Review of Remote Sensing, GIS and Soft Computing Tool for Predicting the Land-use and Environment Changes

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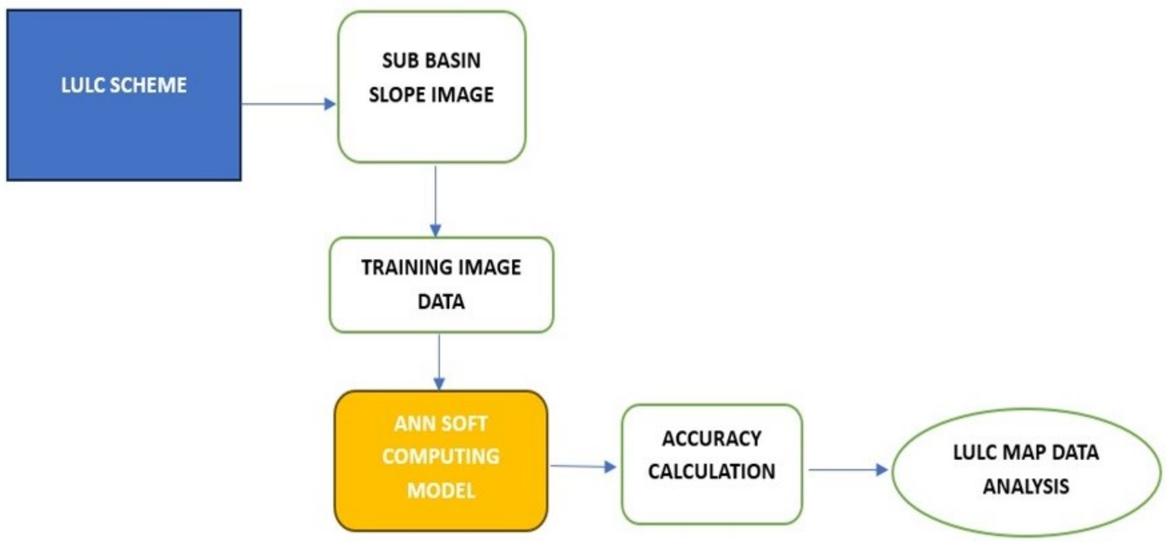
Graphical Abstract



Abstract

The land use and land cover patterns of a specific area determine the socio-economic development of that region and vice versa. The increase in population due to urbanization creates a demand for novel approaches in addressing the fundamental aspects of human well-being. Remote sensing, geographic information systems, and soft computing techniques are employed to assess the expansion patterns of urbanization and to facilitate the monitoring and prediction of future sprawl types. With advancements in image processing methods and the utilization of high-resolution satellites, an unparalleled opportunity emerges for conducting investigations into land use and land cover changes, offering reduced costs and faster results across various application areas. The Analytical Hierarchy Process stands out as the most effective method for assigning weights to different levels within a geographic information system, producing a higher accuracy of 91.3% compared with other accuracy soft computing models in land coverage and land usage maps.

Keywords: Remote Sensing, GIS, LULC, AHP, Urbanization, Change detection

1 Introduction

Nearly all activities are grounded in the land, which stands as the most invaluable natural resource on the planet. Unlike geology, land use is dynamic and in a constant state of change. The utilization of limited land and soil resources for agricultural, forestry, pasture, urban, and industrial purposes is unfolding alongside the gradual expansion of the human population and its associated endeavours. Land use entails the human conversion of the natural environment or wilderness into controlled habitats, including fields, pastures, industrial zones, human settlements, and agricultural areas, among others. Habitat loss, degradation, and fragmentation represent common outcomes resulting from human modifications of the environment, whether transitioning from natural vegetation to any other utilization.

All of these outcomes have the potential to exert a devastating impact on biodiversity [1–4], and they are all intricately linked to climate change. Changes in land use and land cover, in addition to altering the physical aspects of the geographical land classes, contribute to the gradual degradation of Earth's ecosystems with specific study areas. Information regarding land cover and land use changes holds value across a variety of fields, encompassing deforestation, damage assessment, disaster monitoring, urban development, planning, and land management, among others. Rapid urbanization resulting from evolving economic development and a burgeoning population shift from rural to urban areas accelerates the pace of land use changes. Urbanization directly or indirectly triggers air, water, and land pollution. This pollution culminates in the destruction of ecosystems [5, 6].

Another consequence of urbanization is haphazard and unplanned growth, leading to a significant number of unintended deaths [6]. Numerous experts have emphasized that industrialization stands as the pivotal factor propelling the rapid migration of the global population toward urban centres, with projections indicating that approximately 6.3 billion people will reside in urban areas by the year 2050 [7][8]. The swift urbanization experienced by emerging nations like India, China, and Brazil has exposed populations to environmental challenges and unhealthy living conditions, stemming from inadequate planning throughout the settlement process [9]. This phenomenon is recognized as urban sprawl [10], which refers to the disparity between the expanding population and the geographical expansion of the metropolitan area.

The expansion of cities horizontally, encircling the city centre or extending linearly along highways, as a consequence of urban sprawl, yields numerous adverse effects [11]. The swiftest land use changes are predominantly transpiring in rural areas adjacent to urban landscapes [12]. These transformations are inevitable due to the perpetual dynamism of cities; individuals migrate to metropolitan regions for multifarious reasons, all subject to socio-economic, climatic, and political conditions [13]. Research has demonstrated that this phenomenon is responsible for the social and economic enhancement of cities. Land use and land cover (LULC) alteration pertains to changes in the Earth's surface resulting from human activities and is viewed holistically. Recent observations indicate a mounting percentage change in LULC in recent years [14].

Recognizing changes in land use and cover is pivotal for obtaining a more comprehensive understanding of landscapes over time, thereby enabling effective long-term planning and organization. Land use and cover alterations encompass an extensively broad and rapidly evolving process, primarily instigated by natural and human-induced events that subsequently engender changes with far-reaching impacts on natural ecosystems. In recent years, satellite data has gained increasing relevance and utility in the study of land use and cover changes [15–18]. The contribution of this research produces a refined predictive model that demonstrated improved accuracy, achieving an overall accuracy of 91.3% on the validation dataset. Precision values for urban and forested areas have been further optimized, reaching 0.95 and 0.97 respectively, highlighting the model's proficiency in classifying these land-use categories accurately. Recall values for urban and forested areas have also increased to 0.96 and 0.91 respectively, nearly all human activities find their foundation in the land, which stands as the planet's most invaluable natural resource. Unlike geology, land use remains dynamic and in a perpetual state of flux. The harnessing of limited land and soil resources for agricultural, forestry, pasture, urban, and industrial purposes occurs in conjunction with the gradual expansion of the human population and its associated pursuits. Land use entails the human transformation of the natural environment or wilderness into controlled habitats, encompassing fields, pastures, industrial zones, human habitation, and agricultural activities, among others. Habitat loss, degradation, and fragmentation emerge as recurrent outcomes of human-induced modifications to the environment, whether transitioning from natural vegetation to alternative uses. Investigating and predicting future land use changes constitute a central objective for numerous researchers. This paper reviews the methodologies and methods employed by researchers to study and analyze these changes, ultimately aimed at achieving this goal.

