

# Chapter 31

## Building Extraction of Kolkata Metropolitan Area Using Machine Learning and Earth Observation Datasets



Prosenjit Barman  and Sk. Mustak 

**Abstract** Rural-to-urban migration and increasing population has created urban agglomeration, particularly in metropolitan cities. This agglomeration creates pressure on cities which interrupts the city to become sustainable. Evaluation of the pattern of urban growth pattern is a crucial task for a city's long-term development. The building footprint is one of the most important features of a city form to support urban management and development. Previous studies show that high-resolution images are robust to extract building footprints using machine learning algorithms. The main objective of this study is to extract the building footprint from the satellite imagery using machine learning algorithms. In this study, Sentinel-2 multispectral satellite imagery and support vector machine (SVM) linear and radial basis function (RBF) have been used to extract the building footprints in Kolkata metropolitan area. In addition, both pixel-based and object-based image classification approaches have been applied and compared in this study. This result shows that in pixel-based image classification SVM linear gives a high accuracy than the SVM RBF. The accuracy level of SVM linear is 92.58% while Kappa is 0.89. On the other hand, object-based image analysis LULC classification has been done using the SVM ML algorithm. In this image classification, the SVM RBF kernel type gives high accuracy. The overall accuracy of this OBIA image classification is 91.58% and the Kappa is 0.87. For the building extraction in an urban area from the medium-resolution image Sentinel 2 using a machine learning algorithm with high accuracy gives a significant approach. Policymakers and planners can develop the city sustainably from this building footprint in an urban region and use sustainable urban planning to achieve the Sustainable Development Goal.

**Keywords** Building extraction · Machine learning · Earth observation dataset · Kolkata metropolitan area

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P. Barman (✉) · Sk. Mustak  
Department of Geography, Central University of Punjab, Bhatinda, Punjab, India  
e-mail: [prosenjitkm147@gmail.com](mailto:prosenjitkm147@gmail.com)

Sk. Mustak  
e-mail: [sk.mustak@cup.edu.in](mailto:sk.mustak@cup.edu.in)

## Introduction

Currently, cities are home to 55% of the world's population, and if this trend continues, it is predicted that by 2050, that number would more than double to 7/10 of the world's population. Because of the speed and extent of urbanisation, it is difficult to find inexpensive housing, essential services, and employment, especially for those who live in urban informal settlements (Urban Development Overview: Development News, Research, DataWorld Bank). Rapid population growth and rural-to-urban migration put enormous demand on the infrastructure of growing cities. To gain a strong alternative for resource use and further maximising sustainability through land use pattern analysis, the United Nations has concentrated on urbanisation challenges in 2015 to attain the SDG by 2030. Furthermore, Article 76 of the 2030 Agenda declares the use of geospatial data for tracking and monitoring the development of various projects covered by the SDGs. In this regard, it will be crucial to create massive data about cities, specifically the buildings that make up the majority of them (Chandrashekar et al. 2019). Not all cities have an equally dispersed distribution of the enormous population. Most people live in Indian census class I cities. Such massive population growth in cities with a million or more residents has spurred peripheral physical expansion through built-up development. Unfortunately, this rapid physical growth involves unplanned, low-density, fragmented and chaotic patchwork construction, or sprawl, which consumes agricultural land, forests, unoccupied land, villages and anything else in its path (Barnes et al. 2002; Kumar et al. 2007; Mithun et al. 2016). Urban built-up areas can be thought of as an urban expansion pattern, which is the spatial arrangement of a city's physical growth at a specific time period (Bhatta 2010). Researchers have developed a variety of indices and models that are combined with remote sensing and GIS to measure the pattern, process and growth of built-up areas (Bhatta 2010; Kumar et al. 2007; Mithun et al. 2016; Rahaman et al. 2018). Land use/cover classification was carried in several studies using traditional image classification approach which shows lower classification accuracy based on overall accuracy and quality of the map. Machine learning (e.g. SVM-linear, SVM-RBF, etc.) coupled with the object-based classification approach recently increasing using in several studies which shows robust classification outcomes (Anthony et al. n.d.). This is because of the several challenges in image classification such as dimensionality, feature selection, contextualisation, parameter optimisation, over- and undersegmentation and mixed pixel issues.

