Remote Sensing Analysis of Urbanization and Agricultural Land Conversion in Bantwal Taluk, Karnataka

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Summary: Understanding changes in Land Use and Land Cover (LULC) is critical to good environmental management and urban planning. This study uses Landsat 8 Collection 2 imagery to investigate LULC variations in Bantwal Taluk, Dakshina Kannada, between 2013 and 2024. Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Random Forest (RF) were used to identify and classify six LULC classes: dense vegetation, vegetation, waterbodies, built-up areas, barren land, and floodplains. Accuracy points created in ArcMap were confirmed against Google Earth Pro ground truth data. RF had the highest accuracy, with 88.33% in 2013, 90% in 2018, and 86.67% in 2024, surpassing MLC and SVM. The findings revealed major LULC transitions, such as urban expansion by 10.43% and agricultural land reduction by 22,42% between 2013 and 2024. This study provides critical information for environmental planning, disaster management, and sustainable land use in Bantwal Taluk by doing extensive LULC mapping and change analysis.

Keywords: Land Use Land Cover (LULC), Landsat, Pansharpening, Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), Random Forest (RF), Change Detection.

1. INTRODUCTION

Changes in Land Use and Land Cover (LULC) are crucial for monitoring environmental trends and successfully managing resources. Bantwal Taluk in Dakshina Kannada, which borders the Western Ghats, is facing considerable environmental issues as a result of deforestation, urbanization, and unpredictable climate. Intense monsoon rains, landslides, and rising temperatures endanger agriculture, water supplies, and livelihoods, needing prompt mitigation efforts [1].

LULC changes arising from activities such as forestry and urbanization frequently spread beyond their origins, affecting ecosystems worldwide. Their rapid growth desires good management to balance development with environmental preservation while mitigating biodiversity loss and resource depletion [2].

LULC models, which include top-down and bottom-up techniques, help with urban planning and land management. While top-down models examine broader patterns utilizing a variety of variables, bottom- up models concentrate on localized dynamics and individual land-use decisions, providing complementary viewpoints [3].

Bantwal Taluk in Karnataka's Dakshina Kannada District is facing climate concerns such as flooding, landslides, and rising temperatures. LULC mapping and change detection analysis assist in identifying drivers, assessing disaster risks, and guiding sustainable land management.

A study conducted in [4] has shown dramatic LULC changes, such as a 46% forest loss and a built-up area rise from 13% to 55% between 2000 and 2022. However, there is a lack of details on preprocessing procedures, which are critical for enhancing classification accuracy. Furthermore, the machine learning classifiers employed for supervised classification lack clarity, which limits reproducibility and dependability. Another study in Dakshina Kannada ties LULC changes, particularly urbanization and vegetation loss, to diminishing groundwater levels, but ignores agricultural effects. This gap is essential since agriculture, a major local economic engine, has a large impact on groundwater dynamics [5]. In order to fill these gaps, this study uses sophisticated preprocessing methods, such as pan sharpening, to improve picture quality and classification accuracy when constructing LULC maps for 2013, 2018, and 2024. Key transitions like urban sprawl and deforestation are identified and their effects are quantified using a thorough change detection analysis. This study offers vital information that can guide environmental planning, disaster management, and sustainable land use in Bantwal Taluk by carrying out thorough LULC mapping and change analysis. The Bantwal Taluk study area map is displayed in Fig. 1.

2. METHODOLOGY

The methodology followed, illustrated in Fig. 2, encompasses a series of systematic steps to achieve accurate land cover change detection: (1) Acquisition of Landsat 8 imagery for the years 2013, 2018, and 2024 from the USGS Earth Explorer platform; (2) Image preprocessing, including band stacking, pansharpening to enhance spatial resolution, and clipping to the delineated study area to ensure data consistency; (3) Implementation of multiple supervised classification algorithms, such as Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Random Forest (RF), to categorize land cover types; (4) Generation of LULC maps followed by accuracy assessment using ground truth data and confusion matrices; (5) Selection of the optimal classification algorithm based on accuracy metrics to perform change detection analysis; and (6) Utilization of transition matrices to quantitatively analyze LULC changes over the specified periods.

