

Mapping the wetlands of Mumbai and surrounding area using Remotely sensed Sentinel-2b data

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Abstract

Mumbai is richly surrounded by unique types of wetlands such as mudflats, mangroves, saltpans, creeks, freshwater lakes, and estuaries. As the city is highly developed, population explosion and the urbanization are the greatest threat for the wetland ecosystem. Wetland mapping and classification were carried out using the sentinel 2b data for Mumbai and the adjoining areas. Sentinel 2b data from 28th May 2019 was used in this study. The data was processed in the SNAP (Sentinel Application Platform) toolbox. Classification of wetlands has carried out in both pixel-based and index-based techniques. Six different classes were defined in the pixel-based classification they are Backwater, Mangroves, creek water & inland waters, urban area, Forest, and sea. Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Modified Soil-adjusted Vegetation Index (MSAVI2) were calculated in the index-based classification. As per the pixel-based classification results, the percentage of the backwater is 8.54 in the study area, which is 137.077 km². 67.089 square kilometers are classified as Mangroves. Creeks and Inland water are occupying 6.89% of the total study area with the 110.58 km². Saltpans and the Mudflats are the other wetlands found in the study area. Saltpans in Mumbai are around 20km² and it is difficult to classify. Mudflats are mainly found, and around the Thane creek, and the total area of the Mudflat in the Thane creek is classified as 51 km². For the reliability of the result and validating the remote sensing classification, the error matrix technique was carried out. The overall accuracy of the supervised classification result of the study area is found as 0.92. With the overall accuracy of 0.92, the study proved that the sentinel data is more capable of mapping wetlands though it shows less accuracy for classifying the water bodies. The study shows that Saltpans and Mudflats are massively in unsafe conditions. This study confirmed that the Mangrove area is found to be more stable, maybe because of strict orders of the High Court when compared to the past, though they are under threat by urbanization.

Keywords: Wetland; Urbanization; Remote sensing; Mangrove; Mumbai, India

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1. Introduction

Wetlands are areas of land that are temporarily or permanently covered by water, depending on the season variability (Mitsch et al., 2010). Natural wetlands typically include creeks, estuaries, saltmarshes, riverbanks, seashores, backwaters, and coral reefs. Humanmade structures like lakes, abandoned quarries, salt pans, reservoirs, abandoned quarries, and dams also part of wetlands. Wetlands are the most significant yet exposed ecosystems on the Earth (Mitsch et al., 2010). These Wetlands are a treasured natural resource for groundwater recharge, flood control, and water quality enhancement (Rundquist et al., 2001). Wetlands also have an essential significance to the environment and accompanying plant and animal life (Li et al., 2015).

Mumbai is one of the thickly populated cities with nearly about 20 million peoples (*World Urban. Prospect. 2018 Revis.*, 2019). Mumbai has varied biodiversity as the original Mumbai comprises seven Islands (Riding, 2018). Hence naturally, the city is richly surrounded by unique types of wetlands such as mudflats, mangroves, saltmarshes, creeks, freshwater lakes, and estuaries. These wetlands provide a unique ecosystem of Mumbai. Over half of the city's population live in the amorphous grey areas, which are known as Zopadapatti Or slums. The Slums are clustered along roads, railways lines, and extending into some most contaminated and unhealthy places next to creeks and the remnants of once lush mangrove forests (Gandy, 2008). As the city is highly developed, population explosion and the urbanization are the greatest threat for the wetland ecosystem. Mangroves and the other wetlands around Mumbai form an easily fragile environment that is vulnerable to pollution and different demographic densities (Vijay et al., 2005), Hence to understand the threat of these wetlands, the present study has been carried out in and around Mumbai.

Remote sensing technology has confirmed to be a success in monitoring wetlands, and it has an abundant application, and it is proven from 1983 (Butera, 1983), many Indian researchers also demonstrated that (Garg, 2015; Prasad et al., 2002; Ramasubramanian et al., 2006; Samant, 2002; Selvam, 2003) in various parts of India, including Mumbai. Initially, color infrared aerial photography and, most recently, multispectral visible, infrared, and microwave digital imagery gained from airborne or satellite-borne sensors have been used (Butera, 1983; Rundquist et al., 2001). Many researchers used Landsat data for mapping and monitoring wetlands because of its multitemporal data (Baker et al., 2007; Butera, 1983; Li et al., 2015; Lunetta and Balogh, 1999; Samant, 2002).

