MAPPING LAND COVER VIA SATELLITE IMAGES

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ABSTRACT

The current study examines how image fusion impacts land-cover categorization accuracy using a range of machine learning algorithms. According to our research, picture fusion outperforms single-source imagery alone in categorization. This study uses multi-temporal and multi-spectral Landsat satellite pictures to investigate the urban growth in the Bangalore region. The study, which spans 39 years, examines alterations in the land cover in a 2182 km² area utilizing data from remote sensing. India's rapid population growth and urbanization have significantly impacted resource availability, making land use changes need to be monitored. The evolution of Bangalore's land cover is monitored using Landsat's multi-temporal and multi-sensor technology, which includes MST, TTM, and ETM+ pictures from 1973, 1992, 1999, 2002, 2005, 2008, and 2011. By applying the maximum likelihood classification method, temporal alterations were found and four types of land cover were revealed: desert terrain, vegetation, water, and built-up areas. The findings show a significant rise in urban areas, from 6% in 1973 to 25% in 2011, with 43% of the observed changes being attributed to urbanization. This study emphasizes the significance of ongoing remote sensing to monitor resource management and urban growth, as well as the notable shift of arid terrain to densely forested areas, impacting zones of plants and water.

Keyword: Land-cover classification, Machine Learning.

I. INTRODUCTION

Globally, urbanization is a transformative process that is transforming ecosystems and landscapes, mostly due to population expansion and economic development. Rapid urbanization in India has a major effect on the environment's and natural resources' sustainability. Bangalore, a well-known metropolis, is an excellent illustration of these processes because it has experienced notable changes in its land cover. during the previous forty years. This study examines Bangalore's urban expansion during a 2182 km² period

utilizing the Landsat satellite photos taken between 1973 and 2011. Understanding patterns in urbanization and assessing The robust foundation provided by Technologies for distant sensing can be useful. with changes in land cover, particularly when it comes to multi-temporal and multi-spectral data. The city's transformation from primarily rural to increasingly urbanized areas is indicative of larger changes in India's economy and population.

The current investigation seeks to achieve two specific objectives. First, it will map and analyze the geographical and temporal patterns of land use change using advanced techniques for remote sensing in Bangalore. Second, it will assess how urbanization affects natural resources—particularly areas of vegetation and water. Using Landsat imagery, In this work, methods for maximum likelihood classification are employed. to identify and map important land cover types, including vegetation, built-up areas, water bodies, and arid terrain.

The results show a notable rise in urban areas across the course of the study, underscoring the transformation of dry landscapes into heavily inhabited forested areas. This change emphasizes the necessity of resource management plans and efficient land use planning in order to prevent environmental deterioration and maintain Bangalore's urban growth.

This research uses remote sensing, a potent tool for monitoring and controlling the effects of development on ecological systems to offer crucial information about Bangalore's land cover change and urban growth dynamics. Understanding these processes is essential to influence sustainable development policies and practices in India's and other rapidly urbanizing regions.

Objective:

This study's primary objective is to use satellite imagery from Landsat to examine the changes that Bangalore's urban region has undergone during a 39-year period. The study's specific objectives are to:

1. **Map Changes Over Time:** To map and comprehend the changes in Bangalore's terrain, utilize satellite data spanning from 1973 to 2011.
2. **Identify Types of Land:** To ascertain the different types of land, such as dry areas, buildings, plants, and water, use a technique known as maximum probability categorization.
3. **Study Urban Growth:** Examine the effects of urbanization on vegetation, water, and land area covered by each type of plant.
4. **Promote Better Development:** Disseminate our knowledge to assist in developing strategies for the efficient use of land and the protection of natural resources as cities like Bangalore expand.

II. RELATED WORK

N. Vora, A. Patel, K. Shah and P. Saikia, This study classifies land cover (forest, built-up, agricultural land, and water bodies) in Indian regions including Agra, Ahmedabad, and Gandhinagar using Landsat 8 satellite data and temporal analysis. In comparison to k-nearest neighbors and other machine learning models like choice trees and support vector machines, U-Net, a network of convolutional neural networks, has the highest accuracy. The project's goal is to provide accurate land cover maps that are necessary for environmental studies and urban planning. management applications[1].

