Application of Remote Sensing and Machine Learning techniques for LULC Classification

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Abstract

Land Use Land Cover is an effective way to investigate the various land use patterns over the years and predict future land management to achieve sustainability. Machine Learning techniques are efficacious and favoured means for Land Use Land Cover Classification (LULC) using remotely sensed satellite data. The chosen study area is a region covering some parts of the Dhanera area located in Banaskantha district of Gujarat,India where over the years urbanization has changed various landscape uses. In this research we have compared the differences between the various land covers in the years 2002 and 2022 using Landsat 7 and Landsat 9 images respectively in Arc GIS 10.3. Seven major LULC regions which are dense vegetation, vegetation, barren land, floodplains, sandy regions, mountains and built up have been identified and compared for the two years. As a result of urbanisation, population growth, climatic factors,traditional agroforestry systems and various other factors, LULC in the study region has undergone various changes over the past two decades from 2002 to 2022. We have used two machine learning models namely Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC) for classifying these LULC classes.These models were used to accurately classify the various LULC categories in the study region. Using the change detection formula we have calculated the changes of these various land covers over the period of two decades. This research outlines the impact that various factors over a time period of twenty years can have on the land use land cover patterns of the study area and provides valuable insights to help in land management and urban planning in the region.

Keywords: Land Use Land Cover, Remote Sensing, Machine Learning

1. INTRODUCTION

Rapid evolution of human civilisation throughout the centuries with vast improvements in standards of living has directed to large use of raw resources that has significantly altered land surfaces on the earth[34]. The most significant resources used in research, including land use planning, agriculture and natural resource management, business and administrative uses, management, and other activities, are those related to land use and land cover (LULC) [38].

Land use and land cover monitoring are vital in interpreting and managing the Earth's dynamic veneer, encircling the assessment of biological and man made changes in ecosystems, land forms, settlements, and engineered structures[30][3]. The significance of land use and land cover monitoring is emphasized by its profound implications for several integral facets of our environment and society, as highlighted by the following key factors:

- **Water Resource Management:** Approximately 70% of the Earth's surface is swathed by water, and land accounts for the remaining 30%. Human activities have significantly recasted over 50% of the Earth's natural land cover. These transformations include deforestation, desertification, and urbanization; they have far-reaching consequences for water resources. For example, deforestation often leads to shifts in land use, impacting water quality. Contrarily, urbanization results in extensive impassable surface cover, impacting regional hydrology and water quality. Stormwater runoff from urban vicinities can debase water quality, boost runoff volume and rate, and elevate impurity levels, which advance downstream, influencing ecosystems and water bodies [3][7].

- **Environmental Impact Assessment:** Natural processes and human actions frequently drive land use and cover changes. Monitoring these transformations is critical for conducting environmental impact estimations. Researchers and land custodians use land cover data to track the significance of land use changes, whether interconnected to deforestation, urban proliferation, or transformations in agricultural techniques. These assessments are critical for making informed conclusions regarding resource disbursement, conservation efforts, and sustainable land governance[30][36].

- **Climate Change and Biodiversity Conservation:** Land cover monitoring is essential for tracking the consequences of biodiversity loss, climate change, and pollution in aquatic and terrestrial environments [9]. High-resolution satellite snaps survey biodiversity loss, characterize contrasting areas, and assess the ecological impacts of diverse stressors. This information is crucial for the conservation of ecosystems and for materializing mitigation strategies against climate oscillations[13][12].

- **Sustainable Land Resource Management:** For planners, land supervisors, and policymakers, sufficient land cover monitoring is vital. Decision-makers can design sustainable land resource management techniques by constantly estimating land use and cover transformations[22]. This retains optimizing land use routines, pinpointing sites in jeopardy of degradation, and scheduling for catastrophe management[10].

- **Historical and Future Analysis:** Scrutinizing land use and land cover transformations over period is elementary.[27] The historical investigation of maps, aerial shots, and satellite snaps helps understand landscape evolution. Current improvements in satellite imaging technology and geographical information systems (GIS) foster more precise and rapid shift detection. Such data can also foresee future land use and cover changes, aiding in assertive planning [15]

In summary, land use and land cover monitoring, streamlined by remote sensing and geospatial technologies, is essential for understanding the Earth's surface dynamics and handling diverse environmental challenges [8]. It assists in the sustainable governance of resources, contributes to environmental influence assessments, and notifies critical determinations connected to water resource management, biodiversity conservation, and climate change transformation. Remote sensing approaches can monitor and map changes in land use and land cover regionally as well as globally and also assess the influence of changes[26].

1.1. Why LULC analysis is important for future prevention?

Land Use and Land Cover (LULC) analysis is critical for prospective prevention, primarily in climate change and environmental protection [31]. It plays a critical role in comprehending the complex association between land use, climate and land cover transformations and provides valuable insights into methods for mitigation and adaptation. Here is why LULC analysis is important for handling these challenges:

1. **Local Climate Effects:** Land surface shifts impact climate conditions, including temperature and precipitation routines [25]. Land cover types can influence cloud formation, evaporation, and air temperatures. For example, substituting grasslands with agriculture in certain regions can result in a cooling influence due to boosted evaporation. In disparity, the transformation of forests to croplands can guide warming. These insights are valuable for managing urban heat islands, optimizing land use, and mitigating local climate deviations.
2. **Global Climate Impact:** The edifice of buildings and infrastructure, mainly far from existing population centres, contributes to increased energy consumption and greenhouse gas emissions. This link between construction and climate change is significant, emphasizing the need for reliable land use planning and development. Land cover changes, such as deforestation, reduce carbon storage capacity, affecting global carbon proportion. LULC analysis advises strategies to manage these impacts, reduce emissions, and improve carbon sequestration.
3. **Climate Change Effects on Land Use:** Climate change directly influences land use and cover. Variability in climate, including shifts in rainfall patterns, temperature, and CO2 enrichment, can affect agriculture and forests. For instance, temperature changes can lead to extended growing seasons and shifts in suitable agricultural regions. LULC analysis helps anticipate and adapt to these changes, ensuring food security and sustainable land use.
4. **Preservation of Carbon Sinks:** Locations with myriad land cover classes, like wetlands and forests, act as carbon sinks, engrossing and stowing carbon from the atmosphere. Climate change can impact the effectiveness of these sinks. LULC analysis aids in preserving carbon storage areas and optimizing land use to maintain these vital resources.[23]
5. **Natural Ecosystem Resilience:** Climate change can lead to environmental disturbances, including shifts in species distribution, increased fire frequency, and sea-level rise. LULC analysis supports the preservation of habitats and the creation of corridors that enable species to adapt to changing conditions and repopulate impacted areas.[18]
6. **Sustainable Land Use Planning:** Proactive land use planning is essential for minimizing the negative impacts of climate change. This includes restricting construction in flood-prone areas, reducing urban heat effects through green spaces and efficient building materials, pre-

serving habitats to enhance climate resilience, and discouraging shoreline development in response to rising sea levels.

7. **Agricultural and Forest Adaptation:** Climate change may render some areas more suitable for agriculture and forest production while making others less viable. LULC analysis guides land preservation for future agricultural use and enhances the adaptability of the farming sector to changing climates.

In summary, LULC analysis provides the knowledge and tools to address the complex interactions between land use, land cover, and climate change. It informs strategies for preserving carbon sinks, mitigating climate change impacts, and promoting responsible land use planning. By analyzing land use and cover, we can make informed decisions to safeguard our environment and build a more resilient and sustainable future.

1.2. Characteristics of Land Use and Land Cover (LULC) Analysis Using Remote Sensing

Primary Land Use and Land Cover (LULC) models strive to examine the driving influences after anthropogenic land use, including socioeconomic and biophysical facets [24]. Nevertheless, the resulting thematic categories often concentrate on consequential land covers or a blend of land-use and land-cover "categories." [21] It is crucial to elucidate the difference between land use and land cover. Land use pertains to how humans utilize land, while land cover directs to vegetation, structures, or surface traits resulting from distinctive land uses. For instance, farming is a land use, while the distinctive crop, like "corn," conveys land cover. Remote sensing excels at verbatim measuring the surface cover class and state for a given pixel, while determining land use frequently requires coupling the observed land cover with supplementary data, such as socioeconomic details or expert understanding [14].Remote sensing provides an incalculable means of detecting land cover style and state, offering multiple landscape characteristics that LULC models can utilize [42].

Land cover mapping owes its presence to the development of remote sensing technologies, initially through techniques like aerial photography [16]. The help furnished by remote sensing, including exhaustive vicinity coverage, periodic revisits, multi-spectral and multi-source data, and repositories in digital forms compatible with Geographic Information System (GIS) technology, has produced a practical and cost-effective par for precise land cover classification.[4] Several critical considerations impact the facets of land cover details emanating from remote sensing data [32].

- **Purpose:** Land cover data aids varied scientific, policy, planning, and management pursuits. Distinctive needs vary, including land use inventories, forest assessments, biophysical resource inventories, and models of vegetation-atmosphere relations, such as productivity and hydrological models.
- **Thematic Content:** Land cover data is required for occasional distinct cover classes (like forest-non-forest), for veil classes at erratic levels of particular, tailored to detailed model requirements, or as straight variables (like percentage coniferous forest).
- **Scale:** Land cover data might be crucial at local, regional, or global hierarchies, pivoting on the application and goals.
- **Data:** The quality and accessibility of remote sensing data impact the class and accuracy of components that can be extracted.
- **Analysis and Processing Techniques:** The selection of filtering and research techniques at distinct stands of data interpretation dramatically affects the output.

The refinement of technology has directed to incorporating remote sensing data with different structures of data, streamlined by endeavours such as the computerized Landsat data processing system and implements like the Global Land Analysis and Discovery Analysis Ready Data (GLAD ARD)[39]. Collaborations between Earth Observation (EO) data scientists and statisticians offer new opportunities for innovative LULC studies globally.[43] Earth Observation data, a part of big data characterized by high volume, velocity, and variety, necessitates advanced data management capabilities for practical analysis.[40]

In summary, incorporating remote sensing data and collective initiatives is reshaping the domain of land use and land cover analysis, unlocking new horizons for research and applications at various spatial and temporal scales.

1.3. How Machine Learning helps in LULC

Machine Learning (ML) plays a substantial role in Land Use and Land Cover (LULC) monitoring and mapping. The application of ML algorithms in LULC obtains several advantages to the field, as outlined in various sources:

- **Improving LULC Mapping Accuracy and Efficiency:** Standard mapping LULC, such as terrestrial mapping, can be labour-intensive and subject to subjectivity. ML algorithms, when used on satellite images, improve mapping accuracy and efficiency. These algorithms use supervised classification systems with training datasets, decreasing classification errors and furnishing more precise results[41].