The proposed classification approach is robust and recently increasing using for the land use/cover classification of the cities of the global south (Gupta et al. 2021). The use of geospatial technologies for built-up area extraction has been the subject of numerous studies. The various modified Normalised Difference Vegetation Index (NDBI) to extract the built-up area have been explored in one study work. IBI, BUI, NDBI and IBUI have all been used in this work to retrieve the built-up data (Santra et al. 2021). To calibrate the spatiotemporal urban footprint of Kolkata city from the years 1990 to 2017, Chandan et al. attempted to demonstrate a fresh notion of merging PSO with the SELUTH model and compared this to the conventional

approach BFM. To comprehend urban expansion, buildings were retrieved using the high-resolution data sigma nought value obtained from the HH and HV polarised data by Sinha et al. (2018). A sigma nought value was obtained from the HH and HV polarised data by Sinha et al. (2018). The normalised ratio and then equated HH and HV sigma nought pictures are used to create an index that has been validated over several regions using ground truth data. The map has been created using this index to identify the built-up and non-built-up areas. Mithun et al. (2016) used Shannon's entropy and other landscape indices linked with remote sensing and GIS to attempt to examine the built-up dynamics in the Kolkata metropolitan area at three zones: total KMA, KMA urban, and KMA panchayat level during the time period between 1980 and 2010. This study examines the performance of the five spectral indicators stated above using Resourcesat LISS III imageries over India's urban agglomeration of Kolkata and Howrah. The indices were compared, and it was discovered that the innovative IBUI gave the highest level of accuracy (94%) in identifying impervious built-up regions (Santra et al. 2021). For the example of object-based mapping of an agricultural area using Unmanned vehicle imagery (UAV) for object-based image analysis for agriculture pattern recognition. Ma et al. (2017) evaluated the effect of the advanced feature selection method of well-known supervised classifiers like SVM and RF. The high-accuracy robustness algorithm for classification is the classification of the SVM algorithm. Li et al. (2014) applied segmentation-based classification based on pixels to TM Landsat data. They have concluded that the SVM algorithm has successfully classified images in a limited training sample. Using geospatial data from Gaode and Baidu Maps, like point-of-interest (POI) data, building footprints, land use polygons, and highways, there has suggested a framework in this study to determine the building type. Using natural language processing (NLP)-based techniques, POI categories have been automatically reclassified into categories that can be used to infer building kinds. Second, using the type ratio and area ratio as markers of building types, we determined the link between building footprints and POIs (Chen et al. 2020). Norman et al. (2020) have explained that building footprint extraction using object-based image analysis requires segmentation due to a variety of factors, including the complexity of geo-objects and the spatial and spectral resolution of remote sensing images. From high-resolution Worldview 3 (WV3) satellite data, the Taguchi statistical approach and a spatial plateau objective function (POF) were created to extract the building footprint. Using the non-parametric supervised classification SVM technique, five classes were divided, and the accuracy of the classification was evaluated using the ROC curve. Hosseinpor et al. have used a fusion model to extract buildings from data derived from extremely high-resolution remote sensing photography. An end-to-end cross-modal gated fusion network (CMGFNet) has been introduced for obtaining building footprint. Sentinel-2B, a medium-resolution remote sensing image with a 10-m spatial resolution, was used by Norman et al. (2021) to classify the buildings in Selangor, Malaysia. Support vector machine (SVM) and decision tree (DT) classifiers from machine learning (ML) methods have been used to categorise five different classifications, including water, forest, green space, buildings, and roads. By applying ML methods to build extraction accuracy for medium-resolution images, the SVM

classifier may create 20% greater accuracy than the DT classifier, improving OBIA's classification methodologies.

The majority of the previous study mentioned how to recognise the pattern of urban growth by measuring how densely built-up an urban region is. They have classified the built-up and non-built-up areas using a variety of landscape metrics. Studies have looked at building extraction from high-resolution satellite pictures. Very high resolution has been classified using various classical as well as machine learning techniques of pixel and object-based image analysis. The ML algorithm for developing detection performance analysis has not been compared by anyone previously. Here, urban footprint mapping also employs medium-resolution data for building detection. The main objective of this study is to perform an analysis of the SVM algorithm in pixel-based and object-based image analysis for urban footprint mapping.

## Study Area

For the urban footprint mapping, Kolkata metropolitan area has been selected (Fig. 31.1). In this study, area mainly consists of 4 municipal corporations, 38 municipalities and many other villages. This is India's fourth-largest metropolitan area. The largest metropolitan area in north-eastern India is the Kolkata metropolitan area. This metropolitan area has primarily expanded on both sides of the Hooghly River. KMA includes six districts: Kolkata, Howrah, Hooghly, Nadia, North 24 Parganas and South 24 Parganas. These districts are located on each side of the Hooghly River (Kolkata Metropolitan Development Authority n.d.). The KMA, the largest urban agglomeration in West Bengal and the third largest in India, is regarded as the research area. The KMA currently extends over an area of 1886.67 km<sup>2</sup>. The population growth of the KMA has also been very dynamic over time. The KMA had a population of 14.77 million in 2001, which was projected to be 17 million in 2011, and is expected to be 20 million in 2021 and 21.1 million in 2025 (Census of India 2011).

