Land Use and Land Cover Change Detection and Prediction for Urban Planning in Riyadh, Saudi Arabia

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SUMMARY

This study presents a comprehensive analysis of Land Use and Land Cover (LULC) changes in Riyadh over a ten-year period (2013–2023), utilizing the power of the Google Earth Engine (GEE) platform for advanced geospatial data processing. By harnessing the Landsat 8 Image collection and night-time light image collection from May to August for the years 2013 and 2023, we were able to generate insightful datasets capturing the changing landscape of the region. Our approach involved a Random Forest (RF) classification model that consistently displayed commendable precision scores above 92% for both years. A notable discovery from the study was the pronounced urban expansion, particularly around Riyadh city. Within a mere ten-year span, urbanization surged noticeably, affecting the broader ecological environment of the region. Interestingly, the northeastern part of Riyadh emerged as a focal point of this growth, signaling rapid urban growth of urban sprawl and development. A comparison between the two years indicates a 21.51% increase in built-up areas, revealing the transformative pace of urban sprawl. Contrastingly, vegetation cover patterns presented a more nuanced picture. While our initial hypothesis predicted a decline in vegetation, the actual findings depicted both vegetation reduction in certain pockets and new growth in others, resulting in an overall 25.89% increase. This intricate pattern might be attributed to shifting agricultural practices, afforestation efforts, or even satellite image timings not aligning with seasonal vegetation growth. The bare soil, predominant in the desert landscape of Riyadh, saw a marginal reduction of 0.37% over the decade, challenging our initial expectations. Urban and agricultural advancements in Saudi Arabia appear to have slightly reduced the expanse of barren terrains. This study, underpinned by a rigorous methodological framework, reveals the multifaceted land cover changes in Riyadh in response to urban development and environmental factors. The precise, data-driven insights provided by our analysis serve as invaluable tools for understanding urban growth trajectories, guiding urban planning, policy formulation, and sustainable development endeavors in the region.

Key words: Urban Growth, LULC Patterns, Change Detection, and Land Use and Land Cover.

1. INTRODUCTION

1.1 Problem Statement

Land Use and Land Cover (LULC) change analysis is a fundamental component of environmental and urban studies, as it reveals the spatial and temporal interactions between human activities and natural systems. Globally, accelerated urban expansion, agricultural intensification, and infrastructure development driven by population growth, technological advancement, and economic transformation have significantly altered land-use patterns (Seto et al., 2012; Rudel et al., 2009). These transformations exert considerable pressure on ecosystems and pose serious challenges to sustainable land and landscape management, particularly in rapidly urbanizing regions (Seto et al., 2013). Consequently, continuous monitoring and modeling of LULC dynamics are essential to support evidence-based urban planning, environmental protection, and the achievement of Sustainable Development Goal 11: Sustainable Cities and Communities (United Nations, 2015).

The Riyadh region of Saudi Arabia has experienced profound LULC transformations over the past few decades due to rapid urbanization, population growth, and large-scale infrastructural development. Previous studies have extensively documented these changes using remote sensing and GIS techniques. For example, Alqurashi and Kumar (2017) analyzed spatio-temporal LULC changes in Riyadh using multi-temporal Landsat imagery and reported a substantial increase in built-up areas at the expense of vegetation and barren land. Alqurashi & Gharbia (2018) reinforced these findings, documenting the patterns of habitat fragmentation on the urban periphery and highlighting the ecological pressures associated with rapid urban expansion. Similarly, Alsaad et al. (2020) assessed urban expansion patterns and highlighted uncontrolled urban sprawl as a major driver of environmental degradation in the region. Other studies, such as Bahabri et al. (2021), emphasized the socio-environmental consequences of rapid land transformation, including ecosystem degradation, increased surface temperatures, and pressure on limited water resources. Additionally, Alrashed & Kumar (2017) noted a general decline in vegetation cover associated with historical urbanization in the region.

In terms of methodological approaches, most existing studies in the Riyadh region have relied on traditional change detection techniques, such as post-classification comparison, supervised classification, and descriptive statistical analysis of LULC transitions. For LULC forecasting, commonly applied models in Saudi Arabia and similar arid regions include Cellular Automata-Markov Chain (CA-Markov) models, Artificial Neural Networks (ANN), and logistic regression-based approaches (Alqurashi et al., 2015; Alsaad et al., 2020; Koko et al., 2020). While these models have proven effective in simulating future land-use scenarios, many studies focus either on historical LULC changes or on prediction alone, with limited integration of modern cloud-computing platforms and insufficient comparison of spatial dynamics over extended time periods.

Moreover, desert environments such as Riyadh exhibit unique LULC dynamics characterized by fragile ecosystems, sparse vegetation cover, extreme climatic conditions, and acute water scarcity (Zhang & Chen, 2022). These characteristics necessitate more refined and context-specific modeling approaches to accurately capture land transformation processes. Despite the growing body of literature, there remains a research gap in integrating robust geospatial modeling frameworks with long-term spatio-temporal analysis to comprehensively evaluate LULC changes and their implications for sustainable urban development in the Riyadh region.

Rapid and often unplanned urban expansion in Riyadh has also intensified environmental challenges, including increased greenhouse gas emissions, urban heat island effects, air pollution, and declining environmental quality, which directly affect human health and urban livability (Miceli & Sirmans, 2007; Tan et al., 2010). These challenges underscore the urgent need for improved LULC monitoring and predictive modeling to support proactive planning and policy interventions.

Furthermore, there is a pressing need for a contemporary analysis focusing on the period after 2015, which marks a new phase of accelerated development in Riyadh, partly spurred by Saudi Vision 2030. A gap exists for a study that not only quantifies the most recent changes but also establishes a robust, scalable, and scientifically transparent methodological framework using state-of-the-art machine learning techniques.

