of the observed data (Abbaspour *et al.,* 2017). The result of the calibration includes the best parameter set according to objective function as well as the best range for each parameter. While SWAT CUP is widely used for SWAT model calibration, it is not using multi-objective calibration algorithms or genetic calibration approaches.

According to Deb *et al.* (2002) certain research studies, the NSGA-II calibration algorithm for hydrological models performs well. (Zhang *et al.,* 2015). Although SUFI-2 and NSGA-II algorithms are both employed in the calibration of hydrological models, little study has been done to compare the model performance of the two calibration procedures.

Ten algorithms were compared for output performance. Three SWAT CUP calibration algorithms—SUFI-2, GLUE, and ParaSol—were evaluated and they concluded that SUFI-2 was more capable of producing accurate and foretelling findings than either of the other two approaches (Tibebe *et al.*, 2016).

The performance of the algorithms utilised in SWAT CUP was the main focus of the majority of the comparisons described above. Although the SWAT model community frequently uses SWAT CUP.

2.2.2.3 Soil and Water Assessment Tool-Calibration and Uncertainty Procedures (Swat-Cup) – SUFI-2

According to Abbaspour *et al.* (2017), the SUFI-2 programme is one viable method that may easily mimic a large-scale watershed. When simulating streamflow, sediment loads, and nutrient loads, it produces better results. Additionally, they stated that the SUFI-2 can manage a huge number of parameters and was extremely easy to locate the critical parameter in the watershed.

SUFI-2 was demonstrated to be one of the efficient methods for the calibration and uncertainty analysis of any catchment by Schuol *et al.* (2007). The least amount of simulations was necessary for SUFI-2 to produce superior outcomes. Analyses of many sites and multiple variables can also be performed using SUFI-2.

For incorporating various calibration and uncertainty assessments in a Japanese river Catchment, Luo *et al.* (2011) used SWAT-CUP. The catchment analysis was conducted using the GLUE and SUFI-2 methodologies, which produced positive outcomes with high R^2 values of 0.98 and 0.95 for monthly simulation. Daily calculations also produced an important R^2 value of 0.86 for calibration and 0.80 for validation, respectively. According to the study, GLUE calibration findings outperformed SUFI-2 calibration results. The alpha factor for bank storage (ALPHA BNK) and effective hydraulic conductivity in main channel alluvium (CH K2) play a significant role in the calibration and validation of the SWAT model, according to the uncertainty analysis.

Using the SWAT model, Vikhe and Patil (2014) carried out the hydrological modelling evaluation for the Bhima River. For the SWAT-CUP performance evaluation of the model, they employed SUFI-2, and they got good statistical findings for both calibration and validation. For calibration and validation, they received NSE values of 0.81 and 0.77, respectively. Thus, the study demonstrated that the model may be successfully utilised for evaluating management scenarios in watersheds and for making trustworthy water decisions if it is properly validated.

Rouholahnejad *et al.* (2012) conducted research on the SUFI-2's parallel processing for both small- and large-scale models. They claimed that the SUFI-2 operates effectively in both scenarios and that operating faster thanks to parallel processing.

For the Wenjing River Basin in China, Wu and Chen (2014) evaluated uncertainty estimates in distributed hydrological modelling using the SUFI-2, GLUE, and Parasol methodologies. They had good success in evaluating the model.

In comparison to the other two methods, SUFI-2 was able to provide more logical predicted quantitative statistical outcomes.

Calibration and validation are typically performed done separately by splitting the available observed data into two datasets, one for calibration, and another for validation. Most often, data are divided into time periods, making sure that the climate data used for calibration and validation are not significantly different, i.e., wet, moderate, and dry years occur in both periods.

2.2.2.4 Hydrological Studies on SWAT

Xie *et al.* (2018) utilised SWAT model for hydrological modelling in a large watershed in Nigeria. The evaluation was carried out on a daily and intermittent basis. The results of the study demonstrated that sub-daily models were more accurate at reproducing peak flows during the flood season, which is a crucial consideration in the formulation of precise strategies and planning for flood management and water security in river basins. According to the analysis, baseflow contributed to streamflow in the amount of 58% using the sub-daily model as opposed to 34% using the daily model. SWAT showed to be an important tool for conducting different hydrological assessment in similar watershed behavior.

