# IMPACTS OF LAND-USE CHANGES ATTRIBUTED TO DISCHARGE LEVEL OF MAHA OYA RIVER BASIN, SRI LANKA

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# ABSTRACT

River discharge in tropical regions are driven by both rainfall and land-use changes. This study quantifies how land-cover change and altered rainfall regimes have affected discharge in the Maha Oya River basin, Sri Lanka. Previous studies suggest that the river basin had been subjected to serious erosion due to increased soil digging, clay mining, and high flood vulnerability over the last three decades. This study uses Discharge data from 1992 to 2019 were analysed to identify factors influencing flood hazards and to inform disaster management strategies. Two hydrologic models representing historical (1992–1995) and recent (2016–2019) conditions were developed using the HEC-HMS software, incorporating the Soil Moisture Accounting (SMA) method. Land-use maps for 1990 and 2019 were generated through supervised classification of Landsat imagery, achieving overall accuracies of 92.5% and 96%, with Kappa coefficients of 0.90 and 0.95, respectively. Model calibration and validation yielded Nash-Sutcliffe Efficiency (NSE) values of 0.70 and 0.607 for the historical model, and 0.713 and 0.653 for the recent model. Validated model parameters such as Time of concentration, baseflow, recession and groundwater moisture indicates the impact of anthropogenic activities and land-use land-cover changes on groundwater level and baseflow of the catchment. Comparison of the calibrated parameters of the models further demonstrated the decrease in river discharge over the research period, which was mostly due to land-use changes such as increasing sand mining and agricultural development. The findings reveal a clear hydrological shift from an infiltration- to runoff-dominated system, driven by land-use change and rainfall variability, underscoring the urgent need for soil conservation and sand mining regulation to restore baseflow and enhance flood resilience in the Maha Oya Basin

Keywords: Land-use change; HEC-HMS modelling; River discharge; Baseflow; Maha Oya basin.

#### Introduction

Flooding is one of the most catastrophic natural hazards in tropical environment (Bronstert, Niehoff and Bürger, 2002) and it creates a serious risk to the riverine communities. Flood events causes due to high river discharges that inundated the surrounding lands (Davie, 2008). Both climate variabilities such as rainfall pattern changes and human activities influence the river discharge of a particular river; changing rainfall patterns can alter the frequency and magnitude of the high discharge events on the other hand land cover changes (e.g. deforestation, urbanization) alter the runoff and permeability by affecting soil infiltration and storage capacity (Bronstert, Niehoff and Bürger, 2002; McColl and Aggett, 2007; Halwatura and Najim, 2013). The hydrological cycle is the process involved in the sustainable water budget in the hydrosphere of the earth. Mainly runoff depends on the rainfall intensity and the infiltration capacity of the soil. If the rainfall intensity exceeds the infiltration capacity of the soil it creates surplus water on the surface of the earth. Rainfall intensity and infiltration capacities are depending on the rainfall pattern and the land-use pattern for a particular watershed. Therefore, changes occur in the rainfall pattern and the land-use can affect the runoff level and its behaviour. As the population growth rate continues to increase, there has been growing pressure placed on rural regions to convert agricultural lands, wildlife habitats, and other vegetation land spaces to urban areas (McColl and Aggett, 2007).

Hydrologic modelling is a key tool for attributing changes in river discharge to specific drivers (Halwatura and Najim, 2013). The HEC-HMS model (US Army Corps of Engineers) has been widely used to simulate basin hydrology under different land-use and climate scenarios (Kamran and Rajapakse, 2018). Moreover remote sensing is a very powerful tool that allows quantification of land use change and it also could provide reliable input for hydrological modelling (Jenson and Domingue, 1988). Therefore in this study is an approach to combine classified land use change maps with HEC-HMS models to enable controlled experiments in which rainfall or land use changes are varying independently (Packiyarajan Rubyhanusha *et al.*, 2019). This approach has the potential to give an idea on how much of observed river discharge is affected by the land use changes.