Therefore, this study directly addresses the identified gaps by employing a Random Forest (RF) machine learning model within the Google Earth Engine (GEE) cloud-computing platform to analyze historical LULC changes in the Riyadh region from 2013 to 2023. By adopting commonly used and regionally relevant LULC modeling approaches and enhancing them through comprehensive spatial analysis on a modern, scalable platform, this research aims to provide deeper insights into land transformation processes. The primary aim of this study is to provide a detailed and up-to-date assessment of recent land cover changes and to present a methodological blueprint for future monitoring, thereby linking machine learning classification on a cloud-based platform directly to the practical needs of sustainable urban planning in a rapidly developing arid region. The findings are intended to support sustainable urban planning, environmental management, and informed decision-making aligned with long-term development goals in Saudi Arabia.

1.2 Formulation of Hypotheses

Urban expansion typically involves infrastructure development such as roads, highways, airports, and residential areas, often converting open and agricultural lands into built environments. This can lead to increased exposed soil and deforestation due to harsher, drier conditions. This study tests the following hypotheses:

a. Urban expansion in Riyadh has significantly increased built-up land cover.

b. Urban growth has caused a significant decrease in vegetation cover.

c. Desertification has contributed to an increase in bare soil cover.

1.3 Research Objectives

The study seeks to:

a. Monitor and map spatio-temporal land cover changes in Riyadh over the past decade using Landsat satellite imagery.
b. Identify and quantify changes in major land cover types including urban, vegetation, and barren land.
c. Assess the accuracy and reliability of remote sensing and GIS techniques for LULC change detection.
d. Provide valuable insights on urban expansion, urban sprawl, and vegetation dynamics to aid urban planning and policy formulation.

1.4 Scope and Significance of the Study

Focusing on Riyadh — the political, economic, and cultural heart of Saudi Arabia — this study investigates the environmental impacts of rapid urbanization within a unique arid desert context (Al-Tuwaijri et al., 2018). Riyadh has transformed rapidly from a desert town into a major metropolitan area, with significant land use changes driven by population growth and economic development (Alsaad et al., 2020).

Rapid urban growth brings challenges including resource depletion, environmental degradation, and habitat loss (Kumar, 2017). The study spans an extensive temporal range, comparing land cover data from 2013 and 2023 to analyze trends comprehensively.

This research not only contributes to scientific understanding of LULC dynamics in arid urbanizing regions but also informs policymakers and urban planners to balance urban development with ecological conservation. Given Riyadh's dependence on surrounding smaller towns and agricultural zones, studying the broader region provides insights into how urban demands influence agricultural land and vegetation patterns.

2. MATERIALS AND METHODS

2.1 Study Area

The study area encompasses Riyadh city and its surrounding region, located at approximately 24.7136° N latitude and 46.6753° E longitude, covering around 1,913 km² with a population of about 7.8 million. Situated far from coastlines within the Arabian Peninsula's desert, Riyadh has undergone dramatic urban growth, transforming natural desert and agricultural landscapes into urban environments over a relatively short time (Alqurashi & Kumar, 2017).

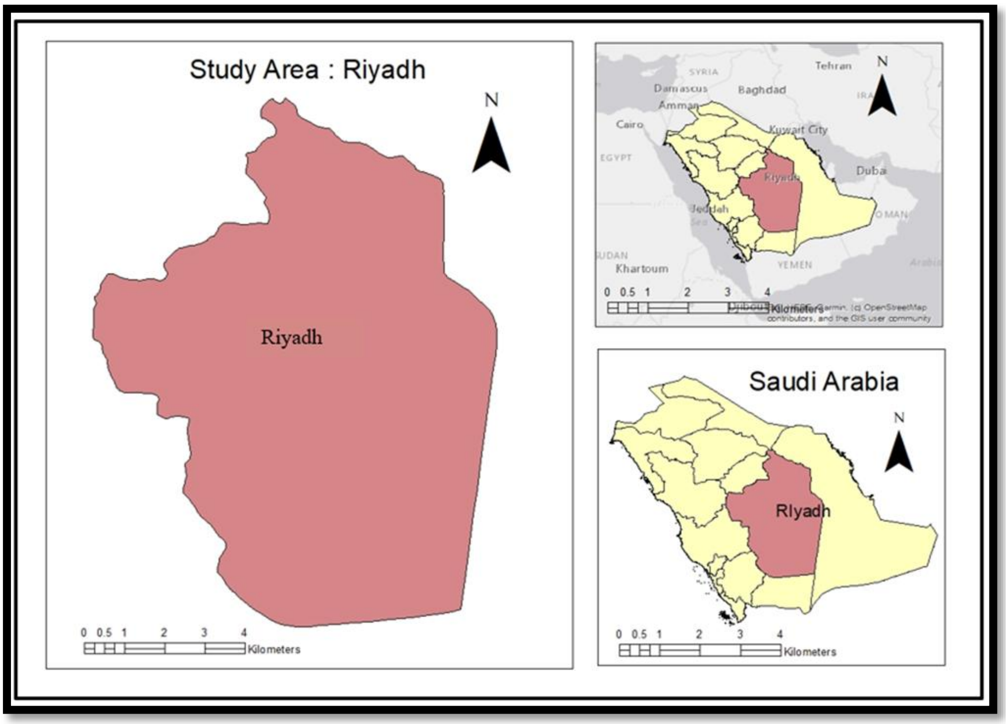

Figure 1: Illustrates the study area map of Riyadh region, Saudi Arabia.

2.2 Data Collection and Analysis,

The analysis was conducted within the Google Earth Engine (GEE) cloud-computing platform, which provides the necessary computational power for large-scale geospatial analysis. The primary datasets employed were multispectral satellite imagery from the Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) and nighttime light data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB).

The selection of the 2013–2023 timeframe and Landsat 8 data was a deliberate methodological choice. This 10-year period was strategically chosen because it aligns with the complete operational lifespan of the Landsat 8 satellite (launched in 2013), which ensures high consistency in sensor characteristics and data quality across the entire study. Furthermore, this decade captures a critical phase of accelerated urban development in Riyadh, partly driven by the announcement of Saudi Vision 2030, making it a highly relevant period for contemporary urban planning. Landsat 8 was selected as the primary sensor due to its optimal balance of spatial resolution (30 m), which is well-suited for regional LULC analysis, its free and open data policy, and the scientific robustness of its Level-2 Tier 1 surface reflectance products.