Singh *et al.* (2012) performed monthly simulations for flows where the simulated flow and actual flow data agree quite well. The SWAT model provided the description of hydrological processes, which was extremely helpful for making decisions about land use management options that affect water quality. The results suggested that model can be used to similar watersheds in India that are located in the same agro-ecological zone.

According to Moriasi *et al.* (2007), SWAT is the most effective techniques for simulating the management of soil and water resources as well as other effects of hydrological processes in the use of watershed models. Quantitative statistics like Nash-Sutcliffe Efficiency, PBIAS, and RSR were suggested for better model evaluation.

For the simulation of daily and monthly discharge from small watersheds, Spruill *et al.* (2000) used the SWAT model. The most important variables included saturated hydraulic conductivity, alpha baseflow factor, recharge, drainage area, channel length, and channel width. Daily evaluation produced low R^2 values of -0.04 and 0.19, respectively, for the years 1995 and 1996. The data's monthly summaries revealed improved performance, with R^2 values of 0.58 for 1995 and 0.89 for 1996. As a result, it was discovered that choosing precise parameters was important for producing simulated streamflow data that closely matched observed values.

In the Lake Tana Basin, Ethiopia, Setegn *et al.* (2008) used the SWAT 2005 model for hydrological modelling. The model was calibrated using the SUFI-2, GLUE, and Parasol algorithms. The flow was more sensitive to the HRU definition thresholds than to the subbasin discretization effect, according to the sensitivity analysis. Performance was strong for SUFI-2 and GLUE. The calibrated model could therefore be applied to additional analyses of climate and land use change as well as to management scenarios for flow and soil erosion.

SWAT used by Schmidt and Zemadim (2014) to investigate the hydrological response of Ethiopia's Upper Nile Basin, which met the model performance criteria. ESCO and CN2 were found to be the most sensitive factors for that watershed after a sensitivity analysis was conducted. Agricultural lands were also the locations that generated the highest runoff, according to the HRU report. Therefore, educating farmers about Rain Water Management (RWM) interventions may increase the productivity of agriculture.

SWAT was effectively used by Kushwaha *et al.* (2013) to test the model's appropriateness in Dabka, Uttarakhand, which is northwest of Nainital and has a drainage area of 69.41 km^2. Despite the study region being mostly covered by forest, the model responded well, with acceptable NSE and R^2 values. SOL_K was more susceptible to flow generation, followed by CN2 and SOL_K1. For baseflow generation, variables like SOL_AWC, SOL_Z and GWQMN were particularly sensitive.

In order to evaluate the hydrological behaviour of the Bandu River Basin in West Bengal, Sahoo S. (2013) employed SWAT. He accomplished surface runoff production well, and the temporal depiction of the surface runoff was positively impacted by the surface runoff lag time. The sensitivity analysis showed that curve number and evapotranspiration were the most important critical factors for estimating surface runoff.

Trevedi *et al.* (2024) estimated the amount of recharge required to fully restore the water in the Kanari River using the SWAT model. The model utilized weather data as a reference to calculate groundwater recharge rates and runoff. Hydrologic Response Units (HRUs) in the SWAT model were identified based on slope, land use, land cover, and soil maps. The region was divided into sub-basins, and 18 HRUs were delineated within the Kanari River basin. The SWAT model provided a water balance analysis for the sub-basin, breaking down precipitation into key components: 46.2% was accounted for as surface runoff, 26.9% for percolation, 26.9% for evapotranspiration, and 1.33% for deep recharge and lateral flow. The Nash–Sutcliffe efficiency (NS) during the calibration period was 0.83, and the coefficient of determination (R^2) for runoff during the same period was 0.92256. For the validation period, the R^2 value was 0.82, while the NS efficiency was 0.71. The annual groundwater recharge estimated by the SWAT model ranged from 75.27 mm to 379.02 mm, depending on the functions and parameters selected.