The Maha Oya river basin in Sri Lanka has suffered evidenced significant environmental degradation over the recent decades. Majorly due to the land use changes associated with urbanization and unsustainable resource extraction (Kaleel, Rinos and Mathanraj, 2016). It is recorded that the Maha Oya riverbank has been subjected to heavy erosion, with the erosion rate increasing from 19.77% in 1991 to 43.41% by 2014. This substantial rise indicates an alarming trend of land degradation (M I M Kaleel, Rinos and Mathanraj, 2016). Also, studies have shown that the clay mining and deforestation, which occurred in the Maha Oya basin has been the major reasons for the heavy erosion (M. I. M. Kaleel, Rinos and Mathanraj, 2016; Chathura Palliyaguru *et al.*, 2022; R. Jayathilaka *et al.*, 2024). The basin's hydroclimatic characteristics further compound these issues. Located in Sri Lanka's Intermediate Climatic Zone, the Maha Oya basin experiences both wet and dry zone conditions. This positioning causes high spatial and temporal rainfall variability, making the region particularly sensitive to shifts in climate patterns (Packiyarajan Rubyhanusha *et al.*, 2019).

The objective of this study is to assess the relative impacts of land-use change and rainfall variation on flood levels in the Maha Oya basin. We compare two periods: a historical baseline (1992–1995) and a recent period (2016–2019). We (1) classify land use for 1990 and 2019 using supervised Landsat classification; (2) develop HEC-HMS models for each period (using the Soil Moisture Accounting loss model); and (3) Compare two models based on calibrated parameters to understand the impact of land use changes occurred over the 28 year period.

Result could provide insight into hoe the land use changes impacted of the hydrological parameters of the catchment resulting changes in the discharge level of the Maha Oya river.

# Materials and Methodology

#### Study area

The Maha Oya is one of the major river basins in southwest Sri Lanka (7°16′N, 79°50′E), river is approximately 134 km long and the draining basin is about 1492 km<sup>2</sup>. River flows through four provinces, suppling water to more than one million people living in the surrounding for domestic, agricultural, and industrial purposes. The catchment receives an estimate of 3,644 million cubic meters of rainfall annually (Kamran and Rajapakse, 2018).



Figure 1: The Maha Oya river basin with data collection stations

## Data and data resources

Daily rainfall data from two gauging stations—Ambepussa Government Farm and Eraminigolla—were obtained from the Department of Meteorology for the periods 1992–1995 and 2016–2019. Discharge data were collected from the Badalgama gauging station, and evaporation data were obtained for Makandura station as shown in the Figure 1. The station selection was justified based on the catchment area being under 1,500 km<sup>2</sup>, meeting criteria set out by (K. Subramanya, 2008). Table 1 summarizes the data.

Data types	Spatial reference	Resolution	Data period	Source
Rainfall	Ambepussa farm (7° 16' 48"	Daily	1992-1995,	Meteorological
	N, 80° 10' 12" E)		2016-2019	Department
	Eraminigolla (7° 17' 60" N,	Daily	1992-1995,	
	80° 22' 48" E)		2016-2019	
Streamflow	Badalgama (7° 19' 30" N <i>,</i>	Daily	1992-1995,	Irrigation
	79° 58' 50" E)		2016-2019	Department
Evaporation	Makandura (7° 19' 12" N	Monthly	1992-1995,	Meteorological
	79° 58' 48" E)		2016-2019	Department

#### Table 1: Summary of the Data collection

#### Land use Classification

Landsat satellite images were used to map land use around 1990 and 2019. We obtained cloud-free Landsat 5 TM (1990) and Landsat 8 OLI (2019) scenes from the USGS EarthExplorer. Available images for 1992 was not in acceptable range of cloud cover to process with the analysis. Therefore 1990 was chosen for the study assuming the changes occurs during 2 years were negligible compared to the 29 years gap. Pre-processing included georeferencing to WGS84/UTM zone 44N, mosaicking, and stacking bands in ArcGIS 10.6. Supervised classification was applied, using training samples verified by Google Earth images. Four classes were delineated: Vegetation, Agricultural land, Urban area, and Water bodies. This limited classification scheme was chosen to minimize confusion in Landsat imagery (Rwanga and Ndambuki, 2017). After classification, accuracy was assessed by comparison to reference points; the 2019 map achieved ~96% overall accuracy (Kappa ≈0.95).

The calculation was done according to the formulation below,

Sensitivity = 
$$\frac{a}{a+b}$$
 (equivalent to producers' accuracy)  
Specificity =  $\frac{d}{b+d}$   
Commission error = 1- Specificity  
Omission error = 1- Sensitivity  
Positive Predictive Power =  $\frac{a}{a+b}$  (equivalent to user's accuracy)  
Negative Predictive Power =  $\frac{d}{c+b}$ 

where:

a = number of times a classification agreed with the observed value

b = number of times a point was classified as X when it was observed to not be X.

c = number of times a point was not classified as X when it was observed to be X.

d = number of times a point was not classified as X when it was not observed to be X.

