RESEARCH ARTICLE

A Remote Sensing and MCDA-Based Assessment of Sustainable Water Availability in Sri Lanka

Thirilojanan Keerthi[1*], Isith Keshara[1]

[1]*Department of Earth Resources Engineering, University of Moratuwa, Colombo, Sri Lanka.*

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Abstract: In Sri Lanka, uneven distribution of water poses significant challenges to the agriculture, environment, and ecosystem stability. Diverse climatic zones, topographical variations, and anthropogenic factors are the main causes of disparities in water availability. Accurate spatial assessments will help to locate these disparities. Therefore, this study proposes a framework that combines Geographic Information Systems (GIS), Remote Sensing, and Multi-Criteria Decision Analysis (MCDA) to produce a Surface Water Availability Index (SWI) across Sri Lanka. For this analysis, four key factors such as rainfall, drainage density, evapotranspiration, and surface water extent were selected, compared, and systematically weighted through the Analytic Hierarchy Process (AHP), with an acceptable Consistency Ratio (1.7%), to generate an SWI for Sri Lanka. District-wise SWI analysis indicates that water availability is limited in some parts of the country, especially in the Northern Province, highlighting the need for targeted interventions. Correlation analysis shows that a moderate negative correlation ($r = -0.44$) can be observed between SWI and LST, which reflects the cooler conditions in water-rich regions. Conversely, SWI exhibited weak correlations with NDWI ($r = -0.21$) and NDVI ($r = 0.25$), which show the complex hydrological and ecological dynamics. Despite some data limitations, this framework will support water conservation, drought mitigation, and efficient environment management. The accuracy of this method can further be improved with the use of higher-resolution, accurate data and relevant environmental and hydrological variables. It provides direct value for policy and planning in support of sustainable agriculture and environmental stewardship.

Keywords: Analytical Hierarchy Process, Decision Support, Environmental Monitoring, Geographic Information Systems, Normalised Difference Indices

INTRODUCTION

Water scarcity and uneven distribution of freshwater sources have become a serious issue nowadays globally due to the rapid development and population growth. This is threatening food security, public health, ecosystem stability, and many more [1], [2]. To address such challenges, there is a need to have tools and technologies, which are capable of mapping, monitoring, and managing water resources at finer spatial and temporal scales. Accurately mapping the water availability is critical in resource planning, irrigation management, and ensuring sustainable land and ecosystem use. In recent years Geographic Information Systems (GIS) and Remote Sensing techniques have been increasingly used, providing tools to assess, monitor, and visualize the spatial variability of water-related parameters at various scales [3].

Sri Lanka is a tropical island country located in South Asia, and it has been experiencing severe challenges in water resources due to its highly variable rainfall patterns and diverse topography. Significant spatial disparities in water availability can be observed due to three major climate zones: wet, intermediate, and dry zones [4]. Droughts and seasonal water shortages are a serious threat to agriculture, which remains the backbone of rural livelihoods and national food security.

**Corresponding author. E-mail address: thirilojanankeerthi@mech.mrt.ac.lk (Thirilojanan Keerthi)*

In Sri Lanka, most existing water management strategies rely mainly on coarse regional assessments. High-resolution, spatially explicit assessments that can capture regional disparities and support more targeted, sustainable water management strategies [5].

The integration of GIS, Remote Sensing, and multi-criteria decision analysis (MCDA) gives an effective, simple way for water resources evaluation and management practices. While Remote Sensing provides timely, wide-area coverage of many parameters including hydrological environmental variables, GIS enables synthesis and spatial analysis [6].

Analytic Hierarchy Process (AHP) is a widely used pairwise comparison-based technique, where multiple factors can be systematically incorporated and weighted to produce composite maps for decision support [7] [8]. Many studies have demonstrated that GIS-MCDA frameworks are successful in generating accurate, policy-relevant water availability maps and drought risk assessments across various scales. Thus, this study aims to develop and validate a composite Surface Water Availability Index (SWI) for Sri Lanka by considering various factors, and the output validated using some Remote Sensing Indices. This integrative approach offers a practical framework for sustainable water planning and spatial prioritization under climate variability.