To create clear, representative images for analysis, median composites were generated from all available Landsat 8 scenes. The slight variation in the date ranges between 2013 (April-

October) and 2023 (January-July) was necessary to secure a sufficient number of high-quality, cloud-free scenes for creating a robust composite image for each study year.

To enhance the analytical power of the satellite imagery, spectral indices were calculated. The most important of these was the Normalized Difference Vegetation Index (NDVI), a widely used indicator for quantifying vegetation health and density. It was calculated using the Near-Infrared (NIR) and Red spectral bands from the Landsat 8 sensor. The formula is as follows:

$$\mathbf{NDVI= (NIR+RED)/(NIR-RED)} \qquad \mathbf{(1)}$$

Where: NIR represents the reflectance value of the Near-Infrared band. RED represents the reflectance value of the visible Red band.

Healthy vegetation reflects more NIR and absorbs more red light, leading to higher NDVI values, which aids significantly in its accurate classification.

Finally, VIIRS nighttime light imagery was also integrated as a separate to refine the discrimination of built-up areas based on artificial light emissions, further improving model accuracy.

A summary of the satellite imagery sources is provided in **Table 1:**

Table 1: Information of Satellite Image.

Sensor	Date of Acquisition	
Landsat 8 OLI/TIRS Operational Land Imager/Thermal Infrared Sensor	2013	Start Date: 2013-04-01
		End Date: 2013-10-29
	2023	Start Date: 2023-01-01
		End Date: 2023-07-30

2.3 LULC Modelling and Classification

A supervised classification approach was used to map LULC for both 2013 and 2023. This involved collecting training data and applying a machine learning model.

All image preprocessing, including cloud masking, atmospheric correction, and surface reflectance extraction, was conducted within the GEE platform using its Python API. NDVI and nighttime light bands were derived and composited with spectral bands (Red, Green, Blue, NIR, SWIR1, SWIR2, TIR1) for both 2013 and 2023. The inclusion of VIIRS DNB data contributed to enhanced discrimination of urban areas, especially for detecting spatial urban growth patterns.

Training samples for three dominant LULC classes (built-up areas, vegetation, and bare land) were created. A total of 17,000+ points were collected and allocated in an 80:20 ratio for training and validation, respectively. These points were manually digitized by an analyst with regional expertise, distributing them across the entire study area to ensure that all variations of the LULC classes (e.g., different types of urban density, varied vegetation health) were adequately represented. The process was guided by visual interpretation of high-resolution historical imagery available in Google Earth Pro, which served as ground-truth data.

Table 2: : Description of Land Cover Type.

Land Cover Type	Description
Built-Up area	Include residences, industrial estates, nuclear power plants, etc.
Vegetation	Agricultural Land, Forest, plants, grasslands, etc.
Bare Land	Areas of exposed soil, roads, isolated and clustered settlements, and barren areas are influenced by human impact.
Water Bodies	Rivers, permanent open water, canals, ponds, and reservoirs

Table 3: : Number of Training Samples Collected for Each LULC class.

Land Cover Type	2013	2023
Built-Up area	1,990	1,990
Vegetation	6,099	1,742
Bare Land	9,000	9,474

A Random Forest (RF) model was implemented to perform the supervised classification. The RF model was specifically chosen over simpler models like a single Classification and Regression Tree (CART) due to its demonstrated superior accuracy and robustness in complex remote sensing applications. Random Forest is an ensemble machine learning algorithm that constructs multiple decision trees using bootstrap sampling and random feature selection, and determines the final classification through majority voting. While CART relies on a single decision tree and is therefore highly sensitive to noise, training sample bias, and spectral confusion among land cover classes, RF mitigates these limitations by aggregating the outputs of multiple decorrelated trees, resulting in improved generalization performance and effectively reducing the problem of overfitting. This characteristic is particularly important in arid and semi-arid environments, such as the Riyadh region, where spectral similarity between built-up areas, bare soil, and desert surfaces often leads to misclassification when single-tree models are applied.

Furthermore, RF is well suited for handling high-dimensional datasets derived from multispectral imagery, vegetation indices (e.g., NDVI), and ancillary variables such as nighttime light data, without requiring assumptions about data distribution. Unlike CART, which may become unstable with increased feature dimensionality, RF effectively captures non-linear relationships and subtle spectral variations among complex LULC classes, leading to more stable and reliable classification outcomes.

The primary spatial inputs to the classification model are illustrated in Figures 2, 3, and 4, which show the RGB composite, the derived NDVI layer, and the nighttime imagery for the Riyadh region, respectively.