Raaj *et al.* (2024) estimated peak flow of the Himalayan river by integrating SWAT model with machine learning based approach. The results indicated that the uncalibrated SWAT model, when combined with machine learning (ML) regression models (uSWAT-ML), demonstrated good performance and was comparable to the calibrated SWAT model (cSWAT). The cSWAT model achieved satisfactory performance with an R^2 value of 0.73 and an NSE of 0.72. Among the uSWAT-ML models, the EN (Elastic Net) and BR (Bayesian Ridge) models produced superior results, achieving R^2 values of 0.89 each and NSE values of 0.87. Furthermore, the uSWAT-ML approach effectively predicted peak streamflow rates, with the BR and EN models achieving an R^2 value of 0.71 for peak flow predictions for each models.

2.3 ESTIMATION OF WATER REQUIREMENT USING CROPWAT MODEL

Crop calendar in *kole* lands outlines the best times for planting and harvesting based on the expected water availability and the dewatering schedule. The crop calendar helps farmers plan their activities efficiently, ensuring that better use of available water resources in the *kole* lands. To ensure the crop calendar is effectively adaptable, it is essential to account for the irrigation demands of the crops. To calculate irrigation demand, it is essential to calculate the net irrigation requirement. CROPWAT, a software developed by the Food and Agriculture Organization (FAO), is commonly used for determining irrigation needs and scheduling. Numerous researchers have used the CROPWAT model to assess actual evapotranspiration, crop water requirements and to plan irrigation schedules (Kuo *et al.*, 2001; Trivedi *et al.*, 2018).

Knežević *et al.* (2013) utilized two software programs, CROPWAT and ISAREG, to calculate the net irrigation requirement (NIR) for a water balance study focused on winter wheat production. The results from both models were compared, revealing that the NIR needed to achieve maximum yield was higher when calculated using CROPWAT compared to ISAREG. From the results, the authors concluded that both models are effective tools for determining the water balance of wheat crops.

Gangwar *et al.* (2017) carried out a study to estimate the net irrigation requirement for rabi crops in the Bina command area of Madhya Pradesh using CROPWAT 8.0 software. The average daily reference crop evapotranspiration was found to be 4.62 mm/day. Wheat, gram (pulses), and mustard were the selected rabi crops, with their water requirements determined to be 349.8 mm, 304.1 mm, and 316.9 mm, respectively, using the software. The study estimated the net irrigation demand for the Bina command area to be 212.27 Mm^3.

In their study, Surendran *et al.* (2017) used the CROPWAT model to assess crop water needs and evaluate water resource availability in the Kollam district of Kerala. The district's overall water balance across agro-ecological units for domestic, industrial, and agricultural demands were estimated for both current and future needs. Findings indicated that future water demand is projected to exceed available resources by 1,550 Mm^3. Although irrigation is essential to maximize crop yields, sustaining agriculture under water scarcity may require a reduction in irrigated areas. Alternatively, implementing water-saving measures such as deficit irrigation, microirrigation techniques, and adjusting planting schedules were suggested to help mitigate the impact of water shortages.

Bai and Rema (2020) estimated irrigation requirement for Chalakudy River Diversion Scheme (CRDS) using CROPWAT software. The net irrigation for the command area of Left Bank Canal (LBC) was found 23.03 Mm^3 and that of Right Bank Canal (RBC) 23.87 Mm^3. The total average annual net irrigation demand of the CRDS command area was obtained as 46.90 Mm^3.

2.4 ESTIMATION OF SEEPAGE LOSS FROM CANALS

Seepage losses from canal systems remain a major challenge for irrigation and water resources in worldwide (Leigh, 2014). Reports from the ICID (1968) indicate that these losses constitute up to one-third of total diverted irrigation water, with some cases reporting losses as high as 60% (Dhillon, 1967).

Seepage from earthen canals can be assessed using both direct and indirect methods. The three most commonly used direct measurement methods are: a) the inflow-outflow test, b) seepage meters, and c) the ponding test. These methods allow for quick and localized estimates of water loss rates, which are valuable for effective irrigation planning and management. Indirect approaches include the use of empirical equations, analytical methods, and simulations via numerical models. (El-Molla and El-Molla,2021).