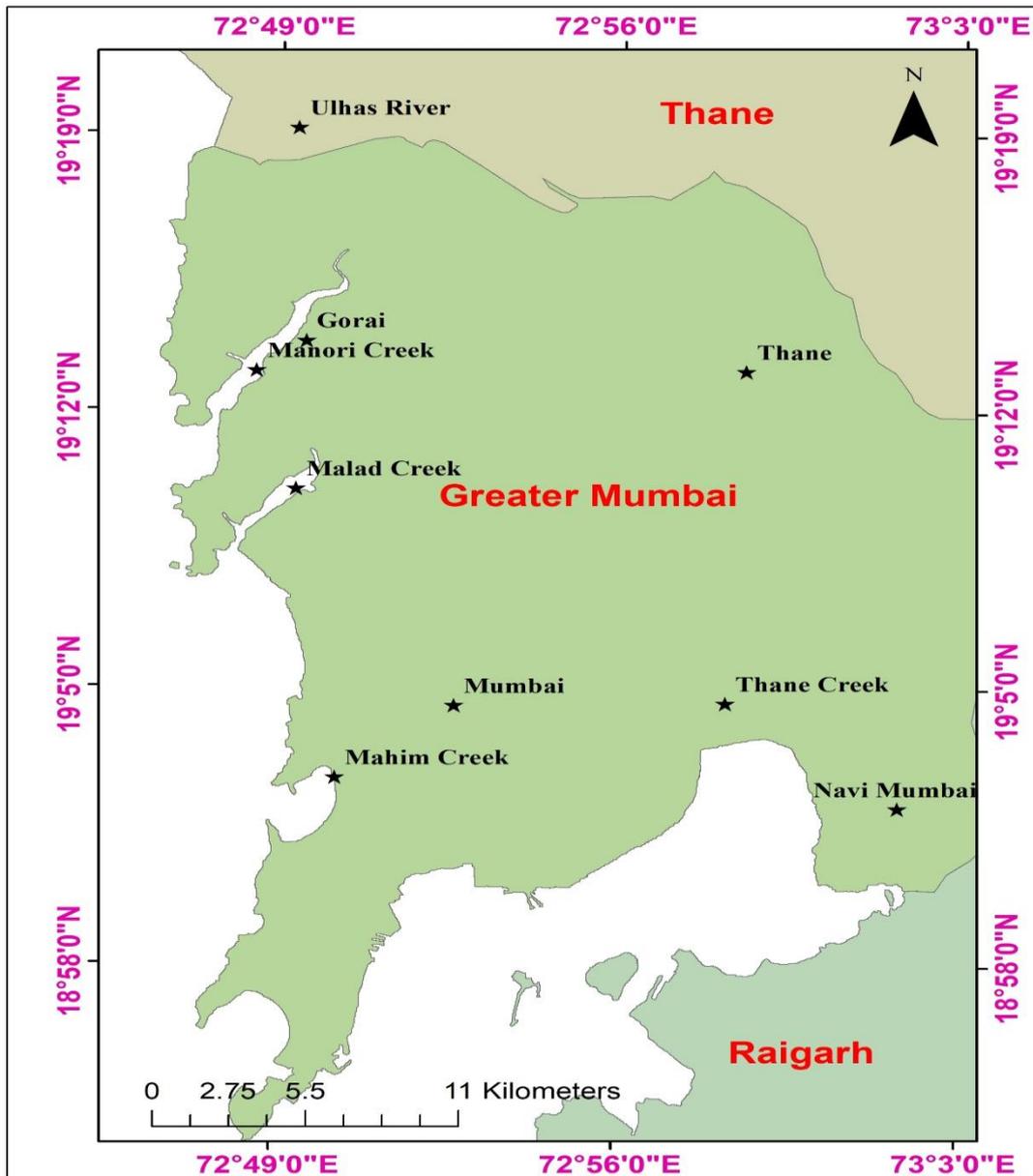
However, some Researchers had noticed some technical drawbacks while using satellite sensors with a low spatial resolution for mapping complex coastal wetlands (Civco et al., 2006; Ramsey and Laine, 1997).

With the advancement of technology, remote sensing studies are more developed than in the past. Thus currently, many satellite sensors are in operation with more spatial and spectral resolution. Sentinel is one of them. Sentinel-2 offers satellite images with a spatial resolution of 10 to 60 meters (Drusch et al., 2012). Paralleling with the Landsat OLI/TIRS, Sentinel-2 has an improved spatial resolution, enhanced spectral resolution in the near-infrared region, and also three Vegetation Red Edge bands with a 20-meter spatial resolution (Kaplan and Avdan, 2017). Some researchers have successfully used Sentinel 2 for wetland mapping and classification

(Kaplan and Avdan, 2018, 2017; Wachid et al., 2017). Thus, Sentinel 2b data was used for this study to understand the wetland distribution in the study area by mapping them.

2. Study Area

The purpose of the present study is to map and demarcate the wetlands of Mumbai and adjoining areas. Mumbai, also known as Bombay, is the capital city of the Indian state of Maharashtra and also the economic capital of India. Mumbai is the most densely populated and crowded city of India and the sixth-largest metropolitan region in the world.



(Figure 1 Location map of the study area)

The modern Mumbai has developed from the group of seven islands off the mainland of North Konkan on the west coast of India (Pacione, 2006).

The Metropolitan area of Mumbai was later called as Greater Mumbai. Further, the Municipal Corporation was known as Brihanmumbai Municipal Corporation (BMC). The BMC area covers two revenue districts, namely Mumbai Urban (city) District and Mumbai sub-urban District. The total area of the selected study area is 1605 km².

2.1 Geomorphology: Enormous variation in the lithological units of the Deccan Traps define the Mumbai region. These Deccan Traps have led to different degrees of resistance to natural and artificial weathering (Parthasarathy and Shah, 1981). Based on various geomorphic features, Rani et al., in 2015, divided the Mumbai into three distinct geomorphic land units as (1) denudational, (2) fluvial, and (3) coastal landform (Rani et al., 2015). Cuesta, residual hill, linear ridges, and simple slopes are the different landforms of denudational origin found in and around the Mumbai region. The best examples of cuestas are hills of the Borivali National Park, Cumbala hill, and Malabar hill.

Alluvial fans, alluvial plains, and deltaic plains are the different fluvial geomorphic features in the study area. Coastal landforms are commonly present in Mumbai, and it includes mudflats, salt pans, Creek lets, sandy and rocky beaches. Mudflats are enclosed by saltwater and occur in the lowland area. Mudflats have a vibrant ecosystem and biodiversity. Mudflats found around Thane, Manori, and Malad creek let areas. The widest mudflats occur around Thane Creek and support mangrove vegetation (Rani et al., 2015). Within the mudflats and beside the creeks, Salt Pans also found.

2.2 Geology: The Island Mumbai forms a part of Deccan Volcanic Province. Deccan Volcanic Province is the leftovers of one of the most significant volcanic activities on earth and is one of the best-studied continental flood basalt provinces in the world (Krishnan, 1982). The researcher Sethna recognized that the Seven distinct lava flows in Mumbai Island (Sethna, 1999). They are mostly Basaltic, Spilitic, and Hyaloclastite. Most of the Spilitic types of rocks found in the South and the Hyaloclastite rocks found in the North. And also several intrusive basic dykes, Lopoliths, Trachytic magmas (Tolia and Sethna, 1990), even one of the rock types in the region. Sandstones with fragments of Shale are found associated in some areas.

2.3 Geography: Mumbai is on Salsette Island off the shore of Maharashtra. The unique seven islands of Mumbai comprised twenty-two hills. Most of the hills were raised to fill in the shallows to link the islands. Within the city limit, three hill ranges can be seen. The Ghatkopar Hill range runs parallel to the Central Railway track of Mumbai.

The Trombay Hills occupy a significant portion of Trombay in the eastern part of the city. Similarly, the Powai Hills conquer the modern city's northern part. There are three lakes in the city. The Vihar Lake and the Tulsi Lake are existing within the National Park, and they are one of the significant sources of the city's drinking water. The Powai Lake is directly south of these two.

Back Bay is the largest bay in the study area, and its shoreline is an overturned C-shaped region of 4 kilometers. North of the Back Bay is Worli Bay. The bay boundary is about two kilometers. Mahim Bay is the second-largest bay in the city. The Mithi River drains into the Mahim Creek, which flows into the bay. The boundary between the city and its suburbs divides the bay.