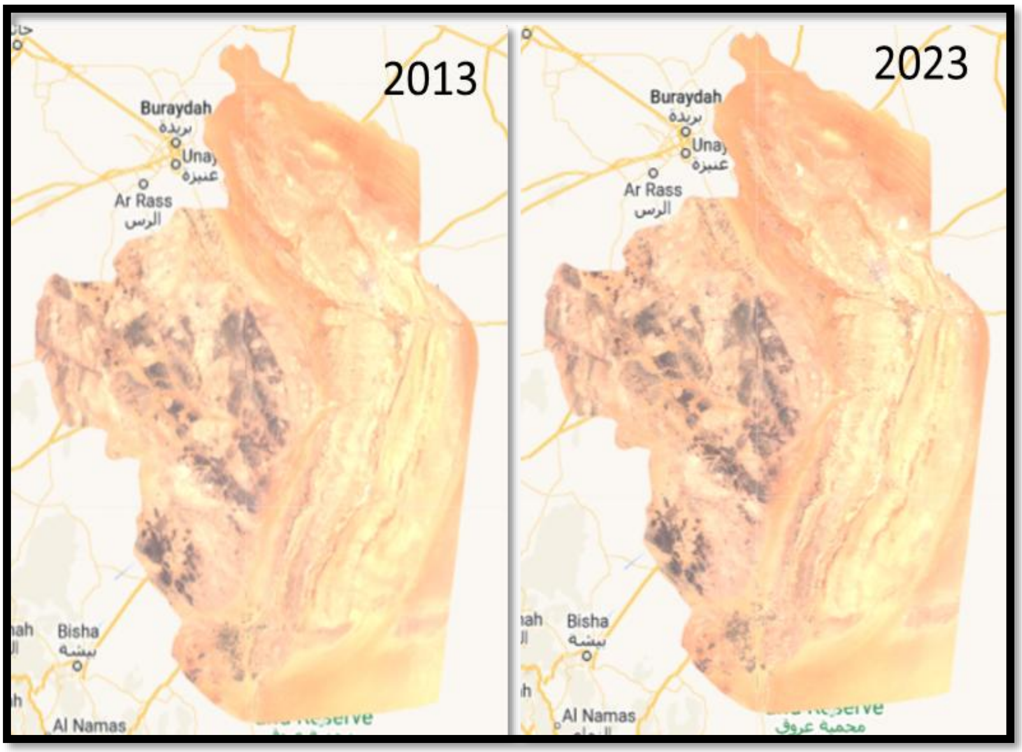

Figure 2: Landsat 8 OLI/TIRS RGB composite bands of the study area.

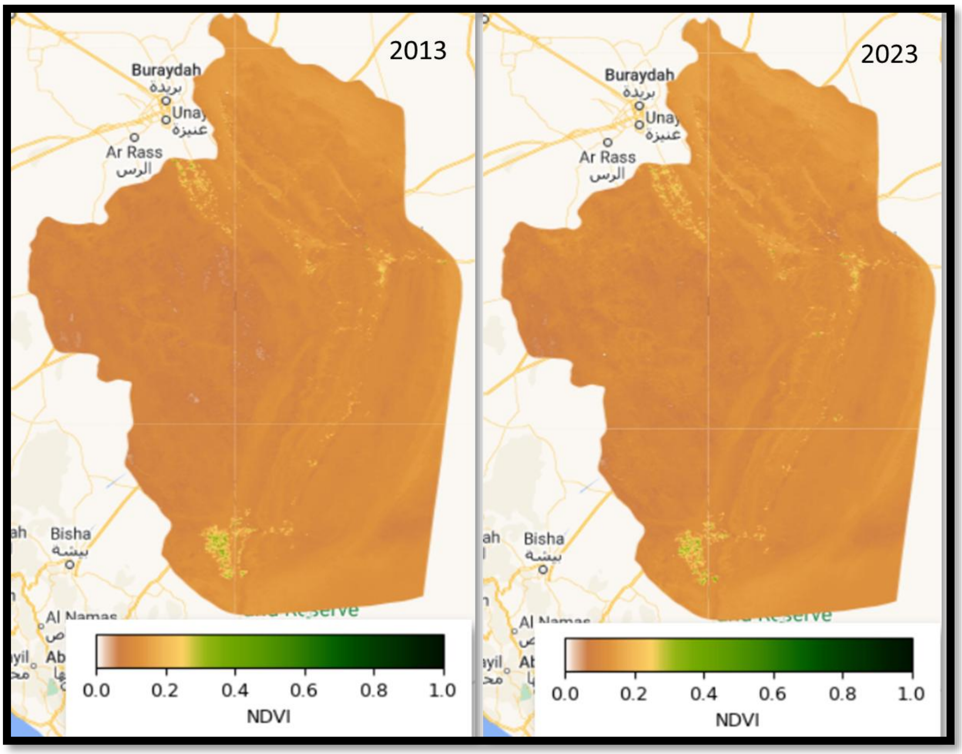

Figure 3: NDVI map of the study area for year 2013 and 2023.

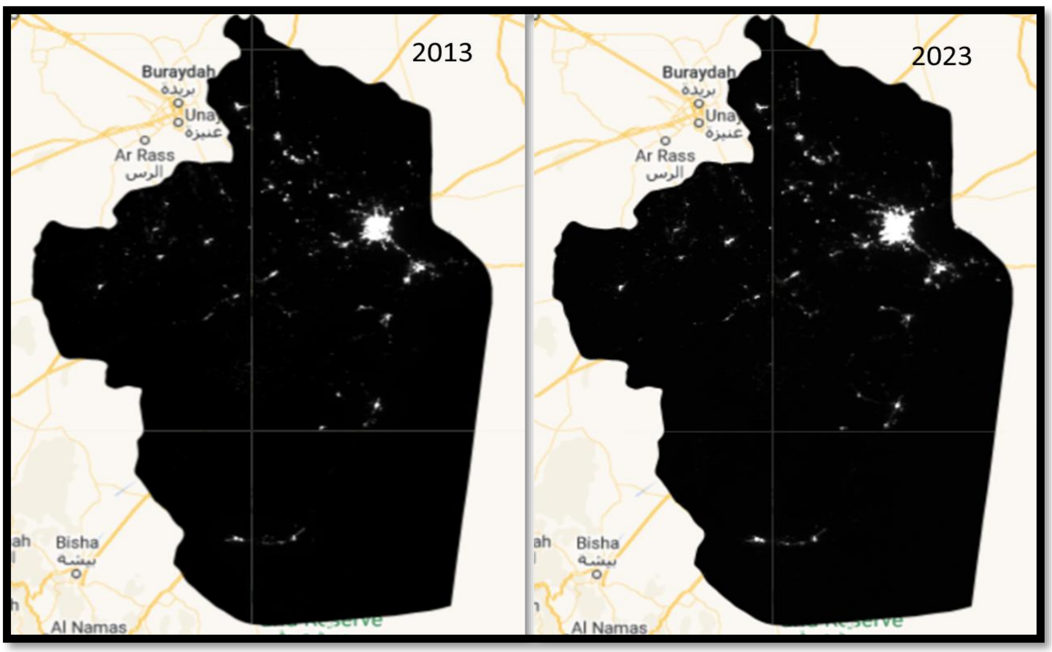

Figure 4: VIIRS Nighttime Day/Night Band Composites data for year 2013 and 2023.

