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Research Article

An effort towards understanding the dynamics of urban sprawl and its influence on land cover: A case study of East Sikkim, India

Chunnu Khawas[1], Mohan P Pradhan[2], Ratika Pradhan[3], Ashis Pradhan[4]
[1,2,3]*Department of Computer Application, Sikkim University, Sikkim, India*
[4]*Department of CSE, Sikkim Manipal Institute of Technology, SMU, Sikkim, India*

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ABSTRACT

East Sikkim is one of the most emerging districts of all the four districts in the state of Sikkim, India. The district, since its very inception, has been the prime hub of administrative, educational, cultural, commercial, and industrial establishments, providing tremendous opportunities for economic prosperity and quality livelihood. The very organization of the state's business affairs has been centric to the East District. These critical attributes have been the driving force behind the unprecedented inflow of population from the surrounding regions and rampant unorganized concretization of low-density residential and commercial provision to cater to the ever-growing needs, consequently resulting in rapid depletion of greenery and forest cover. These irreversible anthropological changes have not only impacted the land use and land cover; consequently, it has also left an indelible mark on the local ecology, bio-diversity, demography, pollution, traffic, and essential resource management such as water and power supply, thereby adversely affecting the quality of life. The rapid increase in the sprawl and unplanned encroachment of open spaces have disturbed the balance between preservation and development crucial to a healthy and sustainable urban lifestyle. Motivated by the specified pertinent problem, this research initiative aims at temporal analysis of Landsat satellite data sets of East Sikkim over an interval of 23 years to determine the rate of depletion of natural vegetation and augmentation in urban sprawl along with identification of inherent patterns and relevant causes. In pursuit of the research objectives, supervised image classification has been performed to identify various land cover classes such as urban spaces, forest, vegetative, and barren-land. The results obtained from the classification have revealed that dense forest, and barren land have decreased from by approximately 12.48 km² and 17.27 km² respectively whereas vegetation, and urban spaces has increased by approximately .93 km² and 36.04 km² respectively. The result was obtained with an average classification accuracy of 91.85% and Kappa of .8581.

Keywords: Urban Sprawl, Supervised Classification, Accuracy Assessment, Landsat

INTRODUCTION

Sikkim, the 22nd state of India, is a green, vibrant, and prosperous state in the north-eastern part of India. Sikkim became part of India on 16th May 1975. East Sikkim is one of the four districts of the state of Sikkim with an estimated area of 964 km². Sikkim initially was portioned into four districts, namely East, West, North, and South as shown in figure 1. On 21st December 2021, the government of the state announced the formation of two more districts. As per the latest portioning, the state of Sikkim has been divided into 6 districts, namely Gangtok, Mangan, Pakyong, Namchi, Soreng, and Gyalshing, for ease of administrative and public convenience. East, West, North, and South districts are now known as Gangtok, Gyalshing, Mangan, and Namchi districts, respectively. Pakyong was created from the East district, whereas Soreng was created from the West district.

Although the state has six districts with decentralized administration, most of the administrative headquarters, educational institutes, establishments of commerce, and industries are concentrated and planned in East District. Accessibility by road, the availability of resources, an uninterrupted power supply, a reliable water supply, the suitability of landscaping, the availability of conveniences, and a better quality of life have all played a significant role in the tremendous influx of population from other districts within the state and neighboring states. The total

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population of the state is estimated at around 0.69 million, of which approximately 0.30 million resides in the East District, amounting to approximately 44% of the total population.

