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LAND-USE CHANGE DYNAMICS AND AUTOMATED FEATURE EXTRACTION USING HIGH-RESOLUTION SATELLITE IMAGERY

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ABSTRACT - The mapping of urban landscapes is a challenging task due to their dense and diverse characteristics. The changing urban environment with developing infrastructure demands constant updates and accurate extraction techniques. Recent advancement in geospatial technology has led to the capture of high-resolution data and its analysis at a finer scale. However, a sustainable development framework necessitates the understanding of spatial patterns incorporating vertical and horizontal components of the built-up volume. This study aims to understand the changing landscape at the pixel level by analysing features along with their volumetric expansion. The findings highlight that Bangalore city's urban growth has shown increment over the period with volumetric expansion in all parts of the city based on events of changing demand and growth. The evaluation metrics indicate that the model can be generalised for any geographical location as well as to different sensor type images.

Keywords: Land use; Urban built-up volume; deep learning; convolutional neural network; feature extraction

1. INTRODUCTION

Cities have always been an integral part of a country. About 85% of the global GDP is generated from cities [1]. The United Nations report projects that by 2050, 68% of the world population is expected to live in cities. This unprecedented and irreversible growth develops tremendous pressure on the existing system without compromising the socio-economic and cultural linkages [2-4]. Furthermore, the process leads to unplanned urbanization that has given rise to paved surfaces including buildings, roads, infrastructures etc. The urban areas of cities like Bangalore, Delhi, and Kolkata have recently experienced horizontal as well as vertical growth in built-up areas due to changes in land use dynamics [4,5]. Therefore, this quantum of population inflow necessitates the understanding of urban dynamics in the context of spatial patterns simultaneously the dense and heterogeneous nature of the urban environment; makes mapping of urban environment a complex task [6,7] Remote sensing and geo-informatics with the fusion of machine learning play a key role in visualizing the horizontal and vertical growth patterns of urban landscapes in predicting land-use changes [8,9]. In the past decades, various traditional machine learning methods were developed to study urban dynamics at a different scale. However, developing automatic methods for diverse built-up environment scenarios within a city is still challenging.

2. MATERIALS AND METHODS

The study has been performed in Bangalore city with a 10km buffer. The city has drawn a lot of interest over the past in terms of real estate development and is expected to continue the trend which would provide higher statistical information about the city, therefore chosen as the study area. Table 1. Details the various spatial data used to carry out analysis and modelling. Figure 1 depicts the detailed procedure. The first stage involves data pre-processing and land use classification using supervised learning-based Gaussian maximum likelihood classification. Open-source platforms such as GRASS and QGIS was used in the analysis. The second stage involves training a CNN-based deep learning model with training masks using the transfer learning technique. The third stage involves the calculation of urban built-up volume using the digital surface model. Using ground truth or validation datasets, the final procedure involves the calculation of evaluation metrics. This analysis was performed using python.

Table 1. Specifications of spatial data used in the study.

Purpose	Satellite Sensor	Resolution (meters)	Year
Land use analysis	IRS Cartosat 1	2.7	2012
Feature extraction	Triplesat	0.8	2018
Built-up volume	Digital Surface Model (DSM) and DTM (Digital Terrain Model)	5	2018