Eshetu and Alamirew (2018) studied seepage loss in both lined and unlined canals in Ethiopia's Tendaho sugar estate, using inflow-outflow method and a current meter to measure water velocity in primary, secondary, and tertiary canals. Average seepage losses were 0.55% per 100 m (0.0126 $l/s/m^2$) for lined primary canals and 0.84% per 100 m (0.0180 $l/s/m^2$) for unlined ones. For secondary and tertiary canals, seepage losses were higher at 3.65% (0.0391 $l/s/m^2$) and 4.27% (0.0248 $l/s/m^2$) per 100 m, respectively.

The inflow-outflow test method determines seepage losses by comparing the volume of water entering a canal section with the volume exiting it. Measurements are performed using current meters, portable or installed flow structures, or a combination of these tools. For evaluations of ponding and inflow-outflow methods, Alam and Bhutta (2004) found that the inflow-outflow method was more susceptible to measurement errors, especially when seepage losses were lower than the accuracy threshold of the flow meters. These errors maybe reduced on longer test sections thus accounting for more seepage.

Sarki *et al.* (2008) conducted experiment on estimation seepage by comparing two different methods an earthen water course in Qaiser in Tando Jam : inflow–outflow and second was ponding method. Before study soil texture of bed of watercourse was analyzed which was varying from sandy soil to sandy loam, and bed slope was calculated with Autolevel, which was 0.0002. Experiment was conducted on a straight reach of water course of 600 m length. This reach was divided into five sections of 120 m each. For inflow-out flow test reach, inflow and outflow were measured by cut-throat flume. Ponding test was conducted over short sections of 30 m each in inflow-outflow sections of 120 m. Seepage loss calculated was 0.0016 m^3 sec^{-1} (LPS)/100 m by inflow-outflow test and 0.00123 m^3/100 m by ponding test. Ponding test measured water losses 23% less than inflow-outflow test. Reason of this difference may be over estimation of discharge through cut throat flume and under estimation of seepage loss through ponding test due to silt deposition in the water course, and actual seepage loss could be expected somewhere between these two.

Compared to the inflow–outflow method, the ponding test provides more precise seepage measurements. The calculated seepage rate can then be used to estimate canal water losses throughout the irrigation season or annually. However, the ponding method requires substantial labour, making it costly and impractical for large irrigation channels, especially with multiple branches or steep slopes.

Numerous studies have quantified seepage losses in unlined irrigation canals, often using the ponding method. For example, Zhang *et al.* (2017) highlighted that applying the Kostiakov formula for seepage calculation can produce results differing from field measurements. Iqbal *et al.* (2002) studied seepage in 13 irrigation districts in Alberta, Canada, by testing at 29 sites with poly-lined earth plugs on 150-meter canal sections. They filled the channels to operational depth and recorded the time for water to drop to 80% of the designed level, finding annual seepage losses of approximately 91 Mm^3 in 1999.

The ponding test method calculates water loss by measuring the vertical drop in water level over a designated time period in a ponded canal section. This approach is widely regarded as the preferred method, as numerous studies indicate it offers higher accuracy and is less impacted by measurement errors but there is evaporation loss during ponding test. Empirical formulas are employed when direct measurement of canal water losses is unavailable or impractical. These formulas are based on observed relationships between water losses and specific hydraulic conditions. Some formulas are tailored for highly localized conditions, while others provide estimates for more general cases, such as unlined or lined canals. Certain formulas also require data on canal discharge/velocity or the saturated permeability of canal soils (Dhillon 1968).

A seepage meter is a confined cylinder inserted into the side or bottom of a canal to measure permeability rates in a small, specific area. Estimating seepage losses with this method depends on conducting multiple tests and averaging the results over the length and perimeter of a canal section. However, seepage meters have limitations: they are generally effective only in water depths less than 0.6 m (Iqbal *et al.,* 2002) and can only be used in earthen or unlined canals.

Mohammadiyeh *et al.* (2010) conducted experiment for quantifying water losses in earthen channels by comparing empirical formulas—including those from Ingham, Davis-Wilson, Moleswerth and Yennidumia, and Misra and Moritz (Kraatz, 1977)—against field observations.

