Original Research Article

Land Use and Land Cover Change Detection Using Remote Sensing in the Kal River Basin, Raigad District, Maharashtra.

Abstract

Land use and land cover (LULC) are distinct yet interrelated concepts that describe the characteristics and utilization of land. Land cover refers to the physical surface, such as vegetation, water bodies, or man-made features, while land use denotes the purpose of land utilization. Changes in LULC significantly impact water resources, making it a critical component in water resource studies. This study aims to detect changes in LULC over a five-year period (2017–2021) in the Kal River basin, a sub-basin of the Savitri River in Maharashtra, India. Sentinel-2 satellite imagery with a 10 m resolution was used, and the supervised classification method, specifically Maximum Likelihood Classification (MLC), was applied to classify LULC into six categories: cropland, bare ground, built-up areas, trees, rangeland, and water bodies. The results show that in 2017, the areas under cropland, tree cover, bare ground, built-up areas, and water bodies were 35.20 km², 187.61 km², 0.133 km², 7.77 km², and 1.89 km² respectively. By 2021, cropland, tree cover and bare ground decreased by 3.82%, 4.85%, and 0.01% respectively while water bodies, rangeland, and built-up areas increased by 0.02%, 8.34%, and 0.32% respectively. The overall accuracy of LULC classification was 77% for 2017 and 91% for 2021 with validation using the Kappa coefficient indicating good to excellent accuracy. This study highlights the importance of monitoring LULC changes for understanding the impacts of human activities and climate on watershed development and water resource management. Such analysis provides valuable insights for decision-makers to plan for sustainable development, land conservation and environmental management, ensuring balanced growth while protecting natural resources in the Kal River basin.

Keywords: Arc GIS, LULC, Kappa coefficient, overall accuracy

1. Introduction

Land Use and Land Cover (LULC) is the term used to describe the type of cover that occupies the surface of the Earth. Although they may seem similar, “land cover” and “land use” are distinct terms. Land cover refers to the biotic and abiotic materials that cover the Earth’s surface, while land use involves the modification of land cover for specific purposes. Land use includes activities such as wildlife management, recreational spaces, and agriculture, whereas land cover encompasses elements like water, grasslands, forests, snow, and bare soil (Yangchan et al., 2014). Changes in an area’s land use and cover result from socioeconomic factors, natural processes and human interactions over time and space. Factors such as topography, slope conditions, soil type, climate and other physical characteristics significantly impact changes in land use and land cover (LULC).

Changes in LULC can directly affect evapotranspiration rates, groundwater infiltration and overland runoff. Generally changes in LULC have adverse effects on climate patterns, natural hazards and socio-economic dynamics at both local and global scales. Information about land use/cover and its proper management is essential for planning, sustainable land resource management, and understanding hydrological processes to meet increasing demands. Rapid resource depletion has altered the world’s land surfaces and contributed to the ongoing advancement of human civilization and improved living standards (A M Li, 2017; Rockstrom et al., 2009). Over 80% of Earth’s natural resources, particularly land surfaces, have already suffered degradation due to human activity (Sanderson et al., 2002; Bonan et al., 2018), with regions of high population density facing the most intense degradation

(Hooke et al., 2012; Goudie and Viles, 2013). Therefore, to achieve sustainable and long-lasting development in line with the Sustainable Development Goals (SDGs), special attention should be given to densely inhabited and degraded landscapes (Rogelj et al., 2016; Bodansky, 2016; Cowie et al., 2018).

The detection of changes in land use and land cover (LULC) is crucial for understanding, monitoring and regulating cultivated areas, urban expansion and landscape utilization. Understanding landscape patterns, changes, and the interactions between human activities and natural phenomena is essential for improving decision-making and ensuring proper land management. Conventional methods of land use mapping are tedious, time-consuming, and labor-intensive. Modern technologies like Geographic Information Systems (GIS) and Remote Sensing (RS) are powerful and cost-effective tools for assessing spatial and temporal changes in LULC. Today, high-accuracy satellite data is freely available on various web portals, making it accessible for land use mapping. Remote sensing data is the most common source for detecting, quantifying, and mapping LULC patterns due to its repetitive data acquisition, ease of processing, and accurate georeferencing. In many developing countries, such as India, changes in land use patterns are closely linked to population growth. Numerous studies in India have examined changes in LULC, revealing that the direction, pattern and degree of LULC change vary across different regions. These studies emphasize that land use mapping is critical for developing environmental protection strategies and ensuring sustainable resource management of watersheds. India is facing significant LULC changes, primarily due to the overuse of natural resources for agriculture and human settlement.