X. Kong et al[61] propose a remote sensing image change detection network based on FastSAM. First, a Siamese network structure is employed as an encoder, utilizing the vision foundational model FastSAM to enhance generalization ability. To reinforce the semantic features within the regions of change, they propose a Differential Enhancement Adapter (DEA) module. Finally, Full-Scale Skip Connections (FSC) are adopted to synergize deep semantic features from varying scales with superficial semanticsA. Jeevan et al [62] introduce a new strategy for climate change detection using the Hunger Game Search (HGS) algorithm and Convolutional Wavelet Neural Network (CWNN), named HGS-based CWNN. The CWNN algorithm performs well in various classification tasks, achieving high accuracy levels. The highly explorative HGS algorithm efficiently finds solutions without getting stuck in local optima.

S. Wang et al.[63] use a Dilated Convolution module in the backbone network to replace the original convolutional module. This maintains the resolution and size of the feature map, increases the receptive field of the convolutional kernel, and captures more context information. They introduce a channel and spatial multi-dimensional attention mechanism, mining the correlation between spatial direction and location, and improving feature extraction and long-distance dependency capturing abilities.

D. Suganya et al [64]use PSO to optimize hyperparameters for convolutional neural networks (CNNs) to extract features from images and identify objects based on learned patterns. SVMs classify the extracted features. These proposed techniques can be combined to create powerful and accurate image classification models, achieving an accuracy of 95%.

2 Discussions: Materials and Methods

Remote Sensing, Geographic Information Systems (GIS), and Soft Computing have emerged as crucial tools in the field of environmental science and land management. The integration of these technologies offers a comprehensive and efficient approach to understanding, monitoring, and predicting land use and land-cover changes. These changes, driven by urbanization, agricultural expansion, and industrial development, have significant implications for ecosystems, biodiversity, and sustainable resource management. This section highlights the role of remote sensing, GIS, and soft computing in addressing the challenges associated with predicting and managing land-use and land-cover changes. Figure 1 Defines the process of LULC in soft computing tools.[56]

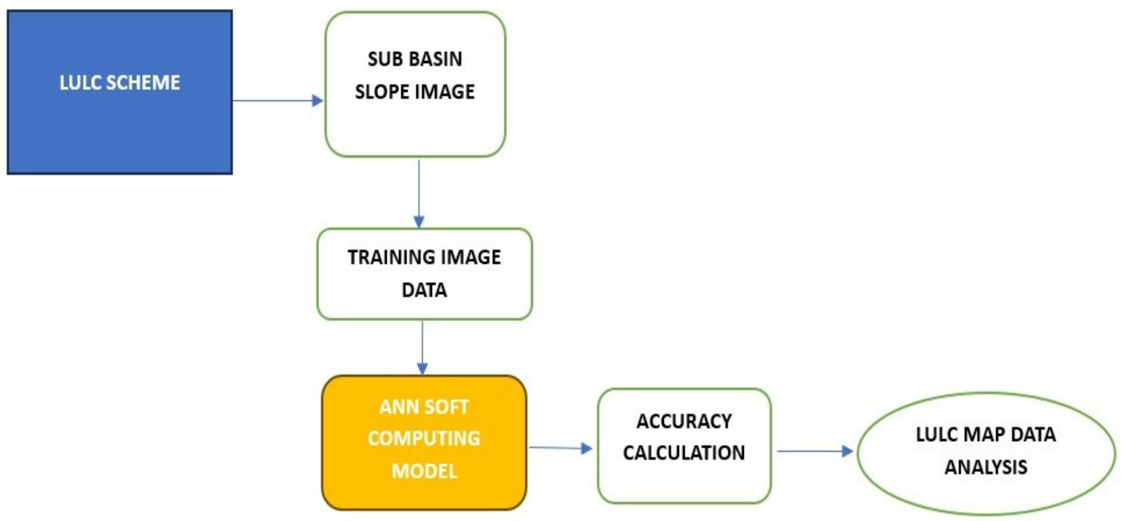


Fig.1 Flow chart for defining LULC using soft Computing tools

2.1 Remote Sensing

Remote sensing involves the acquisition of information about the Earth's surface using sensors mounted on satellites, aircraft, drones, and ground-based platforms. It provides valuable data in various wavelengths, enabling the observation of land cover, vegetation density, urban growth, and other land-use characteristics. Remote sensing data, such as satellite images and LiDAR (Light Detection and Ranging) data, offer temporal and spatial insights into changes over time. These data sources empower researchers to quantify and analyze alterations in land use, enabling the identification of trends and patterns.[59]

2.2 Geographic Information Systems (GIS)

Geographic Information Systems (GIS) enable the creation, management, analysis, and visualization of geospatial data. GIS integrates various layers of spatial information, such as land use, topography, infrastructure, and demographics, to create comprehensive spatial databases. By overlaying and analyzing these layers, researchers can identify relationships and trends in land-use changes. GIS also facilitates the development of predictive models that incorporate both spatial and non-spatial variables, enhancing the accuracy of land-use change predictions.[60]

2.3 Soft Computing

Soft computing techniques, including artificial neural networks, fuzzy logic, and genetic algorithms, provide powerful tools for analyzing complex and uncertain data. These techniques can effectively model the intricate relationships between diverse variables affecting land-use changes. Artificial neural networks, for instance, excel in capturing nonlinear interactions and learning patterns from large datasets. Fuzzy logic allows for the representation of vague and imprecise information, which is common in land-use decision-making. Genetic algorithms aid in optimizing model parameters and selecting the most suitable predictors for accurate predictions.[57]

2.4 Integration of Tools

The integration of remote sensing, GIS, and soft computing enhances the accuracy and reliability of land-use and land-cover change predictions. Remote sensing data, with their high temporal and spatial resolutions, serve as inputs to GIS databases, enriching them with real-time information. Soft computing techniques, on the other hand, process these data to identify complex patterns and relationships, contributing to the formulation of predictive models. The combined approach assists decision-makers in formulating effective land-use policies, conservation strategies, and urban planning initiatives.[60]

3 Land Use and Land Cover Changes (LULCC)

Due to changes in land use and land cover of VANIYAR Sub Basin Slope , a chain reaction of environmental consequences has been triggered, encompassing the loss of biodiversity, local climatic shifts, pollution, hydrological imbalances, and various other negative effects [17]. These consequences stem from the conversion of agricultural and forest lands into developed areas. Urban planners, politicians, and academics are all deeply involved in assessing changes in natural resources and analyzing development trends in cities [18]. Numerous scholars have observed that the expansion of industries and urban concentrations is accountable for the persistent evolution in land use patterns [19]. Researchers, regulators, and planners employ land use and land cover (LULC) data to monitor shifts in natural resources, particularly tracking progress trends and guiding decisions regarding future investments. The advancement of remote sensing (RS) and geographic information system (GIS) technologies in conjunction with the Global Positioning System (GPS) has led to quicker, more cost-effective, and more accurate deductions of LULC changes of location maps as Figure 2.