Mumbai has several creeks which cover the area over 70 km². Mangroves were found on both sides of the creeks.

The Vasai Creek and the Thane Creeks split Salsette Island from the mainland. Within the city, the Malad Creek and the Gorai (or Manori) Creek swamp the suburban region. The Mahim Creek forms the boundary among the two districts. Mahul Creek and Mahim Creeks also situated in the study area. These creeks and tidal inlets have sheltered shores wide-open during

low tide (Vijay et al., 2005). Mumbai has five rivers within its territory they are Dahisar River, Mithi River, Oshiwara River, Poisar River, and Ulhas River.

2.4 Wetlands: Rivers/tanks are the inland wetlands, coastal wetlands like sand/beaches, Creeks, mudflats, Salt marshes, mangroves, salt pans also present in the study area. As the aquatic vegetation is mangroves, hardly any change is seen during the pre- and post-monsoon season. Similarly, there is not much change in the turbidity levels, which varies from low to moderate in the wetland area.

3. Materials and Methods

Sentinel 2b data from 28th May 2019 was used in this study. Sentinel-2b is a part of a Sentinel-2 mission. European Space Agency (ESA), (2015) launched Sentinel 2b satellite on 7th March 2017 (Sentinel-2b) to accomplish global observations to support services such as forest monitoring, land cover changes, detection, and natural disaster management. Sentinel-2b has a spectral resolution of 13 bands, and it has a spatial resolution of 10m in 4 visible bands, 20m in 6 red edge & shortwave infrared bands, and 60m in 3 atmospheric correction bands. The satellite image was downloaded free from the Copernicus Open Access Hub (<https://scihub.copernicus.eu>).

The downloaded data was processed in the SNAP (Sentinel Application Platform) toolbox, which is an open-source and flexible scientific toolbox created by the European Space Agency. The data were re-sampled to get a layer stack of the spectral bands. After the Layer stack, the classification of wetlands in Mumbai has carried out in both pixel-based and index-based techniques.

3.1 Pixel-based Classification: Supervised and unsupervised classifications were performed for sorting out the wetlands from the other land covers.

3.1.1 Unsupervised Classification: In the Unsupervised Classification, classifier separates the Satellite image into several classes based on the natural groupings of the image values, without the help of training data or prior knowledge of the study area (Lillesand et al., 2004; Puletti et al., 2014). K-means method is the most commonly used method for the Unsupervised classification (Blanzieri and Melgani, 2008; Li et al., 2014; Rollet et al., 1998). Hence the Sentinel-2b satellite data was classified with 20 different classes by the K-means method. In unsupervised classification, pixels are clustered based on the reflectance properties of the pixels.

3.1.2 Supervised classification: For supervised classification, many methods are available, including the Maximum Likelihood Classifier (MLC) (Settle and Briggs, 1987), which was used in this study. For the supervised classification representative samples needed for each land cover class, the classification is based on the defined spectral signatures. In this study, six different units were classified: Backwater, Mangroves, creek water & inland waters, urban area, Forest, and sea.

3.2 Index-based Classification: Three different indexes used for wetlands mapping were used in this study, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified Soil-adjusted Vegetation Index (MSAVI2).

3.2.1 NDVI: In 1969, Kriegler et al. (Kriegler et al., 1969) proposed Normalized Difference Vegetation Index (NDVI) for the remote sensing image classification. Since then, the NDVI classification has been widely used for remote sensing of vegetation for many years (Gao, 1996). In this study of Mumbai wetlands, identifying Mangroves and the other vegetation NDVI classification was carried out using the following equation.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

3.2.2 NDWI: There are two types of Normalized Difference Water Index(NDWI) are there; one is used to monitor changes in water content of leaves using near-infrared(NIR) and the shortwave infrared (SWIR) which was proposed by Gao (Gao, 1996) in 1996. McFeeters proposes the second one in 1996 (McFeeters, 1996), which is used to separate the land and water using green waves and the NIR. In this study, we adopted the Gao's NDWI (Gao, 1996) to monitor the Mumbai's wetland vegetation using the equation

$$NDWI = (X_{nir} - X_{swir}) / (X_{nir} + X_{swir})$$

3.2.3 MSAVI2: Qi et al. proposed the modified Soil-adjusted Vegetation Index 2., in 1994 (Qi et al., 1994). MSAVI2 addresses some limitations of NDVI, especially for the highly visible soils. For better understanding the wetland area, MSAVI2 was calculated and mapped for the Mumbai area using the following equation

$$MSAVI2 = \frac{(2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - RED)})}{2}$$

4. Results and Discussion

For wetlands, digital classification is the most used method in remote sensing because of the less time taking, and also, the source data provides a high temporal resolution. In this study, Supervised and unsupervised classifications were carried out under the pixel-based classification method. NDVI, NDWI, MSAVI2 were carried out under index-based classification.

4.1 Unsupervised Classification Results

In the unsupervised classification, classification was carried out with 20 classes, the result of this unsupervised classification differentiates the wetland areas like Mangroves and the creek lets from the other features like forest and the backwater rivers. This unsupervised classification helped carry out the supervised classification using spectral signatures.

The supervised classification method was carried out with the help of the unsupervised classification result and the spectral signatures. Spectral signatures were carefully created by training the data based on the field knowledge.