Accuracy assessment is an important step in land use change analysis, as it provides the information value of the resulting data to the user. The overall accuracy of a classified image compares how each pixel is classified versus the actual land cover conditions obtained from corresponding ground truth data. Errors of omission are measured by the producer's accuracy, which shows how accurately real-world land cover categories are classified. User's accuracy measures errors of commission, representing the likelihood that a classified pixel matches the land cover type at its real-world location (Sari et al., 2021). The objectives of this research are to identify the classification of land use changes in the Kal River basin, Raigad district, Maharashtra, and to calculate the accuracy of land use classification.

2. MATERIAL AND METHODS

2.1 Description of the study area

The Kal river is a major tributary of the Savitri river, flowing into it from the right (north) near Dasgaon in Raigad District, Maharashtra, India. The geographical coordinates of the Kal river lie approximately between North latitude18° 05' and 18° 33', East longitude 73° 43' and 73° 63'. The total study area is 457.82 km2. The study region falls within the subtropical climate zone, which typically experiences alternate dry and wet periods. It is classified as the second VRN (Very High Rainfall Zone) in the agro-climatic zoning system of the Agriculture Department, Government of Maharashtra (2005). The average annual rainfall in the study area is 3590 mm, indicating a relatively high precipitation level. This suggests that the area receives a significant amount of rainfall. The temperature in the study area varies between 12°C and 39°C. This wide temperature range indicates a significant difference between the minimum and maximum temperatures experienced in the region. The lower end of the temperature range (12°C) suggests cooler conditions, while the higher end (39°C) indicates hot temperatures during certain periods. The location map of the study area is shown in Fig 1.

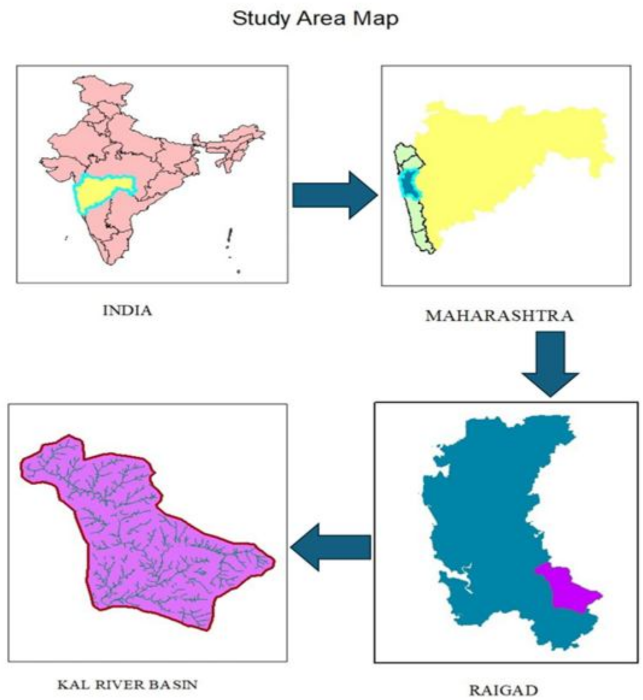

Fig. 1: Location map of study area

2.2 Data and Software Used

ArcGIS 10.8.1 software, available in the Department of Soil and Water Conservation Engineering, CAET, DBSKKV, Dapoli, was used to view and edit geospatial data, delineate boundaries, and create thematic maps. MS Office Suite 2019 was used for documentation, calculations, and organizing notes related to the study. Google Earth Pro was used to verify the accuracy of the land use and land cover (LULC) map. The shapefile of the study area was downloaded from DIVA-GIS (Website: https://www.diva-gis.org).The land cover datasets for the study include Sentinel-2 imagery with a 10 m resolution for the years 2017 and 2021.Sentinel 2 satellite imagery downloaded from Copernicus Data Space Ecosystem (https://dataspace.copernicus.eu) was used to prepare the land use land cover map of the year 2017 and 2021.

2.3 Methodology

Change detection of LULC is the key aspect of this study by using satellite images. The supervised classification method has been used in this study, which is well established. This classification method helps in grouping the LULC sensed from satellite imageries. This method contains the supervision of pixels by an image analyst by a particular algorithm a numerical explanation of different land cover types exists in the scene. Training sites are taken as the representative sample of identified cover type. Then, the training sites are used for compilation to form a key that can explain a numerical value of different land cover expressed by spectral attributes for a particular type of interest (Ramachandran and Reddy 2017). Maximum Likelihood (ML) is one of the widely used algorithms in supervised classification to classify images (Jenson 2005). The principle is the probability function that assumes the training data for each class in each band, which is normally distributed (Basukala 2017). The land use land cover (LULC) mapping process is depicted in a flowchart in Fig 2.

