

## USE OF STREAMFLOW AND SATELLITE REMOTE SENSING SOIL MOISTURE DATA FOR JOINTLY CALIBRATING THE TANK MODEL

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Hydrological modelling in arid river basins is particularly complex due to the pronounced seasonal variability in water levels fluctuating between aridity and inundation. Solely relying on a single parameter, such as streamflow data, to calibrate hydrological models in these basins can be insufficient to capture intricate interdependencies of hydrological processes. This study aimed to optimize the lumped hydrological Tank Model to accurately simulate the complex hydrological behaviour of the Maduru Oya River Basin in Sri Lanka. Further, the research investigated the use of satellite (remote sensing)-derived soil moisture data in the hydrological modelling framework, highlighting the capability of advanced technologies to enhance the reliability of hydrological predictions.

The study commenced with the collection and preprocessing of climatic data, followed by the imputation of missing values using the Closest Station Patching Technique. Root zone soil moisture data derived from the Soil Moisture Active Passive Level 4 (SMAP L4) product were acquired and pre-processed using the Cumulative Distribution Function (CDF) Matching method. The primary focus of the study was the optimization of the Tank Model through a sequential joint calibration technique with the Kling-Gupta Efficiency (KGE) chosen as the optimization criterion. This process involved optimizing the model using both single-variable calibration with streamflow data and multi-variable calibration with streamflow and soil moisture data. Multi-variable optimization was conducted using a weighted approach that assigned different contributions to soil moisture ( $\alpha$ ) and streamflow ( $1-\alpha$ ) in determining model performance. This approach was implemented across 11 distinct calibration scenarios, with the parameter  $\alpha$  varying systematically from 0 to 1 in increments of 0.1.

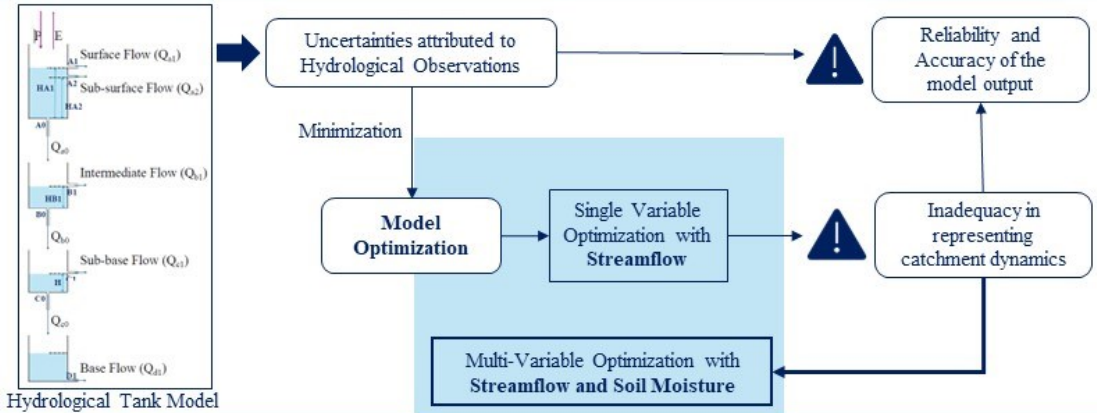
The results demonstrated satisfactory streamflow simulation performance under single-variable optimization, with  $KGE_Q$  values of 0.872 and 0.848 for calibration and validation, respectively. These findings underscored the Tank model's ability to accurately represent the hydrological processes within the Maduru Oya - Padiyathalawa sub-watershed. The inclusion of root zone soil moisture data (RSRZSM) significantly improved model performance, as evidenced by  $KGE_Q$  values exceeding 0.850 for all calibration scenarios except  $\alpha = 1$ . Multi-variable optimization techniques further reinforced the potential for enhanced overall model performance. The most accurate and reliable streamflow simulations ( $KGE_Q = 0.890$ ) were achieved with a minimal 10% and 90% contributions from soil moisture and streamflow respectively ( $\alpha = 0.1$  calibration scenario). Furthermore, the study emphasized the critical role of remote sensing data, specifically SMAP L4 retrievals, in characterizing the soil moisture intricacies of the study area, particularly in regions with limited in-situ measurements.

The study further recommends continued validation to ensure robust model predictions. Due to the short calibration and validation periods used to minimize climatic data discrepancies, long-term validation was deemed essential for assessing model performance. In addition, the study recommended investigating alternative multi-objective optimization approaches, such as Genetic Algorithms, and incorporating more satellite data for other hydrological processes.