Wachyan and Rushton (1987) studied how hydraulic conductivity impacts canal seepage. In this study, a soil layer of lower hydraulic conductivity laid under a more permeable layer. Results indicated that lining only the canal bed, with unlined walls, reduced seepage by 4% compared to fully unlined canals. whereas, lining only the canal walls, with an unlined bed, led to a 2% reduction in seepage relative to the unlined condition.

Yao *et al.* (2012) performed ponding tests on four canal sections in multi-layered soils in Northwest China to examine canal leakage characteristics. The sections had various linings, including concrete, pebble, clay with compacted canal beds, and compacted beds alone. Additionally, they used the HYDRUS-2D numerical model to simulate seepage and identify influencing factors, providing a comprehensive assessment of seepage behavior across different lining types.

Solomon (2014) investigated steady-state seepage from an irrigation canal in asymmetrical trapezoidal concrete-lined canal. They applied a finite element method to calculate the flow volume and examined typical soil permeability values for both single-layer and two-layered subsoils. Additionally, the impact of clay-cement concrete as a lining material on seepage control also assessed.

Salmasi and Abraham (2020) studied on predicting seepage from unlined earthen channels using the Finite Element Method (FEM) and Multivariable Nonlinear Regression (MVNLR) to model seepage in irrigation canals. The study shows that water loss in unlined channels, an issue critical in agriculture, particularly in regions facing water scarcity. By using FEM, the study accurately simulates various soil and hydraulic parameters, while MVNLR provides a predictive formula, which was validated with high accuracy, showing an R^2 value of 0.928. This approach is performed with traditional empirical methods, suggesting that combining numerical and regression modelling can improve seepage estimation.

Jamel (2016) applied the SEEP/W numerical model to analyze seepage rates in both lined and unlined triangular open channels. In lined channels, seepage increased with higher lining permeability, channel height and soil permeability, but decreased with shallower side slopes and reduced freeboard. For unlined channels, seepage also increased with increased soil permeability and channel height, while decreased with shallower side slopes and less freeboard.

El-Molla and Molla (2022) conducted study on SEEP/W model to investigate the effect of compacted earth lining characteristics on seepage from trapezoidal earth eanals. The study quantified seepage reduction through canal lining by examining various scenarios of hydraulic conductivity, lining thickness and placement of compacted earth lining. Results indicated that compacted earth lining could significantly reduce water losses, with up to 99.8% of seepage prevented when high-compaction soil was applied to both the bed and sides.

Malik and Karim (2020) conducted experiment on seepage modelling and analyzing slope stability for the Haditha Dam in Iraq using the finite element method with GEOSTUDIO 2012 software. They stated that GEOSTUDIO is a powerful tool that can perform various analyses, including stress-strain, seepage, slope stability, and dynamic analysis. In particular, SEEP/W and SLOPE/W, two modules within GEOSTUDIO were used to simulate the movement of water and the distribution of pore-water pressure within permeable materials such as soil and rock. This study used the dam as a case study to simulate seepage and slope stability. The input data for the software included the dam's geometry and material properties. SEEP/W generated the flow net, showing the phreatic line, equipotential lines and streamlines, and calculates the seepage flux.

Moharrami *et al.* (2014) conducted a study utilizing the finite element method, using the SEEP/W and SLOPE/W programs, to assess seepage and slope stability in an earth dam. The study showed how multiple horizontal filters, differing in length and position, help to reduce excess pore water pressure due to the rapid drawdown of the upstream water level. Results revealed that increasing the number of horizontal filters had minimal impact on seepage flow.

Fattah *et al.* (2015) applied the finite element method to estimate seepage flux through an earth dam and analyzed dam behavior during rapid drawdown in the reservoir. For this study, the SEEP/W and SLOPE/W modules in GEOSTUDIO 2007 were employed, using the Dau Tieng reservoir in Tay Ninh province, South Vietnam. Results indicated that the seepage through the earth dam gradually decreased over time following the onset of rapid drawdown in the reservoir.

2.5 SIMULATION BASED OPTIMIZATION MODELS FOR WATER MANAGEMENT

Effective water management in *kole* lands requires the planned operation of regulators. The operation of these regulator is similar to operation policies of reservoir. Mathematical modelling techniques play a key role in facilitating this planning process. Researchers have developed various types of mathematical models for optimize water use. Simulation models, optimization models and combined simulation–optimization models are major types of models used in water management.

