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IMPACTS OF URBAN IMPERVIOUS SURFACE EXPANSION ON RICE FIELDS IN NORTH CENTRAL PROVINCE, SRI LANKA: A GIS-BASED TEMPORAL ANALYSIS

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ABSTRACT
Urbanization drives the increase of impervious surfaces, thereby significantly diminishing the rice field areas over time. This study examines the impact of urbanization on rice fields in Sri Lanka's North Central Province, particularly in the Anuradhapura and Polonnaruwa districts. Using quarterly Sentinel-2 satellite imagery and a pixel-based classification approach, the analysis incorporates remote sensing indices such as the Modified Normalized Difference Water Index (MNDWI), Enhanced Vegetation Index (EVI), and Normalized Difference Built-up Index (NDBI) to map and quantify the expansion of impervious surfaces. Conducted on the Google Earth Engine (GEE) platform, this research highlights a significant reduction in rice field areas between 2019 and the fourth quarter of 2023, directly correlated with the growth of impervious urban surfaces. The findings underscore the urgent need for effective land management strategies to mitigate the adverse effects of urbanization on agricultural land use. This study offers critical insights and recommendations for sustainable urban planning, with implications for food security, economic stability, and ecosystem health in the region.

Keywords: Google Earth Engine, Impervious Surface, Rice Fields, Urbanization

1. Introduction
The spread of urban impervious surfaces affects natural landscapes, increases surface runoff, and causes the urban heat island effect, providing significant barriers to sustainable development and environmental management. A critical component of urban expansion is the rise of impervious surfaces, such as buildings, roads, and other human-made structures that prevent water from penetrating the ground (Liu, Yang, & Huang, 2023). The study used remote sensing to evaluate

the environmental impact of impervious surfaces, emphasizing the interference of natural water cycles, the increase in surface runoff, and the contribution to the urban heat island effect. (Liu, Yang, & Huang, 2023). This phenomenon has far-reaching consequences for sustainable city design, environmental management, and agricultural productivity (Yuan & Bauer, 2006).

Several remote sensing indices were utilized in this study to assess and describe land cover changes in the districts of the Anuradhapura and Polonnaruwa areas. The indicators include the Modified Normalized Difference Water Index (MNDWI), Enhanced Vegetation Index (EVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Bareness Index (NDBaI), and Normalized Burn Ratio (NBR) (Dai, Guldmann, & Hu, 2018).

The MNDWI can be determined using the following formula.

$$MNDWI = \frac{\text{Green}-\text{SWIR}}{\text{Green}+\text{SWIR}} \tag{1}$$

MNDWI enhances water body detection using the difference between the green and shortwave infrared (SWIR) bands. It is beneficial for tracking changes in water coverage caused by urbanization and the spread of impervious surfaces (Dai, Guldmann, & Hu, 2018).

The EVI is calculated as shown below.

$$EVI = 2.5 * \frac{(\text{NIR}-\text{Red})}{(NIR+6\times Red-7.5\times Blue+1)} \tag{2}$$

EVI improves the accuracy of vegetation health and density estimates by refining the vegetation signal, which efficiently accounts for atmospheric impacts and canopy noise. This makes it a reliable tool for assessing the influence of urbanization on plant cover (Dai, Guldmann, & Hu, 2018).

NDBI is determined using this formula.

$$NDBI = \frac{\text{SWIR}-\text{NIR}}{\text{SWIR}+\text{NIR}} \tag{3}$$

This is one of the critical indexes for this research. NDBI detects built-up regions by comparing the reflectance of SWIR and NIR bands. It is useful in mapping urban areas and determining the degree of impervious surface growth (Dai, Guldmann, & Hu, 2018).

The NDBaI can be expressed as follows.

$$\text{NDBaI} = \frac{(\text{SWIR}+\text{Red})-(\text{NIR}+\text{Blue})}{(\text{SWIR}+\text{Red})+(\text{NIR}+\text{Blue})} \tag{4}$$

NDBaI discovers barren areas by separating between soil and plant reflectance. It helps monitor barren regions caused by urban development and vegetation loss (Dai, Guldmann, & Hu, 2018).

The NBR is represented using the formula below.

$$NBR = \frac{\text{NIR}-\text{SWIR}}{\text{NIR}+\text{SWIR}} \tag{5}$$

NBR assesses fire-damaged regions by identifying healthy vegetation vs charred land. Therefore, determining the impact of fires on land cover is critical, particularly in areas impacted by urban heat islands (Dai, Guldmann, & Hu, 2018).