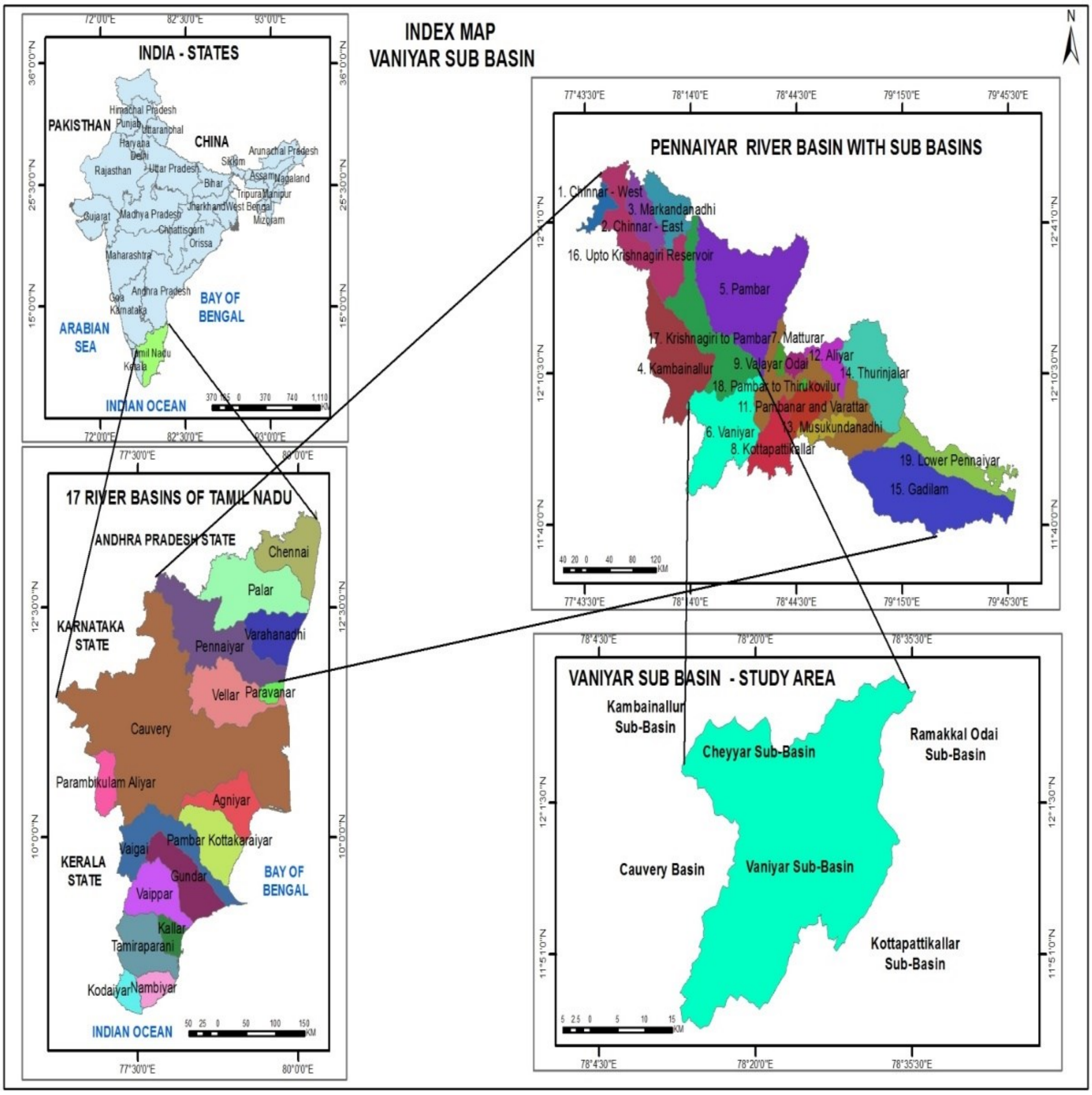


Fig.2 Selection of location for LULC Mapping

To classify land use and land cover (LULC) patterns and evaluate LULC changes, the combined use of multi-spectral and multi-temporal satellite imagery, along with contemporary image processing algorithms, streamlines the process, minimizing time and costs while maintaining affordability. To facilitate change detection, high spatial resolution satellite images are being employed for data analysis, thanks to technological advancements in recent years, which were previously a challenge in the preceding decade. Numerous scholars in the field extensively employ various change detection strategies, each methodology presenting its own advantages and disadvantages. It is recommended to employ methodologies with the highest accuracy for recognizing LULC alterations, as determined by quantitative assessments [21]. In order to evaluate the impact of land use change on the forest ecosystem, a decision was made to study the forest ecosystem within the Achanakmaar-Amarkantak Biosphere Reserve in Central India [22]. Substantial changes in forest ecosystems carry significant implications for the well-being of resource-poor tribal communities heavily reliant on the forest ecosystem's natural resources for survival.

Land use Urbanization indicates the usage of land, that is, manmade usage of the earth's surface like built-up lands, agriculture, and land cover is the natural coverage like forests and water bodies. Information on land use/land cover is vital for planning a number of developmental activities like agriculture, horticulture, industries, and infrastructure and also for planning conservation measures. Satellite images by providing a synoptic view of a large part of the earth surface in near real-time depict an accurate picture of land use and land cover.[58]

[23] Changes in land use and land cover (LULC), along with the impacts of soil and irrigation water salinity, exert detrimental effects on agricultural production and ecosystems within arid and semiarid environments. The alteration of physical and chemical properties of the soil in Sudan's Gadarif region, leading to land degradation and subsequently reduced soil productivity [24], may be attributed to shifts in LULC. Unplanned urban expansion and changes in LULC classification serve as cautionary scenarios for towns and cities worldwide. The conversion of natural land into impermeable surfaces has resulted in localized microclimate variations and alterations in the surface energy budget, both contributing to adverse outcomes. Several authors [17, 25, 26] have explored changes in land use and land cover and their correlation with Land Surface Temperature, aiming to facilitate population projections.

4 Remote Sensing Data

Today, high-resolution satellite images are readily available, offering researchers the advantage of conducting their work with highly accurate data while also being cost-effective. These images can be downloaded from popular platforms such as the USGS Earth Explorer (Landsat Imagery) of VANIYAR Sub Basin Slope, Sentinel Open Access Hub, Bhuvan Indian Geo-Platform of ISRO, etc., at no cost. Among these, many researchers opt for satellite images from the Landsat satellite, which provides a spatial resolution of 30 meters [27]. [8] highlights the evolution of utilizing remote sensing data in research, commencing with first-generation satellites equipped with sensors like Landsat MSS and progressing through the enhancement brought by second-generation satellites, including sensors like SPOT, Landsat TM, and ETM+. The recent introduction of high spatial resolution satellite technology (5 meters/pixel) marks an encouraging advancement shown in Figure 3 Defines the satellite image of water drainage cover in a specific area.