Ralph (1993) defined simulation model is a representation of a system used to predict the behaviour of the system under a given set of conditions. Alternative executions of a simulation model are made to analyze the performance of the system under varying conditions, such as for alternative operating policies. The study shows that simulation model reproduces hydrologic system and economic performance of reservoir system. Also, Simulation models have been routinely applied for many years by water resources- development agencies and other entities responsible for planning, construction, and management of reservoir projects.

Simulation models remain in practice a prominent tool for reservoir systems planning and management studies. Simulation models associated with reservoir operation are usually based on mass balance equation and represent the hydrological behaviour of reservoir systems using inflows and other operating conditions. Some models however represent economic performance of the reservoir system. Application of simulation techniques to water resources planning and management started with U.S. Army Corps of Engineers (USACE) doing simulations of the Missouri River. The famous Harvard Water Program applied simulation techniques to the economic design of water resources (Maass *et al.* 1962).

Simulation is a modelling technique designed to replicate the performance of complex water resource systems. It is especially valuable in situations where optimization techniques may fall short due to their inherent limitations. While simulation is not an optimization method on its own, it can help achieve near-optimal results. In the context of water resources modelling, these near-optimal solutions can be just as useful as the actual optimal solutions.

The studies of large-scale systems (Chaturvedi and Srivastava, 1981) have indicated that even with the use of simple programming approaches such as LP, valuable results can be obtained to simplify simulation. In a pure simulation model, reservoir releases are determined using predetermined operating rules. They reviewed a variety of operating policies for reservoirs in series and in parallel, which are useful for real-time, seasonal, and long-term operations of multi-reservoir systems. Identifying effective pre-defined operating rules for complex multi reservoir systems with simulation is a challenging task. To overcome this problem the researchers generally employ optimization methods within simulation models (Johnson *et al.* 1993). Tejada-Guibert *et al.* (1993) compared SDP and SDP within simulation, for defining the operation policy of a multi-reservoir system. The authors found that the latter approach was superior.

A simulation- mixed integer LP (MILP) approach was used by Randall *et al.* (1997) for long-range water supply planning in the Alameda County Water District (California). The authors showed that MILP engine used in long-term simulation model had demonstrable advantages over network approaches. Karamouz *et al.* (2004) analyzed regional water resources issues in a complex system using a combined optimization-simulation model. A methodology (Wang *et al.* 2005), combining the constraint technique, decomposition iteration and simulation analysis has been presented to alleviate the dimensionality difficulty in solving the stochastic multi-objective optimization problem of reservoirs in parallel.

A simulation model comprises several key components, including inputs, outputs, physical relationships between variables, constraints, and operating rules. The model processes inputs into outputs based on these physical relationships and constraints. To conduct a simulation, the first step is to decompose the complex system into sub-systems and establish appropriate linkages between them. Computer programs are then developed for each sub-system to facilitate the transfer of information between them. Verification of the model is essential, using known inputs and outputs to ensure its accuracy. Once verified, the model can be run with various input sets to generate corresponding outputs. Each simulation run produces a specific output for each input set, and the results of multiple simulations are referred to as response surfaces (Vedula and Mujumdar, 2005).

Bejranonda *et al.* (2011) conducted a simulation study to the increasing water demands for agriculture in Thailand, where rice is a predominant crop. They investigated and simulated the interaction between surface water and groundwater using a mathematical model for groundwater flow, revealing significant seasonal interactions between the two water sources in the study area. By simulating scenarios with the maximum possible drawdown of hydraulic head, they estimated the groundwater potential of the region. The authors concluded that utilizing unused surface water during the transition from the wet to the dry season for groundwater recharge, along with appropriate allocation of this groundwater for conjunctive use, could effectively address the water scarcity issue in the area.

Simulation is a vital method for evaluating alternative water resource systems and plans. It serves as an effective tool for performance assessment by tracking the behavior of complex systems (Mohan and Jyothiprakash, 2003). Through computer programs tailored to specific problems, simulation can provide insights into expected system performance. By applying various operating policies or decisions, the output of the system can be analyzed using simulation models. Input variables should characterize the system, while inputs and inflows—such as rainfall and other hydrological parameters—must also be incorporated into the simulation model.