Total points = N = (a + b + c + d)

KAPPA analysis is a discrete multivariate technique used in accuracy assessments. KAPPA analysis yields a Khat statistic (an estimate of KAPPA) that is a measure of agreement or accuracy.

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_i + X x_{i+1})}{N^2 - \sum_{i=1}^{r} (x_{ii} X x_{i+1})}$$

The Khat statistic (Kappa estimate) is computed as;

where;

r = number of rows and columns in error matrix, N = total number of observations(pixels)  $X_{ii}$  = observation in row *i* and column *i*,

Xi+ = marginal total of row *i*, and X+*i* = marginal total of column *i* 

A Kappa coefficient value close to 1 indicates a perfect agreement with the accuracy, when close to 0 marks it means that the agreement is no better than would be expected by chance (Rwanga and Ndambuki, 2017).

From the classified maps, area statistics were computed. Figure 2 & Figure 3 shows the maps. Table 2 summarizes class areas and percentage changes. Between 1990 and 2019, vegetation cover declined dramatically, while agriculture and urban land expanded. Waterbody area changed less (Table 2).



Figure 2: Land use delineation for 1990



#### Figure 3: Land use delineation 2019

Table 2: Class areas and percentage changes

Class name	Areas (km <sup>2</sup> ) for 1990	Areas (km <sup>2</sup> ) for 2019	Percentage change (±)
Vegetation	1313.118 (87.98%)	862.7794 (57.81%)	- 30.17%
Agricultural lands	137.1186 (9.19%)	504.4722 (33.80%)	+ 24.61%
Urban area	32.7771 (2.20%)	114.2896 (7.66%)	+ 5.46%
Water bodies	9.4365 (0.63%)	10.869 (0.73%)	+ 0.1%
Total	1492.4502 (100%)	1492.4502 (100%)	

## HEC-HMS Hydrologic model development

In this study two lumped rainfall- runoff models were constructed using HEC-HMS version 4.7.1. First, the watershed was delineated using ASTER GDEM (30 m) in the HEC-GeoHMS toolkit. The delineation produced sub-basins and stream network in accordance with topography. Sub-basin parameters such as slope, area, and flow length were also derived from GIS based terrain tools. Two separate models were then built: one representing 1992–95 conditions, and one for 2016–19 conditions. Each model used the same sub-basin structure but different land-use inputs at the initial step.

The Hydrological model was developed using the Soil Moisture Accounting (SMA) loss method, as it reliably represents catchment wetness storage and has been used for similar Sri Lankan basins (Kamran and Rajapakse, 2018). SMA parameters (initial loss, soil storage, impervious fraction, etc.) were initially set using values from Kamran & Rajapakse (2018) and then tuned. Canopy and Surface storage values were estimated initially based on land use specific values suggested by (Bennett and Peters, 2000). Clark's unit hydrograph was used for runoff transformation, while the Recession method estimated baseflow components. (Fleming and Neary, 2004). Thiessen polygon method was applied to develop the precipitation model using station-based rainfall data and the channel was routed using the Muskingum method.

Each model was calibrated by adjusting parameters to match observed hydrographs in a "continuous simulation" mode. The first three years (1992–94 and 2016–18) were used for calibration, and the next year for validation. Objective functions included the Nash–Sutcliffe efficiency (NSE) and bias; final NSE exceeded 0.70 for both models, indicating good performance.

#### Results

#### Land use changes

The supervised classifications produced detailed land-use maps (Figure 2 & Figure 3). The 1990 basin was ~88% vegetated, with minor agriculture and urban land. By 2019, vegetation had shrunk to ~58% of area (Table 2), largely replaced by agriculture (from 9.2% to 33.8%) and expanded settlements ( $2.2\% \rightarrow 7.7\%$ ). Water bodies (mainly reservoirs/river) occupied 2–3% of the area in 1990 but only 0.7% in 2019 (likely due to classification differences in inundation). These changes indicate widespread deforestation for cultivation and growth of built-up land.

#### Hydrological Model Performance

Figure 4 compares the observed versus simulated flow for the calibration of the 1992-1995 model (Model 01). It closely reproduces the observed hydrograph peaks and the baseflow. Calibration (NSE = 0.70) validation for 1994-1995 with (NSF = 607). The 2016–19 model (Model 02) Figure 5, similarly matches its observations (NSE = 0.713 for Calibration, 0.613 for Validation for 2008-2019). Both models capture the timing of flood peaks and recession limbs satisfactorily.