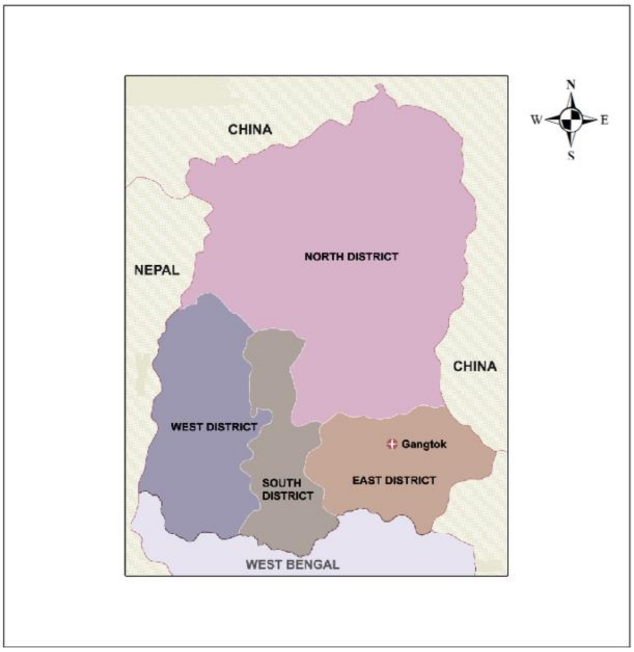

Figure 1. District Map of Sikkim

Although the state has six districts with decentralized administration, most of the administrative headquarters, educational institutes, establishments of commerce, and industries are concentrated and planned in East District. Accessibility by road, the availability of resources, an uninterrupted power supply, a reliable water supply, the suitability of landscaping, the availability of conveniences, and a better quality of life have all played a significant role in the tremendous influx of population from other districts within the state and neighboring states. The total population of the state is estimated at around 0.69 million, of which approximately 0.30 million resides in the East District, amounting to approximately 44% of the total population.

Since early 2000, East Sikkim has been amidst the great industrial revolution. At the heart of it are the pharmaceutical industries and hydropower projects. With a lure for economic prosperity and prospective employment opportunities, these establishments have increased demand for provisions and conveniences as well as completely disrupted the serenity and pristine beauty of the landscape, local ecology, and biodiversity (Rawat & Kumar, 2015).

In addition, Sikkim has been at the centre of the tourist map in the North-East, and of all the districts, East District is the most visited; therefore, promoting initiatives for the development of avenues for generating revenue through tourism has been one of the prime objectives.

These unprecedented situations have created an acute drought in the availability of commercial and residential provisions, resulting in rampant construction of buildings and settlements encroaching on natural vegetation and rural spaces. Furthermore, the developed commercial and residential areas exhibit low density due to limited space availability and vertical restrictions imposed by the state government, given that Sikkim is located in the high-risk seismic zone, specifically zone IV in the Indian seismic zoning map. Consequently, the growth has been more cross-sectional than vertical, resulting in greater area coverage and increased urban sprawl.

Cumulatively, these factors have resulted in

- Leapfrog settlements: Non-contiguous development along the terrain has led to abnormal distribution of sprawl across the landscape resulting in over-exploitation and underutilization of available space.
- Loss of open spaces: Loss of open spaces has hampered air-circulation, flourishment of local flora and fauna, regulation and maintenance of the water table, public amusement, fitness, social wellbeing and community cohesion.

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- Strain on existing infrastructure: Over exploitation of existing infrastructure such as road network, drainage network, sewerage network, and other public facilities has put tremendous strain on these facilities resulting in its rapid deterioration. The dire condition of the national highway NH10 that links the state to the neighbouring states has further aggravated the problem by disrupting and disturbing the supply-chain.
- Non-optimal utilization of resources: Increasing demand and lack of adequate and timely supply of amenities has resulted in inflated cost of living, Gangtok is fast becoming one of the most expensive cities to live in the entire North-East India.
- Strain on facilities for public convenience: Effective management of garbage and sewerage have become difficult due to increased production, overflowing and flooding of drainage networks, excessive strain on the water and electricity supply networks. Gangtok has already started experiencing acute shortage of water supply and daily commodities due to increased consumption.
- Worsening traffic crisis: Since last few years Gangtok has been battling the worst of traffic crisis due to increased automobile dependencies resulting from lack of adequate public transportation provisions, narrow roads, lack of avenues for road network expansion, and concentration of avenues for public services towards East district.
- Inappropriate zoning: Urban planning in East district has followed mixed-use rather than single-use zoning due to lack of spaces, therefore this has resulted in a situation of chaos.
- Induced Vulnerabilities: The pursuit for rapid urbanization along the young and steep slopes has paved the way for many man-made disasters such as landslides, surface run-off, chocking of the drainage and road networks, erosion, pollution, rise in temperature, ecological imbalance, loss of bio-diversity, loss of forest cover, and flooding.
- Social issues: Cases of law-and-order violations are on the rise.