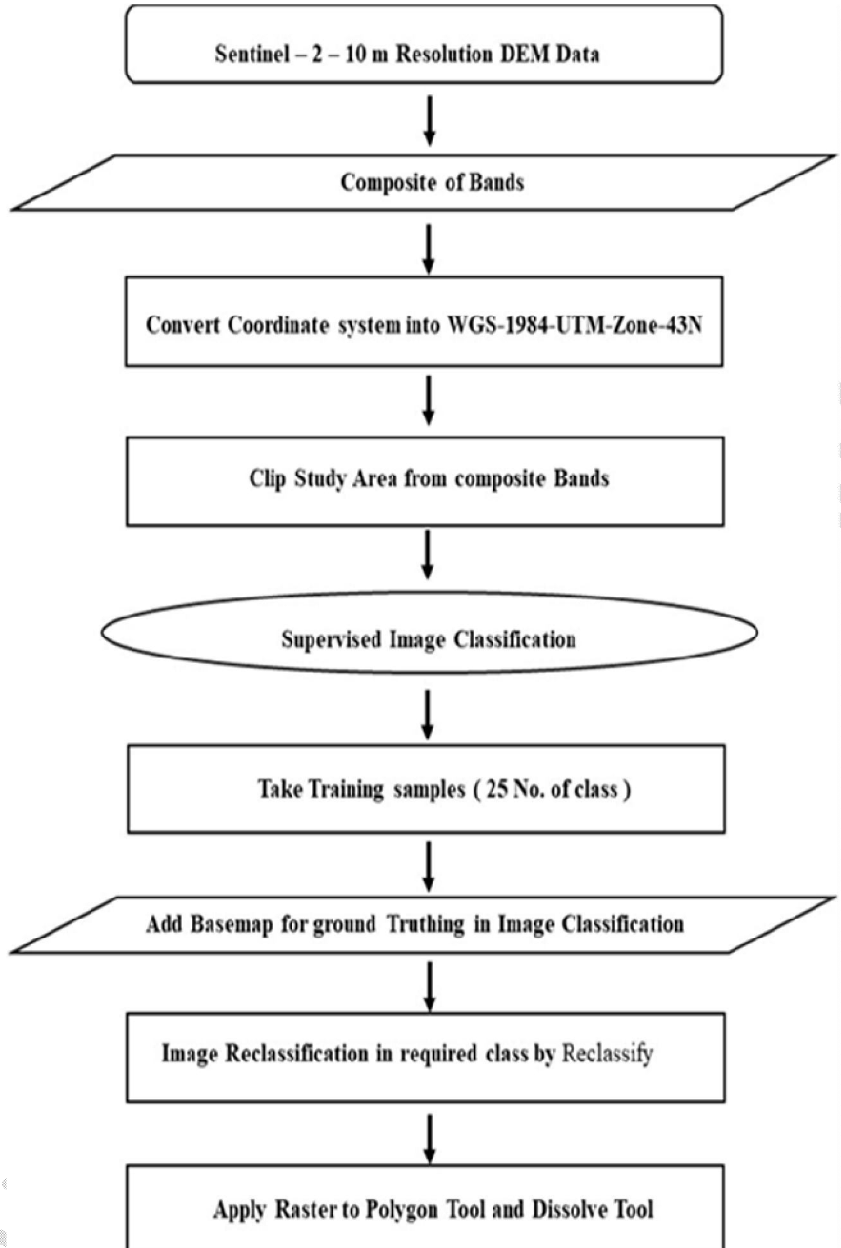

Fig.2 Flowchart for preparation of land use/ land cover classification map

2.4 Detection of Changes in Land Use Patterns in the Study Area Over the Study Period

Land use and land cover is a dynamic process. The change can be detected by making maps of land use land cover patterns for different time periods. For the current study land use land cover maps for the years 2017 to 2021 were prepared. The change in the LULC was calculated by comparing the area under each LULC pattern for the years 2021.