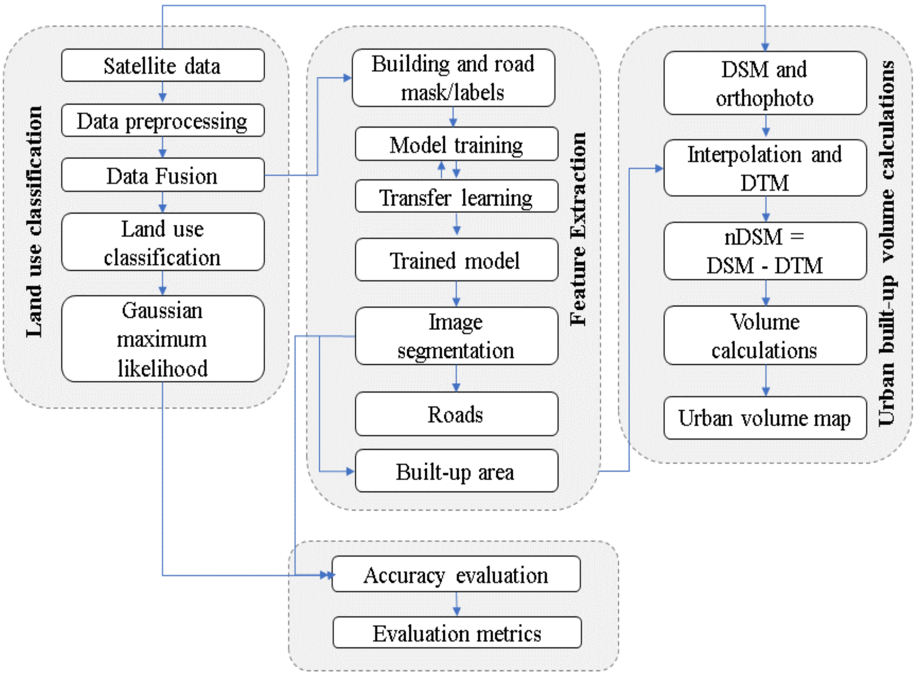

Figure 1. Flowchart showing the overall method adopted for the study.

3. RESULTS AND DISCUSSIONS

3.1 Land use dynamics

The city's land-use dynamics have witnessed an increase in built-up from 7.97% (in 1973) to 58.33% (in 2012) as shown in figure 2. Moreover, the dense vegetation cover has declined from 68.27% to less than 25% in 2012. Analysis was performed based on ward wise aggregation that shows the city has about 1.478 million trees, in other words, one tree for every seven persons makes the situation inadequate in Bangalore to even remove respiratory carbon. Based on various studies one person should have 8 trees to have adequate oxygen [10]. The adopted method was found to be useful in identifying tree cover.

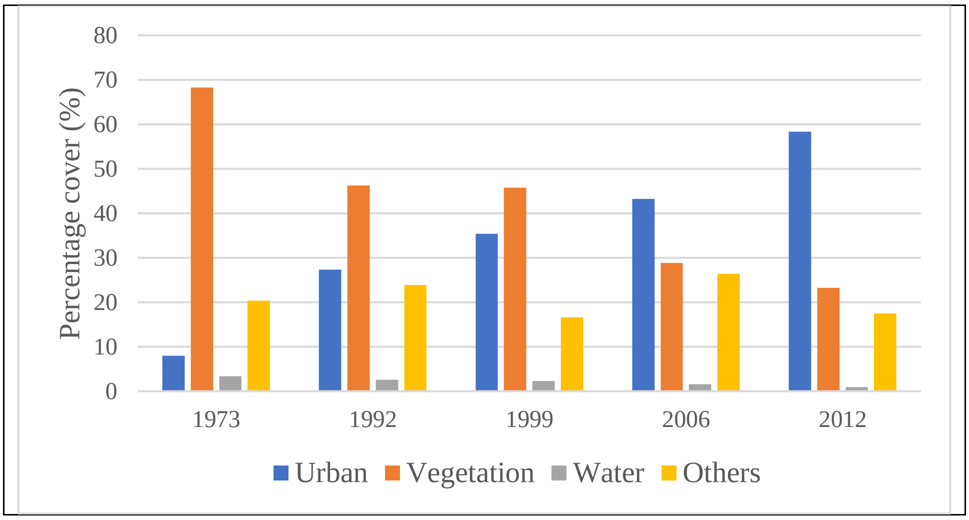

Figure 2. Temporal land-use dynamics of Bangalore from 1973-to 2012

3.2 Feature extraction

A CNN-based deep learning model has been developed to extract building and road features from high-resolution satellite imagery. The contracting path and the expanding path, also called encoder and decoder respectively utilizes a series of convolution and pooling technique to generate high level features with reduced spatial resolution. The purpose of using Unet model is that it can easily cope with features of different sizes and dimensions. The model is trained using a transfer learning technique for 579 training and 167 validation images of dimension 256*256. The model was implemented with the Kera’s framework. For fast convergence, we have used Adam optimizer with weighted binary cross entropy as loss function. The close examination of results indicates that few roads were misinterpreted into buildings due to the same spatial properties as buildings. Several buildings with irregular shapes were also poorly captured that further complicates the model to understand and discriminate. The model was evaluated using parameters such as accuracy, precision, recall and IOU. The overall accuracy of 0.95 is achieved using the UNET model.