R. Qin, H. Chen, In contrast, W. Liu and C. Xiao In this piece, a team of Random Forests is utilized. algorithms to accurately map land cover on a broad scale using satellite pictures. Enhancing classification accuracy, producing high-resolution maps of land cover, and supplying trustworthy data for well-informed decision-making in environmental and urban planning contexts are among the main goals[2].

S. Mishra and S. Jabin, This study examines the spatiotemporal changes in Uttarakhand's Following the 2013 flash floods, the usage of cover (LULC) was assessed using Landsat satellite imagery. With a precision level of over 92%, it uses remote sensing techniques and geographic information systems (GIS), including the NDVI and the Maximal Likelihood Algorithm, to classify the area into categories such as mountains, vegetation, water, and glaciers. Assessing and recording notable LULC changes in the wake of natural disaster is the goal[3].

M. L. Clark, The study used Random Forests and MESMA classifiers to analyze hyperspectral and multispectral imagery for mapping different land-cover types in the San Francisco Bay Area. It compared summer-only imagery from HyspIRI, Landsat 8, and Sentinel-2 to multi-temporal data (spring, summer, and fall), and discovered that Random Forests outperformed MESMA. The research demonstrated how hyperspectral measures could increase accuracy by identifying important spectral patterns associated with structural and chemical attributes[4].

T. W. S. Warnasuriya, This study uses medium-resolution Landsat satellite pictures to examine how land-use patterns have changed in Matara District, Sri Lanka, during the previous few years. It looks into how accurate remote sensing data works with GIS to map and comprehend these changes in an economical and efficient manner. The goals include utilizing Maximum Likelihood Classification to estimate land-use changes with high accuracy across the study period and extracting ground features, such as plant cover and bodies of water, using single band and NDVI approaches, respectively[5].

This paper's primary goal is to increase accuracy by combining the level set method (LSM) with convolutional neural networks, also known as or CNNs. of land coverage mapping in satellite photos. With an emphasis on satellite data from Kasetsart University, the project hopes to outperform conventional approaches like Hopfield and Pixel-Swapping by combining these strategies[6].

This study uses multi-temporal Landsat satellite photos covering 39 years to examine and track changes in land cover and urban growth in the Bangalore region. The study intends to evaluate the effects of increasing urbanization on natural resources such water bodies, vegetation, and barren lands by utilizing categorization methods and data from remote sensing. shedding light on the processes of urban growth and its long-term environmental implications is the aim [7].

The purpose of the task is to assess spectral vegetation indices (SVIs) for table grape production and quality parameters from veraison to harvest that are obtained via satellite (Landsat 8) and proximate sensing (Crop Circle ACS 470). It focuses on evaluating connections across three cultivation years in a commercial vineyard between SVIs (NDVI, GNDVI) and grape characteristics (berry diameter, pH, deformation). The goal is to determine how effectively each sensing method delivers timely and precise data in order to maximize the yield of table grapes[8].

This work's primary goal is to evaluate the efficacy of artificial intelligence techniques for categorizing land cover and utilization in a boreal environment using Sentinel-2 satellite data. Analyzing the effectiveness and accuracy of multiple machine learning methods for classifying different types of land cover, including random forest, and and support vector learning, and Neural Networks. The work aims to offer important insights into the potential and constraints of these algorithms for mapping and tracking changes in land cover in boreal regions by utilizing Sentinel-2 images[9].

The study intends to increase the scene classification accuracy in high-resolution remote sensing images (HRRSI) by utilizing an attention-based deeper feature fusion (ADFF) framework. The objective is to achieve more robust classification performance by mitigating intra-class diversity, handling repeated textures efficiently, and improving discriminative region focus through the integration of Grad-CAM attention maps, multiplicative fusion of deep features, and a center-based cross-entropy loss function[10].