Area under each LULC pattern was calculated by using equation as

$$\text{Pixel count of land use pattern} \times \text{cell size of one pixel} \ldots (1)$$

The Sentinel -2 has a resolution of 10 metres. Therefore, the formula becomes-

$$\text{Area(m)} = \text{Pixel count of particular land use pattern} \times 10\text{ m} \times 10\text{ m.} \qquad \ldots (2)$$

The per cent area covered by each land use pattern was calculated as-

$$\text{Area (\%)} = \frac{\text{Area under specific land use (ha)}}{\text{Total area (ha)}} \times 100 \qquad \ldots (3)$$

The land use land cover maps need to be compared with the referenced data in order assess the accuracy of classification. The detection of the land use land cover pattern of any area cannot be considered valid until its accuracy has been determined. The land use land cover maps were compared with Google Earth images for the years 2021. The user accuracy, producer accuracy and overall accuracy was calculated in the present study using Kappa coefficient to quantify the accuracy of land use land cover maps. The flow chart to calculate user accuracy, producer accuracy and overall accuracy is given in Fig 3.

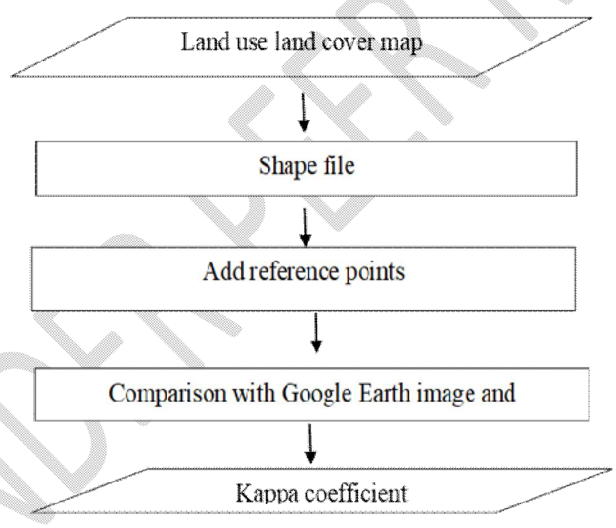

Fig 3. Flowchart for calculating Kappa coefficient

2.5 Accuracy Assessment

Accuracy assessment is an important step in the for-processing land use change analysis. It contains the information value of the resulting data to a user. The overall accuracy of the classified image compares how each of the pixels is classified versus the definite land cover conditions obtained from their corresponding ground truth data. Producer's accuracy measures errors of omission, which is a measure of how well real-world land cover types can be classified. User's accuracy measures errors of commission, which represents the likelihood of a classified pixel matching the land cover type of its corresponding real-world location.

The field data is used for the accuracy assessment process for the year 2021, the classification results of the Sentinel-10 m resolution data satellite image. A total of 100 random points were used for the validation and accuracy of the classification results. Determination of the random points is carried out to identify the area that represents each desired land cover class and build a numerical description of the spectral properties of each land cover. Random points are selected based on field data and analyzed into statistical information on land use types.

The users of LULC maps need to know the level of accuracy of the map so that it can be used more efficiently and correctly.

According to (Anderson et al, 1976), the interpretation accuracy of land use and land cover change is not allowed below 80%. The most widely promoted classification accuracy is in the form of error matrix which can be used to derive a series of descriptive and analytical statistics. The step is a very effective way to show accuracy in that the accuracies of each category are plainly described along with both the errors of commission errors and errors of omission errors present in the classification. Overall accuracy, producer's accuracy, user's accuracy, and Kappa statistics are generally reported, and these terms have been explained in detail in many studies.

The formulae to calculate user accuracy, producer accuracy and overall accuracy as given below-

$$\text{User's Accuracy} = \frac{\begin{array}{c}\text{Number of correctly classified}\\ \text{pixels in each category}\end{array}}{\begin{array}{c}\text{Total number of reference points}\\ \text{in the category (the row total)}\end{array}} \times 100 \qquad \ldots (4)$$

$$\text{Producer Accuracy} = \frac{\begin{array}{c}\text{Number of Correctly classified}\\ \text{Pixels in each category}\end{array}}{\begin{array}{c}\text{Total number of reference pixels}\\ \text{in the category(the column total)}\end{array}} \times 100 \qquad \ldots (5)$$

$$\text{Total overall Accuracy} = \frac{\begin{array}{c}\text{Total Number of correctly}\\ \text{classified pixels (diagonal)}\end{array}}{\text{Total number of reference points}} \times 100 \qquad \ldots (6)$$

$$\text{Kappa coef icient} = \frac{(\text{Ts}\times\text{Tcs}) - \pounds(\text{column total}\times\text{Row total})}{(\text{Ts})\verb|^|2 - \pounds(\text{column total}\times\text{Row total})} \qquad \ldots (7)$$

Where, Ts = Total Sample

Tcs = Total Corrected Sample

The values of different accuracy indicate the quality of land use mapping. The higher the value of user accuracy, producer accuracy and overall accuracy, the higher the precision and quality of the data. The classification of the quality of work according to value of Kappa coefficient is shown in Table 1.