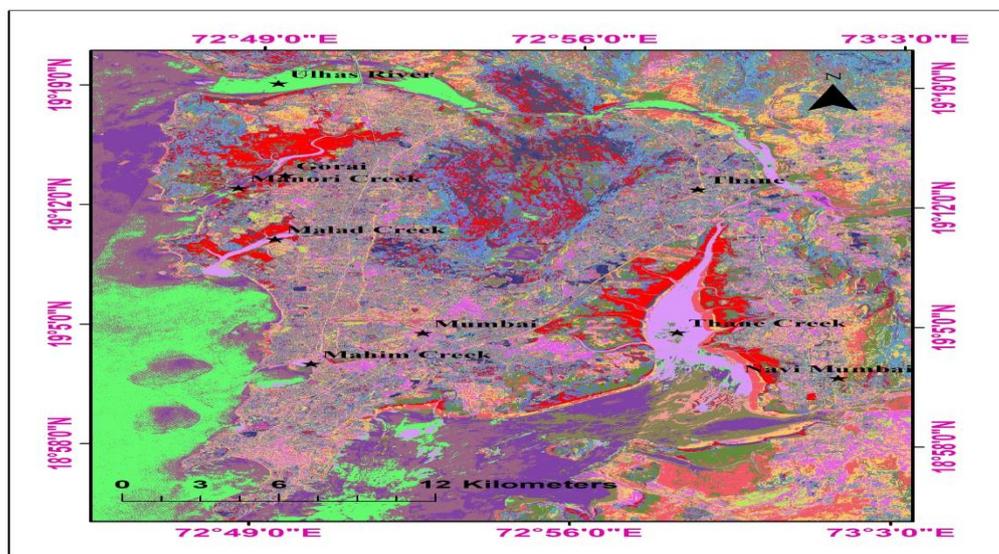


Figure 2: Unsupervised classification

4.2 Supervised Classification Results

Six classes were classified in the supervised classification method for the entire study area with the help of the spectral signatures. They are Backwater, Mangroves, creek water & inland waters, urban area, Forest, and sea (Figure 3). Furthermore, the other details of each class are given in Table 1.

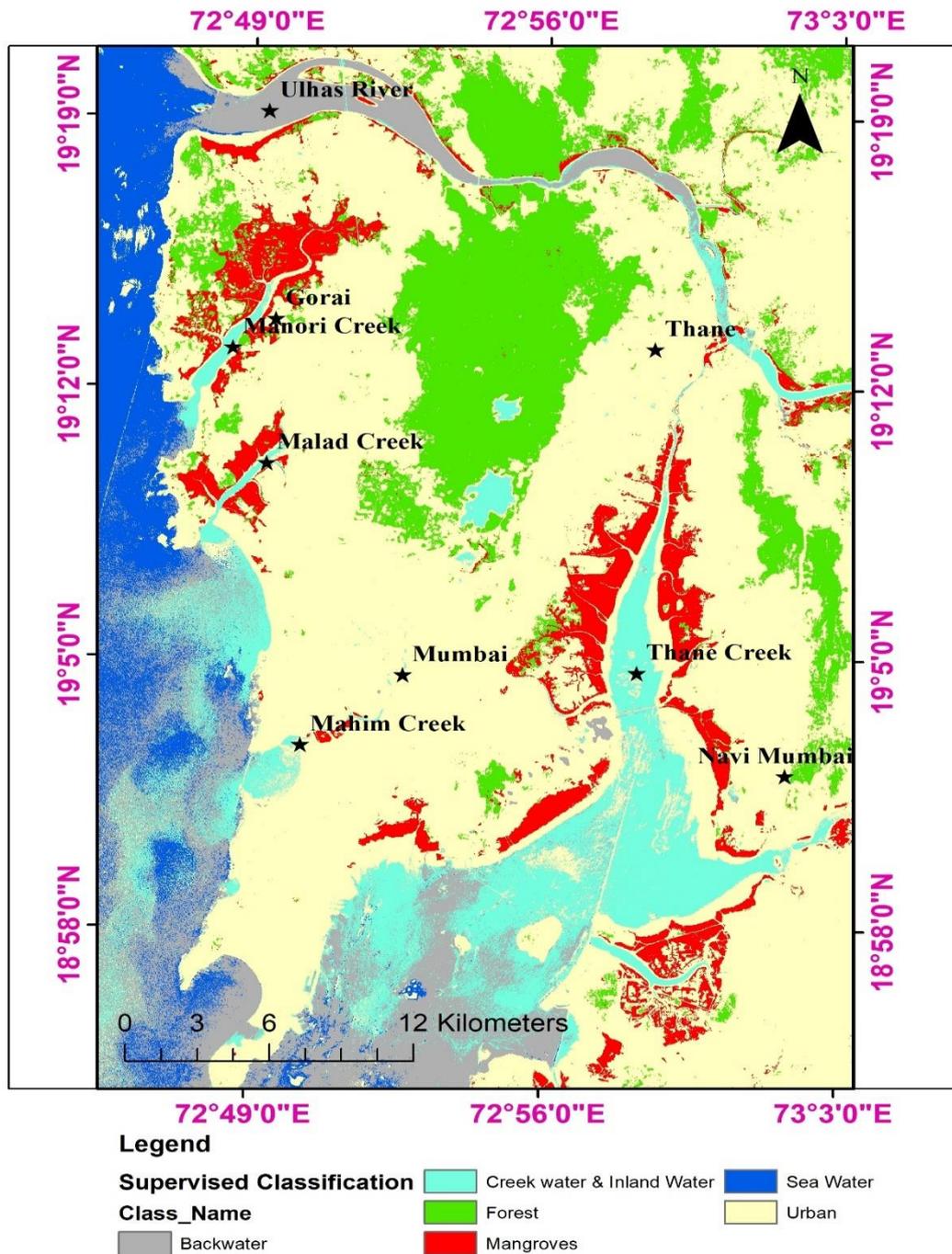


Figure 3: Supervised classification

OBJECTID	Pixel_Count	Class_Name	Percentage	Area in Km2
1	498015	Backwater	8.54	137.077
2	243849	Mangrove	4.18	67.089
3	401267	Creek Water&Inland Water	6.89	110.58
4	714096	Forest	12.24	196.45
5	3014416	Urban	51.68	829.464
6	961221	Sea	16.47	264.34

Table 1 Supervised Classification of the Study Area

In this classification, Backwater, Mangrove, Creek water & Inland water are recognized as the part of wetlands, whereas Forests are classified because to separate the Mangroves from the other Vegetation, Urban is the populated area, and the sea is the remaining part.

4.2.1 Backwater

As per the classification results, the percentage of the backwater is 8.54 in the study area, which is 137.077 km². Ulhas river's mouth part is mainly classified as the backwater in the supervised classification result. Ulhas river flows into the Arabian sea; the outlet of the river is intensely affected by tides. As a result, fresh and saline water become mixed to form an estuarine environment, and it is a part of the wetland.

4.2.2 Mangrove

Totally 67.089 km² areas are classified as Mangroves in the study area. Vijay et al. (Vijay et al. 2005) estimated around 56.40 km² area of the mangroves in the Mumbai suburban area in the year 2005 compared to that this study area included Mumbai urban. In 2005 Mumbai High Court ordered that the mangroves should be categorized as forests then there has been an intensive effort to protect them. Because of that, they are found more protected compared to the past, though they are threatened by urbanization. These classified Mangroves are mainly found in and around creeks.