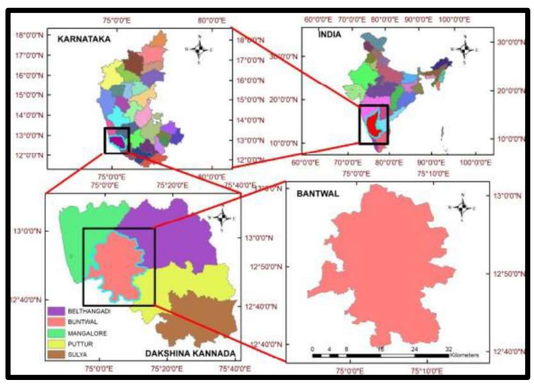


Fig. 1. Study area map of Bantwal Taluk.

2.1. *Data Source*

This study makes use of primary LANDSAT 8 OLI/TIRS satellite data from the USGS EarthExplorer platform in 2013, 2018, and 2024. Excellent surface reflectance and spatial precision are guaranteed by the Level-1 TOA Reflectance (L1TP) data, which is categorized as Collection T1. These images were chosen for their cloud-free conditions, which allowed for accurate LULC change analysis. They were projected in WGS_1984_UTM_43N and covered WRS Path 145/Row 51 for Bantwal Taluk.

2.2. *Preprocessing*

In order to improve spatial resolution for in-depth LULC analysis, this study used band stacking and the ESRI pan-sharpening approach on Landsat 8 images. While pan-sharpening combined the spectral richness of the multispectral bands with the 15 m spatial detail of the panchromatic band, band stacking combined seven multispectral bands with a resolution of 30 m into a coherent dataset. By refining multispectral bands to a 15 m resolution, this procedure made it possible to observe land cover features more finely [6], especially in the region of interest for Bantwal Taluk. The LULC categories—Dense Vegetation, Vegetation, Waterbodies, Built-Up, Barren Land, and Floodplain—were applied to Landsat imagery from 2013, 2018, and 2024. Visual image interpretation was used to identify distinct training patterns for every class.

2.3. *Classification*

Following the preparation of training samples, images were categorized into LULC classes using machine learning classification methods. Three classifiers were used in this study: RF, SVM, and MLC.

A popular parametric technique based on the Bayes principle, MLC assumes that data clusters form hyper-ellipsoids in multidimensional space. Using the covariance matrix, prior probability, and mean feature vectors, it determines the likelihood that each pixel belongs to a class and designates the class with the highest likelihood [7] [8]. Research demonstrates the efficacy of MLC for LULC categorization, particularly in watershed and agricultural study [9] [10] [11].

SVMs, which combine binary classifiers, are ideal for multi-class LULC classification because they are excellent at handling high-dimensional data. To ensure reliable pixel-based classification, the method finds the best hyperplanes in feature space to divide classes [12] [13]. Studies demonstrate that SVM performs better than more conventional techniques like MLC [9] [14].

Random Forest, an ensemble technique, uses bagging to merge several decision trees and increase classification accuracy. Compared to boosting approaches, it provides faster computation, can handle a variety of predictors, and is immune to noise and overfitting. [15] [16] [17]. RF has become well-known for its reliable remote sensing capabilities