## Materials and Methods

### *Materials*

To measure the urban compactness in the Kolkata metropolitan area, there has been used many datasets which have mentioned and the entire methodology which has followed in this study has been presented (Fig. 31.2). The Kolkata metropolitan area's Sentinel 2B image was obtained from the cloud-based version of Google Earth Engine in the year 2021 (Table 31.1). There are ten bands in the Sentinel 2B satellite image

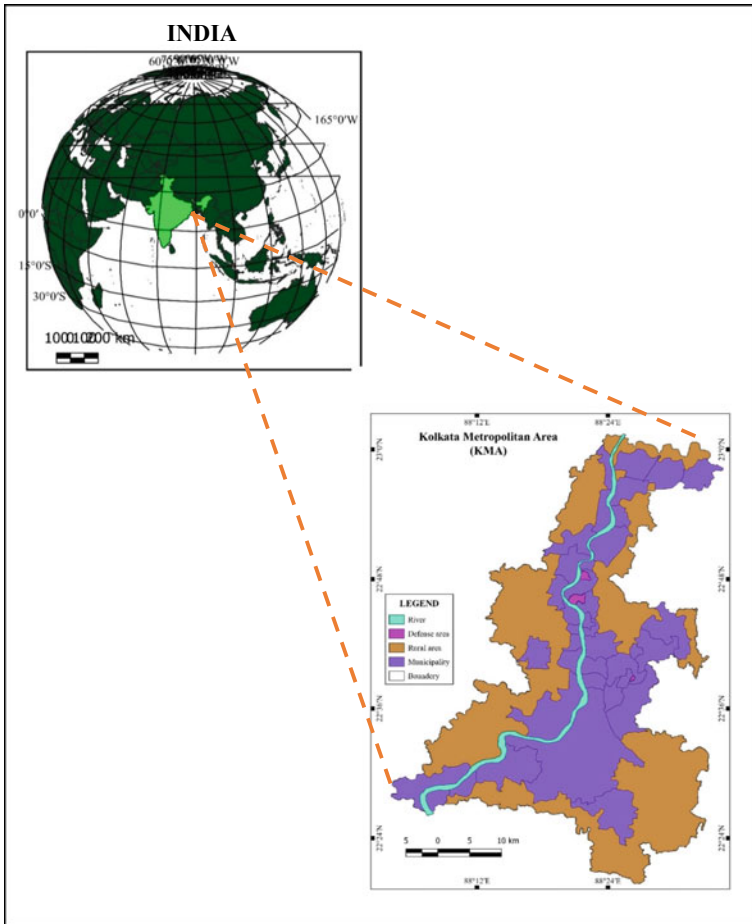


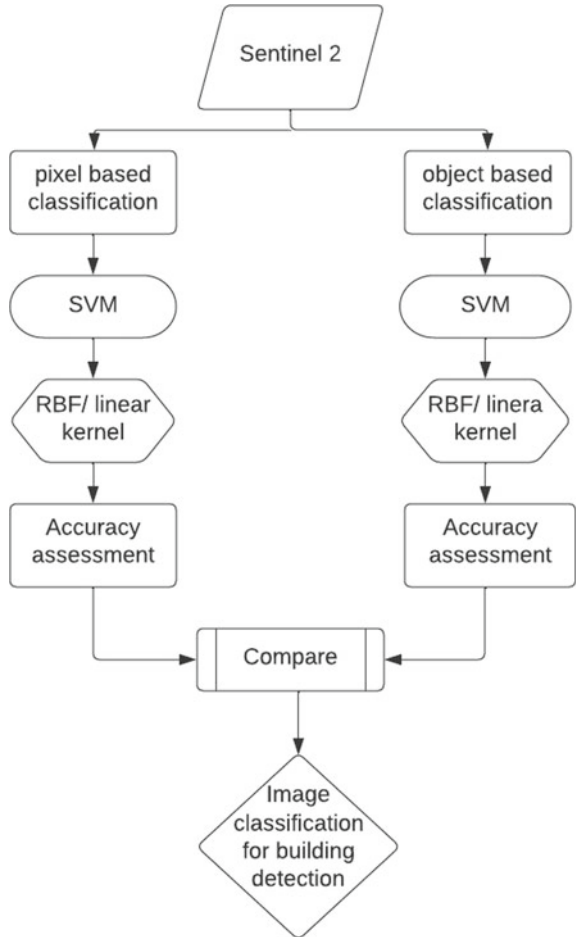
Fig. 31.1 Location of study area (KMA)

collection. The files essentially consist of bands with a 10- and 20-mm resolution (Table 31.1).

### Methods

The methodology has been broken down into three sections: first, preprocessing the bands and normalising them; second, pixel-based image classification for the extraction of buildings; and third, object-based image classification for the extraction of urban buildings. In this study, land use/cover classification was done using SVM machine learning algorithm. For the LULC in Kolkata metropolitan area, five LULC

**Fig. 31.2** Methodological flowchart



classes were selected. These LULC classes are 1. Waterbody, 2. Wetland 3. Built-up 4. Agriculture land 5. Vegetation. The LULC classes were selected after the reviewing some papers related to LULC analysis in KMA (Ghosh et al. 2019; Mithun et al. 2021).