2.4 Assessing LULC Change and Accuracy

The accuracy of the LULC classification results for the years 2013 and 2023 was systematically evaluated to ensure the reliability and robustness of the Random Forest classification outputs prior to change detection analysis. Model validation was performed using an independent validation dataset, comprising 20% of the total reference samples that were not used during the training phase, thereby ensuring an unbiased assessment of classification performance. Reference data were generated through a stratified random sampling approach. A total of 500 validation points were selected for each classified year, ensuring adequate representation of all LULC classes across the study area. These reference points were visually interpreted using high-resolution imagery available in Google Earth Pro, and were treated as ground truth data for accuracy evaluation.

A confusion matrix (also known as an error matrix) was constructed for each classified LULC map by cross-tabulating the predicted class labels with the corresponding reference classes. This cross-tabulation approach enabled a detailed comparison between the classified outputs and the reference data, allowing class-wise and overall accuracy metrics to be computed. The confusion matrix provides a comprehensive assessment of both classification agreement and misclassification patterns.

From this matrix, several standard accuracy metrics were calculated, including Precision and Overall Accuracy. The parameters for these metrics are defined as:

- **True Positives (TP):** Pixels correctly classified as the class of interest.
- **True Negatives (TN):** Pixels correctly classified as not belonging to the class of interest.
- **False Positives (FP):** Pixels incorrectly classified as the class of interest (a "commission error").
- **False Negatives (FN):** Pixels that belong to the class of interest but were incorrectly classified as something else (an "omission error").

The formulas are calculated as follows:

$$\textbf{Precision} = \mathbf{TP / (TP + FP)} \quad \textbf{(2)}$$

$$\textbf{Overall Accuracy} = \mathbf{(TP + TN) / (TP + TN + FP + FN)} \quad \textbf{(3)}$$

These metrics provide a reliable, quantitative estimate of model performance, which is critical for a valid change detection analysis.

2.5 Detecting the Past and Present State of Urbanisation

To detect and quantify changes in LULC and the state of urbanisation, a post-classification comparison technique was employed. This involved a direct, pixel-by-pixel comparison of the final 2013 and 2023 LULC maps within the GEE platform. A class transition matrix was generated to quantify the magnitude and nature of land transformation (e.g., how many hectares of 'Bare Land' became 'Built-Up'). This approach allowed for the precise extraction of spatial and statistical trends in urban growth, vegetation shifts, and land degradation over the decade. While this study focuses on change detection, the resulting classified maps and change statistics provide the essential baseline data required for future predictive modeling of urban sprawl in the region.

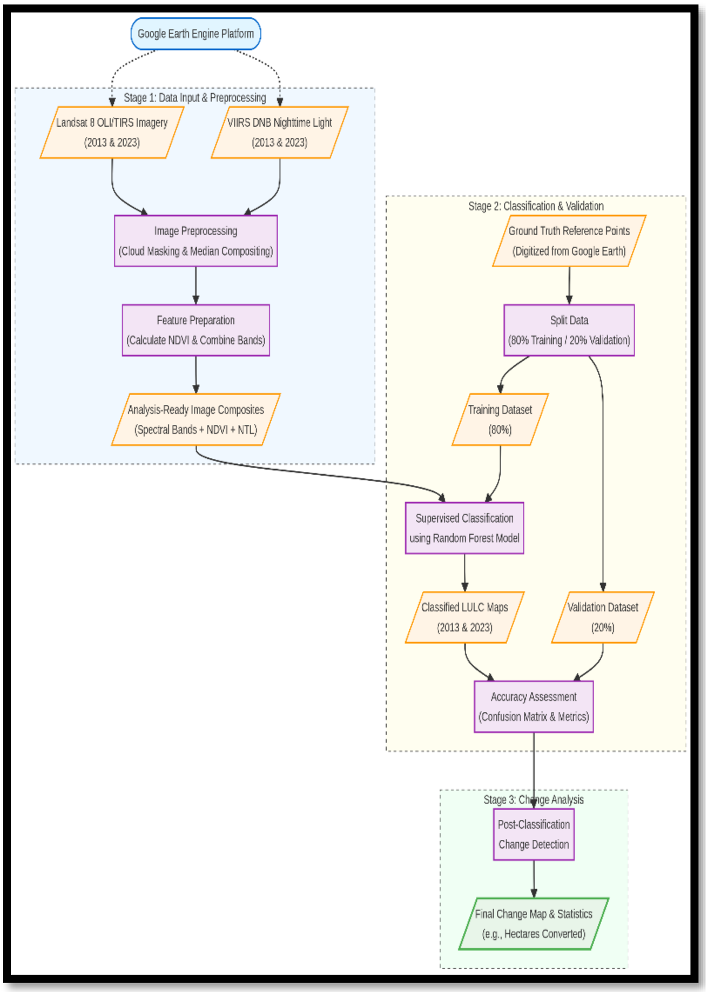

Figure 5: Methodological workflow of LULC classification for year 2013 and 2023 of Riyadh region.

3. RESULTS

The Land Use and Land Cover (LULC) classification was executed within the Google Earth Engine (GEE) platform using the Python GEE API. Training samples were utilized along with Landsat 8 Image collections and night-time light imagery from May to August for both 2013 and 2023. Median composites were generated from these collections to reduce noise and enhance image quality. Selected spectral bands were used to perform classification via a Random Forest (RF) model. Post-classification, a majority filter was applied to eliminate noise and isolated pixels, and waterbody features were appended using the Dynamic World dataset.

3.1. Classification Accuracy:

Table 4 presents the accuracy metrics of the classification model. The precision scores for each land cover class exceeded 92% for both years, with an overall classification accuracy of 95% for 2013 and 96% for 2023, indicating strong model performance.

Table 4: LULC Classification Accuracy Assessment Metrics Based on Validation Dataset.