METHODOLOGY

A. Study Area

Figure 1: Study Area

Figure 1 shows Sri Lanka (study area), which is one of the tropical islands in South Asia, located between 5.91 to 9.83 degrees north latitude and 79.52 to 81.87 degrees east longitude. Administratively, the country is divided into 25 districts, 331 Divisional Secretariats (DS), and 14,022 Grama Niladhari Divisions (GNDs). According to the Asian Development Bank (2024), the country has a total extent of 65,610 km², a population of over 23.1 million, and a population density of about 368 people per km². Approximately the island contains 2,020 km² of water bodies and 20,258 km length of streams, indicating its significant hydrological infrastructure. According to UNESCO, in 2021, around 80.1% of the population had access to improved drinking water resources. It shows clearly that some areas have limited water availability, and therefore spatial-based assessments of water availability are essential to support more sustainable and equitable water management practices across the country.

B. Factor Identification & Data Collection

Various factors were identified under different criteria based on the literature and availability of the data for assessing water availability. Openly available data were used, which were obtained from satellite imagery and Open Street Map (OSM). Table 1 shows the factors and their data sources.

Table 1: Factors and data sources for water availability

Factor	Data Source
Rainfall	CHRS PERSIANN-CDR
Drainage Density	OSM
Surface Water Area	OSM
Evapotranspiration	MODIS MOD16A2

C. Data Processing & Normalisation

Through Google Earth Engine, rainfall and evapotranspiration data were downloaded for October 2024. Then, proper cloud masking and downscaling techniques were applied. Stream networks were obtained from OSM, and their lengths were calculated in kilometers. A drainage density raster was created by the line density tool in ArcGIS Pro. Similarly, tanks data were obtained from OSM, and their areas were calculated in square kilometers. Then, the kriging interpolation method was used to create a continuous surface water area raster.

Finally, all layers were projected to the Sri Lanka Kandawala coordinate system (EPSG: 5234) and resampled to a common resolution of 50 × 50 meters. Normalisation brings input variables with different units and scales into a common comparable range. Thus, min-max normalisation was applied to each layer to make it suitable for MCDA. Output layer values vary between 0 and 1 [6].

The min-max normalisation formula used in this study is:

$$X' = \frac{(\mathrm{X} - \mathrm{Xmin})}{(\mathrm{Xmax} - \mathrm{Xmin})}$$

Where X is the original value, Xmin and Xmax are the minimum and maximum values of the dataset, and X' is the normalized value.

D. Analytical Hierarchy Process (AHP)

AHP was used to identify the significance of each factor to find the water availability. It involves pairwise comparisons between criteria to assess their relative importance in finding the availability of water through the systematic decision-making process. A pairwise comparison matrix was created with respect to Saaty's 1 to 9 scale, with the larger number demonstrating the stronger importance of one criterion over another. The sum of all the weightage values must be equal to 100. The Consistency Ratio (CR) is calculated in AHP to assess the consistency of the pairwise comparisons; a CR value below 10% (0.1) indicates an acceptable level of consistency [7], [8]. In this case, the calculated CR was 1.7% (0.017), demonstrating a high level of consistency in the judgments used for deriving the weights. Table 2 shows the weightage of factors derived from AHP.

Table 2: Weightage of factors (from AHP)

Factor	Weightage
Rainfall	63.21 %
Drainage Density	20.09 %
Surface Water Area	10.70 %
Evapotranspiration	6 %

E. Surface Water Availability Index and Zonal Analysis

The Surface Water Availability Index (SWI) was produced by multiplying each normalised raster with the respective weight derived during the AHP process. The outcome raster is the merged influence of all factors in which higher values indicate greater water availability. This raster was further reclassified into five classes using the natural breaks method. The extent of each class was calculated. Additionally, the district-wise sum of water availability was computed to assess spatial variations and to identify districts with relatively high or low water availability. A high-accuracy land use/land cover layer was obtained from the ESRI Living Atlas and reclassified into five main classes. The mean water availability value was then calculated for each land use class to assess how the water availability varies by land use.