OBJECTIVES

The research initiative is motivated towards the attainment of the following objectives:

- Determine prominent LULC classes within the district boundary of East district, Sikkim.
- Determining temporal changes to the identified LULC classes across the different years.
- Perform accuracy assessments through spatial comparison.
- Build a statistical comparison of the temporal change.
- Suggest need-based reformative initiatives to deaccelerate the sprawl trends.

STUDY AREA AND DATA USED

East district is located along the south-eastern end of the state of Sikkim, India. The district shares its intra-state boundary with two other districts: North on the northern side and South on the western side. The district shares an inter-state boundary with the state of West Bengal on the southern side and an international boundary with the neighboring country of Bhutan on the eastern side. Geographically, the district is located between latitudes 27008' 05" and 27025' 24" North and longitudes 88026' 27" and 88055' 06" East as shown in figure 2. The district is characterized by a mountainous landscape, including valleys, and steep terrain with an altitude ranging from a minimum of 212 meters to a maximum of 5,191 meters (Ahmad & Quegan, 2012). The district has a total area of 964 km². The population of the state is expected to reach 3.32 lakhs in 2024. The weather is pleasant throughout the year, with temperatures varying between 50C (during winters)-250C (during summer).

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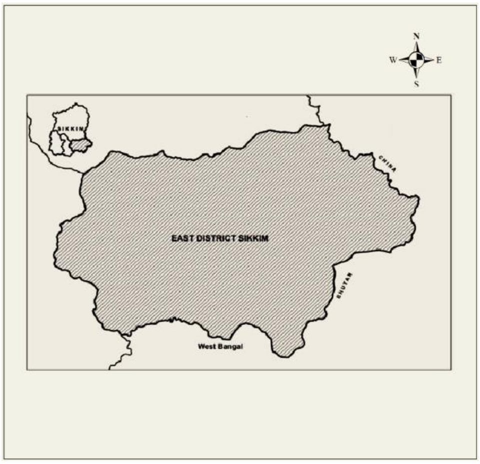

Figure 2. East District

Gangtok, the capital city of Sikkim, is located in East Sikkim, some of the glimpses are shown in figure 3. The entire state administration, commercial establishments, educational establishments, medical establishments, real estate projects, infrastructural projects, industrial establishments, and establishments for hospitality and tourism are located and are still being planned in the district, resulting in a greater influx due to increased demand. This, in fact, has created a magnified need and increased exploitation of open spaces, natural resources, and daily supplies. These developmental activities at the cost of economic prosperity are not only disturbing the serenity and beauty of the landscape but also adversely affecting the ecology, biodiversity, water table, and environment in unimaginable proportions. In addition to ecological influences, social and cultural drifts are also being observed.

Figure 3. Gangtok City

As the research initiative is motivated towards determining temporal changes in LULC changes over the region of East District, Landsat TM data has been deemed suitable. Landsat 7 data from the year 2000, Landsat 8 data from the year 2013, 2015, 2018, and Landsat 8-9 data for the year 2023 has been used in the research initiative for temporal analysis. (Source Earth Explorer (USGS)).

METHODS

The inherent steps involved in this research initiative can be schematic represented in figure 4.

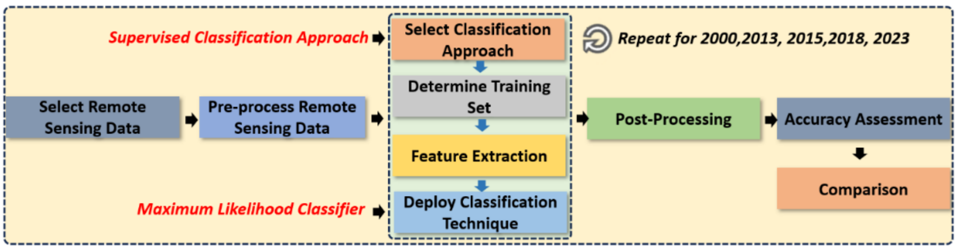

Figure 4. Proposed Solution.

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- Select Remote Sensing Data

In this research initiative, Landsat TM data from the years 2000, 2013,2015,2018 and 2023 has been used for temporal analysis.

- Pre-process Remote Sensing Data

A need-based preprocessing operation has been planned and deployed to restore data problems arising from sensor feed, image registration, and atmospheric correction.

- Select Classification Approach

In this research initiative, supervised classification approaches have been pursued as LULC classes are well known and defined.