Table 1 Quality of land use mapping according to Kappa coefficient range

Sr. No.	Kappa coefficient	Rate	Source
1	< 0.4	Poor	Tewabe and Fentahun, (2020).
2	0.4 - 0.55	Fair	
3	0.55 - 0.7	Good	
4	0.7 - 0.85	Very good	
5	> 0.85	Excellent	

3. Results and Discussion

Land use/land cover in Kal river basin is undergoing rapid changes due to urbanization. To analyze these changes, remotely sensed satellite data such as Sentinel-2 was used. In this study, the land use/land cover maps were extracted from Sentinel- 2 (10 m) data, as described in Table 2 and fig 4. The images were classified into six general classes using the supervised Classification with maximum likelihood classification in ArcGIS 10.8.1 software.

Land Use and Land Cover (LULC) is an important source of information for watershed development as the land use and land cover significantly affect the volume and velocity of the runoff. The study area was classified into six land use land cover classes: i) Bare ground (ii) Built up area (iii) Crop cover (iv) Rangeland (v) Tree cover (vi) waterbodies.The area covered by different land use signatures in the year 2017 is shown in Table 2.

Table 2:Land cover and land use in the Kal river basin for year 2017.

Sr. No	Land Cover	Area (km^2)	Percent
1	Bare Ground	0.133	0.03
2	Built Up Area	7.779	1.70
3	Crops	35.205	7.69
4	Rangeland	225.194	49.19
5	Tree cover	187.611	40.98

6	Water bodies	1.900	0.41
Total		**457.823**	**100**

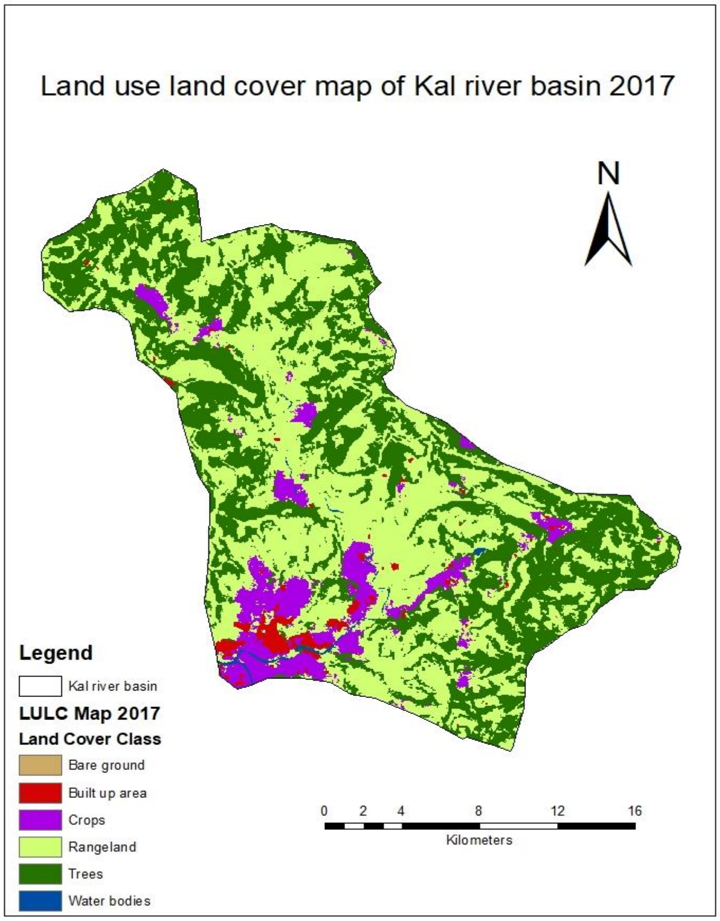

Fig 4: Land use land cover map of Kal river basin for year 2017

During the year 2017 (Table 2 and fig 4) the majority of land in Kal river basin comes under rangeland (49.19%). Next dominating land use land cover was trees which covers (40.98%) followed by crops (7.69%), built up area (1.70%), water bodies (1.90 km^2) and bare ground (0.133 km^2). It was found that almost 90% of land is covered under two major classes: Rangeland and Trees which together cover almost 90% of the land in the Kal River basin. Rangelands are typically used for grazing livestock, while trees might represent forests, woodlands, or other types of vegetative cover dominated by trees.