4.2.3 Creek Water & Inland Water

Malad, Manori, Mahim, and Thane are the four significant creeks in the study area. In that, the Thane creek is the largest of them all. These creeks are enriched in biodiversity with the Mangroves in them. Five rivers are flowing in the study area, namely Dahisar River, Mithi River, Oshiwara River, Poisar River, and the Ulhas River. Moreover, three freshwater Lakes also located in the study area, namely Vihar Lake, Tulsi Lake, and Powai Lake. These all are classified under the Creek Water & Inland Water category. These Creeks and Inland water are occupying 6.89% of the total study area with the 110.58 km² area.

4.2.4 Other wetlands in Mumbai

Salt pans and the Mudflats are the other significant wetlands found in the study area.

4.2.4.1 Salt pans

Salt pans are placed within the low tideland and the high tideland. The salt pans in Mumbai are in Mulund, Bhandup, Ghatkopar, Chembur, Wadala, Trombay, and Jogeshwari areas. Optical remote sensing data cannot distinct enough the salt pans and the wetlands (Turkar, Rao, and Deo 2014), and also, an area of these salt pans in Mumbai is around 20km² which is very less compared to the other wetlands. These salt pans are significant in the flooding's prevention as they are acting as natural barriers. Along with mangroves, these salt pans hold the seawater from entering the mainland and reduce the amount of flooding.

4.2.4.2 Mudflats

In the study area, mudflats found nearby Manori, Malad creek, and the Thane creek let areas. The broadest mudflats occur in the Thane Creek area. During the low tide, these mudflats are open to the environment, and in prime tide time, they filled by the water. In many areas, the mudflats are overrun by the Mangroves, so it is difficult to classify the mudflats in those areas. In Thane creek, these mudflats are widened enough to classify from the help of the Remote sensing data. Hence the Thane creek was classified separately using the supervised classification (Figure 4). The total area of the Mudflat in the Thane creek is classified as 51 km².

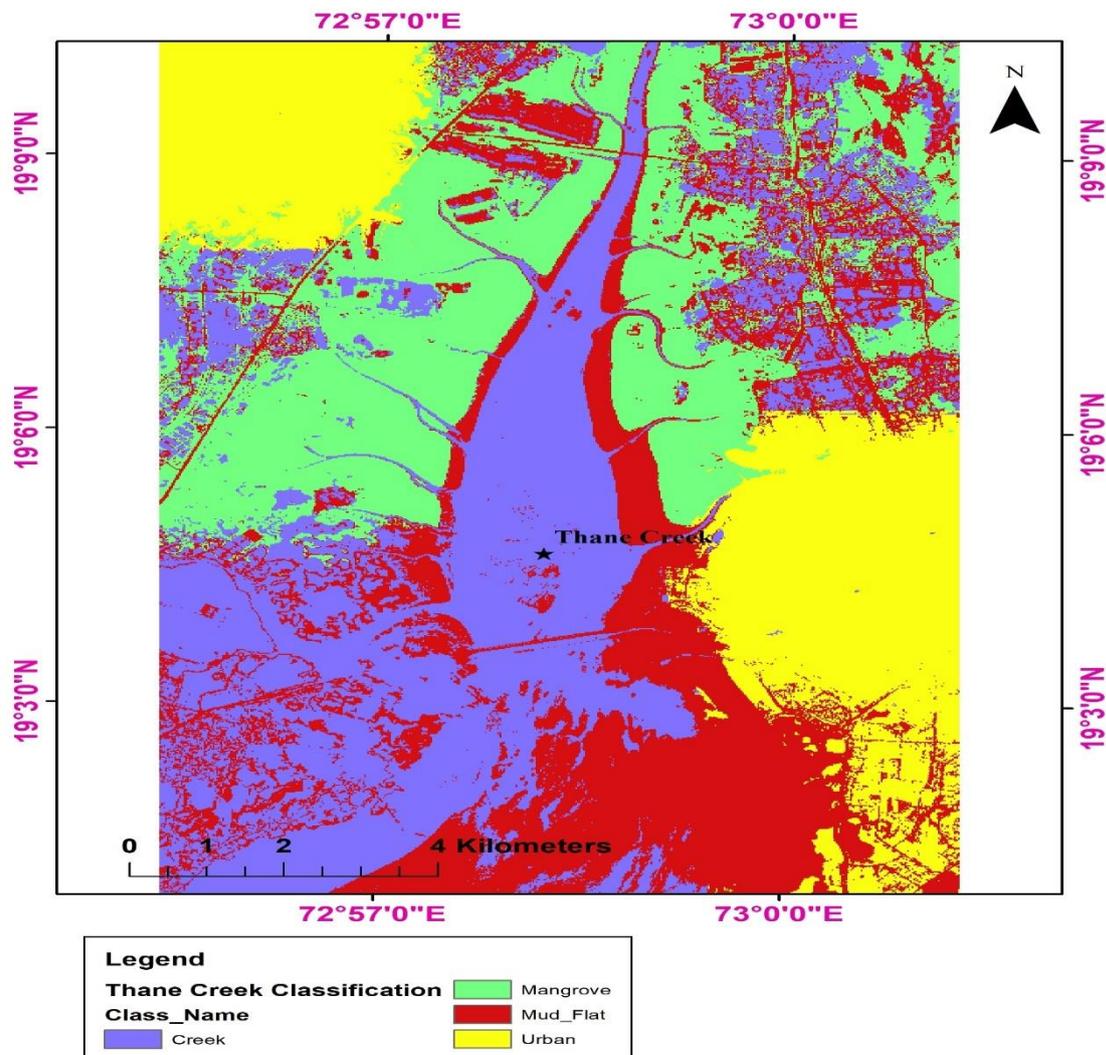


Figure 4 Classification of Thane Creek

OBJECTID	Pixel_Count	Class_Name	Percentage	Area in Km2
1	140870	Creek	29.66	55.5
2	109917	Mangrove	23.14	43.5
3	128878	Mud_Flat	27.13	51
4	95220	Urban	20.07	37.73

Table 2 Supervised classification of the Thane creek

4.3 Index-Based Classification Results:

NDVI classification certainly differentiates the vegetation from the other land covers. It demarcates the Mangroves and the other vegetated fields in the study area (Figure 5). In this study, the NDVI index defines values stretching from -0.2 to 0.78. In these high values representing greens, where negative values are blue, which are mainly formed from water bodies, and values close to zero are primarily formed from rocks and the urban area. Moderate values (from 0.2 to 0.3) represent shrubs and meadows like forests, while large values (from 0.6 to 0.78) indicate the mangroves. In these Wetland monitoring, this NDVI classification successfully shows which parts of the study area have water, urban, forest, and the mangroves area.