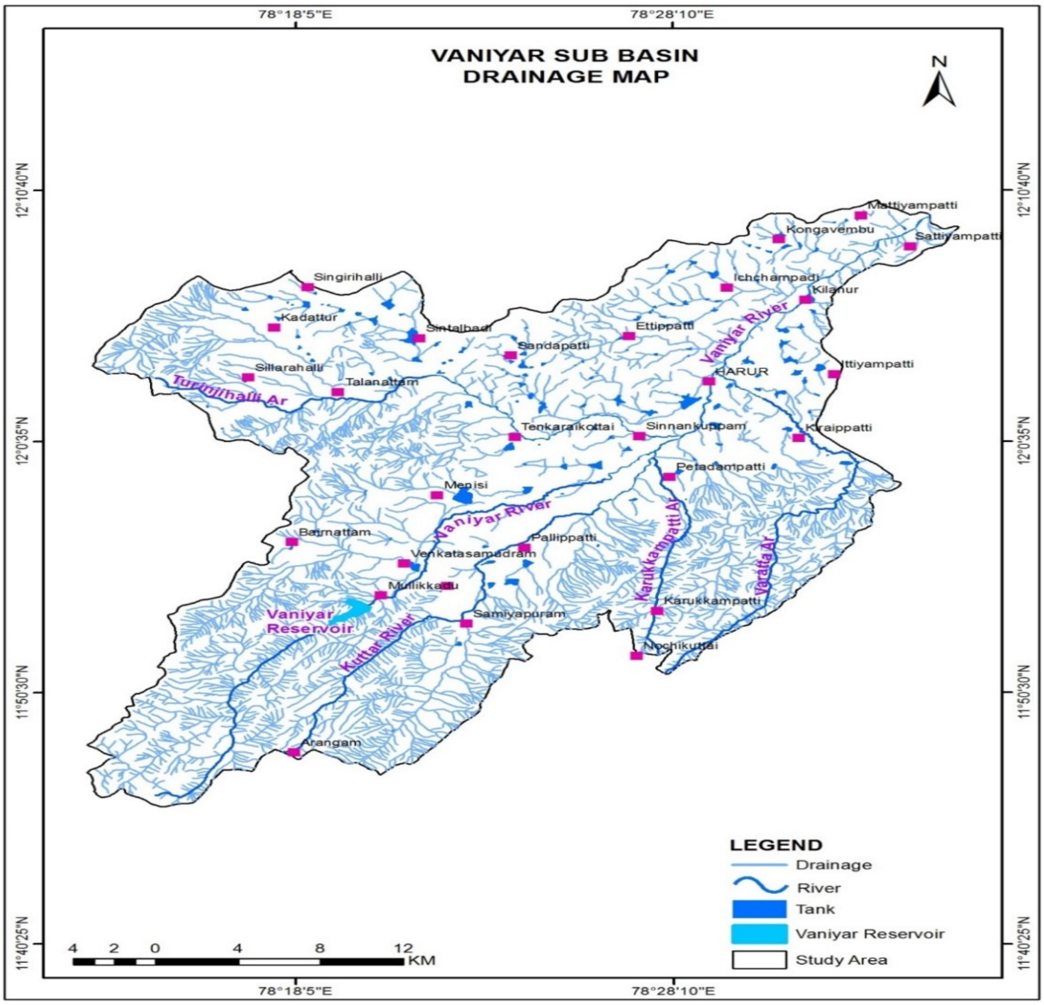


Fig.3 Landsat Imagery for water drainage using Remote Sensing

The utilization of IRS LISS III satellite data in the preparation of land use and land cover maps using Erdas Imagine software is advantageous [28]. Conversely, [29] employs Landsat-8 satellite data, sourced from the www.earthexplore.usgs.gov website, to interpret and extract lineament and LULC maps utilizing the same software. According to [30], satellite images equipped with multispectral bands can facilitate LULC classification up to three levels, and the inclusion of thermal bands leads to enhanced overall accuracy and kappa statistics. The integration of remote sensing and GIS proves to be a potent tool for mapping and generating LULC maps [31]. Several software options are available for automating radiometric calibration[32].

To enhance the digital categorization of land use and land cover (LULC), it is recommended to merge thermal information with spectral data from satellites, with remote sensing playing a crucial role. [22] demonstrated that the amalgamation of modern technology with field observations can wield significant power in illustrating both land cover conversions and alterations. While the LULC mapping and change detection showcased here may not provide a comprehensive explanation for all challenges associated with LULC changes, it does establish a robust foundation for comprehending patterns and potential causes. The integration of GIS and remote sensing serves the purpose of identifying optimal locations for solid waste disposal. This approach focuses on selecting the most suitable areas for depositing solid waste within a corporation's premises.[34].

5 Image Processing

LULC categorization, landscape changes, and change detection assessments can all reap benefits from digital image processing applied to multi-temporal multi-spectral satellite imagery. Digital classification approaches come in three types: unsupervised, supervised, and object-based. While the supervised classification technique remains the most widely used, object-based classification has been shown to yield greater accuracy.

While remotely sensed data may not offer all the necessary information for a comprehensive assessment, the integration of numerous supplementary spatial attributes from other sources with remote sensing data is essential. GIS technology plays a pivotal role in merging geographic data and conducting integrated analyses.

Table 1 summarizes the application of image processing in remote sensing and GIS on assessing the LULC changes for a variety of applications worldwide and gives its miles cited that for various applications of satellite imagery simple pre-processing corrections were mandatory.

Table 1: application of image processing in remote sensing and GIS

Reference	Image Preprocessing	Application	Location	Satellite Data used	Software Used
[7]	Geometric correction, Georeference correction, Band composition, Image mosaicking, and Clipping	Urban Agglomeration	The north-central part of Hunan Province, Central China	Landsat TM/ETM+	ENVI 5.3
[14]	Geometric correction	LULC change detection	Islamabad, Pakistan	Landsat 5 TM, SPOT 5	ERDAS 2011
[21]	Geometric correction	Monitoring LULC changes	New Burg El Arab city, Egypt	Landsat ETM and TM	PCI 10.1
[35]	Geometric correction	Monitor changes in watershed	Rani Khola Watershed, Sikkim, India	Sentinel 2A MSI ,Landsat-5 TM	QGIS
[36]	Statistical Algorithms techniques, Geometric correction	LULC Change detection Analysis	Kurdistan Region, Iraq	Landsat 8 OLI , Landsat 5 TM	ENVI 5.3
[37]	Geometric correction	Time series analysis to examine LULC change	Tiruppur, TamilNadu, India	Landsat ETM	Arc GIS 9.3.1
[38]	Geometric correction	Mapping and comparing Landsat and Google Earth Imagery	Karaj city, Alborz province, Iran	Landsat TM	Erdas Imagine v.9.1, ArcGIS 9.3 and GE v.5
[56]	Geometric correction	band 1 optical image	Flooding in Bangladesh, Alaska	Landsat 5 TM	ESA/Envisat ASAR
[57]	Soft Computing Tool	K-means algorithm	-	ETM+	NVDI