- Determine Training Set

Training datasets have been carefully selected for various LULC classes; the training dataset is further used to train the selected classification method for the classification of spectral data.

- Feature Extraction

The selection of appropriate spectral bands for classifications of LULC classes is crucial to the success of any classification technique.

- Deploy Classification Technique

In this research initiative, a maximum likelihood classifier has been deployed as it is probabilistic in nature, robust, efficiently handles multispectral data, efficiently incorporates variability, enables quantization of performance metrics, facilitates accuracy assessment, and effectively handles miscalculation probability.
Where, the likelihood Lk is defined as the posterior probability of a pixel belonging to a LULC class k (Ahmad & Quegan, 2012).

$$L_k = P\left({}^{k}/_{X}\right) = \frac{P(k) * P\left({}^{X}/_{k}\right)}{\Sigma_1^m P(i) * P\left({}^{X}/_{i}\right)} \text{.... equation 1}$$

Here,

- P(k/X) is the posterior probability that a pixel belongs to class k given X (observed feature)
- P(k) is the prior probability of the pixel belonging to class k
- P(X/k) is the likelihood of observing the feature X provided that the pixel belongs to class k

Implies that L_k depends on $P\left({}^{X}/_{k}\right)$
Were,

$$P\left({}^{X}/_{k}\right) = \frac{1}{\sqrt{(2\pi)^d|\Sigma_k|}} \exp\left(-\frac{1}{2}(X-\mu_k)^T\Sigma_k^{-1}(X-\mu_k)\right) \text{ .... equation 2}$$

Here,

- μ_k is the mean vector of class k
- $\sum_k$is the covariance matrix of class k
- D is the dimensionality of the feature vector X

Maximum likelihood classifier has two inherent steps the training phase and the classification phase.

- In the training phase the training dataset is used for determining the mean vector and covariance matrix for each LULC class.
- In the classification phases likelihoods is computed for determining the inclusion of a pixel to any of the LULC classes based on distribution estimated followed by assignment of the pixel to a particular LULC class based on the probability/ highest likelihood.

Maximum likelihood classifier proves ineffective in situation when the data required for determining mean vector and the variance-covariance is insufficient, there is very high correlation between different bands, and population does not follow the normal distribution.

- Post-Processing

In situation where if the classifier wrongly includes a pixel into a class or wrongly excludes a pixel from a class due to sheer influence of the physical environment then ancillary data may be referred to modify the result of classification process for improving the quality of the results obtained. For example, satellite data pertaining to mountainous

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region is greatly influenced by the presence of geo-morphological landforms and their impression on each other with regards to positioning of the sensor and the light source. Therefore, two pixels belonging to the same class may look entirely different due to the influence of physical environment.

- Accuracy Assessment

The accuracy of the classification results is determined with the help of error matrix. It includes Overall Accuracy (OA), User's Accuracy (UA), Producer's Accuracy (PA), Error of Commission (EC), Error of Omission (EO), and Kappa Coefficient (KC).

i) User's Accuracy (UA)

UA is the proportion of pixels correctly classified by the classifier into a LULC class to all the pixels that are classified into a LULC class. UA for a given LULC class k is estimated as

UA(k)=(TP(k))/(TP(k)+FP(k)) ....equation 3

Here,

- UA(k) is the Users Accuracy for a given LULC class k
- TP(k) is the representation for true positive i.e. number of pixels of LULC class k classified in LULC class k
- FP(k) is the representation for false positive i.e. number of pixels not belonging to LULC class k classified in LULC class k

Lower value of UA indicates inability of the classifier to correctly identify pixels into a given LULC class leading to increased misinterpretation, therefore higher value of UA is desired.

ii) Producer's Accuracy (PA)

PA is the proportion of pixels correctly classified by the classifier into a LULC class to all the pixels that actually belongs to the LULC class. PA for a given LULC class k is estimated as

$$\mathrm{PA(k)} = \frac{\mathrm{TP(k)}}{\mathrm{TP(k)} + \mathrm{FN(k)}} \text{ .... equation 4}$$

Here,

- PA(k) is the Producers Accuracy for a given LULC class k
- TP(k) is the representation for true positive i.e. number of pixels of LULC class k classified in LULC class k
- FN(k) is the representation for false negative i.e. number of pixels belonging to LULC class k not classified in LULC class k