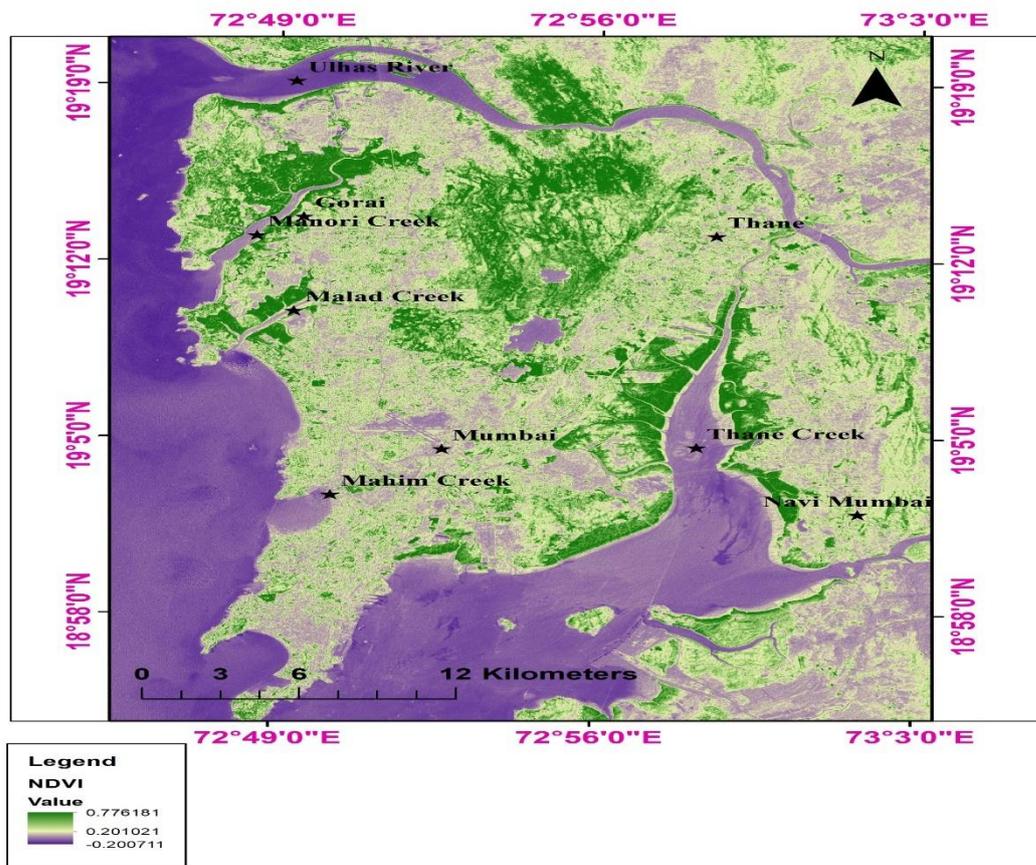


Figure 5NDVI

The NDWI index is most suitable for wetland mapping (Figure 6). The wetlands have even absorbability and low radiation in the range from short wave infra-red to infra-red wavelengths. So, the index uses the short wave infra-red and Near Infra-red bands of Sentinel 2b imagery based on this phenomenon. The NDWI enhanced the water information effectively in the study area, and also it differentiates the urban areas.