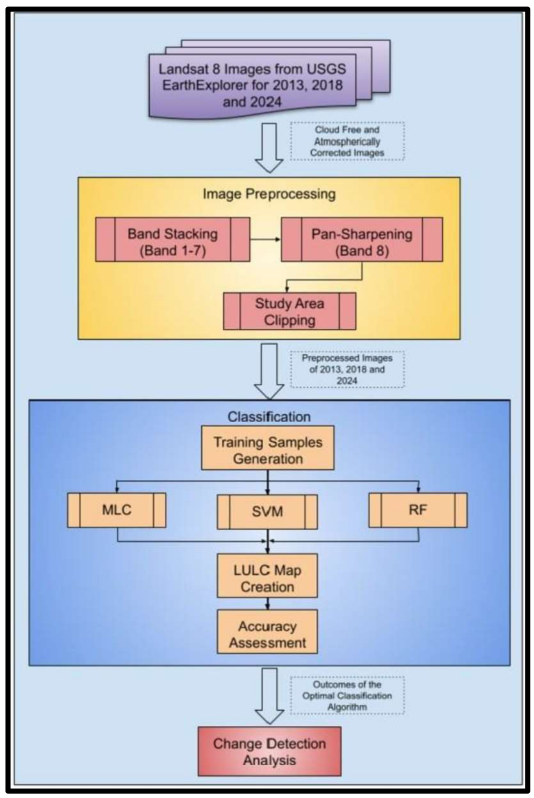


Fig. 2. Methodology

2.4. *Accuracy Assessment*

It is imperative to assess machine ML classifiers following their application to picture classification tasks in order to comprehend their efficacy and guarantee their dependability. The effectiveness of MLC, SVM, and RF classifiers for LULC classification (2013, 2018, 2024) was assessed by comparing projected classes with ground truth in confusion matrices. Calculations were made for metrics like recall, accuracy, precision, F1 score, and Kappa coefficient. To ensure dependable and thorough classification performance, precision gauges prediction accuracy, recall analyzes detection capacity, and the Kappa coefficient assesses agreement beyond chance.

2.5. *Change Detection*

This study applied the widely utilized post-classification comparison method [4] for change detection [18]. Each time period's images were classified separately, and the outcomes were arranged in a transition matrix [19]. This matrix shed light on the spatial distribution of LULC changes by recording and measuring inter-class transitions to highlight landscape change patterns.

3. Results and Discussions

Six LULC categories—Dense Vegetation, Vegetation, Waterbodies, Built-Up, Barren Land, and Floodplain—were identified from Landsat 8 images captured in 2013, 2018, and 2024 using MLC, SVM, and RF algorithms. The LULC maps for each approach are displayed in Figure 3 emphasizing variations in classification outputs over time brought about by the various methods.

Fig. 3. LULC Maps using MLC, SVM and RF for the years (a) 2013, (b) 2018 and (c) 2024

The overall accuracy of the LULC classification in Bantwal Taluk is displayed in Figure 4, where the RF classifier had an average overall accuracy of 88.3%. By contrast, MLC and SVM both demonstrated reduced accuracy, with MLC reaching 71% and SVM 72.7%. With an average F1-score of 0.88, precision of 0.89, recall of 0.88, and a kappa value of 0.85, the RF classifier performed better than both MLC and SVM on all measures, as indicated in Table 1. On the other hand, MLC obtained a kappa value of 0.62, an F1-score of 0.71, a precision of 0.76, and a recall of 0.71. With an F1-score of 0.74, precision of 0.79, recall of 0.73, and a kappa value of 0.65, SVM performed marginally better than MLC. Compared to MLC and SVM, which need more parameter tuning and have limits in capturing fine details, RF is more effective and dependable for LULC classification due to its robust ensemble method, convenience of use, and capacity to handle complicated data.

The RF-based LULC classification observations for Bantwal Taluk show significant variations between 2013 and 2024. Dense vegetation grew from 61.47 sq. km in 2013 to 248.46 sq. km in 2024, while overall vegetation cover decreased, especially between 2013 and 2018, most likely due to urbanization. Built-up areas increased from 28.43 sq. km in 2013 to 105.71 sq. km in 2024, demonstrating urban growth. Barren land reduced from

115.19 sq. km in 2013 to 23.16 sq. km in 2024, indicating land rehabilitation. Water bodies and floodplains changed little, with water bodies decreasing somewhat from

11.38 to 10.26 sq. km. These transitions reflect ongoing land conversion, notably from agricultural to developed areas.