The Google Earth Engine (GEE) code editor is a robust cloud-based tool for evaluating planetary-scale satellite data and its cloud masking techniques to assure data quality (Liu, Yang, & Huang, 2023). GEE allows us to rapidly scan and analyze vast amounts of satellite images to follow and understand the urban expansion and its influence over time (Lu, Li, Kuang, & Moran, 2013). However, inaccuracies in cloud masking and misclassification remain significant problems that might compromise the accuracy of estimating the influence of impervious surfaces on rice crops. These methodical challenges emphasize the necessity for robust approaches and precise data processing to give reliable insights into the effects of urbanization on agricultural output (Lu, Li, Kuang, & Moran, 2013). Research on the impact of urbanization on agricultural land, specifically rice fields, has faced challenges due to limited focus on impervious surface covers. Despite progress in remote sensing, there remains a significant gap in understanding how urbanization influences paddy fields. To address this, a temporal study is necessary to observe changes over time and gain a more comprehensive understanding of urbanization's effects on agricultural land.

The North Central Province of Sri Lanka, including the districts of Anuradhapura and Polonnaruwa, is rapidly urbanizing, requiring a thorough investigation of its impervious surface dynamics (Mahakalanda, 2022). With its rich historical and cultural legacy, this region is seeing growing urbanization, which, along with extreme weather occurrences, has significantly influenced regional paddy production, with bad climate circumstances resulting in more agricultural failures than successes (Mahakalanda, 2022). Rice is essential to Sri Lanka's agricultural economy, contributing significantly to food security and rural livelihoods. The rapid expansion of urbanization into rural regions threatens rice production, notably in the North Central Province, where growing urbanization offers severe challenges to agricultural productivity and water resource management. However, recent studies have given very little attention to the influence of quarterly temporal changes in impervious surface cover on paddy, leaving a substantial gap in understanding the full scope of urbanization's effects on agricultural land. This study looks into detailed insights into the link between urbanization and rice field decrease resulting in considerable changes in land use and cover (V., Nair, A, & S., 2015).

2. Literature Review

Impervious surfaces, such as roads, buildings, and other man-made structures, have gained greater attention because of their massive impact on urban environments and natural ecosystems (Zhang, Lin, & Wang, 2018) Numerous studies have examined these surfaces' temporal and geographical dynamics, providing insights into how they interact with various environmental circumstances (Angerbjorn, Tannerfeldt, & Lundberg, 2001). A single study established a unique technique for detecting urban impervious surfaces using synthetic aperture radar (SAR) images, illustrating both the limitations and opportunities offered by remote sensing in urban planning (Zhang, Lin, & Wang, 2018). Utilizing spatial-temporal rules and thick Landsat data series stacks, it is possible to monitor the continuous dynamics of impervious surfaces effectively (Wang, Chen, Zhu, Hao, & Xu, 2019). These discoveries highlight advancements in remote sensing technology, which enables more precise and comprehensive monitoring of impervious surfaces (Wang, Chen, Zhu, Hao, & Xu, 2019).

Urbanization has a significant impact on land surface temperature (LST) and other environmental factors (Strohbach, 2019). For example, a study in Sri Lanka's Colombo Metropolitan Area discovered that rapid urbanization led to bigger urban heat islands due to an increase in impervious surfaces and a loss of vegetation. However, this does not discuss one specific vegetation type (Fonseka, 2019). Furthermore, to evaluate urban heat island effects, researchers used impervious surface area (ISA) and the normalized difference vegetation index (NDVI), and they observed a significant association between larger impervious surfaces and higher LST (Fonseka, 2019). These findings emphasize the need to monitor the impacts of urbanization on local temperatures and ecosystems (Fonseka, 2019). These relationships emphasize the critical responsibility of urban planners and politicians in monitoring and managing the impacts of urban expansion on local climates and ecosystems (Fonseka, 2019). Cities may mitigate the detrimental effects of UHIs by adding green areas, increasing vegetation cover, and implementing sustainable urban designs (Dai, Guldmann, & Hu, 2018). Tracking NDVI with ISA is an essential tool for understanding and resolving the thermal dynamics of urban environments, ensuring a healthy balance between development and environmental health (Angerbjorn, Tannerfeldt, & Lundberg, 2001).