**Preprocessing**

For the image classification, data preprocessing is a very important step. For preprocessing data, first feature extraction has performed NDVI and NDBI. NDVI and NDBI are calculated using the following formula.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{31.1}$$

**Table 31.1** Sentinel-2 data specifications

Bands	Spectral bands	Spatial resolution (mm)
B2	Blue (B)	10
B3	Green (G)	10
B4	Red (R)	10
B5	Red-edge 1	20
B6	Red-edge 2	20
B7	Red-edge 3	20
B8	Near-infrared (NIR)	10
B8A	Near-infrared narrow	20
B11	Shortwave infrared 1 (SWIR1)	20
B12	Shortwave infrared 2 (SWIR2)	20

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{31.2}$$

**Normalisation**

Then normalise every single band and stack it as an image for image classification. The normalisation of bands has been done by using the following formula.

$$Normalisation = \frac{Image - Image_{minimum}}{Image_{maximum} - Image_{minimum}} \tag{31.3}$$

Normalisation formula has been defined as image subtracts by the respective band minimum value divided by the subtraction of respective band maximum and minimum value.

**Selection of Machine Learning Algorithms**

**Support Vector Machine (SVM)-Linear:** SVM is one of the supervised image classification algorithms used in machine learning. One of the key kernel types in the SVM ML approach is linear. When the data can be linearly separated—that is, divided along a single line—linear kernels are utilised. It is one of the most often utilised kernels. It is typically utilised when a given dataset contains a significant number of features. One instance is text categorisation, where each alphabet represents a unique feature. In these situations, linear kernels can be utilised. One benefit of this linear kernel is that it can train an SVM more quickly than any other kernel. Additionally, optimising the C regularisation SVM linear kernel when training an SVM requires

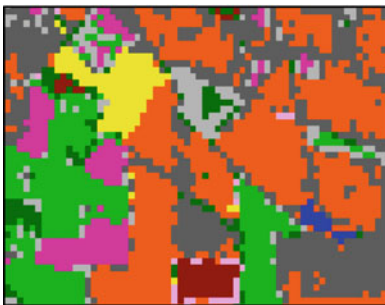
the least amount of time (Creating Linear Kernel SVM in Python—GeeksforGeeks 2018).

**Support Vector Machine (SVM)-RBF:** In the SVM, machine learning method another important kernel is RBF. The radial basis function kernel, also known as the RBF kernel, is a common kernel function utilised in many kernelised learning algorithms. Particularly, it has been utilised frequently in classification using support vector machines. RBF kernel is the most generalised form of kernelisation and the most widely used kernel due to the similarity of Gaussian distribution. The similarity or distance between two points is generally computed using the RBF kernel function. RBF kernel also uses a K-NN-like algorithm; therefore, it benefits from K-NN advantages and solves the space complexity issue (Radial Basis Function (RBF) Kernel: The Go-To Kernel by Sushanth Sreenivasal Towards Data Science 2020).

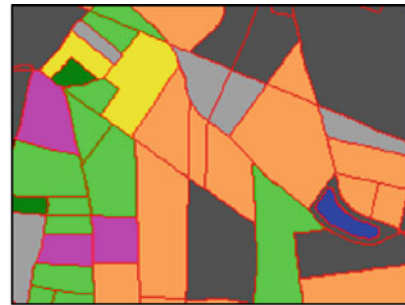
### Selection of Classification Approach

Pixel-based (Fig. 31.3a) and object-based (Fig. 31.3b) image classification was described.

**Pixel-based image classification:** Pixel-based classification technique was performed for the image classification to a pixel in one class by the spectral similarities. This pixel-based classification technique is also used to extract the low level features but in overlapping region will be misclassified due to the confusion of classes (Sibaruddin et al. 2018). Machine learning algorithms like the SVM algorithm have been used to classify pixels in images for building extraction. To begin with, gather 350 samples of each of the five classes from the map in evenly spaced intervals. This sample has been divided into two parts about 50% for equal training and test sample. Then image statistics has been calculated, and one SVM train model has been calculated.



(a) Pixel-based classification



(b) Object-based classification

**Fig. 31.3** Land use/cover classification approach. *Source* Aplin and Smith (2008)



**Table 31.2** Training and test samples

Image classification	Training sample	Test sample
Pixel-based classification	174	174
OBIA	174	174

In machine learning, there have been created models to predict the outcome of certain events. The train/test method has been used to determine whether a model is adequate or not. In general, this technique evaluates the model's correctness (Python Machine Learning Train/Test, W3school). The training and testing sample for this study consisted of 174 people. 50% of the sample as a whole has been divided (Table 31.2).

**Object-based image classification (OBIA):** OBIA technique was performed by the segmentation of image data into object. It is a bottom-up region merging approach that groups the neighbouring homogeneity pixel into meaningful segments or objects. OBIA technique is highly significant for the land use classification at present day. This technique considers shape, texture and spectral information for the LULC classification. For the high-resolution land use classification, OBIA technique gives the high accuracy than the pixel-based classification (Sibaruddin et al. 2018). After segmentation on the raw image and calculate zonal statistics, 348 training samples were collected from various segment areas across the map (Table 31.2) and divided equally into two groups of 50%. The zonal statistics has been added by the location of the training sample. Following the creation of the SVM model file, object-based image classification was completed using image classification. Then the accuracy assessment was performed by using a 50% test sample.