- **Enhancing Classification Performance:** ML algorithms, including k-nearest Neighbors (kNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forest (RF), have been successfully used on LULC classification. They outperform traditional techniques such as Maximum Likelihood Classification (MLC) and Decision Trees (DT). These algorithms combine computer science and data mining techniques, solving classification difficulties and minimizing classification uncertainties[41].

- **Cost-Efficient and Large-Scale Coverage:** ML algorithms are specifically valuable when performing with satellite images, which provide cost-efficient and comprehensive Earth surface data coverage over extensive geographical areas. They facilitate the accurate classification of land cover types and the detection of shifts in land cover at various spatial scales[41].

- **Challenges of Processing Time and Coarse Resolution:** While satellite images are a helpful resource, the processing time needed to develop precise LULC maps, especially with coarse-resolution satellite images, remains problematic. ML algorithms help mitigate this challenge by improving efficiency and reducing the time needed for processing[41].

- **Application to Multidisciplinary Research:** LULC change information is vital for various fields, such as urban and regional planning, environmental assessment, disaster monitoring, and agricultural management. ML algorithms provide quantitative estimation and prediction of LULC dynamics, encouraging more useful management and knowledge of landscape modification[37].

- **Overcoming Spectral and Spatial Limitations:** ML algorithms have been involved in reducing the spectral and spatial restrictions that can affect the precision of LULC classification using medium- and low-resolution satellite observations. These algorithms help overpower limitations and provide high-precision LULC maps[37].

  In summary, Machine Learning is a beneficial tool in LULC mapping and monitoring, offering enhanced accuracy, efficiency, and the ability to address the challenges associated with the processing of satellite images. It plays a crucial role in various multidisciplinary research fields and offers the possibility for high-precision LULC mapping.

2. STUDY AREA

The study was done for the area around Dhanera which is located in the district of Banaskantha in the state of Gujarat in India. The village is located in the northern region of Gujarat. It expands from 24.52°N and 72.02°E. The moderate height of the area is 128 meters. The region encircled by this study is about 440 square kilometres.

According to the 2011 Census India 2011, Dhanera has 37893 households, inhabitants of 230741, within which 119504 are men and 111237 are women. The population of minors under the age of 6 years is 40759, which makes up 17.66% of the total population. The sex proportion of the Dhanera community is about 931, approximated to the standard of the total state, which is 919. The literacy pace of the community is 48.56%, within which 60.34% men are literate and 35.9% women are literate. Out of the complete inhabitants, 87.18% of the residents live in Urban zones, and 12.82% live in Rural zones. The caste proportion is 9.06% Scheduled Tribe (ST) and 12.43% Scheduled Caste (SC) of the total inhabitants in Dhanera. Dhanera Gram Panchayat governs the district. It comes under Kankrej Community Development Block. Patan which is the nearest town from the district is about 22 kilometers away from Dhanera.

In this area, the arid season is sizzling and mostly explicit, and the moist season is somewhat foggy. The temperature varies from 53°F to 105°F and

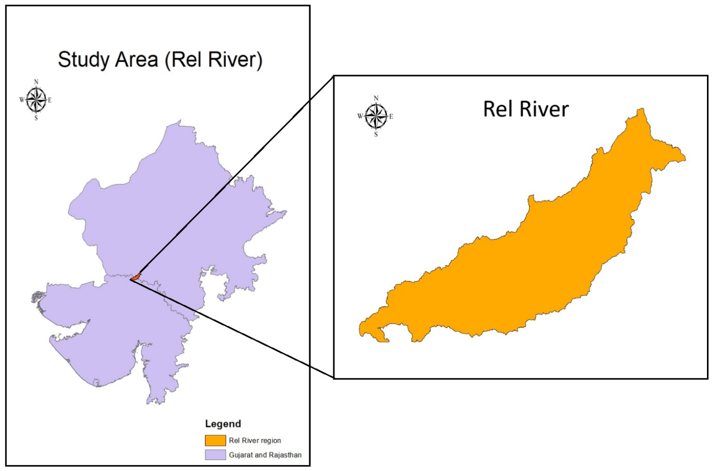

Figure 1: Study Area

is seldom under 48°F or beyond 110°F throughout the year.

3. METHODOLOGY

3.1. Data Collection

We have used the data collected by Landsat 7 and Landsat 9 for LULC classification. The website [1] is used for this purpose. The data from dates 1st December to 31st December for years 2002 and 2022 was downloaded for this purpose. For the year 2002 Landsat 7 was used, while for the year 2022 Landsat 9 was used. Data downloaded has 10 percentage of cloud cover. The data downloaded in each case is downloaded as a collection of images of the same regions. Each of these images represents a specific band or the image of the region when captured from a specific wavelength band. In this classification we have used seven bands from both the satellites Landsat 7 and Landsat 9. The seven bands used with their corresponding wavelengths here are mentioned in 3.