E. Remote Sensing Indices and Validation

Remote Sensing Indices provide quantitative measures of key environmental properties such as surface water extent, vegetation health, built-up areas, and land surface temperature, all of which are critical for understanding spatial water dynamics. In the research, three main indices were calculated using Landsat 8 data in October 2024: Normalised Difference Water Index (NDWI) [9], Normalised Difference Vegetation Index (NDVI), and Land Surface Temperature (LST) [10]. Table 3 shows the indices and their equation, used in this study.

Table 3: Used Remote Sensing Indices and their formula

Factor	Equation
NDWI	(Green- NIR) (Green+ NIR)
NDVI	(NIR - Red) (NIR+ Red)
LST	Derived from Modelling of Thermal Infrared (TIRS) band

In the case of Landsat 8 (OLI/TIRS) imagery, Band 3 is green, Band 4 is red, Band 5 is near infrared (NIR), and Band 10 is thermal infrared (TIRS). Pearson correlation analysis was used to assess the correlations between water availability and the selected Remote Sensing Indices. Pearson's r measures the strength and direction of the linear relationships between different variables, and values close to +1 or -1 indicate strong correlation, while values near 0 indicate weak correlation [11]. 500 random points were generated across Sri Lanka to assess the correlation between these indices.

The main aim of the correlation between the Surface Water Availability Index (SWI) with NDWI, NDVI, and LST is to validate the reliability and physical relevance of the SWI by comparing it with independently derived Remote Sensing proxies for water, vegetation, and surface temperature. Moreover, the correlation between NDWI and the rest of the indices (NDVI and LST) were also calculated to analyse the interactions among surface water, land cover, and thermal characteristics better. Five correlations were tested altogether: SWI against NDWI, NDVI, and LST, as well as NDWI against NDVI and LST, to better understand the influencing factors and spatial variability of water availability.

RESULTS

A. Surface Water Availability Index

Figure 2 presents the MCDA output, illustrating the spatial variation of water availability across Sri Lanka. This was categorized into five zones based on water availability levels, and this shows the area values of each zone.

Table 4: Extent of water availability Zones

Water Availability Zone	Class Area (Sq. Km)	Percentage (%)
Very Low	12946.33	19.73 %
Low	12919.53	19.69 %
Moderate	12928.68	19.71 %
High	13784.85	21.01 %
Very High	13028.83	19.86 %

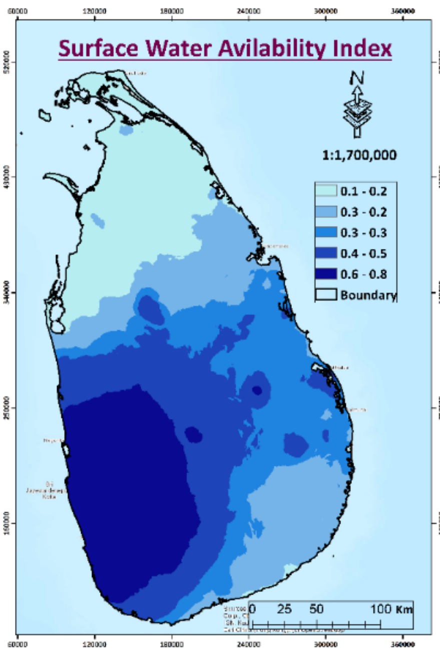

Figure 2: Surface water availability map

Surface water availability by Land use classes

Table 5: SWI by Land use

Land use	Mean value of WAI
Built-up Area	0.2752
Vegetation	0.3230
Agriculture	0.2693
Water	0.3868
Barren/ other land	0.2587

Analysis of mean SWI values across major land use classes illustrates significant variations (Table 5). Water bodies, with a mean SWI value of 0.3868, show the greatest water availability, as expected. The relatively high mean SWI value (0.3230) is observed in vegetation areas, indicating the association between natural water retention and healthy ecosystems. On the other hand, the means of SWI values for agricultural lands (0.2693), built-up lands (0.2752), and barren or other land categories (0.2587) are lower, indicating the limitation of water availability.