Several research has focused on improving methods for mapping and monitoring impervious surfaces, which is critical to understanding urbanization and its environmental consequences (Wang, Chen, Zhu, Hao, & Xu, 2019). One novel research created a multi-level categorization system based on path features extracted from time series data, allowing for exact monitoring of impervious surface expansion over time which is very useful for temporal analysis (Dai, Guldmann, & Hu, 2018). This advanced methodology is critical for understanding urban growth trends and making effective planning decisions. Some projects investigated various techniques for extracting impervious surfaces from satellite imagery, addressing issues like mixed pixels in complex metropolitan areas (Wang, Chen, Zhu, Hao, & Xu, 2019). They demonstrated the need for high-accuracy classification models to ensure the exact identification and mapping of impervious surfaces (Shao , Cheng , Fu, Li, & Huang , 2023). These sophisticated approaches are crucial to urban planners and academics because they provide consistent data for monitoring urban expansion, assessing environmental consequences, and promoting sustainable development policies (Wua, Lib, Liu, Hu, & Xiua, 2020).

In Sri Lanka, researchers applied a geospatial predictive analytics model to identify urban impervious surfaces in the North Central Province, highlighting the region's urbanization trends and their implications for urban planning but not talking about one specific land type (Mahakalanda, 2022). This research, like others, emphasizes the need to undertake region-specific evaluations when designing effective urban management strategies. While previous research has mostly focused on the general effects of impervious surfaces on urban environments and vegetation, this study takes a fresh approach to the particular implications of urban growth on rice fields in Sri Lanka's North Central Province. This study, which uses advanced remote sensing techniques and geospatial analytics, fills a fundamental gap in understanding how urbanization impacts agricultural output and land use.

3. Methodology

The study aims to determine land cover and compute areas in two Sri Lankan districts, Anuradhapura and Polonnaruwa. Google Earth Engine (GEE) played an essential role in carrying out these tasks by providing an effective tool for processing and managing satellite imagery and spatial data. The boundaries for these districts were derived from the FAO GAUL dataset, which identified the regions of interest (ROI) as shown in Figure 1 below. These borders were filtered, and the geometries were combined into one ROI. An empty picture was made to represent the district borders, which were then painted red and put on the map.

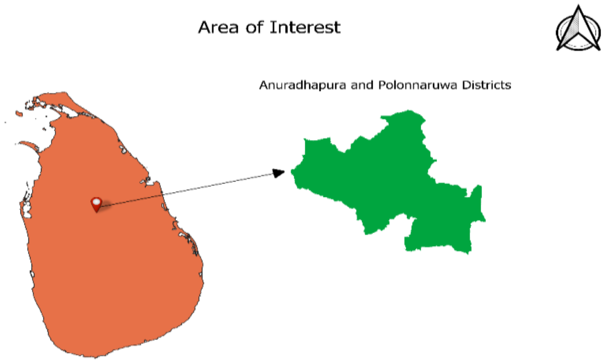

Figure 1: Anuradhapura and Polonnaruwa District Boundaries (ROI).

Satellite images have been obtained from the Sentinel-2 surface reflectance harmonized dataset. A cloud masking algorithm based on the Sentinel-2 Scene Classification Layer (SCL) was used to remove clouds. The footage, which ranged from the years 2019 and 2023 quarterly, was then filtered, and a median composite image was created. The images were normalized by dividing by 10,000 and trimmed to suit the ROI of Anuradhapura and Polonnaruwa.

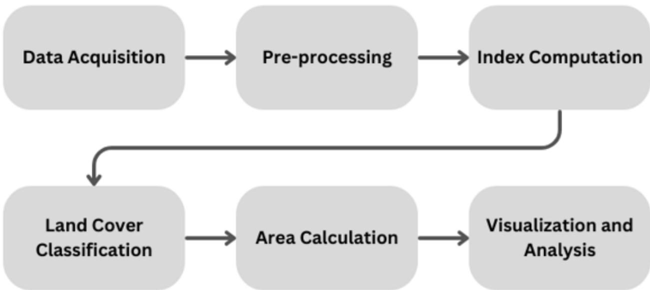

Figure 2: Methodology of Land Cover Classification and Area Computation.