**Keywords:** Maduru Oya, Multi-variable optimization, SMAP L4, Tank model

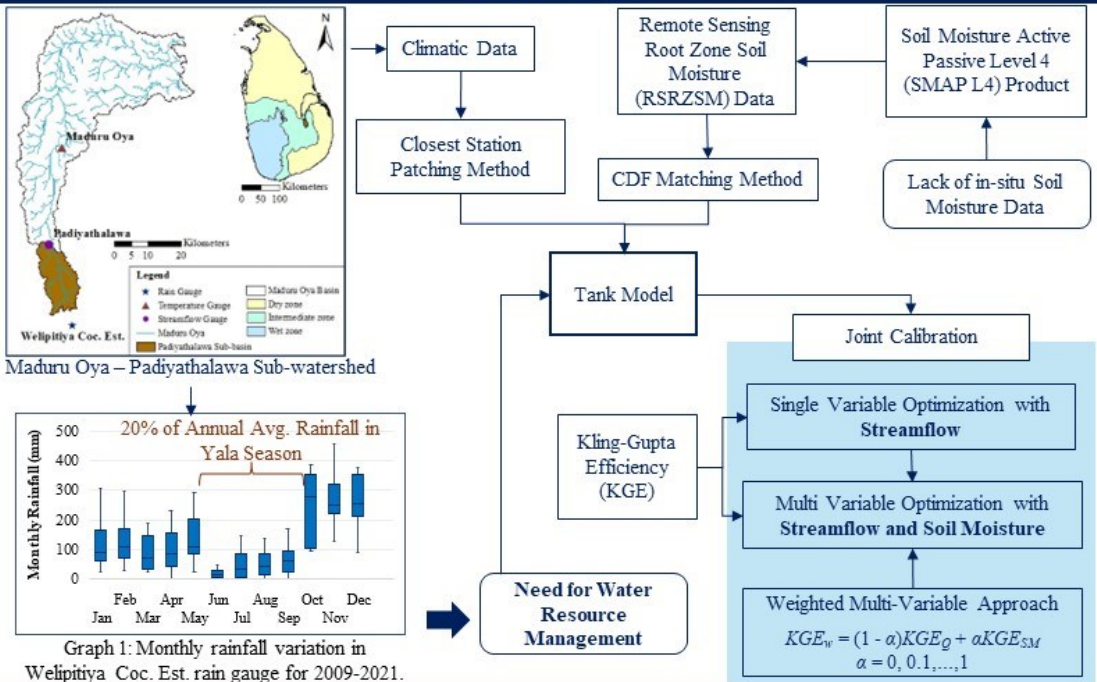
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### Background

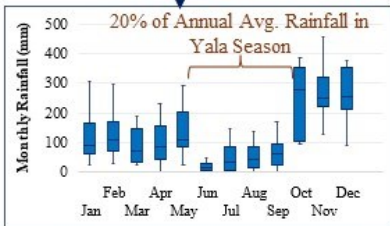


Hydrological Tank Model

### Methodology

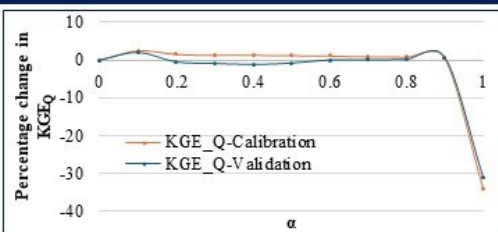


Maduru Oya – Padiyathalawa Sub-watershed

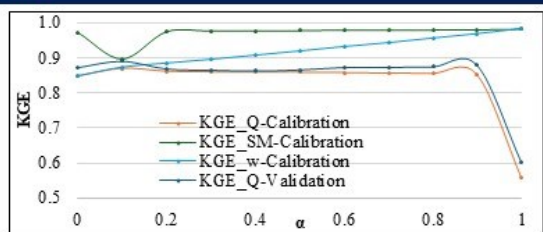


Graph 1: Monthly rainfall variation in Welipitiya Coc. Est. rain gauge for 2009-2021.

### Results



Graph 2: Percentage change in  $KGE_Q$  with respect to the calibration scheme  $\alpha = 0$  (Single objective optimization with streamflow).



Graph 3: Variation of  $KGE$  with  $\alpha$  value during calibration and validation using multi-objective optimization.