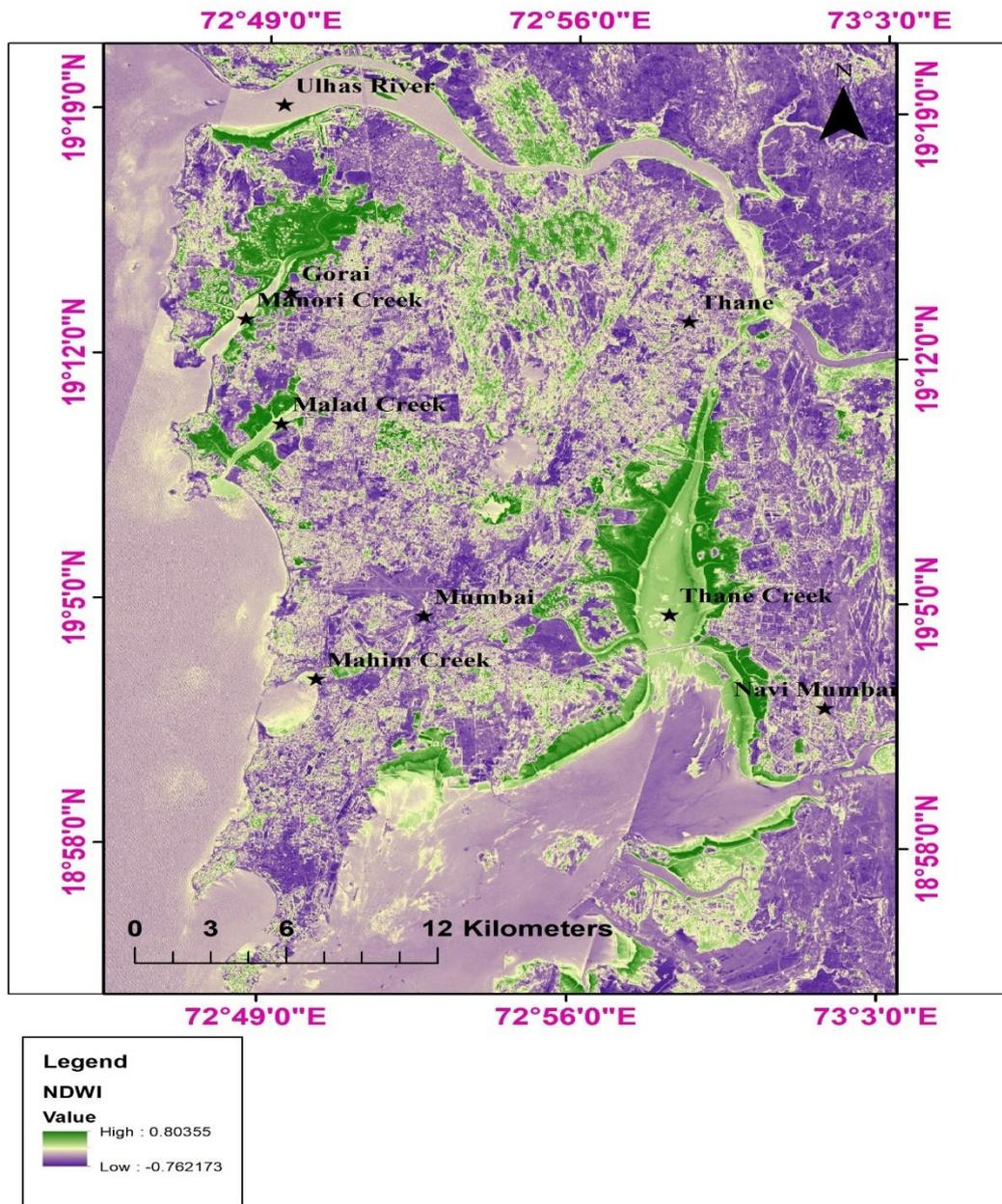


Figure 6 NDWI

The modified soil-adjusted vegetation index 2 (MSAVI2) is a vegetation index, which is used to boost limits on applying NDVI to the highly urbanized areas (Figure 7). MSAVI2 is used in the areas where NDVI provide invalid data, mostly due to a small amount of vegetation, or due to a lack of chlorophyll therein. Thus, the index is used to reduce the soil background influence and to increase the dynamic range of vegetation signal. The value ranges from -0.3 to 0.68 in the study area.

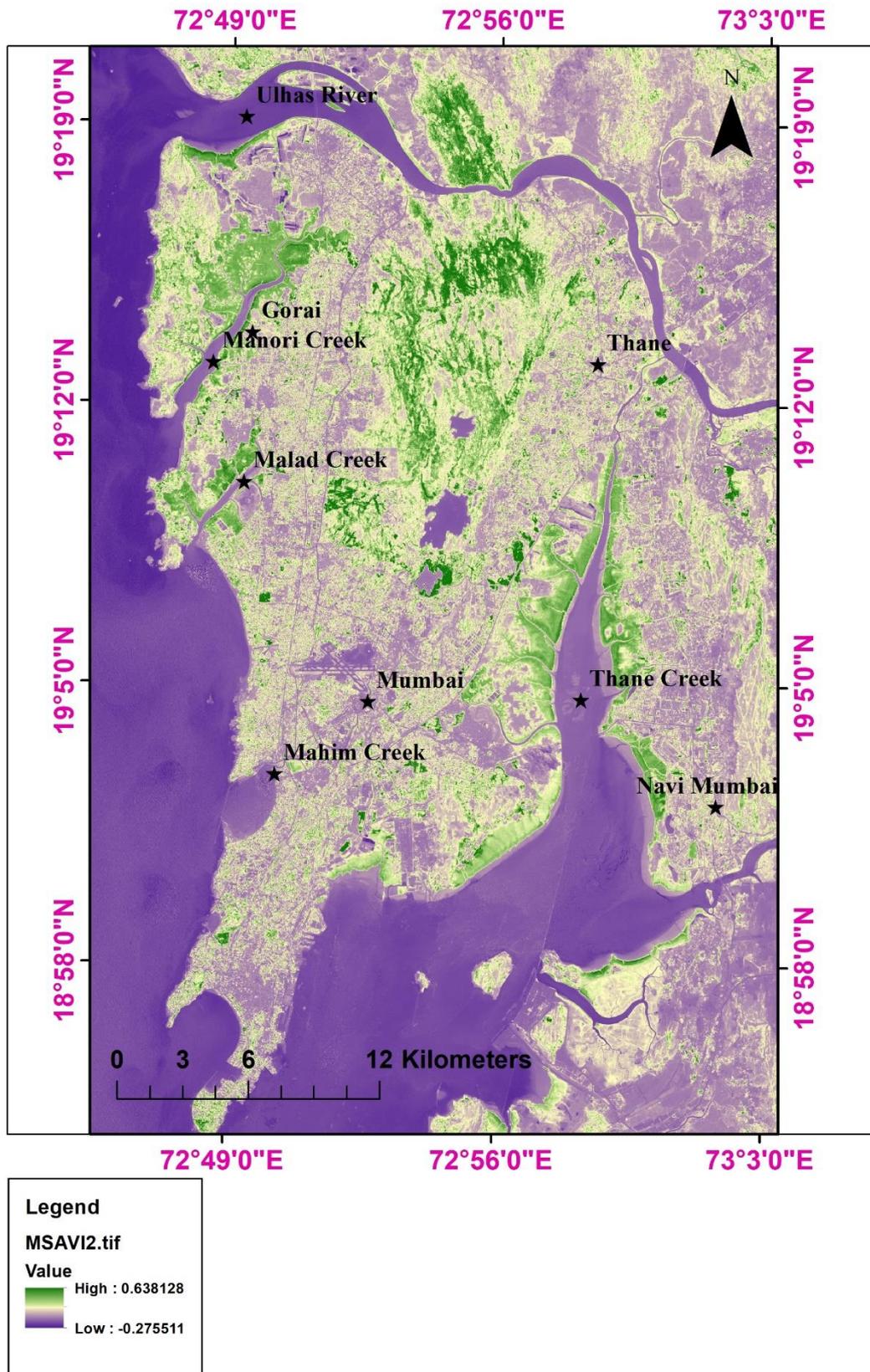


Figure 7 MSAVI2

4.4 Validating the supervised classification

With the complexity of digital classification, there is more of a need to assess the reliability of the results (Congalton, 1991). For the reliability of the result and validating the remote sensing classification, the error matrix technique was carried out. Error matrix (confusion matrix) – compares ground truth data with results of classification. Total 452 random points using the Google Earth based on the field knowledge, selected for the accuracy assessment. The details are given in Table 3 and Figure 8