The relevant bands (BLUE, GREEN, RED, NIR, SWIR1, and SWIR2) were selected for index computation. The Modified Normalized Difference Water Index (MNDWI), Enhanced Vegetation Index (EVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Bareness Index (NDBaI), and Normalized Burn Ratio (NBR) were all computed and presented as maps (Dai, Guldmann, & Hu, 2018). The NDBI index is used to identify the impervious surface cover, which is shown as built ups on the image. Another categorization method begins by differentiating between water and land using the EVI index. The land area was further categorized as wetland, dryland, and vegetation using the MNDWI and NBR indexes (GÁCSI , SZABÓ, & BALÁZS, 2016). The vegetation category was divided into dry and wet vegetation, low and high vegetation, and specialized varieties such as marshes, swamps, bushes, and woods. Built-up regions and barren fields were also discovered. Moreover, each land cover type was given a class value, and a complete land cover picture was generated and put on the map.

During the area calculation step, the pixel area for each land cover class was calculated to establish the category's geographic extent (Liu, Yang, & Huang, 2023). These areas were then aggregated using the reduced Region function, which grouped them into eight land cover classes. To make the results more understandable, the aggregated area values were transformed into percentages, indicating the proportion of each land cover type compared to the overall area of the Region of Interest. Finally, the computed percentages for each land cover class were presented in the console, giving a clear picture of the distribution and extent of various land cover categories in the research region.

For better comprehension, a legend panel was built, presenting land cover classifications and their associated colors. This panel has been added to the map. The final land cover image was exported to Google Drive in GeoTIFF format for further analysis by using QGIS, removing unwanted layers, and generating the temporal analysis. To conduct that eight images were used from 2019 and 2023 quarterly.

4. Results/Analysis and Discussion

The central part of this research is to identify the temporal changes in the land cover, especially the increase of impervious surface. Below figure 3 shows how the land types change over the period of 2019 and 2023 from the Sentinel-2 satellite data after removing unwanted layers and cloud masks. This analysis is crucial for understanding the impact of urbanization on rice fields and other land types in Sri Lanka's North Central Province. Analyzing the images reveals strong seasonal differences across different quarters, particularly in the fourth quarter of each year. This period features a significant rise in natural/plantation forests, due to the rainy season. Increased rainfall enhances the growth of plants, resulting in denser and more widespread forest coverage.

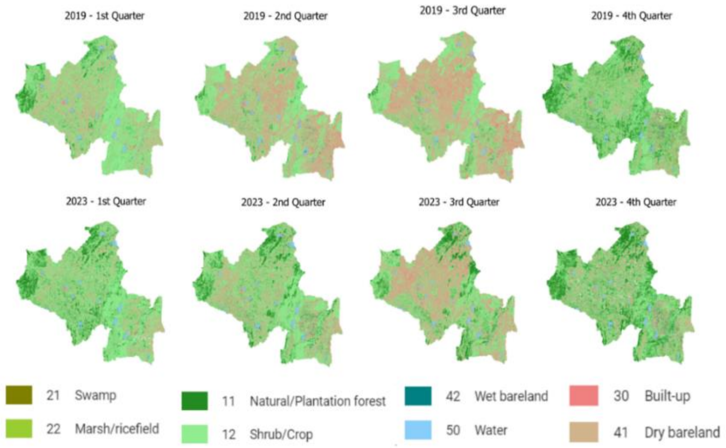

Figure 3: Temporal Changes in Different Land Types in North Central Province, Sri Lanka.

Furthermore, comparing the images over time shows a clear tendency to increase impervious surfaces/built ups. This tendency is especially clear in the 2023 figures, which show a minor but considerable rise in areas covered by buildings, roads, and other infrastructure. This shows that urbanization and development continue in the examined locations, indicating changes in land use and the possibility of additional environmental effects.

Figure 4 illustrating the proportion of marsh and rice field land cover from 2019 Q1 to 2023 Q4 demonstrates considerable variations. Starting at 1.14% in early 2019, the percentage falls to 0.28% by mid-2019 before rapidly increasing to 3.89% by the end of 2019. This rise indicates the presence of seasonal or agricultural cycles. After 2019, the percentage fell again, reaching 0.16% in mid-2023 before rebounding to 2.69% by the end of 2023, a significant loss compared to Q4 in 2019. These changes show that marsh and rice field regions are susceptible to environmental, climatic, and agricultural influences. The unpredictability emphasizes the significance of proper land management in protecting these critical ecosystems, which are influenced by seasonal planting and water availability.