Figure 4: Model 01 Calibration (92-95)



Figure 5: Model 02 Calibration (16-19)

## Calibrated Model Parameters

#### Table 3: Comparison of calibrated parameters in Model 01 and Model 02

Parameters	Unit	Model 01 (1992- 95)	Model 02 (2016-19)
Clark Unit Hydrograph - Storage Coefficient	HR	89.92	107.81
Clark Unit Hydrograph - Time of Concentration	HR	38.51	13.96
Recession - Initial Discharge	M3/S	17.78	8.93
Recession - Ratio to Peak		0.28	0.10
Recession - Recession Constant		0.99	0.30
Simple Canopy - Initial Storage	%	0.00	0.05
Simple Canopy - Max Storage	MM	1.52	1.59
Simple Surface - Initial Storage	%	0.00	0.33
Simple Surface - Max Storage	MM	20.80	16.82
Soil Moisture Accounting - GW1 Percolation	MM/HR	0.47	0.73
Soil Moisture Accounting - GW1 Storage	MM	80.52	127.61
Soil Moisture Accounting - GW1 Storage Coefficient	HR	11.43	9.58
Soil Moisture Accounting - GW2 Percolation	MM/HR	0.40	0.66
Soil Moisture Accounting - GW2 Storage	MM	10.00	8.09
Soil Moisture Accounting - GW2 Storage Coefficient	HR	30.50	15.31
Soil Moisture Accounting - Initial GW1 Content	%	73.12	12.28
Soil Moisture Accounting - Initial GW2 Content	%	80.01	23.15
Soil Moisture Accounting - Initial Soil Content	%	79.87	28.95
Soil Moisture Accounting - Max Infiltration	MM/HR	4.56	3.14
Soil Moisture Accounting - Soil Percolation	MM/HR	0.34	0.27
Soil Moisture Accounting - Soil Storage	MM	461.41	484.04
Soil Moisture Accounting - Tension Storage	MM	22.51	21.06

A close comparative look at the calibrated parameters from the Model 01 and Model 02 indicates significant differences across the vital hydrological processes (Table 3). These changes reflect the transformation in the Maha Oya river basin's hydrological response over time due to land use changes and soil disturbances that happened over time.

Among the notable changes, Clark unit hydrograph time of concentration decreased significantly from 38.51 hr to 13.96 hr, and the storage coefficient increased from 89.92 hr to 107.81 hr. This indicates faster runoff generation and greater short term water storage in recent years. The initial discharge and baseflow recession values also indicates a shift, the initial discharge reduced from 17.78 m<sup>3</sup>/sec to 8.93 m<sup>3</sup>/sec and recession constant declined from 0.99 to 0.30, signalling a reduced baseflow support and quicker flow recession.

In the Soil Moisture Accounting (SMA) parameters, initial groundwater concentrations (GW1 and GW2) significantly decreased (from 73.12% and 80.01% to 12.28% and 23.15%, respectively), whereas percolation rates experienced a minor rise, indicating diminished groundwater recharge and modified subsurface flow dynamics. Furthermore, the maximum infiltration capacity decreased from 4.56 mm/hr to 3.14 mm/hr, and the initial soil moisture content diminished by over 50%. These changes indicates a potential soil compaction and vegetation loss observed in the land use analysis.

Moreover, canopy and surface storage parameters showed minor increases in comparing two models. Possibly due to expanded built surfaces and vegetation loss. For example, initial surface storage rose from 0.00% to 0.33%, while maximum surface storage decreased from 20.80 mm to 16.82 mm, signifying diminished depression storage or a severe groundwater extraction.

## Discussion

The variations in calibrated model parameters from 1992–1995 to 2016–2019 provide important information about how the hydrologic behaviour of the Maha Oya basin has changed over time. In line with less vegetation and more impermeable surfaces, the sharp decline in time of concentration and early soil/groundwater moisture points to a basin that is now more vulnerable to flashier runoff events.(McColl and Aggett, 2007; M. I. M. Kaleel, Rinos and Mathanraj, 2016). The basin has transformed from infiltration dominated (92-95) to runoff dominant (2016-2019).