III. METHODOLOGY

Remote sensing technology maps the landscape through satellite photos, classifying and identifying different forms of land cover, including woodlands, towns, bodies of water, and agricultural land. Monitoring shifts in For various purposes, such as urban planning, management of the environment, and the preservation of natural resources, surface area and use throughout time are crucial. Satellite images offer crucial details for this purpose. When use satellites to map land cover imagery, the following essential steps are usually involved in the methodology:

3.1 Data set used:

Satellite Photography :

Multispectral Images: Data obtained from satellites such as Sentinel, MODIS, or Landsat offer multispectral images that span several electromagnetic spectrum bands, such as visible, near-infrared, and thermal. The spectral and spatial data that these photos record about the Earth's surface is crucial for differentiating between the many forms of land cover.

Ground Truth Information:

Field surveys: On-the-ground observations and measurements taken to confirm the kinds and conditions of land cover.

High-Resolution Imagery: Detailed photos taken by drones or aerial surveys that offer exact geographical data regarding the cover of the land.

Current Land Cover Maps: These are historical maps that are used as benchmarks when developing and certifying machine learning models.

Features Derived:

Vegetation Indices: Measures of vegetation's health and density, as measured by the Biodiversity Index with Normalized Difference (NDVI), the Enhanced Vegetation Index (EVI), and the Soil-Adjusted Vegetation Index (SAVI), are computed using satellite data.

Features of Texture: captured utilizing methods such that Gray-Level Co-occurrence Matrix (GLCM) to characterize land cover fluctuations and spatial patterns.

Spectral Signatures: Reflectance values that differentiate between distinct land cover classifications across multiple bands in satellite photos

3.2 Data Acquisition:

In this step, satellite photos covering the study area of interest come from multiple sources, like as The Sentinel-2, Landsat's, and Planet Scope. These satellite images provide crucial details regarding the surface of the Earth, including details about flora, metropolitan areas, water bodies, and land cover.

Figure 1: Photos that can accurately reveal the geo-position of an object (see Figure1.).

3.3 Pre-processing:

The pre-processing of satellite images is essential to guarantee the precision and dependability of the subsequent analysis. This process corrects distortions of geometry in the images, eliminates noise, and accounts for atmospheric variables. By pre-processing the data, researchers can enhance the image quality and lower errors that could affect the categorization process.

3.4 Image Classification:

Sorting use machine learning techniques like random forests, decisions trees, Support Vector Machines or neural networks to classify satellite photos into distinct land cover categories is a critical stage in the process. These algorithms enable the construction of thematic maps by analyzing the spectral properties of the picture pixels and classifying them into several land cover groups.

3.5 Validation:

To evaluate the precision of the land cover classification outcomes derived from the image classification procedure, validation is required. In this step, the classified land cover map is compared to reference datasets or field-collected ground truth data. Validation aids in determining any inconsistencies or mistakes in the findings and assesses the categorization algorithm's dependability.

3.6 Post-processing:

Post-processing entails getting rid of any mistakes, discrepancies, or incorrect classifications that might have happened all over the process of classifying images to enhance the land cover classification findings. Scholars may utilize spatial filters, smoothing techniques, or alternative approaches to enhance the overall caliber of the theme maps produced from the categorized photos.

3.7 SVM Land Mapping Algorithm

Preparing satellite data, extracting pertinent features, training the SVM model, classifying land cover types, and evaluating classification accuracy are all phases involved in mapping land cover using SVM. Over time, this technology's precise mapping and analysis of land cover change produces useful data for managing resources and development, and planning. and environmental monitoring.