### Accuracy Assessment

The classification of image using the various classification algorithm does not give the perfect result because of many reasons like undistinguishable classes, preparing of training samples with wrong labelling and imperfect classification algorithm so the accuracy assessment is very necessary of an image classification. Various methods are available for the measurement of accuracy of image classification like omission error, overall accuracy, producer accuracy, kappa coefficient ( $k$ ) in accuracy measurement this method has some merits and demerits also. In this study, for an LULC overall accuracy and Kappa coefficient were applied (Bhatta 2008).

## Results and Discussions

This study assessed the most appropriate classification for building removal in the greater Kolkata area. SVM machine learning algorithm has been used to do pixel-based and object-based image analysis categorisation. The accuracy of these two methods has been compared to see which is best for accurately determining the urban footprint.

### *Training and Test Samples*

In this study, the land use and land cover classification was done using the SVM machine learning algorithm. For this LULC analysis needs to collect the training and test sample from the satellite image. For LULC analysis in KMA, total 348 samples were collected. These 348 samples were divided into 50% using the QGIS. 174 samples were considered as training samples, and another were considered validation samples (Table 31.2).

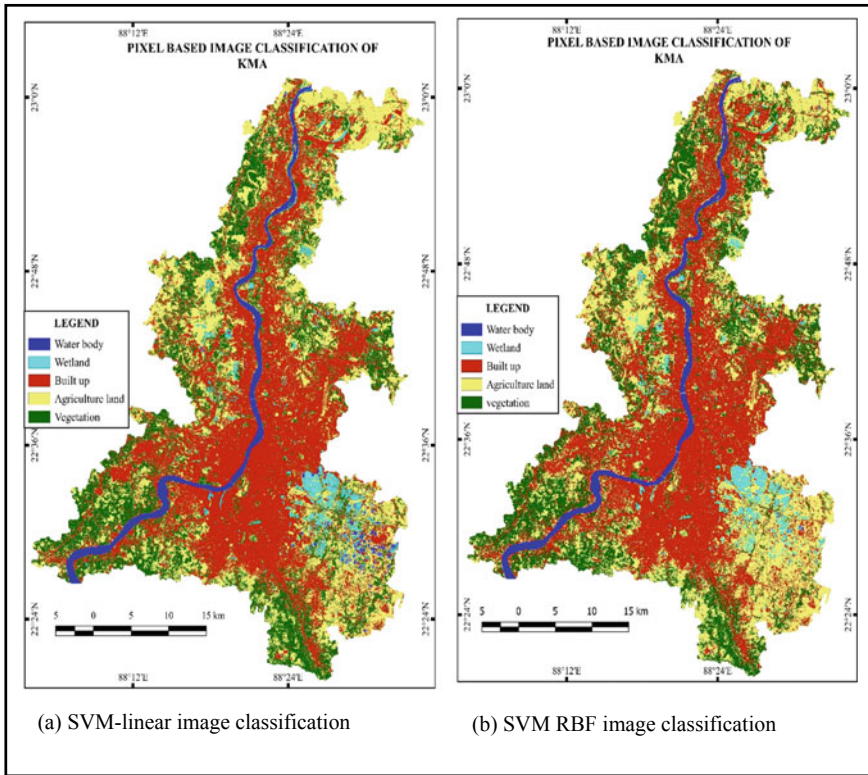
### *Land Use/Land Cover Classification*

In this study, land use/cover analysis was done using the machine learning SVM algorithm with two different Kernels Linear and RBF. This SVM algorithm was applied on pixel-based and object-based image analysis.

#### **Pixel-Based Land Use/Cover Classification**

The most often used method for classifying images is pixel-based classification. Pixel-based image classification using the SVM machine learning algorithm has been performed for the image classification to extract the urban building. One of the more reliable ML algorithms for classifying images is the SVM method. Many different algorithms (including linear and RBF) have been used to achieve the best possible categorisation using SVM (Fig. 31.4a, b). According to the SVM linear ML algorithm, there will be 73,264 ha of built-up area in total in 2021 (Table 31.3). In the Kolkata district, there is a high density of buildings, and along the Hooghly River, there is a high density of buildings relative to the surrounding area. In contrast, the built-up area in the SVM RBF ML technique picture classification is 72,913 ha. Built-up areas have expanded more in the surrounding area in SVM RBF image classification. The overall accuracy for SVM linear image classification is 92.58%, which is quite impressive and 0.89 for the accuracy of the Kappa hat classification (Table 31.5). The SVM linear ML algorithm's picture classification accuracy in the

Kolkata metropolitan area is above 90%. On the other hand, the SVM RBF ML algorithm’s overall accuracy for classifying pixel-based images is 88.31%, and its Kappa hat classification accuracy is 0.83. In contrast to SVM RBF ML algorithm image classification, SVM linear algorithm accuracy is high for pixel-based image classification in the Kolkata metropolitan area.