As noted in the (Ranasinghe, 1997; Meredith Corea Talbert and Talbert, 2012) likely due to clay mining and loss of riparian zones that formerly supported groundwater recharge, the baseflow associated parameters such as initial discharge, recession constant are decreased. It indicates that the baseflow in the Maha Oya river basin has been depleted over time. This finding complements the reduced dry-season flows observed in hydrographs and supports concerns about sustainable water availability.

Soil-related SMA parameters reflect a decline in the basin's infiltration and moisture retention capacity. The lower maximum infiltration rate and percolation values, alongside decreased initial soil moisture, indicate soil compaction or exposure, both of which reduce the subsurface buffering capacity. This could be a consequence of expansion of the agricultural lands and the unsustainable clay and sand mining which damages the soil layers and leads into compactions. Additionally, the increase in canopy and surface storage could be due to the localized ponding or interception caused by artificial land use modifications. As suggested in the Ranasinghe (1997), the unsustainable land excavation maybe the reason for the result. Overall, when looking at the result of the study it reflects a reduction in hydrologic resilience happened over time in Maha Oya river basin.

The These parameter changes do not merely adjust the model's numerical output; they represent real physical changes in how water moves through the basin. Importantly, they validate the land-use

classification and erosion-based findings (M. I. M. Kaleel, Rinos and Mathanraj, 2016) and indicate a shift from a baseflow-dominant regime to a more surface-runoff-dominated one—heightening both flood risk and dry-season water scarcity.

Despite providing valuable insights on the hydrological impacts of land use changes happened in Maha Oya river basin, the models in this study in under several limitations. Lumped nature of the model did not provide true representation of the spatial variability of parameters and rainfall. While basin wide calibration gives a reasonable representation, distributed or semi distributed modelling could further explain the results more effectively. However, data availability was another concerning factor to develop a continuous model for Maha Oya basin. Discontinuity of the available datasets limits the model development for four years in this study. Furthermore, land-use classification accuracy, although high, may still be affected by cloud cover, seasonal image variations, and classification confusion (especially between urban and bare land). Future work could benefit from higher-resolution imagery and field-verified land-use ground truthing to refine classifications. Lastly the model does not simulate channel erosion and sediment transportation explicitly.

These limitations highlight the need for integrated modelling approaches, better datasets, and continuous monitoring to further improve the predictive capability and management applicability of flood modelling efforts in tropical basins like Maha Oya.

## Conclusion

This study used a combination of remote sensing, GIS, and HEC-HMS modeling to assess the hydrological effects of land-use changes in the Maha Oya River Basin during a 28-year period. The hydrological conditions of 1992–1995 and 2016–2019 were represented by two calibrated models. Significant changes in watershed behavior were found by carefully comparing important model parameters, particularly a decrease in time of concentration, baseflow contribution, and infiltration capacity, which indicated a move toward a hydrological regime that was more dominated by surface runoff.

Between 1990 and 2019, land-use classification verified widespread urbanization, agricultural growth, and deforestation. Reduced baseflow during dry seasons and sharper peak flows during rainfall events are the results of these changes, which, when combined with rainfall variability, have drastically changed the river's runoff dynamics. Parameter study also revealed a loss of hydrological buffering capacity, indicating a drop in groundwater storage and an increase in probability of flash flooding.

The observed baseflow depletion appears to be irreversible without significant restoration of natural channel morphology, soil structure, and riparian buffers including more nature based solutions. Therefore, the study strongly recommends policy interventions focusing on regulating unsustainable land excavations and extreme groundwater extractions across the basin. It can ensure the long-term water security and ecological stability of one of the most economically significant river basin in Sri Lanka.

The modeling approach had some limitations, including the use of lumped parameters, scarce hydrometeorological data, and simplified assumptions in the model structure, even if it was successful in capturing broad trends and offering insightful information. To better understand and forecast complicated flood behaviors in tropical river basins, future research should focus on integrating coupled groundwater–surface water interactions, higher-resolution spatial data, and distributed hydrological models.

# DATA AVAILABILITY

The data associated with this study can be made available upon reasonable request from the corresponding author.

# ACKNOWLEDGEMENTS

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## CRediT authorship contribution statement

R.N. Sameera: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Subramaniam Ganadeepan : Methodology, review & editing

# Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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#### SUPPLIMENTARY INFORMATION

Supplementary information allows authors to include additional details or results that could not be included in the main paper. Sensitivity assessments, additional results generated to address reviewer concerns, and other similar details should be included here. It would be normal for the Supplementary Information to increase in length through the review process.