Algorithm for Tracking the Land Cover Using SVM Steps

- Obtain multispectral photos from satellites (such as Sentinel and Landsat).
- Apply picture enhancement techniques, cloud masking, and radiometric and geometric corrections. To measure vegetation density, compute vegetation indices (e.g., NDVI, EVI).
- For spatial patterns, extract textural elements using techniques such as GLCM. Examine spectral signatures in various bands to distinguish between various types of land cover.
- Utilize current land cover maps or field surveys to collect data that is accurate. For every relevant land cover class, create labeled training samples.
- Assemble data from satellite images into feature vectors, or spectral values of pixels. Choose a suitable kernel function (such as linear, RBF, or polynomial) according to the characteristics of the data.
- Use labeled training data to train the SVM classifier To be able to optimize the hyperplane. The trained SVM classifier should be used to classify each pixel in satellite pictures.
- To make the map of the ground surface better apply post-processing techniques (such as majority filtering and spatial smoothing).
- Check the map of classified land cover using higher-resolution photos or ground truth data.
- Determine measures to assess classification performance, such as Overall Accuracy, User's Accuracy, and Producer's Accuracy.

Calculate the Accuracy Assessment

For example: You contrast the classification outcomes with following the SVM classifier's application to a satellite image, ground truth data. The following confusion matrix pertains to the four land cover classes—forest, water, urban, and agricultural—is the outcome of the comparison.

Classified \ Actual	Forest	Water	Urban	Agriculture	Total (Classified)
Forest	50	2	3	5	60
water	1	45	2	2	50
urban	4	5	40	3	50
agriculture	5	0	5	40	50
Total(actual)	60	50	50	50	210

1. **Overall accuracy**

$$\frac{\Sigma \text{ true positive}}{\text{Total number of pixels}} \quad X100\%$$

True positives =50(forest)+45(water)+40(urban)+40(agriculture)=175

The total quantity of pixels =210

Overall accuracy=175/210X100%=83.33%

2. Users Accuracy:

Forest= 50/60X100%=83.33%

Water=45/50X100%=90%

Urban =40/50X100%=80%

Agriculture=40/50X100%=80%

3. Producer Accuracy:

Forest=50/60X100%=83.33%

Water=45/50X100=90%

Urban=40/50X100=80%

Agriculture=40/50X100=80%

These metrics offer a thorough assessment of the mapping of land cover by the SVM classifier ability, showing a high degree of accuracy and consistent classification outcomes.

VI. RESULT AND ANALYSIS

Figures are essential in studies that use satellite images to map land cover because they show the geographic distribution of various land cover categories. They aid in the effective transmission of findings and provide an illustration of complex spatial information, but they further advance our understanding of the changing patterns of land cover. in the studied area. Below Figure 2 describes A detailed visual analysis of land-cover classification methods.

Figure 2: Visual analysis of land-cover classification methods

Precision of Categorization Outcomes

Accuracy in land cover mapping with a support vector machine (SVM) refers to how closely the categorized land cover map conforms to ground truth data or other reference data. It measures the accuracy and dependability of the SVM-derived classification results.

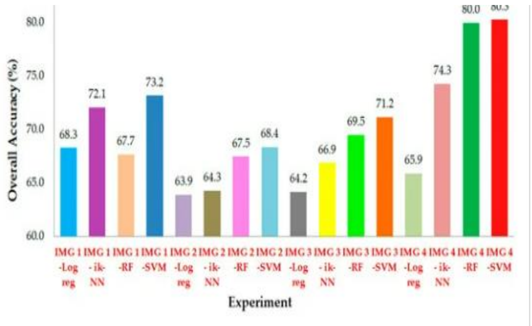

Figure 3: Total accuracy across all combinations.

V. CONCLUSION

Finally, using extensive remote sensing and GIS tools, this study shows notable changes in Bangalore's land cover and urban expansion over almost 40 years. The results show a considerable growth in built-up areas at the expense of natural landscape features like water and vegetation. The availability of resources and local ecosystems are impacted by this urban expansion, which has consequences for environmental sustainability. In order to reduce these environmental effects, proactive urban planning initiatives must incorporate green infrastructure solutions and give priority to sustainable development practices. For Bangalore and other similar cities All around the world to develop evidence-based policies targeted at building resilient and environmentally balanced urban ecosystems, ongoing remote sensing technology monitoring and implementation will be crucial.

VI. REFERENCES

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