B. Water availability by districts

The district-wise analysis of the Surface Water Availability Index (SWI) demonstrates considerable spatial variability across Sri Lanka (Figure 3). The cumulative water availability is highest in Kurunegala, with a total sum of SWI of about 795,482, followed by Ratnapura (735,586) and Anuradhapura (577,812). Other districts like Monaragala (564,611), Ampara (470,736), and Kegalle (436,948) have also shown a significant amount of water availability, which are in the moderate-to-high trend. Conversely, in the northern districts, the values are very low, with the SWI sum in Jaffna being the lowest (52,243), followed by Mannar (92,173) and Kilinochchi (69,003), which indicates limited water resources and the highest exposure to a shortage. Most other districts, such as Colombo (177,076) and Matara (197,582), are at a moderate level.

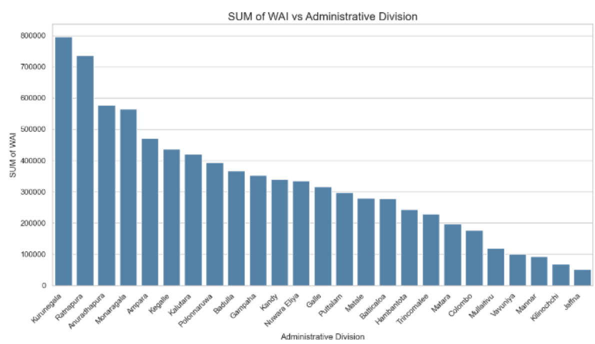

Figure 3: The total surface water availability by district.

A. Remote Sensing Indices and Correlation with SWI

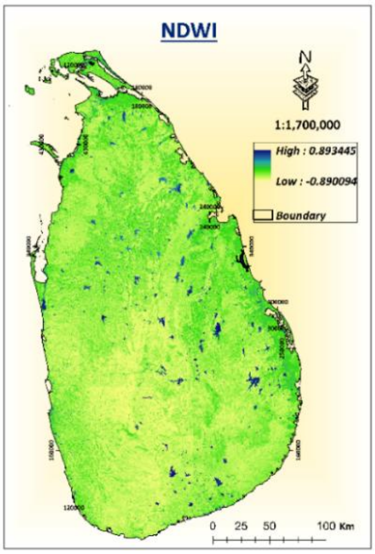

Figure 4: NDWI Map of Sri Lanka

Correlation analysis (Figure 7 to 11) demonstrates that various relationships were found between the Surface Water Availability Index (SWI) and the chosen Remote Sensing Indices (Figure 4 to 6). SWI showed a poor negative correlation with NDWI (r = -0.21). The correlation between SWI and NDVI was weak and positive (r = 0.25). Land Surface Temperature (LST) and SWI showed a moderate negative linear correlation with a Pearson r of -0.44. Looking at its relationships with other indices, it has been found that the correlation between NDWI and NDVI was strong but negative (r = -0.96), and the correlation between NDWI and LST was weak but positive (r = 0.18).