Table 2. Confusion matrix and accuracy parameters to evaluate the model’s performance

Actual Values				Accuracy= TP+TN/(TP+FP+FN+TN) Precision = TP/(TP+FP) Recall = TP/(TP+FN) IoU = TP/(TP+FN+FP)
Predicted values		Positive	Negative	
	Positive	True Positive	False Positive	
	Negative	False Negative	True Negative	

3.3 Urban built-up volume calculations

The prediction results of the adopted model give an overall accuracy of 89%. The findings show that the eastern part of Bangalore exhibits a higher built-up volume than the central part, indicating the presence of high-rise buildings. However, the outskirts of the city fall under the “very low” built-up category, the reason being sparse buildings and sprawl.

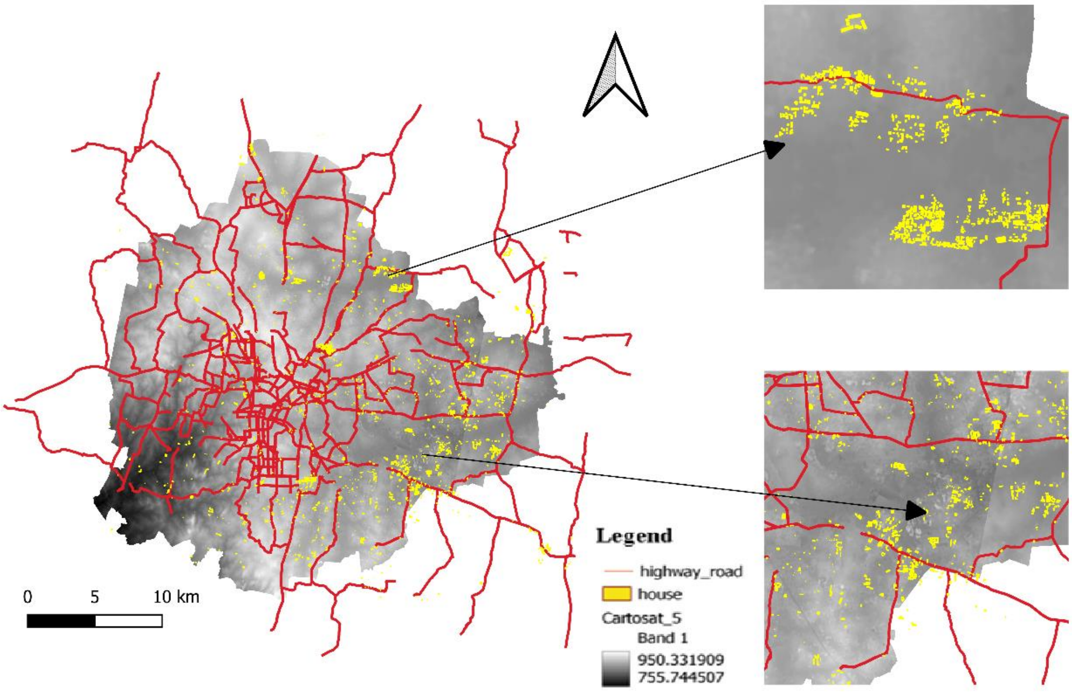

Figure 3. Built-up and road features of Bangalore city.

4. CONCLUSION

The study ensures that the proposed model successfully demonstrates the urban landscape expansion within the city in context to spatial patterns. The proposed CNN model could produce better building and road feature predictions than state-of-the-art models with better evaluation metrics. Finally, the urban built-up volume is an excellent parameter to understand the horizontal urban growth phenomenon. Future work may involve temporal urban growth and integrating other parameters of land-use dynamics.

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