Lower value of PA indicates inability of the classifier to correctly identify pixels into a given LULC class leading to exclusions. Higher value of PA indicates increased credibility of the classifier.

iii) Error of Omission (EO)

EO is the proportion of correct pixels excluded by the classifier from a LULC class to all the pixels that actually belongs to the LULC class. EO for a given LULC class k is estimated as

$$\mathrm{EO(k)} = \frac{\mathrm{FN(k)}}{\mathrm{TP(k)} + \mathrm{FN(k)}} \text{ .... equation 5}$$

Here,

- EO(k) is the Error of Omission for a given LULC class k
- TP(k) is the representation for true positive i.e. number of pixels of LULC class k placed in LULC class k
- FN(k) is the representation for false negative i.e. number of pixels belonging to LULC class k not classified in LULC class k

Lower value of EO indicates ability the classifier to correctly identify pixels into a given LULC class.

iv) Error of Commission (EC)

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EC is the proportion of wrong pixels included by the classifier into a LULC class to all the pixels that are classified into the LULC class. EC for a given LULC class k is estimated as

$$\mathrm{EC(k)} = \frac{\mathrm{FP(k)}}{\mathrm{TP(k) + FP(k)}} \quad \text{.... equation 6}$$

Here,
- EO(k) is the Error of Omission for a given LULC class k
- TP(k) is the representation for true positive i.e. number of pixels of LULC class k placed in LULC class k
- FN(k) is the representation for false positive i.e. number of pixels not belonging to LULC class k classified in LULC class k

Lower value of EO indicates ability the classifier to correctly identify pixels into a given LULC class.

v) Kappa Coefficient (κ) (Cohen's Kappa)
In this research initiative Kappa Coefficient is a use to determine the agreement between a classifier and ground truth.1,0, and -1 indicates perfect, random, and worst agreement.

$$\kappa = \frac{P_o - P_e}{1 - P_e} \quad \text{.... equation 7}$$

Here,
- Po is the observed agreement, were

$$P_o = \frac{\Sigma TP_i}{\text{Total number of instances}} \quad \text{.... equation 8}$$

- Pe is the expected agreement, were

$$P_e = \Sigma_i \frac{\text{Row Total}_i * \text{Column Total}_i}{\text{Total number of instances}^2} \quad \text{.... equation 9}$$

vi) Classification Accuracy
Classification accuracy may be estimated as

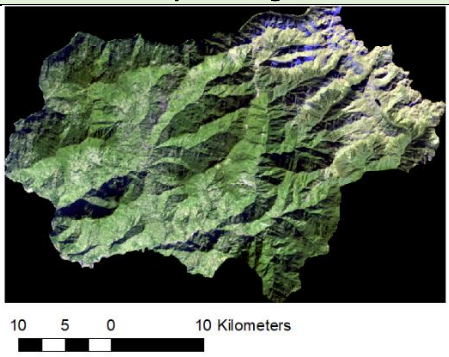
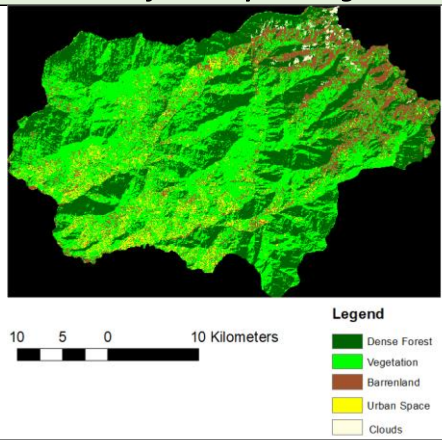
$$\mathrm{EC(k)} = \frac{\mathrm{TP(k) + TN(k)}}{\mathrm{TP(k) + TN(k) + FP(k) + FN(k)}} \quad \text{.... equation 10}$$

vii) Comparison
Represent the result obtained from the temporal analysis into graphs for representing there increase and decrease in the proportion of the LULC classes.