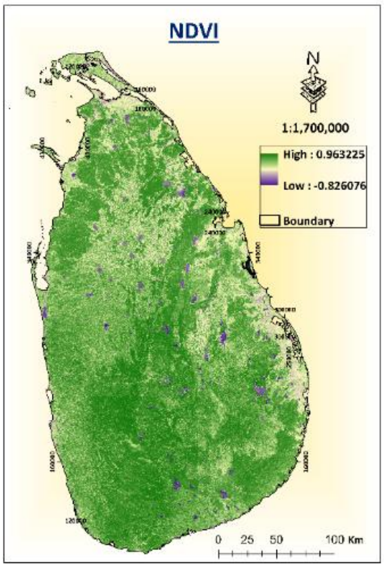

Figure 5: NDVI Map of Sri Lanka

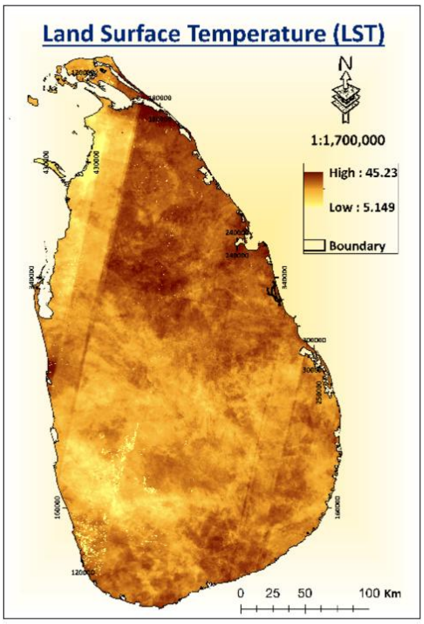

Figure 6: LST Map of Sri Lanka

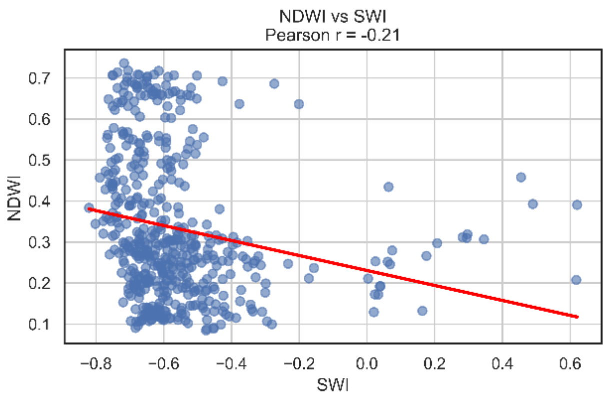

Figure 7: Correlation between SWI and NDWI

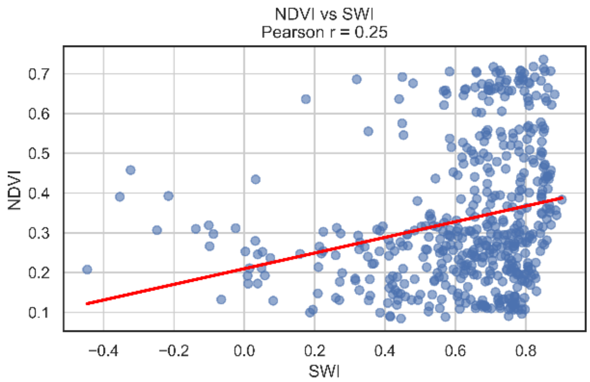

Figure 8: Correlation between SWI and NDVI

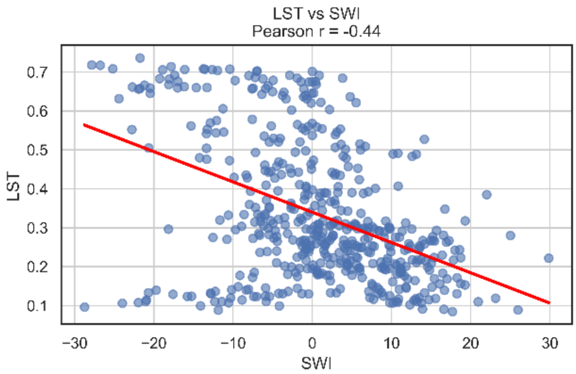

Figure 9: Correlation between SWI and LST

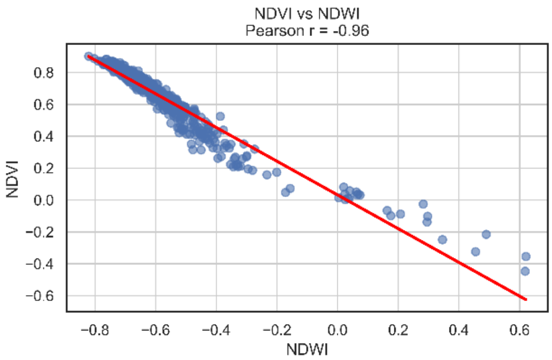

Figure 10: Correlation between NDWI and NDVI

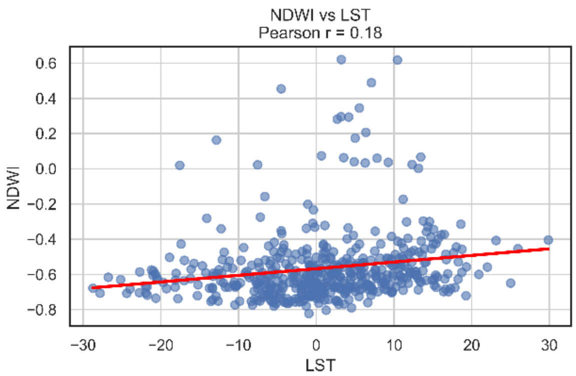

Figure 11: Correlation between NDWI and LST

DISCUSSION

Sri Lanka's varied climate zones, topography, and land use classes create significant spatial disparities in water availability. To address this, the study selected the entire country of Sri Lanka as the study area. For accurate spatial analysis, proper cloud masking and downscaling techniques were applied to enhance the quality and reliability of satellite data. To bring diverse input parameters to a uniform scale, normalisation techniques were used. Among them, min-max normalisation was used for its simplicity and effectiveness, allowing meaningful integration within the MCDA framework while preserving original data patterns. The AHP was used to derive the weight systematically and scientifically through an expert judgment decision-making process. The consistency and reliability of these judgments are confirmed by the achieved CR (1.7%). Here, rainfall was the most influencing factor with 63.21%, while evapotranspiration is the least influential factor with 6% to find the water availability index. Remote Sensing Indices NDWI, NDVI, and LST were chosen as independent validation measures because they have proven relevance to surface water, the health of the vegetation, and temperature changes. To ensure spatial representativeness, 500 sample points were used for assessing the correlations.

The SWI map classified nearly 20% of the area as high-water availability zones, while approximately 39% of the area was categorized as very low or low water availability zones. The dominant factor, rainfall, directly affects the variation in water availability, as proved by district-wise analysis. Since this analysis was conducted in the month of October 2024, the districts such as Kurunegala, Ratnapura, and Anuradhapura received higher rainfall, resulting in high total water availability values. This was further supported