During the year 2021 the majority of land in Kal river basin comes under rangeland (57.53%). Next dominating land use land cover was tree cover which covers (36.13%) followed by crops (3.87%), built up area (2.01%), and bare ground (0.0817 km^2). It was found that almost 90 % of land is covered under two major classes: rangeland and Trees. Spatial Coverage of land use land cover of Kal river basin during the year 2021 are presented in Table.3 and Fig 5.

Table:3. Land cover and land use in the Kal river basin for year 2021

Sr.No	Land Cover	Area (Km^2)	Percent
1	Bare Ground	0.0817	0.02
2	Built Up Area	9.22	2.01
3	Crops	17.71	3.87
4	Rangeland	263.38	57.53
5	Tree cover	165.42	36.13
6	Water Bodies	1.99	0.43
Grand Total		**457.82**	**100**

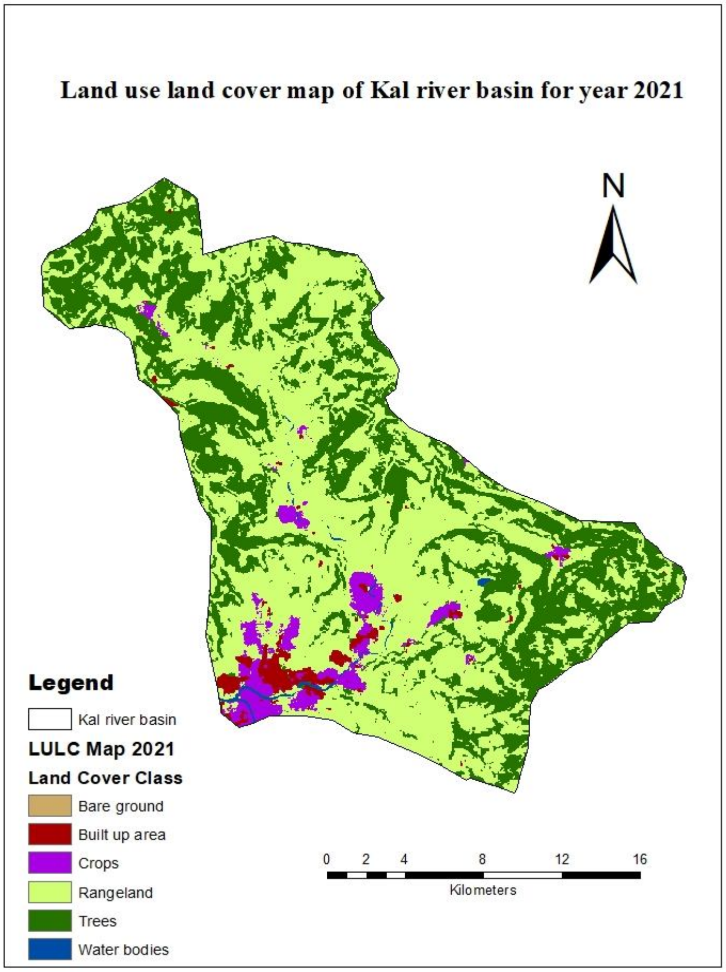

Fig 5: Land use land cover map of Kal river basin for year 2021

The land use was classified into six categories as crop land, trees cover, rangeland, bare ground, water bodies and built-up area using the supervised classification method. The area under Crop land, Trees cover, bare ground, built up area and water bodies for Kal river basin in the year 2021 was 3.87%, 57.53%, 0.02%, 2.02% and 36.13%, respectively.

Change Detection in Land Use Patterns Over Time

To detect the changes in land use patterns in Kal river basin Raigad district of Maharashtra from the year 2017 to 2021 Sentinel-2 (10 m resolution) data along with Arc GIS 10.8.1 and Google Earth software was used. The land use was classified into six categories as crop land, trees cover, rangeland, bare ground, water bodies and built-up area using the supervised classification method. Land use and land cover are dynamic properties of any area. The extent of LULC changes spatially and temporally due to human needs and other climatic conditions. The changes in the land use land cover of the study area obtained from this study were mentioned in Tables 4.

Table 4: Land cover change detection in the Kal river basin using Sentinel-2 satellite data.