**Fig. 31.4** Land use/cover of KMA (2021), using pixel-based SVM

**Table 31.3** Land use/cover classes (2021) using of pixel-based image classification approach (SVM-linear)

S. No	Land use/cover classes	Area (ha)
1	Waterbody	6390
2	Wetland	6540
3	Built-up	73,264
4	Agriculture land	46,693
5	Vegetation	47,040
Total		179,928

### Object-Based Land Use/Cover Classification

One of the most important pictures classification methods is object-based classification. The item serves as the basis for this image classification. The majority of this image classification is vector-based. The entire image has been divided into several portions. There have been a lot of samples gathered in a point of diverse segments for OBIA image classification (Fig. 31.5a, b). Then, for image classification, use the SVM RBF and SVM linear ML algorithms. KMA's built-up area is 69,106.14 ha (Table 31.4) according to OBIA image classification. The Kappa hat classification is 0.87, and the accuracy level is 91.52% (Table 31.5). SVM RBF ML algorithm has higher accuracy than SVM linear ML technique in OBIA image categorisation. The OBIA vector classification has been converted to raster format for accuracy assessment, and accuracy assessment has been carried out.

Pixel-based and object-based image analysis has been used for image classification in KMA for building extraction. To compare the important algorithm for image classification, SVM linear and SVM RBFML have also been used. SVM linear algorithm accuracy in pixel-based image classification is much higher than the SVM RBF algorithm. In contrast, the SVM RBF method outperforms the SVM linear

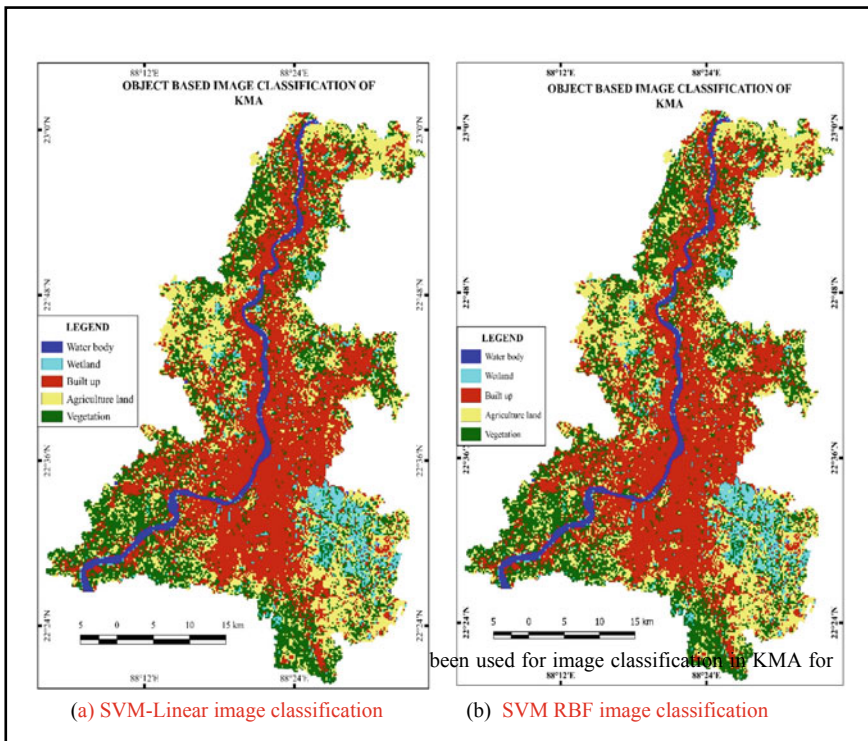


Fig. 31.5 Land use/cover of KMA (2021), using object-based SVM

**Table 31.4** Land use/cover classes (2021) using of object-based image classification approach (SVM-RBF)

S. No	Land use/cover classes	Area (ha)
1	Waterbody	5780
2	Wetland	9064
3	Built-up	69,106
4	Agriculture land	49,431
5	Vegetation	46,548
Total		179,928