Significant changes in land cover throughout Bantwal Taluk are highlighted by the transition matrices derived from the LULC maps produced using the RF approach for the years 2013–2018 in Figure 5 (a-d) and 2018–2024 Figure 5 (e-h). These matrices show how land use has changed over time by providing comprehensive data on the area (in square kilometers) of each land cover type. Key trends are highlighted in Figure 5, which graphically depict the significant transitions seen in the study area.

Table 1. Performance metrics for the RF, MLC, and SVM classifiers.

Classifier	Precision	Recall	F1-Score	Kappa Value
MLC	0.89	0.88	0.71	0.62
SVM	0.79	0.73	0.74	0.65
RF	0.89	0.88	0.88	0.85

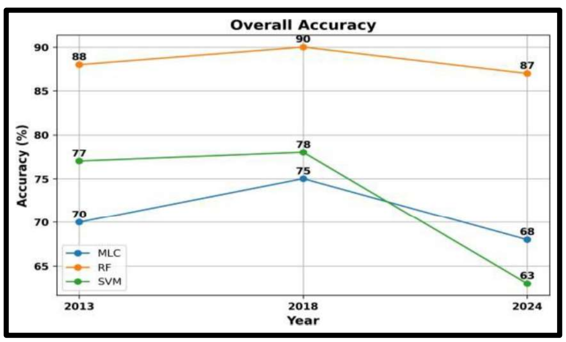
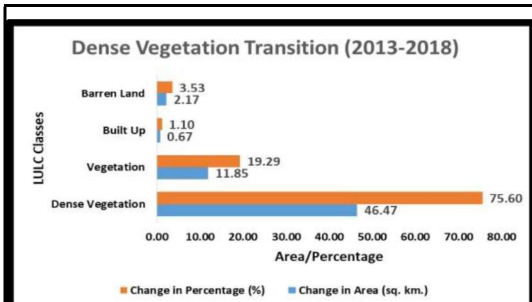
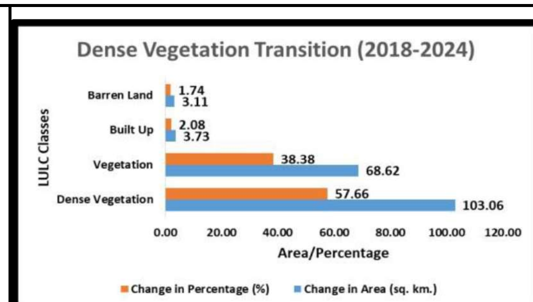


Figure 4. Average overall accuracy of MLC, SVM and RF



(a)



(e)