Sr.no	Land Cover	2017 Area (km^2)	2021 Area (km^2)	Change (km^2)	Percentage (%)
1	Bare Ground	0.133	0.0817	- 0.0517	- 0.01
2	Built Up Area	7.778	9.225	1.447	0.31
3	Crops	35.205	17.710	- 17.494	- 3.82
4	Rangeland	225.194	263.387	38.192	8.34
5	Trees	187.611	165.426	- 22.184	- 4.85
6	Water bodies	1.899	1.99	0.095	0.02

In this study, LULC detection of Kal River basin over from the year 2017 to 2021 had analyzed. The area under crop land, trees cover, bare ground, built up area and water bodies for Kal river basin in the year 2017 was 35.20 km^2, 187.61 km^2, 0.133 km^2, 7.77 km^2, 1.89 km^2, respectively.Over the considered study period of five years, in 2021, the change in the area under crops, trees and bare ground was found to be decreased by 3.82%, 4.84 % and 0.01 %, respectively. At the same time area under water bodies, rangeland, and residence or built-up was increased by 0.02%, 8.34% and 0.32%, respectively.

The reason behind this conversion can be attributed to the decline in agricultural facilities, with more people moving into industries rather than agriculture, along with decreasing crop prices. Additionally, environmental, technological, biotic, and abiotic factors may also play a role (Liliana et al., 2020). Some areas have been converted to agricultural land due to the shortage of such land and the rising demand for food driven by population growth (Hugo, 1983). Meanwhile, former agricultural land has decreased due to its conversion to rangeland and built-up areas, which may be linked to climate change and reduced soil fertility (Chen et al., 2021; Islam et al., 2022). Increased human migration has also occurred due to growing economic activity and job opportunities (Nabi, 1992), with poverty and a lack of employment opportunities further driving this migration (Kartiki, 2011).

During the dry season, crops are primarily grown on low-lying wetlands. Such land has experienced significant pressure due to rapid population growth, leading to its conversion into residential areas, industrial infrastructure, crop production, and other land use types (Shapla et al., 2015). These changes in land use and land cover are crucial for understanding how human activities and climatic conditions impact watershed development and water resource management in the study area. This understanding aids in making informed decisions related to land conservation, sustainable development, and environmental management in the Kal River basin. By tracking these changes, decision-makers can better plan for future challenges and work towards preserving the region's natural resources. Similar findings were reported by Dhaigude et al. (2021).

Accuracy Assessment of Land Use Mapping

The accuracy of land use land cover for Kal river basin was calculated using the Kappa coefficient. The different reference points selected from the land use maps of Kal river basin were compared with the Google Earth image. The results obtained from the comparison of the reference points of Kal river basin during the year 2017 and 2021 with Google Earth images are presented in Table 5 and 6 respectively.

Table 5: Accuracy assessment of land use mapping of Kal river basin during the year 2017

Sr.No.	Class Value	Water bodies	Tree Cover	Crops	Built up area	Bare ground	Rangeland	Total
1.	Water bodies	1	0	0	0	0	0	1
2.	Tree cover	0	35	4	0	0	0	39
3.	Crops	0	2	4	0	1	2	9
4.	Built up area	0	0	0	1	1	0	2
5.	Bare ground	0	0	0	0	0	0	0
6.	Rangeland	0	5	0	1	7	35	48
	Total	1	42	8	2	9	37	99

Table 6: Accuracy assessment of land use mapping of Kal river basin during the year 2021

Sr.No.	Class Value	Water bodies	Tree Cover	Crops	Built up area	Bare ground	Rangeland	Total
1.	Water bodies	1	0	0	0	0	0	1
2.	Tree cover	0	32	0	0	3	0	35
3.	Crops	1	0	2	1	1	0	5
4.	Built up area	0	0	0	3	0	0	3
5.	Bare ground	0	0	0	0	0	0	0
6.	Rangeland	0	1	0	0	2	53	56
	Total	2	33	2	4	6	53	100

It was observed from Table 5 and 6 that sample points of water bodies, tree cover, Crops, built up area, bare ground and rangeland respectively, were compared with the Google Earth image. Table 5 and 6 reveal that correctly identified points are positioned diagonally from the top left to the bottom right. The total reference points used for comparison are aggregated in the user total column, while all points identified as specific land use are summed up in the producer total row. The numbers in the matrix signify the counts of instances for each combination of predicted and actual classes. In the present study, The diagonal elements denote accurate predictions for each class, while the off-diagonal elements represent misclassifications. The Total row and column provide the overall number of instances for each class. In this study, Table 5 and 6 gives a detailed breakdown of the model's performance for each class and overall, during year 2017 and 2021. It helps to understand where the model performs well and where it might have challenges in classifying instances correctly.