by dense drainage networks and large surface water bodies. On the other hand, the northern provinces show lower water availability. This may be due to limited rainfall, sparse drainage, higher evapotranspiration rates, and drought conditions. The results of the land use-based analysis demonstrated that the SWI of water bodies were to be expected, with the built-up lands, as well as agricultural and barren lands, having a lower water availability, which also suggests a possible water scarcity problem because of anthropogenic influence. The correlation analysis showed that SWI is moderately and negatively correlated with LST and has a weak relation with both NDVI and NDWI, and NDWI is strongly and inversely correlated with NDVI. These results confirm the spatial complexity of water, vegetation, and temperature interactions, which support the significance of planning integrated, spatially explicit water management in Sri Lanka.

CONCLUSION

This research uses a combination of MCDA, AHP, GIS and Remote Sensing to assess the spatial variation of water availability across districts and different types of land use associated with climatic, topographic and anthropogenic factors. District-level analysis highlighted the vulnerable regions, particularly in the Northern Province, emphasizing urgent needs for targeted sustainable water resource management and agricultural interventions. Correlation of SWI with Remote Sensing Indices such as NDVI, NDWI, and LST enhances the reliability of the derived SWI, demonstrating its potential as a robust tool for environmental monitoring. Although certain limitations exist, particularly in the datasets, this methodology provides a scalable and practical framework for national and regional-level water resource planning. By incorporating high-resolution satellite images, relevant hydrological variables such as permeability, soil moisture, groundwater distribution with additional socio-economic variables into the MCDA framework, these results can be further enhanced. It will support the implementation of sustainable environment and agriculture policies by identifying priority areas for water conservation, drought mitigation, and sustainable land-use planning.

Finally, this research offers a replicable geospatial methodology that can support informed decision-making in water-scarce regions beyond Sri Lanka.

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