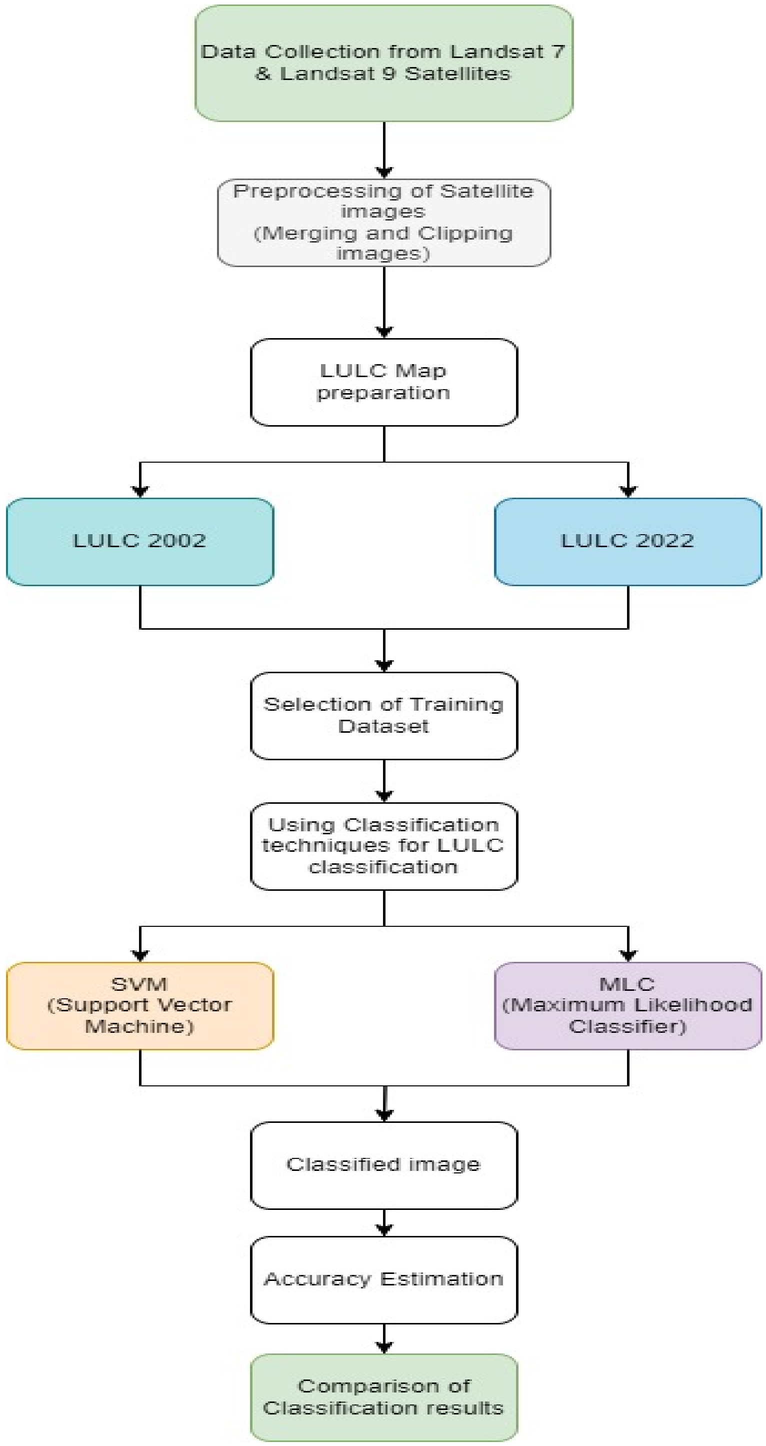

Figure 2: Methodology Flowchart

Bands	Wavelength(in μm)
B1 - Blue	0.45 - 0.52
B2 - Green	0.52 - 0.60
B3 - Red	0.63 - 0.69
B4 - Near - Infrared	0.77 - 0.90
B5 - Shortwave Infrared 1	1.55 - 1.75
B6 - Thermal	10.40 - 12.50
B7 - Shortwave Infrared 2	2.09 - 2.35

Bands	Wavelength(in μm)
B1 - Coastal Aerosol	0.43 - 0.45
B2 - Blue	0.45 - 0.51
B3 - Green	0.53 - 0.59
B4 - Red	0.64 - 0.67
B5 - Near - Infrared	0.85 - 0.88
B6 - Shortwave Infrared 1	1.57 - 1.65
B7 - Shortwave Infrared 2	2.11 - 2.29

Figure 3: Bands used for Landsat 7 and Landsat 9

3.2. Data Preprocessing

The aforementioned seven bands each for Landsat 7 and Landsat 9 are selected and merged to form a single image. This is done using the merge tool present in the ArcGis Tool Box(ATB). Further the shapefile of the study area, i.e, Dhanera region is taken to clip the satellite image, clipping an image in ArcGIS refers to the process of using a boundary or mask to extract a portion of an image dataset or layer, thereby creating a new image or layer that only contains the data within the specified boundary. The merge and clip procedure is followed for both the years 2002 and 2022 in the satellites images of Landsat 7 and Landsat 9. Thus we finally get two images each representing the Dhanera region's geography for the years 2002 and 2022.