According to Anderson et al., 1976 the contingency matrix contains someinformation, there are producer's accuracy, overall accuracy, and kappa accuracy. Producer's accuracyand user's accuracy are estimators of overall accuracy. The producer's accuracy is the accuracy seen fromthe side of the map producer, while user's accuracy is the accuracy seen from the user's side of the map. The accuracy test of the classification results is depicted in Table 7 and 8.

Table 7. User and producer accuracy of Kal river basin during the year 2017

Sr. No.	Land use pattern	User accuracy (%)	Producer accuracy (%)	Overall accuracy (%)
1	Water bodies	100	100	77
2	Tree cover	90	83	
3	Crops	44	50	
4	Built up area	50	50	
5	Bare ground	0.00	0.00	
6.	Rangeland	73	95	

Table 8.User and producer accuracy of Kal river basin during the year 2021

Sr. No.	Land use pattern	User accuracy (%)	Producer accuracy (%)	Overall accuracy (%)
1	Water bodies	100	50	91
2	Tree cover	91	97	
3	Crops	40	99	
4	Built up area	100	75	
5	Bare ground	0	0	
6.	Rangeland	95	100	

Overall Accuracy and Kappa

The overall accuracy, user's accuracy, producer accuracy and Kappa Coefficient was calculated using the procedure described in the methodology equation No.4,5, 6& 7. User Accuracy (Producer's Accuracy): This is the proportion of correctly classified instances for each class out of the total number of instances in that class. It is calculated by dividing the diagonal element by the sum of the column. Accuracy is the overall measure of correct predictions in the classification, computed as the sum of accurate predictions divided by the total number of predictions. For each class, it is determined by dividing the diagonal element by the sum of the corresponding row.

Based onoverall accuracy and kappa coefficient(Table 9) Overall Accuracy for the year 2017 is 77 % and 2021 is 91% and kappa coefficient is 0.63 in 2017 and 0.85 in 2021. Based on these results, the accuracy and kappa coefficient values have good criteria and can be used for further analysis. Islami et al, 2022 found similar findings. Based on overall accuracy and kappa coefficient, Overall Accuracy for the year 2021 is 91% indicating an excellent quality grade and it is presented in Table 9. Calculated values of user's accuracy, producer accuracy and overall accuracy are shown in Table 9.

Kappa for each class

This indicates how well the model performs for each specific class, taking into account chance agreement. A Kappa value of 1 means perfect agreement, 0 means agreement equivalent to chance, and negative values indicate agreement worse than chance. The Kappa coefficient, a metric for inter-rater agreement adjusted for chance, measures agreement between predicted and actual classifications. A higher Kappa value indicates better agreement. The kappa coefficient is 0.85 can be concluded that the land use classification has a great correlation. The Kappa coefficient was calculated using 100 reference points and was found to be greater than 0.63 and 0.85 percent, indicating good and excellent quality grade in 2017 and 2021. These results are presented in Table 9.

Table: 9 Quality of land use mapping according to overall accuracy Kappa coefficient range

Sr.No.	Year	Overall accuracy (%)	Kappa Coefficient	Grade
1.	2017	77	0.63	Good
2.	2021	91	0.85	Excellent

Conclusion

In this study, LULC detection of Kal river basin, Raigad district over from the year 2017 to 2021 had analyzed. The area under crop land, trees cover, bare ground, built up area and water bodies for Kal river basin in the year 2017 was 35.20 km^2, 187.61 km^2, 0.133 km^2, 7.77 km^2, 1.89 km^2 respectively. Over the considered study period of five years, in 2021, the change in the area under crops, trees and bare ground was found to be decreased by 3.82%, 4.84 % and 0.01 %respectively. At the same time area under water bodies, rangeland, and residence or built-up was increased by 0.02%, 8.34% and 0.32% respectively. The validation of land use mapping was done using Kappa coefficient. It was observed that the grade of accuracy was good and excellent. The overall accuracy of land use mapping of Kal river basin for the year 2017 and 2021 was found to be 77% and 91% respectively. These changes in land use and land cover are important for understanding how human activities and climatic conditions impact the watershed development and water resources management in the study area. It can help in making decisions related to land conservation, sustainable development, and environmental management in the Kal River basin. By tracking these changes, decision-makers can better plan for future challenges and work towards preserving the natural resources of the region.

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