**Table 31.5** Accuracy assessment of land use/cover classification

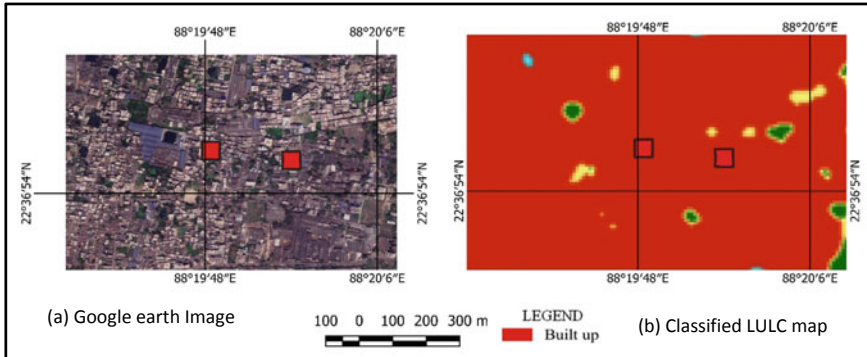
Image classification	Kernel type	Overall accuracy	Kappa	Built-up area (ha)
Pixel-based	SVM linear	92.58	0.89	73,264
OBIA	SVM RBF	91.58	0.87	69,106

algorithm in object-based picture classification. Pixel-based image classification and OBIA classification provide the highest level of image classification accuracy. In comparison with OBIA classification, pixel-based image classification provides great accuracy for vast areas like the Kolkata metropolitan area. An important method for classifying images is pixel-based image classification.

### ***Validation and Accuracy Assessment***

A total of 348 samples were collected for the pixel-based image analysis and OBIA, and these samples were divided into two categories: training samples and validation samples. The Google Earth image (Fig. 31.6a) was used to validate the training samples and LULC classified image (Fig. 31.6b). Two training samples with a latitudinal range of 22°36'54" to 22°37' and a longitudinal range of 88°19'48" to 88°20'06" were visualised to relate the training sample and image classification. In the Google Earth image, this training sample represents the built-up region, and the image classification also represents the built-up area at the same latitude and longitudinal extension (Fig. 31.6).

In this study, built-up area was extracted by the LULC classification using machine learning SVM algorithm. This built-up class area was validated based on the literature review. In 2020, the built-up area of Kolkata metropolitan area was around 726.82 km<sup>2</sup> (Das et al. 2022). In 2021, the LULC pixel-based classification of KMA using SVM linear algorithm reveals the built-up area is 73,264 ha which represents the 732.64 km<sup>2</sup>. So, it depicts that the pixel-based LULC classification of KMA using SVM linear machine learning algorithm is a highly accurate than the object-based image classification in this perspective area. Pixel-based and object-based



**Fig. 31.6** Validation and accuracy assessment (pixel-based SVM-linear)

image classification using SVM machine learning algorithm with high accuracy was performed (Table 31.5).

### ***Built-Up Development in Kolkata Metropolitan Area***

The KMA's LULC categorisation can be used to estimate the urban footprint and determine the size of the urban area. The classification also indicates which part of KMA region is heavily urbanised as well as where the built-up area is expanding. The major cities and municipality areas on the LULC map of the KMA were labelled (Fig. 31.7), which makes it easier to distinguish between the built-up developed and built-up developing areas. The classify image shows that the areas on both sides of the Hooghly River, particularly the Kolkata district, the Haora municipality, the Bally, the South dumdum, the Dumdum, the Kamarhati, the Panihati, and the North dumdum, are highly developed municipal areas; also, it generates a compact development.

There is also a large built-up growth in the northern section of the KMA, but it is less intense than in the southern half of the region on both banks of the Hooghly River. The high-built-up municipalities in the northern section are Kalyani, Kanchrapara, Naihati, Bhatpara and Baidyabati. The map (Fig. 31.7) also demonstrates that the eastern portion of the Hooghly River has a larger built-up density than the western portion. Excluding the sides of Hooghly River built-up has grown up in the marginal area of KMA. The municipality of Barasat has grown in a condensed manner. Two cities in the peri-urban area that are developing rapidly are Rajarhat Sonarpur and Baruipur of South 24 parganas district. Rapid development in the Mahestala municipality region leads to outlying development in the peri-urban area of KMA. In the Haora district, peripheral cities and villages are also growing built-up areas. Manoharpur City, which is part of the Dankuni municipality is developing quickly, while Bansberia municipality has a highly built-up development area. Based on the growth patterns of the built-up areas in KMA, it can be prophesied that the