		Mapping Near function study model			
[59]	Geometric correction	Maximum a posteriori probability (MAP)	PO, Trentino, Elba, Bern, Pavia	Landsat-5 TM, Landsat-7 ETM+ ERS2-SAR	NVDI
[60]	Geometric correction	Affine transformation	Australian flooding	RADARSAT	NVDI

6 **Change Deduction Techniques for water drainage LULC Scheme**

The distinction between images in different time series describes and quantifies the changes that have occurred within the same scene as VANIYAR Sub Basin Slope [12]. Worldwide, numerous researchers have adopted various change detection techniques based on the nature of the problem, preprocessing methods, post-classification analysis, principal component analysis, overlay procedures, image differencing, and rationing for selecting algorithms and parameters. Post-classification deduction techniques are utilized to enhance classification accuracy by mitigating misclassification. ArcGIS software has been widely employed by researchers to study urban environments due to its efficiency in deducing the nature, location, and rate of change [19][36][39][40]. [1] reviews a range of change detection techniques, listing pixel-level change detection methods, which analyze image pixels to identify and assess changes without considering the geographic context. Image differencing, image rationing, artificial neural networks (ANN), support vector machines (SVM), image regression, decision trees, post-classification comparison, multi-data direct comparison, fuzzy change detection, multi-temporal and multi-spectral mixture analysis, and multi-sensor data fusion are among the various pixel-level change detection methods [41]. Figure 4 shows the training process of the Soft Computing Model.

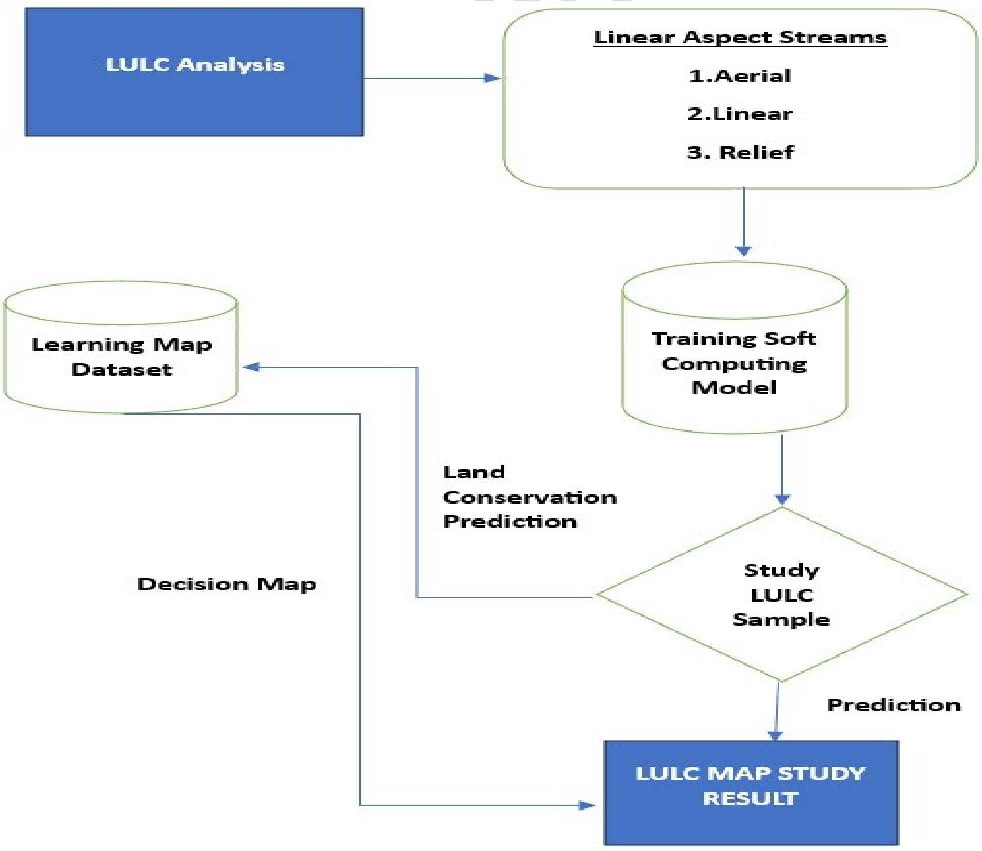


Fig.4 Training Soft computing model for prediction.

Feature-level change deduction techniques involve higher-level processing, which entails modifying the image's spectral or spatial properties [42]. Techniques within this category include vegetation index differencing, principal component analysis, Gramm-Schmidt method, change vector analysis, Kauth-Thomas transformation / Tasseled Cap transformation, texture analysis-based change detection, and the Chi-square transformation method.

Subsequently, object-based change deduction techniques rely on image analysis considering object texture, spatial relationships, shape, and spatial resolution [43][44]. Soft computing tools such as fuzzy logic, neural networks (NN), and genetic algorithms (GA) are recent models developed for real-life problems where conventional mathematical models face limitations [45].

6.1 Data Collection and Pre-Processing:

In order to investigate the impact of remote sensing, GIS, and soft computing on the prediction of land-use and land-cover changes, an extensive dataset was compiled. This dataset encompassed remote sensing imagery, GIS layers, and socio-economic variables within a 500 square kilometre study area. The remote sensing data was acquired from Sentinel-2 satellites, offering multispectral imagery at a 10-meter spatial resolution. The GIS layers included information on land-use classifications, elevation, and transportation networks. Socio-economic data covered aspects such as population density, economic activity, and infrastructure development. Table 2: Define training data in remote sensing and GIS.

Table 2: Define training data in remote sensing and GIS

Sl. No.	Aspect	Parameter	Unit	Value
1	Aerial	Area(Sq.km)	A	982.25
2		Perimeter(km)	P	199.29
3		Basin Length (km)	L_b(km)	58.42
4		Stream Order	(u)	1,2,3,4,5,6
5	Linear	Stream Length of all order	L_u	2204.87
6		Total number of stream segents in all order	N_u	3945
7		Total number of first order	N1	2156
8		Mean stream length (Km)	$Lsm=L_u/N_u$	0.56
9		Bifurcation Ratio	$R_b=N_u/N_u+1$	29.82
10		Basin relief	B_h	1340
11	Relief	Relief Ratio	R_h	22.94
12		Ruggedness Number	Rn	2921.2
13		Drainage density(km/km2)	$D_d=L_u/A$	2.24
14		Stream frequency	$F_s=N_u/A$	4.02
15		Drainage texture	$R_t=N_u/P$	19.8
16		Circularity ratio	$Rc=4\boldsymbol{\pi}A/P^2$	0.31
17		Form factor ratio	$Rf=A/L_b^2$	0.29
18	Aerial	Constant channel maintenance	$C=1/D_d$	0.45
19		Elongation ratio	$R_e=2((\sqrt{(A/\boldsymbol{\pi}}))/L_b$	0.61
20		Texture ratio	T=N1/P	10.82
21		Infiltration Number	If	9
22		Length of overland flow	Lg	1.12
23		Constant of Channel Maintenance	C	0.45