According to Rani (2013) simulation was an initial step in planning large-scale systems. However, given the extensive options for configurations, capacities, and operating policies, using simulation alone—without prior screening through optimization—can be highly time-consuming. Preliminary optimization helps narrow down feasible options, making the subsequent simulation process more efficient. The optimization methods have been proved of much importance when used with simulation modelling and the two approaches when combined give the best results.

Besides the traditional optimization methods, ANN and Evolution Algorithm (EA)s have also been used in combination with simulation in reservoir systems management. For example, Cancelliere *et al.* (2002) derived monthly operating rules for an irrigation reservoir using DP and ANN, which were further validated by simulating the behaviour of the reservoir over a shorter period, not included in the period used for training the networks. A combined neural network simulation–optimization model with multiple hedging rules was used for screening the operation policies by Neelakantan and Pundarikanthan (1999).

Koutsoyiannis and Economou (2003) proposed a low dimensional Parameterization simulation–optimization approach using the methodology of parametric rule introduced by Nalbantis and Koutsoyiannis (1997). Simulation was used to obtain values of the performance measure, which was optimized by a nonlinear optimization procedure. In a study by Suiadee and Tingsanchali (2007), combined simulation– Genetic Algorithm (GA) model software with a graphical interface capability was developed. GA was used to determine the optimal upper and lower rule curves which were used in simulation. The authors found that the annual net benefit using combined simulation–GA model was slightly higher than those computed by HEC-3, SOP and the existing actual operation.

Dhar and Datta (2008) proposed a linked Genetic Algorithm (GA) based simulation–optimization methodology for optimal control of water quality, downstream of a reservoir. The model links an elitist GA and a surface water quality simulation model (CE-QUALW2). They concluded that the methodology can be extended to multireservoirs; however, the increase in number of reservoirs with a longer time horizon will increase the computational burden, as CPU time required even for single reservoir problem was quite large. Authors suggested that development of a parallel code or use of metamodels, such as, ANNs may be very useful in reducing CPU time for solving large and complex reservoir systems operation problems.

Combined optimization and generalized simulation model have also been used in many studies (Labadie 2004). Recently, efforts have also been made to link CI and generalized computer simulation models. For example, Shourian *et al.* (2008) developed a hybrid PSO-MODSIM model to propose optimum sizes of the planned water storage and transfer facilities in the upstream Sirvan basin in Iran. In this procedure MODSIM has been embedded in PSO algorithm. The design and operation variables are varied and evolved using PSO, while MODSIM is called to simulate the system performance and to evaluate the fitness of each set of these design and operation variables with respect to the model's objective function.

Latif *et al.* (2020) developed reservoir water balance simulation model for Klang Gate Reservoir, Malaysia. Model was developed by using inflow, release of dam, initial and final storage of the reservoir. By using the final and initial storage of reservoir, release, and inflow data from the year 1997 to 2007, the Klang Gates Reservoir water balance simulation model was successfully developed to predict the monthly water losses. The proposed model provided monthly forecasting with maximum root mean square error of ± 20.07%.

An optimal solution represents the mathematically best outcome achievable for a given system or situation based on its formulated mathematical model. Check In water management, regulator/reservoir operation an optimal relase from dam is the scenario may prove sub-optimal for another. To address varying conditions, optimization techniques such as linear programming, nonlinear programming, and dynamic programming are used to identify the best solutions for each specific scenario (Safavi *et al.*, 2010).

Vedula *et al*. (2005) developed a mathematical model utilizing linear programming to determine an optimal allocation policy for canal and groundwater in a reservoir-canal-aquifer system with multiple crops in its command area. The primary objective of the study was to maximize the sum of relative yields from various crops by integrating irrigation from canal water and groundwater pumping. Crop water allocations for different growing periods were achieved through the conjunctive use of these water sources while adhering to three major constraints: maintaining a mass balance of water in the reservoir, ensuring soil moisture balance for each crop, and controlling groundwater level fluctuations. The authors validated the model's applicability by conducting a study in the command area of a reservoir located in the Chitradurga district of Karnataka State.