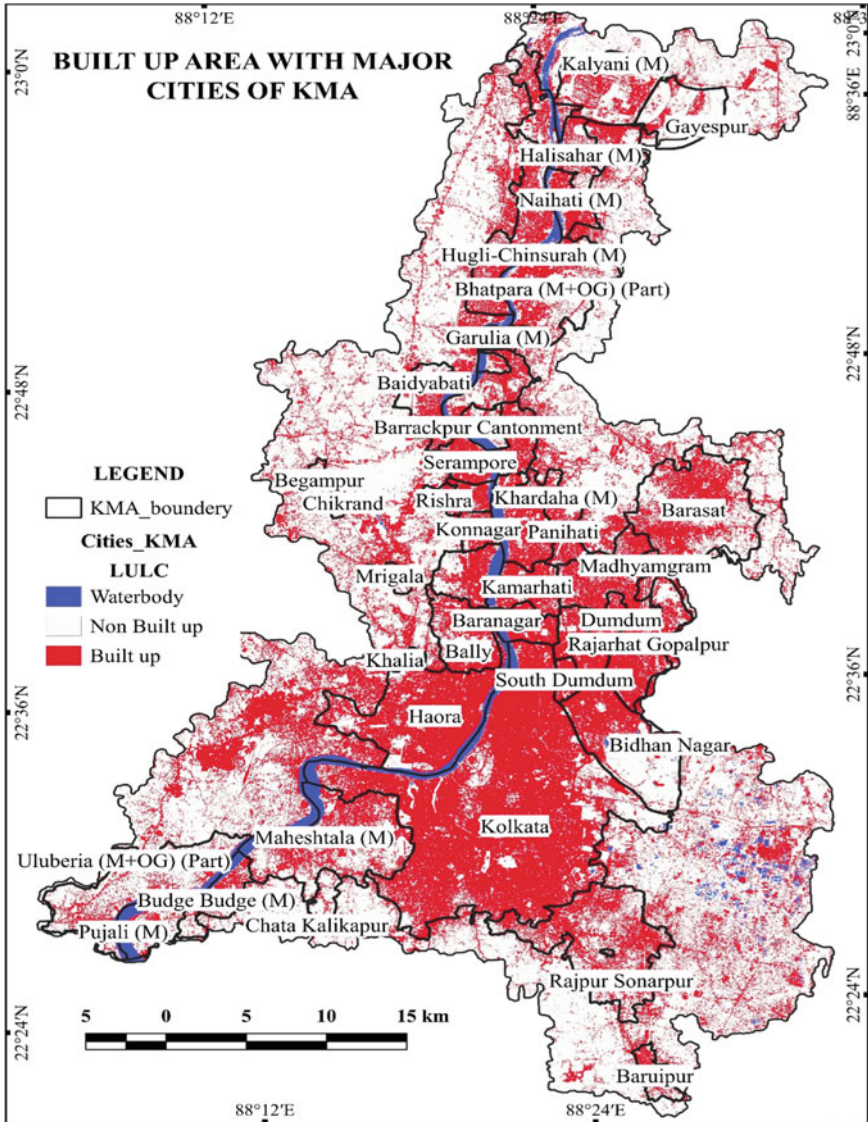


Fig. 31.7 Built-up with major cities of KMA

surrounding areas of the Kolkata district, such as Mahestala, Rajarpur Sonarpur and Baruipur, the Haora municipality and its surroundings, such as Uluberia, Krishnapur and Jagadishpur, Gayespur, Kanchrapara municipality area, and the Barasat municipality, will experience rapid growth in the near future.

## Conclusion

Urban footprint mapping is a very important stage in tracking Kolkata's metropolitan area's progress. OBIA classification and pixel-based analysis play a key role in extracting buildings in metropolitan areas. There is a sizable urban agglomeration in the Kolkata metropolitan area. The built-up area has been expanding mostly in the per-urban area as the city grows day by day. So, measurement is crucial for the expanding city. Building extraction monitoring is a key strategy for comprehending urban growth. For that, pixel classification has been carried out in the greater Kolkata area. Pixel-based, OBIA, SVM linear, and SVM RBF ML algorithms have all been used for each image classification technique, making a total of two image classification techniques used here. This classification has demonstrated that SVM RBF delivers good accuracy in OBIA classification while SVM linear gives great accuracy in pixel-based classification. The result shows that the pixel-based SVM-linear (92.58% overall accuracy) outperforms the object-based SVM RBF (e.g. 91.58% overall accuracy) because object-based image classification is robust on very high-resolution satellite image (e.g. > 2 m). In addition, pixel-based image classification is robust (based on overall accuracy and quality of the map) in low-resolution image (e.g. < 2 m) because of the lower chances of producing mixed pixel in classified map and tracing out the geometry of the object from the image. The accuracy of the classification map depends on the several factors like dimensionality, number of training samples, selection of the machine learning algorithms and morphology of the land uses. The proposed land use/cover classification approach and algorithms are robust for the cities of developing countries. In addition, more investigations are required to address the challenges faced (e.g. oversegmentation, undersegmentation, etc.) in this study like to add more contextual features, training and test samples, ensembles model, etc.

Additionally, pixel-based classification delivers higher accuracy than OBIA classification in KMA's picture classification. Pixel-based classification is much more appropriate than OBIA for the classification of large-area images. OBIA can be more effective for picture classification in limited areas. It is exceedingly expensive to classify images from high-resolution data, and hence, employing an ML algorithm to classify images from medium-resolution data is ideal. It is exceedingly expensive to classify images from high-resolution data, and hence, employing an ML algorithm to classify images from medium-resolution data is ideal. The machine learning algorithm for mapping the urban extension, commonly referred to as the urban footprint, is extremely important. The map provides a general notion of the urban area's size, which provides a general concept of how urban and rural areas are divided. This study will help policymakers and planners to develop the sustainably, compact, resilient and transit-oriented city development to support Sustainable Development Goals (e.g. SDGs-11).



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