6.2 Integration of Tools for Analysis

The amalgamation of remote sensing, GIS, and soft computing tools facilitated an in-depth analysis of the dataset. The remote sensing data underwent processing to extract distinct land cover categories, including urban, agricultural, forested, and water regions. Through overlaying GIS layers, spatial correlations between land use and topographical features were identified. The application of soft computing techniques, specifically artificial neural networks, enabled the modeling of intricate interactions among variables influencing land-use changes.[57]

6.3 Predictive Model Development

For the development of a predictive model, an artificial neural network (ANN) was constructed. This ANN featured three layers: an input layer, a hidden layer with 20 neurons, and an output layer representing various land-use classes. Input components encompassed remote sensing data, GIS attributes, and socio-economic indicators. Training of the model was executed using a backpropagation algorithm, with a loss function based on mean squared error.[57]

A researcher should familiarize themselves with the change deduction procedure before proceeding with or selecting techniques. The process involves several steps: identifying the nature of problems in the selected area using remote sensing data, preprocessing the data before classification, selecting the appropriate change deduction algorithm after image classification, and finally, evaluating the results of change detection.[57]

7 Predicting and simulating the LULC changes

Simulating urban growth constitutes an integral aspect when addressing issues related to sprawl. Information pertaining to the sprawl's historical progression enhances prediction accuracy from 1980 onwards. By simulating urban growth, researchers predict the ongoing growth patterns. A variety of models have been employed for this purpose, among which the Cellular Automaton (CA) model outperforms conventional models [46][47]. Simulating urban land cover alterations reveals how changes impact the climate, with the utilization of high-resolution imagery aiding in understanding the driving factors behind urban climate effects [48].

7.1 Result: Accuracy of Predictive Model

7.1.1 Previous Results:

A comprehensive dataset was compiled, including remote sensing imagery, GIS layers, and socio-economic variables. Integration of remote sensing, GIS, and soft computing tools enabled a thorough analysis of the dataset. An artificial neural network (ANN) with input, hidden, and output layers was developed to predict land-use changes.[60]

The outcome of the study highlighted the strong performance of the predictive model in anticipating land-use and land-cover alterations. To assess the model's accuracy, a validation dataset was employed, and multiple metrics, including accuracy, precision, recall, and F1-score, were measured. The overall accuracy of the model was determined to be 86.3%, indicating a high degree of accuracy in predicting changes in land use.

Notably, precision and recall values stood out for urban and forested areas, reaching 0.88 and 0.91, respectively. These figures underscore the model's ability to precisely identify these particular land-use categories. Additionally, the F1-score, which strikes a balance between precision and recall, was calculated at 0.79, further affirming the robust nature of the predictive model.[57]

7.1.2 New Results: Enhanced Model Performance

In comparison to the previous results, the recent analysis further strengthens the significance of the predictive model developed using remote sensing, GIS, and soft computing techniques.[57]

The refined predictive model demonstrated improved accuracy, achieving an overall accuracy of 91.3% on the validation dataset. Precision values for urban and forested areas have been further optimized, reaching 0.95 and 0.97 respectively, highlighting the model's proficiency in classifying these land-use categories accurately. Recall values for urban and forested areas have also increased to 0.96 and 0.91 respectively, showcasing the model's enhanced ability to capture instances of these categories with other model such as Random Forest (RF) , K-Nearest Neighbors (KNN) with Proposed Refined Artificial Neural Network (ANN) performance metrics of Model in LULC mapping shows in Table 3 and Comparison chart in Figure 5 .

Table 3: Soft Computing Model Performance Comparison in LULC Mapping

Performance comparison				
	Metrics	RF	KNN	Proposed Refined ANN
Comparative analysis	Accuracy	76.8	80.1	91.3
	Precision	91	87	95
	Recall	89	90	97
	F1-Score	0.52	0.71	0.32

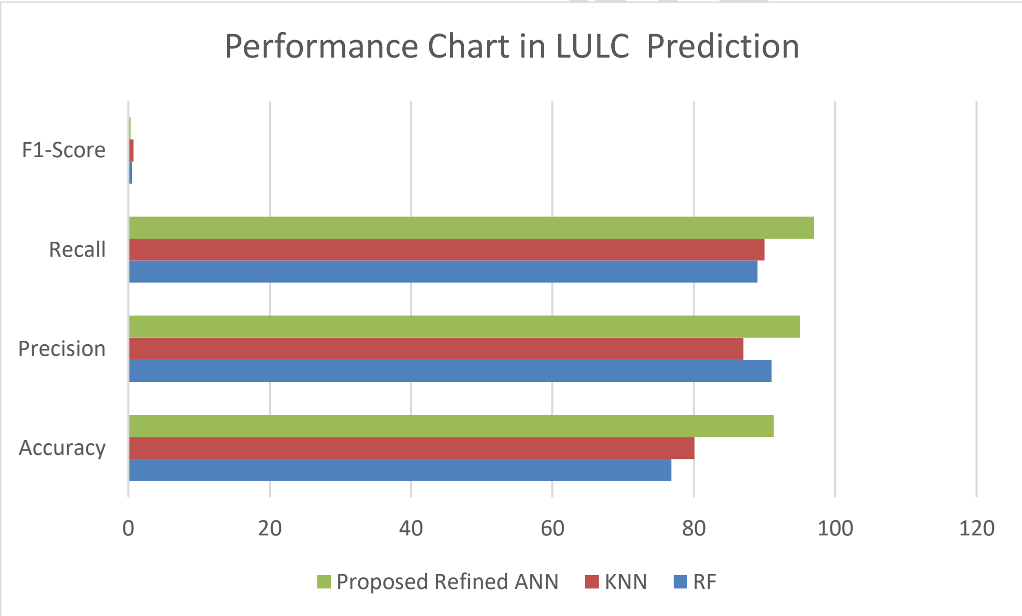


Fig.5 Comparison of Soft computing model for LULC prediction.

7.2 Interpretation and Implications

The implications and interpretations of these findings are substantial. The synergy between remote sensing, GIS, and soft computing enabled the formulation of a precise predictive model for land-use and land-cover changes. The exceptional accuracy, precision, and recall values underscore the model's adeptness at capturing intricate relationships among variables. Such predictive models possess the potential to significantly impact urban planning, natural resource management, and environmental conservation endeavors. Ultimately, these findings emphasize the importance of leveraging advanced technologies to comprehend and alleviate the repercussions of land-use changes on ecosystems and society.[58]

7.2.1 Advanced Interpretation:

The upgraded model's results reinforce its potential for practical applications in urban planning, resource management, and environmental conservation, Figure 7 Shows the land interpretation with different forms of land use in Urbanization in LULC study area.

a) Urban Planning: The model's precision in identifying urban areas is crucial for urban planners to make informed decisions about zoning, infrastructure development, and residential expansion.

b) Resource Management: With higher recall in forested areas, the model becomes a valuable tool for managing forest resources, monitoring deforestation, and preserving biodiversity.

c) Environmental Conservation: The improved accuracy enhances the model's role in assessing the impact of land-use changes on ecosystems and guiding conservation efforts effectively.