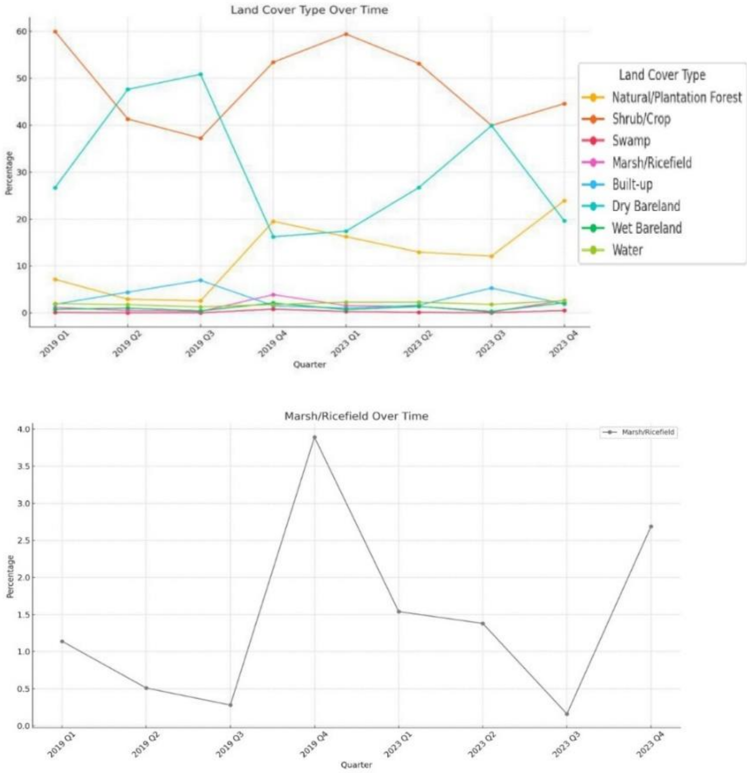

Figure 4: Temporal Changes in Land Cover Types and Marsh/Ricefield Areas (2019-2023).

According to Figure 5, we can see there is an increase in the impervious surface area over time and it increases by 0.34%. Moreover, there was an increase in the natural/plantation forest during the time period and it is around 4.41% increase, while there was a decrease in rice fields compared to 2019. Therefore, we can compare the associations between different land types and how they change over time. The findings are intended to assist urban planners and policymakers in implementing sustainable development plans in Sri Lanka's rapidly urbanizing regions of Anuradhapura and Polonnaruwa, which are historically and agriculturally significant, particularly for sustainable paddy field prediction, drainage system maintenance, and a variety of other urban planning activities.

5. Conclusion and Implications

This study highlights the significant impact of urbanization on rice fields in Anuradhapura and Polonnaruwa, mainly due to the expansion of impervious surfaces. Continuous monitoring of land cover changes is crucial, emphasizing the necessity to support sustainable urban planning and agricultural practices. The results demonstrate that urban expansion leads to an increase in impervious surfaces and a corresponding decrease in rice fields, prompting concerns regarding the adverse effects of urbanization on agricultural land use and food security.

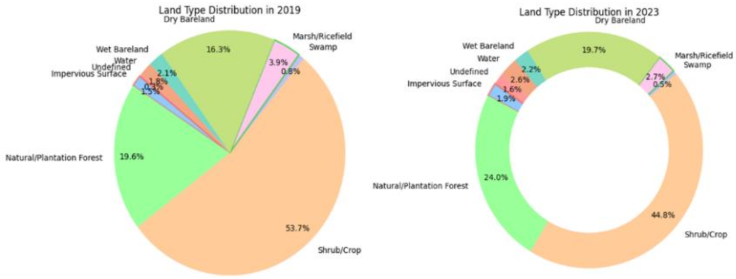

Figure 5: Area Distribution and Proportional Representation of Land Cover Classes from 2019 and 2023.

The increase in forest cover may indicate positive environmental outcomes from conservation efforts or natural seasonal cycles. However, the study acknowledges limitations in representing localized urbanization impacts and detecting forest quality or biodiversity changes. Urban planners must use these findings to develop strategies that counteract urbanization's adverse effects, such as reducing green spaces. They should prioritize implementing green infrastructure and preserving natural areas for sustainable development. Future research should focus on conducting detailed assessments at localized scales to better understand specific changes and impacts. Broadening the scope of the study to cover different periods and environmental factors would provide a more comprehensive understanding. These initiatives are crucial for advancing sustainable urban development and effective environmental management in rapidly urbanizing regions. The conversion of rice fields into impervious surfaces raises LST and reduces the cooling effect these agricultural regions offer. Future research directions can address the spatial autocorrelation of land surface temperature (LST) and built-up regions to better understand the urban heat island (UHI) phenomena, as well as how rice fields are affected. And policy interventions ought to promote sustainable urban planning approaches.

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