Land Cover Type	Precision Score -2013	Precision Score -2023
Built-Up area	0.97	0.98
Vegetation	0.92	0.95
Bare Land	0.99	0.94
Overall Accuracy	95%	96%

3.2. LULC Change Detection:

The supervised classification revealed significant shifts in land cover between 2013 and 2023. Figure 6 displays the classified images for both years. A distinct increase in built-up areas was observed, especially in northeastern Riyadh (Figure 7), with built-up land increasing from 178,565.85 ha to 216,970.02 ha**,** marking a 21.51% increase**.** Urban expansion was also evident in other cities like Al-Dawadmy, Afif, and Al-Majma'ah**.**

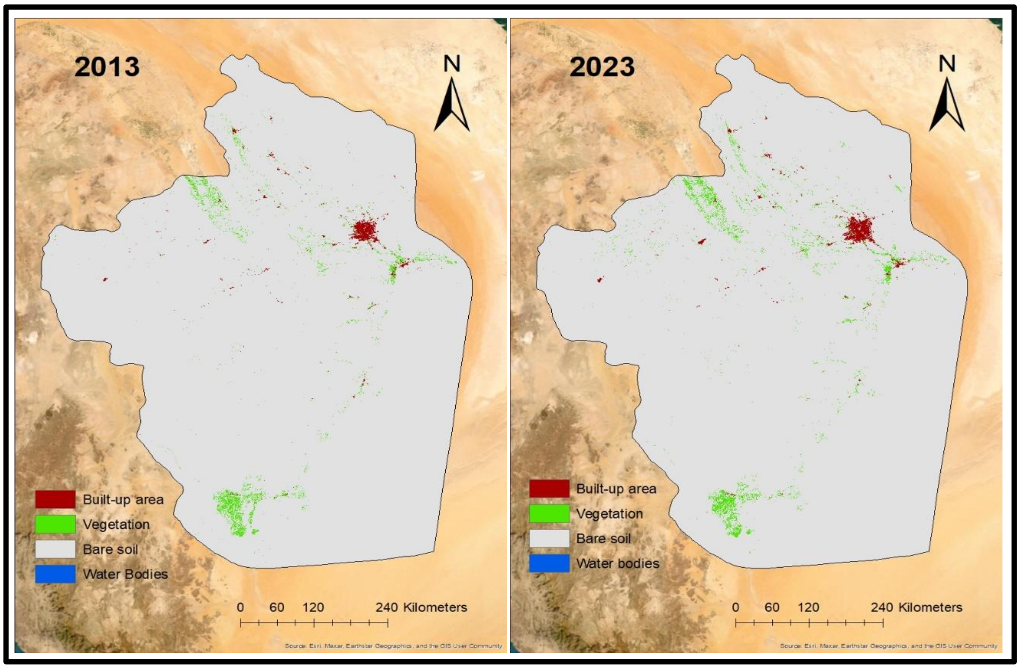

Figure 6: Classified Image of Riyadh, Saudi Arabia for year 2013 and 2023.

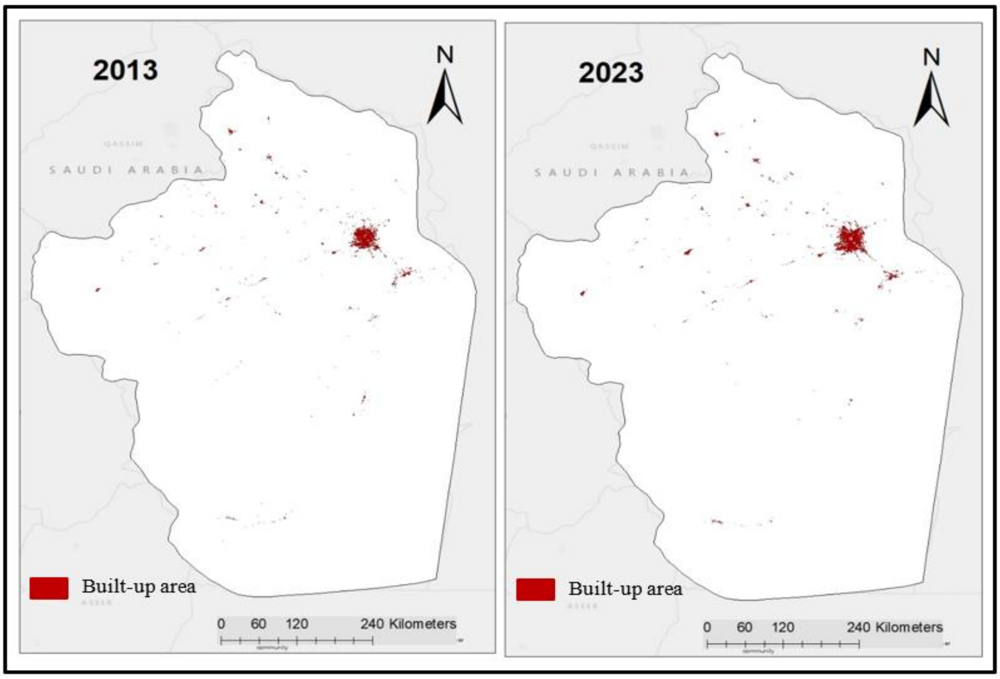

Figure 7: Spatio-Temporal Variation in Built-up area from year 2013 to 2023.

3.3. Vegetation Cover:

Vegetation also showed a substantial increase from 443,946.69 ha in 2013 to 558,833.58 ha in 2023, a 25.89% rise (Figure 8). Notable vegetation expansion occurred near Sajir, Hadir, and Khurayman. However, seasonal variation was not accounted for, as analysis was limited to May–August.