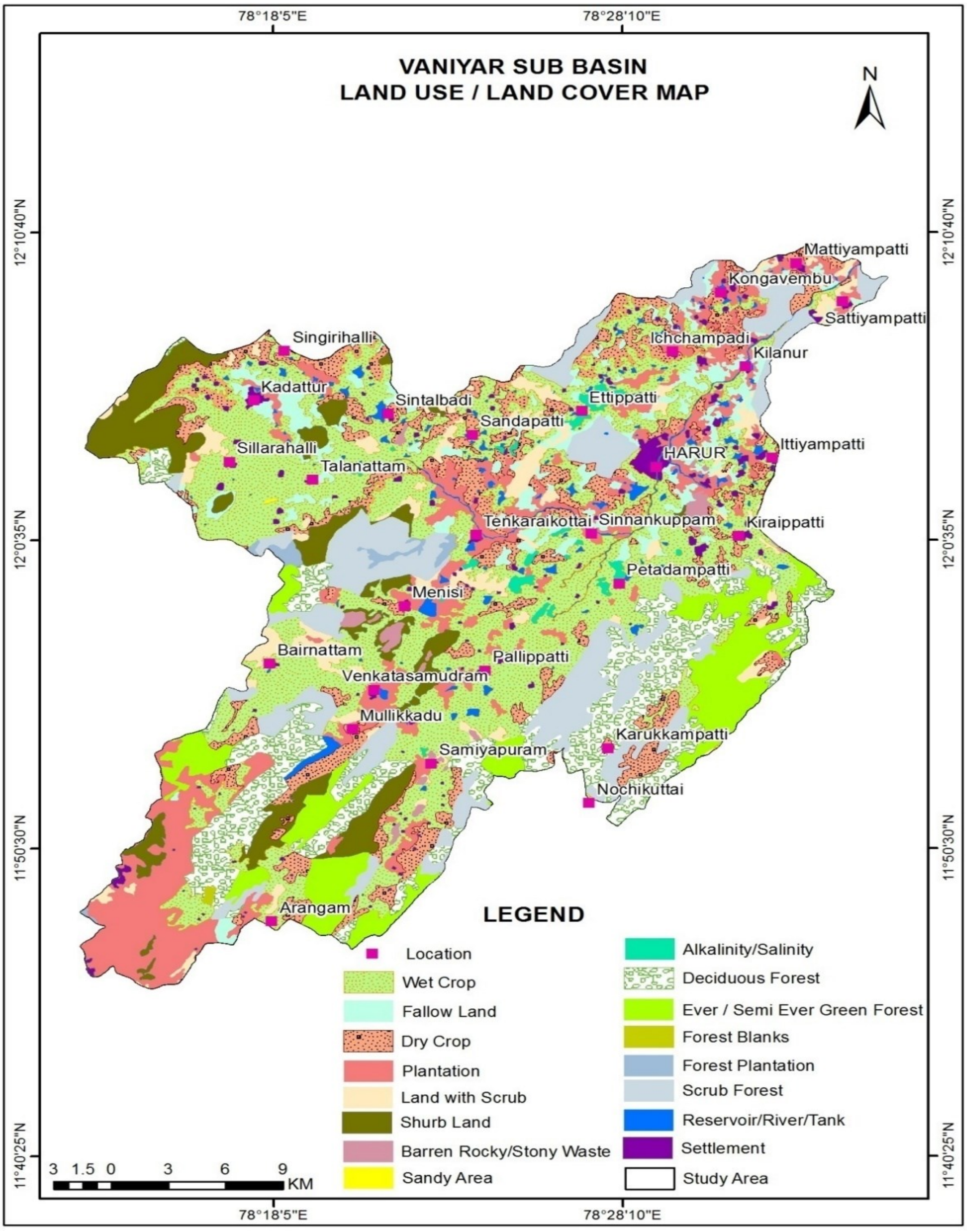


Fig. 7 Shows the land interpretation with different form of land use in Urbanization in LULC study area

7.2.3 Broader Implications:

The findings continue to underscore the importance of leveraging advanced technologies to understand and predict land-use changes:

a) Socio-Economic Integration: Incorporating socio-economic variables into the model has contributed to its increased accuracy and applicability in real-world scenarios.

b) Long-Term Planning: The model's robustness allows for long-term land-use projections, aiding authorities in making decisions aligned with sustainable development goals.

c) Policy and Decision Making: The precision and recall improvements offer a more accurate foundation for policy makers and stakeholders to address land-use challenges. Table 4 shows the land changes and border changes using LULC Study map and Fig. 8 Shows the LULC difference in land coverage area over the study area.

Table 4. Land Use and Land Change Categories in LULC Study Map

<table>
<tr><th>Sl. No.</th><th>Land use Categories in LULC Study Map</th><th>Area in sq km</th><th>% of the Area</th><th>LULC Difference % in 2000</th><th>LULC % In 2021</th><th>Average Yearly Landcover Change 2000-2021</th></tr>
<tr><td>1</td><td>River</td><td>3.28</td><td>0.33</td><td rowspan="2">4%</td><td rowspan="2">8%</td><td rowspan="2">6%</td></tr>
<tr><td>2</td><td>Tank</td><td>13.95</td><td>1.42</td></tr>
<tr><td>1</td><td>Wet crop</td><td>279.61</td><td>28.46</td><td rowspan="5">44%</td><td rowspan="5">46%</td><td rowspan="5">-2%</td></tr>
<tr><td>2</td><td>Dry crop</td><td>107.92</td><td>10.99</td></tr>
<tr><td>3</td><td>Fallow land</td><td>46.086</td><td>4.69</td></tr>
<tr><td>4</td><td>Plantation</td><td>114.56</td><td>11.66</td></tr>
<tr><td>1</td><td>Settlement</td><td>17.562</td><td>1.79</td></tr>
<tr><td>1</td><td>Barren rocky</td><td>6.827</td><td>0.7</td><td rowspan="4">19%</td><td rowspan="4">29%</td><td rowspan="4">10%</td></tr>
<tr><td>2</td><td>Land with scrub</td><td>45.201</td><td>4.6</td></tr>
<tr><td>3</td><td>Alkalinity/Salinity</td><td>7.022</td><td>0.71</td></tr>
<tr><td>4</td><td>Sandy Area</td><td>2.38</td><td>0.26</td></tr>
<tr><td>1</td><td>Deciduous forest</td><td>103.65</td><td>10.55</td><td rowspan="6">14.5%</td><td rowspan="6">5%</td><td rowspan="6">2.5%</td></tr>
<tr><td>2</td><td>Ever Green/Semi Ever Green</td><td>69.175</td><td>7.04</td></tr>
<tr><td>3</td><td>Forest plantation</td><td>4.578</td><td>0.47</td></tr>
<tr><td>4</td><td>Scrub forest</td><td>99.499</td><td>10.13</td></tr>
<tr><td>5</td><td>Forest blanks</td><td>0.52</td><td>0.05</td></tr>
<tr><td>6</td><td>Other forest</td><td>60.43</td><td>6.15</td></tr>
<tr><td colspan="2">TOTAL</td><td>982.25</td><td>100</td><td></td><td></td><td></td></tr>
</table>