3.3. Classification

The two images finally created for the given region are used select training data which are further feed to different machine learning models which finally give the LULC classification as the result. After considering the geography of the study area seven majors areas are taken for the LULC classification: Dense Vegetation, Vegetation, Barren Land, Flood Plains, Builtup, Sandy Regions and Mountains. To train different models first training samples are collected for both the images individually. Training samples collection involves selecting the regions for each of the aforementioned categories. The sample collection is done using the training sample manager in ARCGIS. Sample representing each of the aforementioned regions are selected this data is recorded by the training sample manager. [19]

In the original Natural Color Composition(NCC) image it is very difficult to differentiate visually between these regions thus False Color Combination is used for this purpose. In this method in which different wavelength of light is assigned as red, green and blue. Due to the fact that the reflectance

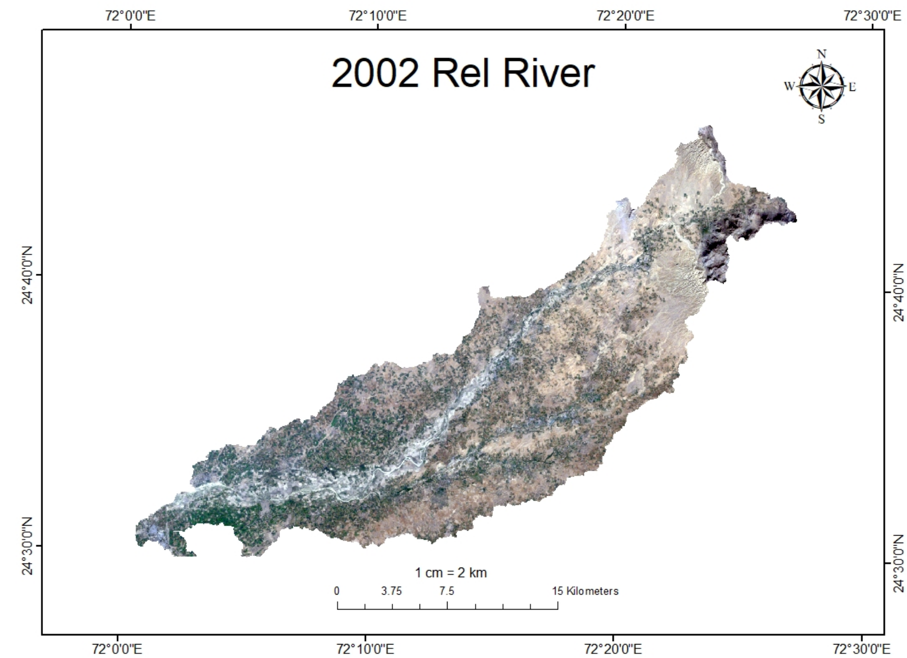

Figure 4: NCC 2002

of different regions is different or in other words different objects have different spectral signatures, and some may also have their spectral signatures in the invisible region of light, FCC is proved to be legitimate technique to visually detect different regions and thus facilitates efficient training sample collection.

After successfully sample collection, samples that belong to same regions are grouped to form a class. For each class 40-50 samples were collected. Thus we generate a training sample file which can be fed to different machine models to get the final LULC classification. There will be two training sample files generated one for both years 2002 and 2022. The machine models used here are Support Vector Machine(SVM) and Maximum Likelihood Classifier(MLC).

3.3.1. SVM

The basic working principle of SVM is to linearly separate data by finding a hyperplane that separates different classes of data. The hyperplane is chosen such that it maximizes the minimum distance between points of the data of the two classes. It comes under the category of non-parametric

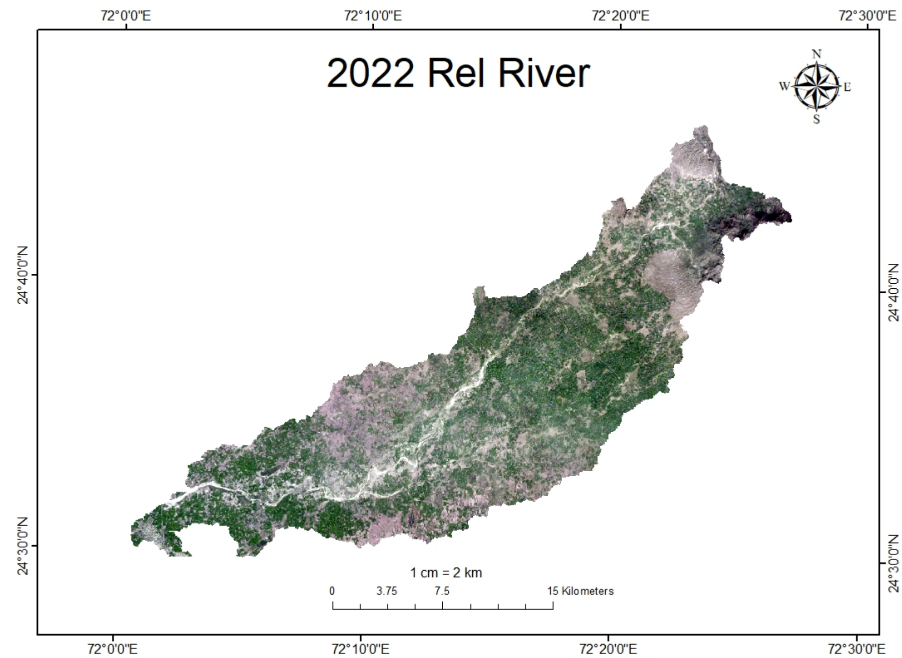

Figure 5: NCC 2022

classifier. SVM was first formulated by [11] and later a detailed study on SVM was given by the authors in [5]. In LULC classification kernel function are used which modify the dimensions of the data points and create a linearly separable data space [33].