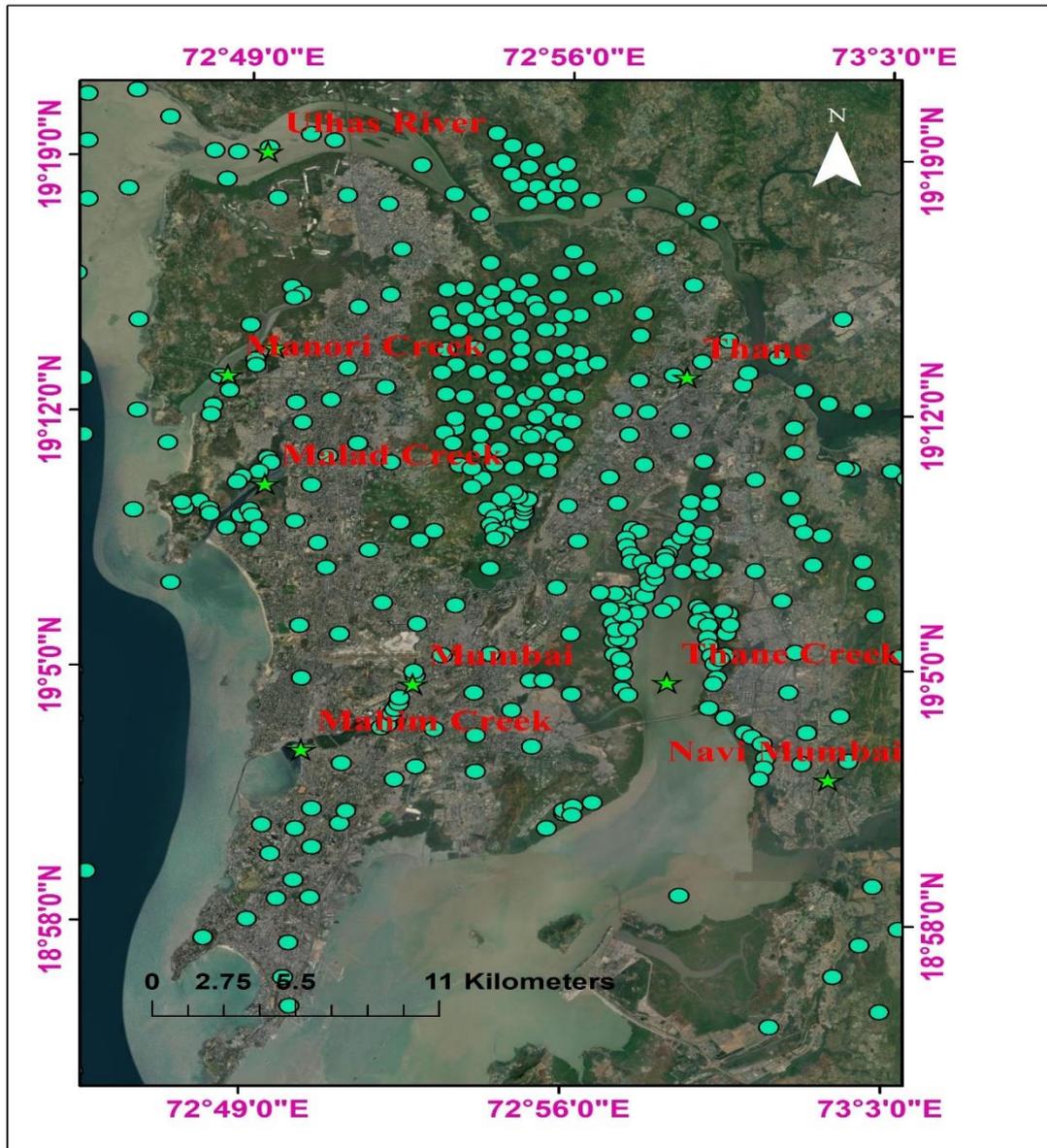


Figure 8 Google Earth random points

Class name	Truth1 Back Water	Truth2 Mangroves	Truth3 Creek & Inland water	Truth4 Forest	Truth5 Urban	Truth6 Seawater	Row Total
Back water	13	0	1	0	0	6	20
Mangroves	0	119	2	0	0	0	121
Creek & Inland Water	1	0	36	0	0	1	38
Forest	0	2	0	112	1	0	115
Urban	1	3	12	0	91	1	108
Sea water	6	0	0	0	0	44	50
Column Total	21	124	51	112	92	52	452

Table 3 Error matrix

4.4.1 Producers Accuracy

Producers Accuracy measure indicates the probability of a reference pixel being correctly classified and is really a measure of omission error (Congalton, 1991). The producer's accuracy is identified using the following formula for each class.

Truth / Column Total

Producers Accuracy

Back water = $13/21$ which is 0.62

Mangroves = $119/124$ which is 0.96

Creek water & Inland Water = $36/51$ which is 0.70

Forest = $112/112$ which is 100

Urban = $91/92$ which is 0.99

Sea Water = $44/52$ which is 0.85

Producer's accuracy proved that the forest, urban, and mangroves were classified with high accuracy, where the water bodies show less.

4.4.2 Users Accuracy

The Users Accuracy is revealing of the possibility that a pixel classified on the image actually represents that category on the ground (Story and Congalton, 1986). The user's accuracy is calculated using the following formula for each class

Truth/row total

Users' accuracy

Backwater = 13/20 which is 0.65

Mangroves = 119/121 which is 0.98

Creek water & Inland Water = 36/38 which is 0.95

Forest = 112/115 which is 0.97

Urban = 91/108 which is 0.84

Sea Water = 44/50 which is 0.88

4.4.3 Overall Accuracy

The overall accuracy is calculated using the following formula

Sum of the total Truth/row total

The sum of the total truth is 415 /452. Hence the overall accuracy of the supervised classification result of the study area is found as **0.92**.

5. Conclusion

Sentinel 2b data was used in this study for mapping the wetlands of Mumbai. The mapping was carried out based on supervised and index-based classification. Six classes were classified in the supervised classification method for the entire study area with the help of the spectral signatures the six classes are backwater, mangroves, creek water & inland waters, urban area, forest, and the sea. In these, Backwater, Mangrove, Creek water & Inland water are recognized as part of wetlands. The percentage of the backwater is 8.54 in the study area, which is 137.077 km². Ulhas river's mouth part is mainly classified as the backwater. Totally 67.089 km² areas are classified as Mangroves in the study area. Creeks and Inland water are occupying 6.89% of the total study area with the 110.58 km² area. Saltpans and the Mudflats are the other wetlands found in the study area, which are under massively unsafe conditions. With the overall accuracy of 0.92, the study proved that the sentinel data is more capable of mapping wetlands though it shows less accuracy for classifying the water bodies. This study confirmed that the Mangrove area is found to be more stable because of strict orders of the High Court when compared to the past, though they are under threat by urbanization.

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