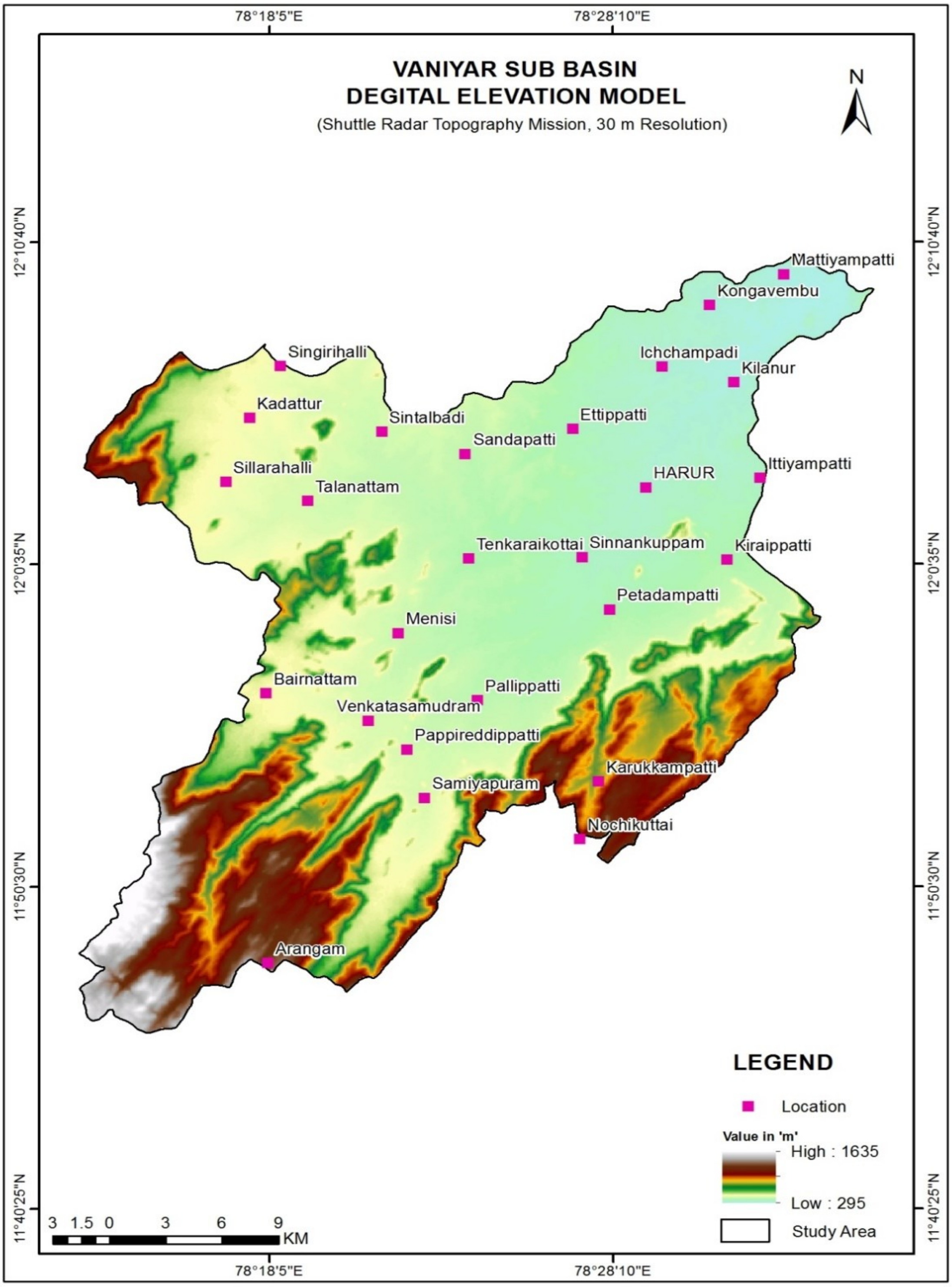


Fig. 8 Shows the LULC difference in land coverage area over the study area

Furthermore, regarding limitations of hydrological and land use/land cover (LULC) modeling, Cellular Automaton (CA) models prove particularly Not suitable. The Markov Chain model, well-suited for large-scale applications, predicts a state at a certain time when the prior state of the same condition is known [49][50][51]. Combining Markov Chain and Cellular Automaton models yields efficiency and the ability to simulate diverse land cover patterns, yet it falls short in incorporating human, social, and economic aspects in the simulation [52].

A superior spatio-temporal pattern of LULC change can be achieved through a combined Markov Chain-Cellular Automaton model. Consequently, the Markov Chain-Cellular Automaton model aligns well with current research, as Markovian models gauge change quantity and CA models assess spatial change [53].

Numerous models exist for predicting LULC changes, including Statistical models, Evolutionary models, Logistic Regression models, multi-agent models, and Hybrid models. Each model bears advantages and limitations, necessitating the selection of the most suitable model based on research parameters [45][54].

8 Conclusion

This paper reviews a GIS and remote sensing-based study that derived a time series of an area's land use and land cover (LULC) to identify regions most susceptible to change due to various driving forces. Change detection is a challenging process without a universally optimal strategy that works across all scenarios. To comprehend the underlying reasons for these enduring shifts, changes in LULC must be assessed in terms of geographical extent, intensity, and magnitude. No single approach fits all change detection situations. Factors like sensor spatial resolution, atmospheric influences, and sun angle are considered when selecting an effective change detection method for a given area. Classification-based change detection approaches can mitigate these challenges, although they require more comprehensive development efforts. When adequate training data is available, post-classification evaluation becomes a viable option. GIS methodologies can be valuable when multiple data sources are accessible. Significantly improved change detection outcomes can be achieved using advanced techniques like artificial neural networks (ANN) or a combination of change detection methods. The refined predictive model, built upon the integration of remote sensing, GIS, and soft computing techniques, exhibits enhanced performance in accurately predicting land-use changes. The improved precision, recall, and overall accuracy further validate the model's practical significance in various domains. The results emphasize the pivotal role of advanced technologies in comprehending and mitigating the effects of evolving land-use patterns on both natural systems and society. Similarly, various models are available for more precise prediction of LULC changes. The prudent selection of a model rests in the hands of a skilled researcher.

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