3.3.2. MLC

It is another supervised learning technique used for LULC. It is a type of parametric classification. The authors in [36] have given a detailed note on this classifier. They state using an algorithm to calculate the value of likelihood $\mathcal{L}$ of an unknown data point $\mathcal{U}$ from known data points $\mathcal{V}_i$, based on the following equation.

$$\mathcal{L} = ln(p) - [0.5ln(|Cof_i|)] - [0.5(\mathcal{V}_i)O(Cof_i - 1)(\mathcal{U} - \mathcal{V}_i)] \tag{1}$$

Here O is the transposition function, p is the probability percentage for any pixel to belong to a particular class i, I being a distinct class. The coefficient Cov_c is a matrix of covariance of the pixel values for the class i, further | Cov_c | is the determinant value of the same matrix.

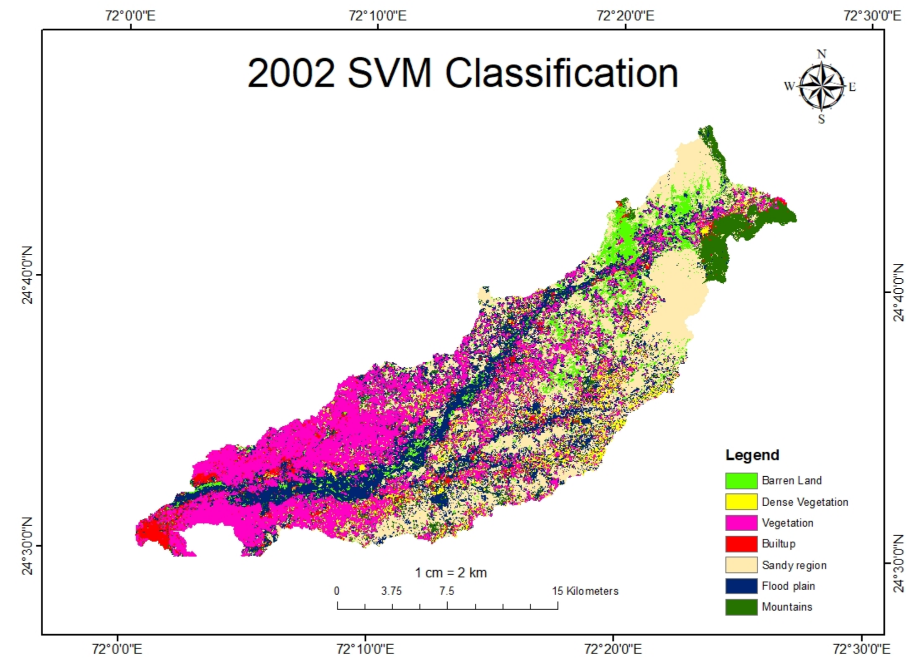

Figure 6: SVM 2002

After LULC classification is performed by both the classifiers we get the final classified images. These images have color mapped to each of the seven regions. Thus, at the end of the classification we have four images, two from each classifier for the years 2002 and 2022. Furthermore we calculate the total area covered by each region in each of these images. This is done using the raster to polygon and dissolve function present in ArcGIS. First the classified image is feed to the raster to polygon tool which convert the image to small polygons and has each polygon has a specific value of the region to which it belongs. Then this converted image is feed to the dissolve function which merges all the polygon belonging to the same region into a single class. Next the geometry class is used to calculate the total area covered by each region.

3.4. LULC change Detection

The net difference between the total area of region of the year 2002 and 2022 is calculate using the following formula. This difference in percentage is used to detect the net change and is used in application

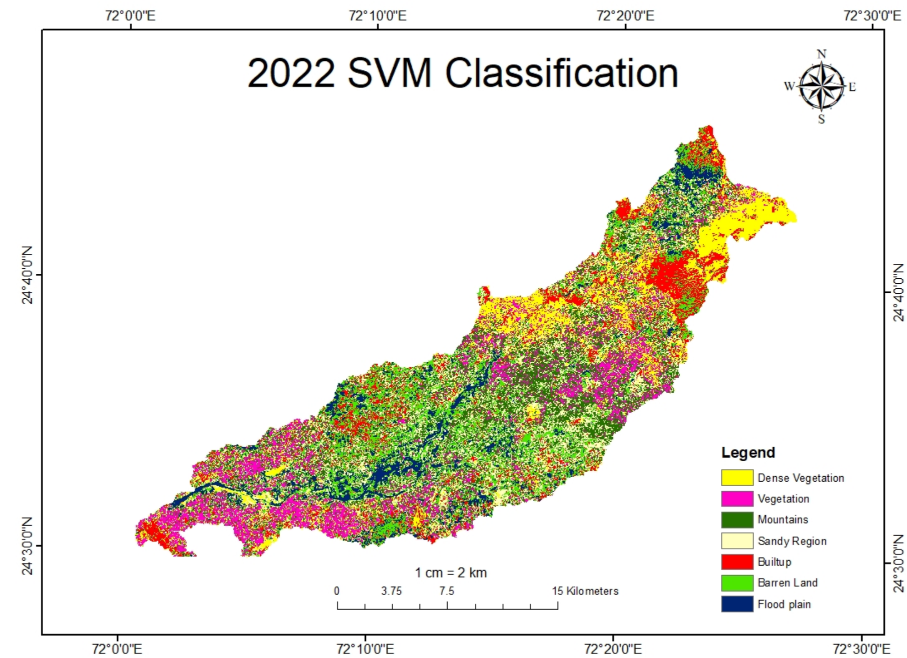

Figure 7: SVM 2022

$$p_k = \frac{a_{k2022} - a_{k2002}}{a_{k2002}} \cdot 100 \tag{2}$$

In this equation k represents different regions. The same procedure is repeated for both the classifier and the results are specified in section 4.