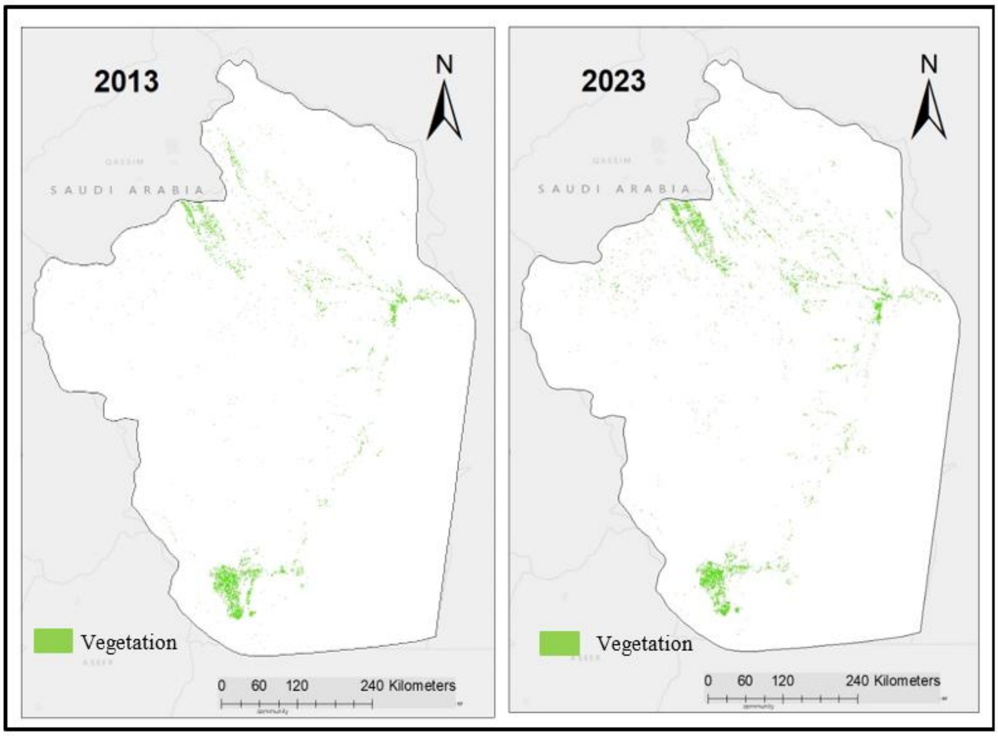

Figure 8: Spatio-Temporal Variation in Vegetation from year 2013 to 2023.

3.4. Bare Soil:

Despite being the dominant land cover due to Riyadh's desert environment, bare soil coverage slightly declined from 40,648,857.03 ha to 40,495,565.61 ha, equating to a 0.37% reduction (Figure 9). This indicates some replacement of bare land with vegetation or built-up areas.

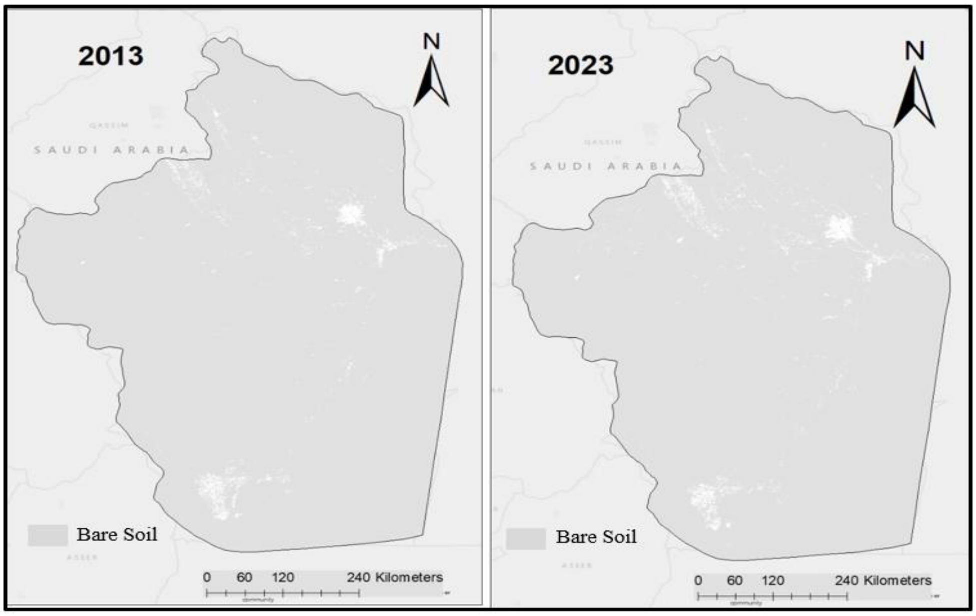

Figure 9: Spatio-Temporal Variation in Bare Soil form year 2013 to 2023.

3.5. Summary of LULC Changes:

Table 5: LULC Change in Riyadh Region.

Land Cover Class	2013 (Ha)	2023 (Ha)	Changes (Ha)	Changes (%)
Built-Up area	178565.85	216970.02	38404.17 (+)	≈ 21.51% (+)
Vegetation	443946.69	558833.58	114886.89 (+)	≈ 25.89% (+)
Bare Land	40648857.03	40495565.61	153291.42 (-1)	≈ 0.37% (-)

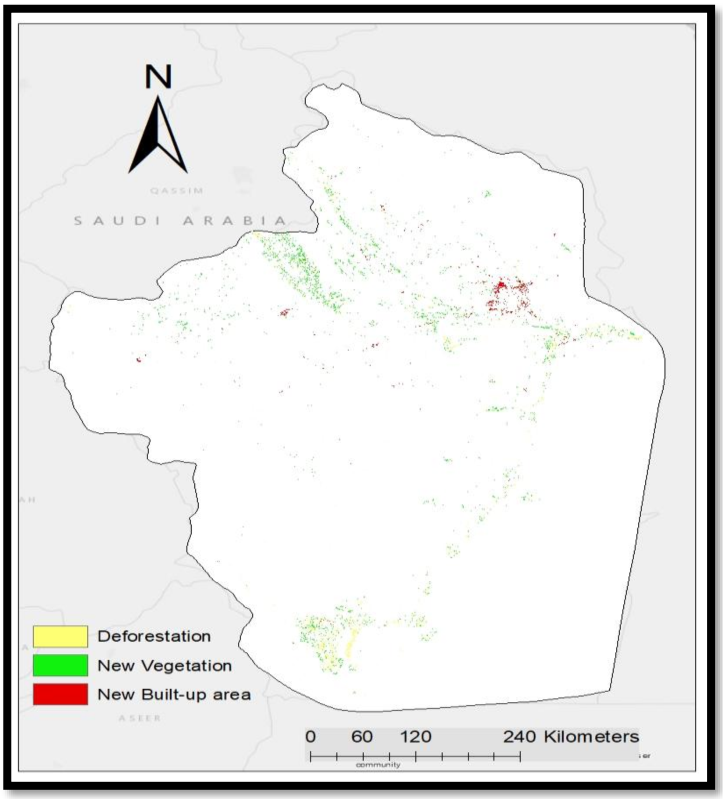

Figure 10: Land Use & Land Cover Transformation Map in between 2013 and 2023.