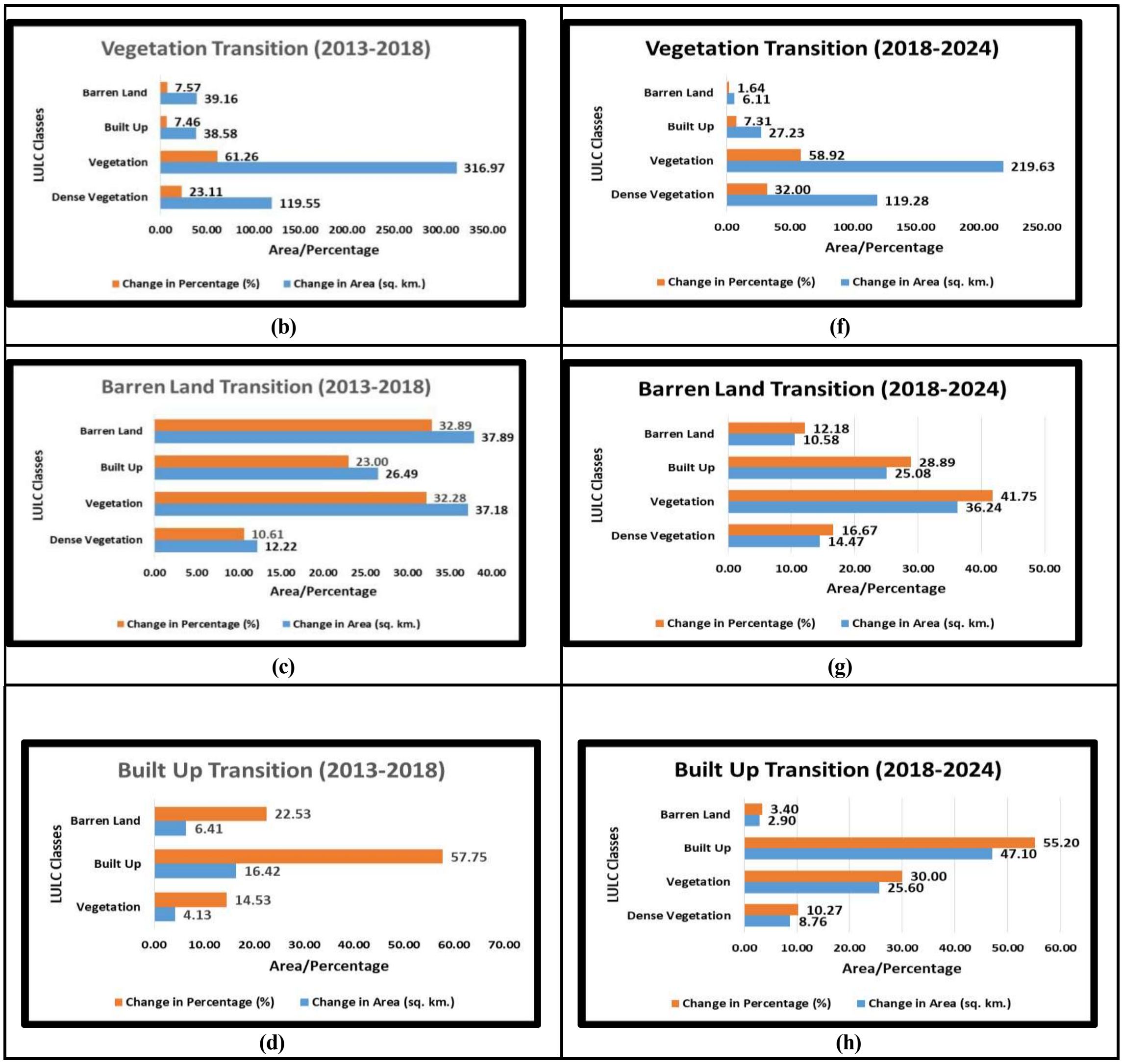


Figure 5. Land Cover Transitions: Area and percentage changes between categories.

4. Conclusion

This study looks at LULC trends in Bantwal Taluk, Dakshina Kannada, using Landsat 8 images from 2013, 2018, and 2024. MLC, SVM, and RF algorithms were employed to categorize six LULC types: dense vegetation, vegetation, waterbodies, built-up regions, barren land, and floodplains. Accuracy assessments demonstrated the superiority of RF, with accuracies of 88.33% in 2013, 90% in 2018, and 86.67% in 2024. Key findings revealed rapid urbanization, with urban areas expanding from 3.84% in 2013 to 14.27% in 2024, while agricultural land declined from 69.85% to 47.43% within the same time period. These transitions highlight potential environmental and economic issues in the region. Comprehensive LULC mapping and change analysis offer crucial insights for ecological planning, disaster preparedness, and sustainable land use. The findings provide important recommendations for regulating urban expansion and protecting agricultural resources in Bantwal Taluk.

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