4. RESULTS AND DISCUSSION

Urbanisation, population growth, climatic factors and changing agricultural methods have all had an impact on the region's LULC over the past two decades from 2002 to 2022 [35].

Using supervised learning the area covered by Dense Vegetation in the year 2002 was 52 square kilometers and for the year 2022 was 49 square kilometer. This implies a decrease of 5.76% in the dense vegetation cover. This can be due to the changes in various non vegetation cover in the past 2 decades using equation 2.The area under vegetation had a significant increase from 60 square kilometers to 202 square kilometers from 2002 to 2022 which

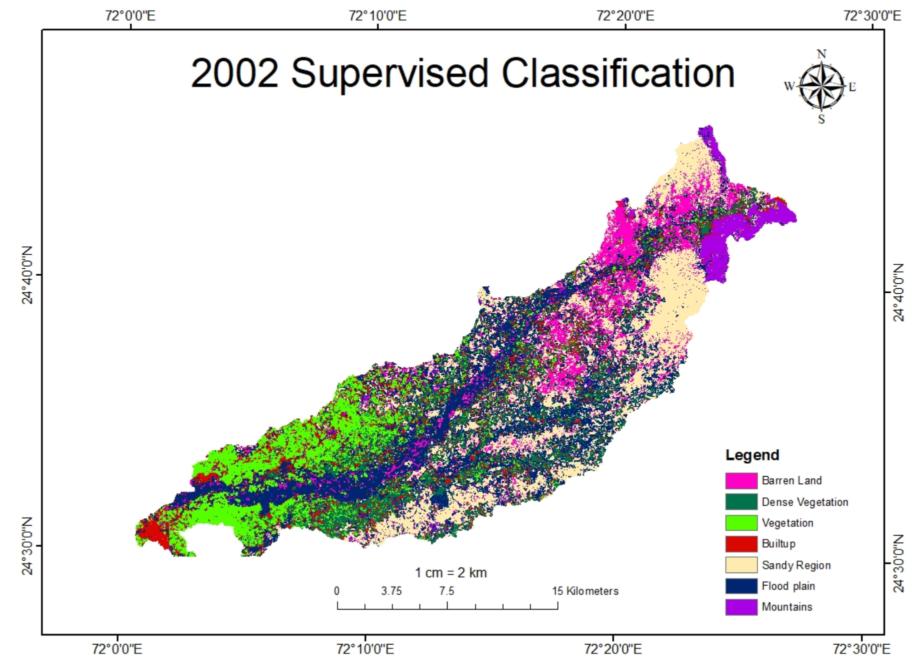

Figure 8: MLC 2002

marked an increase of 236.67%. This is remarkable growth in the vegetation cover which shows improved land management practices and sustainable practices improving the area under vegetation. Various practices like crop rotation, contour farming have contributed in this increase over the years [28]. Barren land meanwhile witnessed an increase of 42.22% growing from 45 square kilometers in 2002 to 64 square kilometers in 2022. The floodplains occupied 124 square kilometers in 2002 and the area for 2022 was 30 square kilometers which meant a decrease of 75.80%. Meanwhile Sandy Regions in 2002 had 105 square kilometers area and decreased to 27 square kilometers in 2022 implying a decrease of 74.28%.The area under mountains went up from 21 square kilometers to 25 square kilometers in 2 decades. This was an increase of approximately 19%. Finally Built up saw an overall growth of 8 square kilometers from being 38 square kilometers in 2002 to rising to 46 square kilometers after 20 years. This was an increase of 21.05%.This rise can be a result of population growth, higher urbanisation and infrastructure developments in the region[20]. Building facilities like roads, transport networks, buildings, schools can spur urban growth [17].