4. DISCUSSIONS

The LULC analysis illustrates a dynamic transformation in Riyadh's landscape driven by urban expansion, agricultural development, and environmental responses. The classification results reveal several key trends:

4.1. Urbanization Trends and Drivers

The observed 21.51% increase in built-up areas confirms that Riyadh is undergoing an accelerated and spatially heterogeneous urbanization process rather than urban sprawl alone. This pattern is consistent with previously reported land transformation trends in the Riyadh region, where rapid population growth, economic diversification, infrastructure expansion, and government-led development initiatives have jointly driven urban expansion (Alqurashi & Gharbia, 2018; Alqurashi et al., 2019; Alharbia et al., 2019). These studies documented substantial growth of built-up land at the expense of barren and vegetated surfaces, highlighting the influence of both planned and unplanned urban development.

Our findings, which show concentrated growth in northeastern Riyadh and in smaller surrounding cities, align with the patterns of habitat fragmentation identified by Alqurashi & Gharbia (2018). Urban expansion in Riyadh is not solely the result of horizontal sprawl but is also influenced by policy-driven urban densification, large-scale residential and industrial projects, transportation corridor development, and the expansion of service and economic zones associated with Vision 2030 initiatives. The concentration of built-up growth in northeastern Riyadh can be attributed to improved accessibility, proximity to major highways, availability of developable land, and targeted urban planning strategies, which collectively shape the spatial configuration of urban growth.

The ecological implications of these urbanization processes are substantial. Increased impervious surface coverage disrupts natural hydrological cycles by reducing infiltration and increasing surface runoff, while habitat fragmentation and land cover conversion negatively affect ecosystem connectivity and biodiversity. Furthermore, even in desert environments, soils contain Soil Organic Carbon (SOC), and urban development through soil sealing results in the permanent loss of this carbon stock, contributing to carbon emissions rather than sequestration. These findings align with earlier studies that reported rising environmental pressures associated with rapid urban growth in arid cities, including increased surface temperatures and ecological stress (Alqurashi & Gharbia, 2018; Alharbia et al., 2019).

4.2. Vegetation Dynamics:

The study found a significant overall increase in vegetation (25.89%), a result that appears to contradict the general trend of vegetation decline predicted in earlier historical studies like Alrashed & Kumar (2017). This discrepancy highlights the complex and non-linear dynamics of land use in the region. The expansion we observed, particularly near Sajir, Hadir, and Khurayman, is likely attributable to recent, large-scale agricultural projects and localized afforestation efforts rather than natural vegetation recovery.
At the same time, our findings also show pockets of vegetation decline in some southern areas, which aligns partially with the findings of Alqurashi et al. (2015) who noted land abandonment and degradation in certain areas. This dual trend—large-scale agricultural expansion alongside localized decline—paints a more nuanced picture than previous studies, suggesting that broad regional trends can mask significant local variations driven by specific economic activities or land management practices.

4.3. Bare Soil Fluctuations:

Although bare soil remains the dominant land class, its marginal reduction highlights ongoing land cover conversion. Urban and agricultural growth replaced 153,291.42 ha of bare land. This contradicts the initial hypothesis expecting an increase in bare soil, underlining the complexity of anthropogenic and environmental factors influencing land transformation.

4.4. Spatial Insights from Figure 10:

The transformation map illustrates stark contrasts across the region:

- **Northeastern Riyadh**: notable increase in both vegetation and built-up areas.
- **Southern areas**: decline in vegetation, suggesting localized deforestation or abandonment.
- **Urban Sprawl Zones**: clear emergence of new built-up clusters outside the city core.

4.5. Hypothesis Evaluation:

- **Urban Growth Hypothesis**: **Confirmed**. Built-up area expansion is well-documented and exceeds 21%.
- **Vegetation Decline Hypothesis**: **Inconclusive**. While some regions saw deforestation, others gained greenery.
- **Bare Soil Increase Hypothesis**: **Rejected**. Instead, urban and agricultural development reduced bare soil coverage.

These findings stress the need for nuanced interpretations of land cover trends. Urbanization and agricultural intensification are reshaping Riyadh's landscape in unexpected ways. The limitations of remote sensing, such as seasonal image timing, also caution against broad generalizations without in-depth spatial and temporal context.

5. CONCLUSIONS

This study successfully quantified the significant Land Use and Land Cover (LULC) transformations in the Riyadh region between 2013 and 2023 using a robust machine learning framework within the Google Earth Engine platform. Our analysis revealed two keys, and seemingly contradictory, dynamics shaping the contemporary landscape.

First, the region experienced a rapid 21.51% increase in built-up areas, a finding that confirms and accelerates the historical growth trends identified in previous studies by Alqurashi & Kumar (2017), who documented substantial urban expansion between 1990 and 2014. This recent expansion, concentrated in the northeastern corridor and surrounding secondary cities, underscores the intense and ongoing pressure that urban development places on the region's ecological resources, including the irreversible loss of Soil Organic Carbon due to soil sealing.

Second, contrary to the historical vegetation decline noted by researchers such as Alrashed & Kumar (2017), our study identified a substantial 25.89% net increase in vegetation cover. This highlights a recent shift in land-use dynamics, where large-scale, targeted agricultural and afforestation projects are now major drivers of landscape change, creating a complex mosaic of greening in some areas and degradation in others. This finding suggests that the post-2015 period, particularly following the announcement of Saudi Vision 2030, has introduced new land management priorities that differ markedly from earlier decades.

In conclusion, the Riyadh region is at a critical juncture, defined by the dual forces of rapid urbanization and large-scale greening initiatives. This research provides a vital, up-to-date baseline that demonstrates the power of modern cloud-based remote sensing to monitor these complex dynamics efficiently and accurately. The findings serve as an evidence-based call to action for policymakers to formulate sustainable land management strategies that can balance development goals with the urgent need for ecological preservation in one of the world's most rapidly changing arid urban environments.

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BIOGRAPHICAL NOTES

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