Chaves and Kojiri (2007) conducted experiment on water quality and optimization models for the assessment of planning operations of a storage reservoir. The purpose of this paper is to consider a multipurpose reservoir, under different water demands and uses from societies, concerning reservoir water quality. The proposed optimization is realized through the use of dynamic programming combined with stochastic techniques that can handle the probabilistic characteristics of inflow quantity and quality. For the water quality assessment, the UNEP/ILEC one-dimensional model with two layers called PAMOLARE is applied. Finally, sensitivity analysis was carried out using a genetic algorithm model.

Most water management systems are large and complex, making them challenging to model using either optimization or simulation alone. In such cases, combination models are essential, with simulation-optimization (SO) models being particularly suitable. In this approach, the simulation model forecasts the outcomes of different management strategies, while the optimization model identifies the mathematically optimal management strategy. The simulation model typically generates near-optimal solutions, which the optimization model then refines to achieve an optimal solution. This process allows the simulation model to streamline the size and complexity of the optimization model. Today, simulation-optimization models are commonly employed to address conjunctive water management challenges. Many of these models now incorporate multi-objective considerations, often involving conflicting objectives in the context of conjunctive water management (Vedula and Mujumdar, 2005).

Kumar *et al.* (2013) developed an integrated modelling framework that included irrigation demand, canal water supply, and groundwater balance in a canal-irrigated area. The framework aimed to assess the effects of various levels of scenario analysis. Among the three scenarios tested—design supplies with the current cropping pattern, design supplies with an increased cropped area, and optimum supplies with an increased cropped area—the third scenario was determined to be optimal. This model was applied in a case study at the Srisailam RBC project in Andhra Pradesh, revealing that regulating canal water supply could facilitate sustainable groundwater use while saving up to 48% of canal water. The conserved water could then be redirected to other areas to promote equitable water distribution.

Chen *et al. (*2016) developed an integrated simulation and optimization model for scheduling irrigation in a multi-crop command area to mitigate the impacts of seasonal drought. This model utilized the combined operation of reservoirs and ponds, with the primary objective of maximizing annual net benefits. The integrated model consists of two key components: an operating policy model and an allocation model. The operating policy model optimized water releases from reservoirs and ponds, accounting for the regulatory function of the ponds.

Chang *et al.* (2017) developed a simulation-optimization model aimed at minimizing water shortages for irrigation within a reservoir-pond irrigation system in China. The integrated model consists of two main components: an optimal model that optimizes water releases from the reservoir, and a simulation model that simulates the water supply from both ponds and reservoirs. This model was implemented in the Yarkant River Basin, China. The results indicated that the combined operation of reservoirs and ponds in the Yarkant River Basin could lead to a 51.21% reduction in average annual water shortages following the construction of all three reservoirs in the sub-irrigation regions of the Yarkant River. Additionally, the conjunctive operation of these reservoirs also helped to maintain ecological flow in the river, providing further environmental benefits.

Nourani *et al.* (2020) optimized the operation rule curve of the Shahrchay reservoir in the north-west of Iran under climate change. The results showed that the average long-term annual runoff volume may be decreased between 0.08% and 2.27% in the future with regard to the base period, and the simulation results for present and future conditions indicated a decrease in water availability. Water shortages of 882.62 Mm^3 and 879.59 Mm^3 in 2025 and 2030 respectively found out from simulation model. The optimum storage should be maintained in the reservoir- 88.93 Mm^3 in April and 133.9 Mm^3 in June respectively for the Shahrchay reservoir

Spreadsheets and object-oriented simulation environments such as LOUTUS 1- 2-3 and STELLA (Systems Thinking, Experiential Learning Laboratory, with Animation) are popular approaches for constructing reservoir systems models. software like General Algebraic Modeling System (GAMS) , MATLAB ,LINGO, ASPEN Plus, COMSOL, and Hysys are powerful tools for optimizing process engineering tasks. However, they are designed primarily for professionals, as they require extensive expertise and a deep understanding of the software. Optimization problem can be solved by means of Excel – Solver by developing spreadsheet (Briones and Escola, 2019).