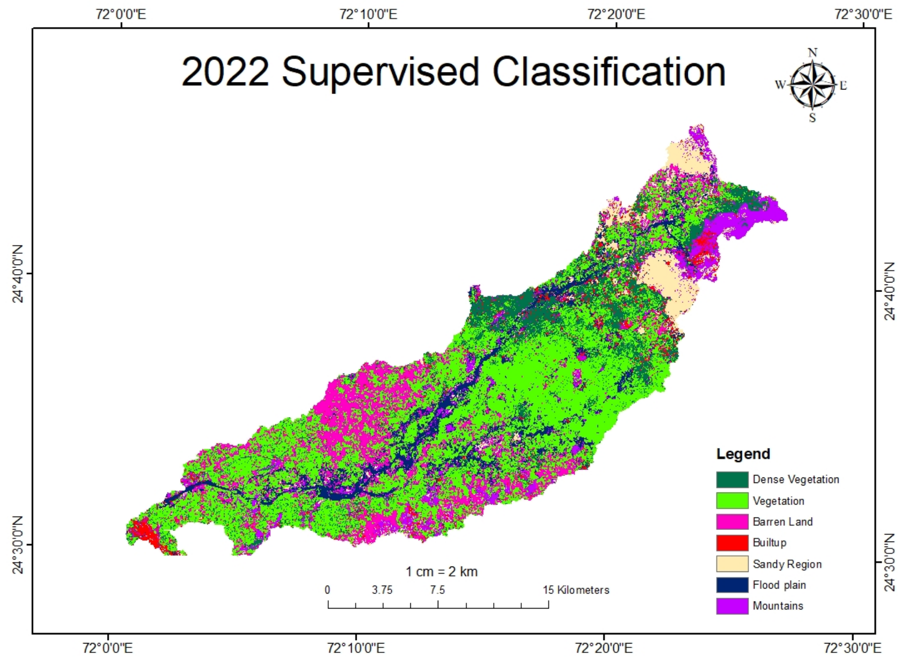

Figure 9: MLC 2022

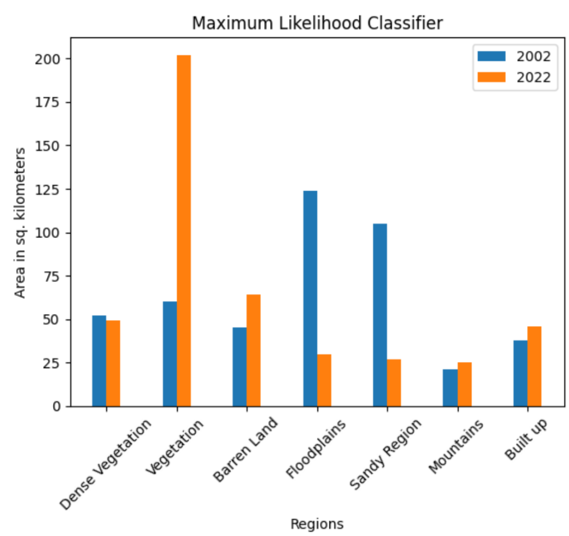

Figure 10: Results using Maximum Likelihood Classifer

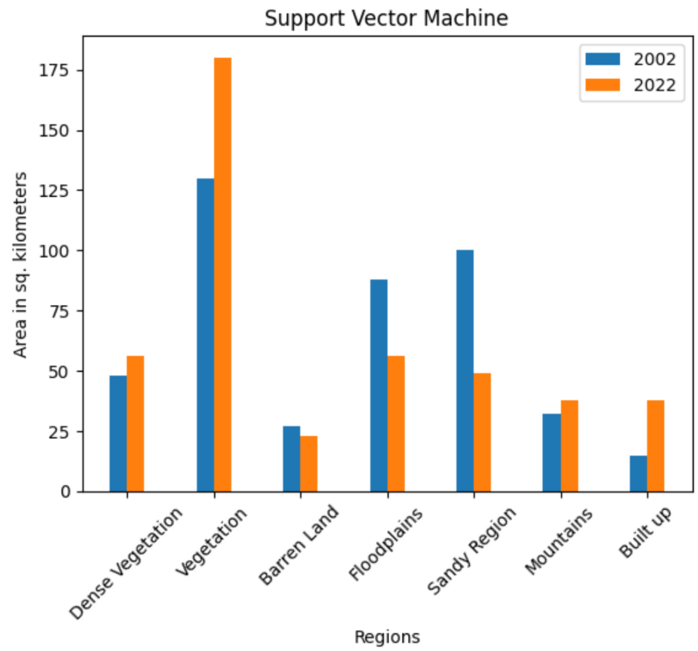

Figure 11: Results using SVM Classifier

As mentioned earlier we have also used SVM model for LULC Classification. Using SVM we have observed and calculated the various changes in the different land covers of 2002 and 2022. Dense Vegetation covered an area of 48 square kilometers in 2002 and rose up till 56 square kilometers marking an increase of 8 square kilometers in 2 decades which can be due to reforestation.This was an increase of 16.67% in the dense vegetation land cover. Vegetation land witnessed upsurge from 130 square kilometers to 180 square kilometers implying and increase of 38.46%. Since both vegetation and dense vegetation classes witnessed a growth this can be attributed to natural factors like favorable climate conditions that has encouraged the growth of vegetation and human efforts like reforestation initiatives, conservation efforts, and urban greening projects [6].The area under barren land decreased by 14.81% from being 27 square kilometers in 2002 to 23 square kilometers in 2022 implying that afforestation and reforestation have transformed barren lands into vegetation land forms which reflect positive changes in the ecosystem [29]. Floodplains meanwhile decreased from 88 square kilometers to 56 square kilometers in 2022 marking a change of 36.36% The Sandy Regions also decreased from 100 square kilometers in 2002 to 49 square kilometers after 20 years implying a decay of 51%. This can be due to agricultural expansion, natural succession, land reclamation and climatic changes among other factors. The area under mountains slightly went up from 32 square kilometers in 2002 to 38 square kilometers in 2022 which is an increase of 18.75%. This can be associated to climatic variability and human activities that can reclassify the land as mountains due to engineering activities [2]. Finally Built up saw raise of 153.33% expanding from 15 square kilometers in 2002 to 38 square kilometers in 2022. The main reason for this as affirmed before is due to the economic growth and rise in housing infrastructure.

5. CONCLUSION

In this paper we have utilised machine learning models like Support Vector Machine (SVM) and Maximum Likelihood Classifier(MLC) along with ArcGIS for assessing Land Use Land Cover (LULC) changes in the study area for the years 2002 and 2022. The study area was a part of the Dhanera region in Banaskantha district of Gujarat state. The results obtained from this research shows the potential of using remotely sensed data from satellite images and machine learning models in providing a detailed insight of the land cover dynamics in a region over a period of time. The result of this study helps in making proper and well informed decisions regarding land management and urban planning in the study area. With the help of continuous advancements in technology we can address critical issues related to sustainable land use practices and environmental conservation along with urbanisation and economic development.

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