RESULTS

Classification results

Table 1. Classification Result

Years	Input Image	Classified Output Image
2000		

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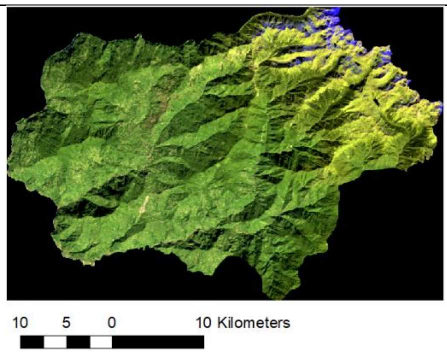
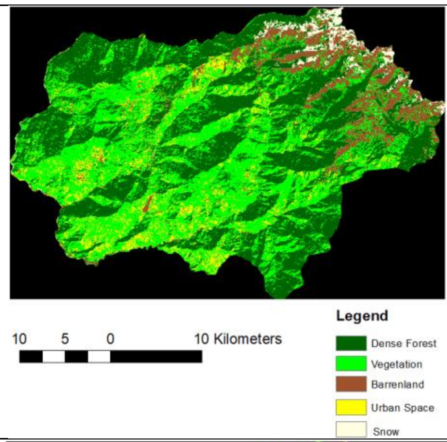
<tr><td>2013</td><td>
</td><td>
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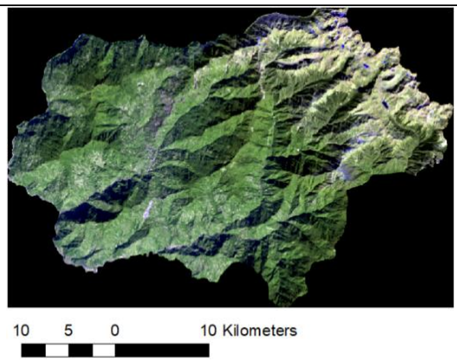
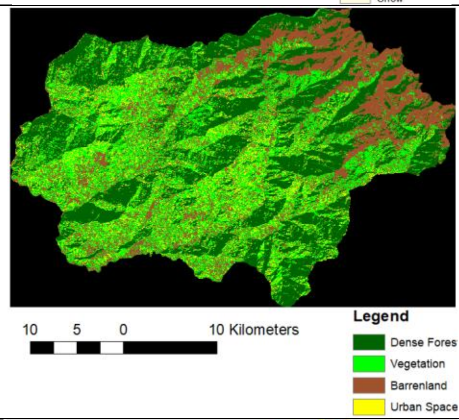
<tr><td>2015</td><td>
</td><td>
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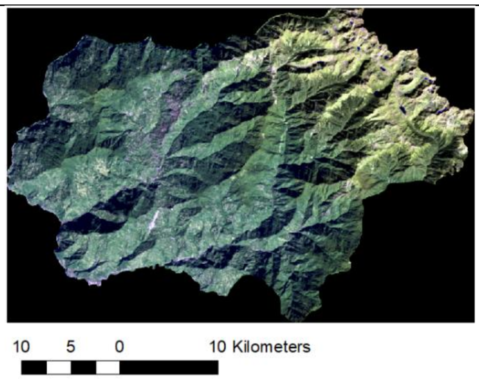
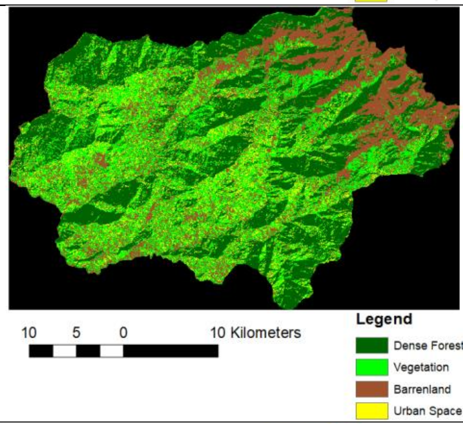
<tr><td>2018</td><td>
</td><td>
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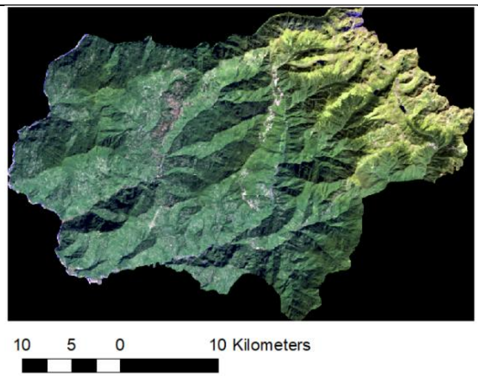
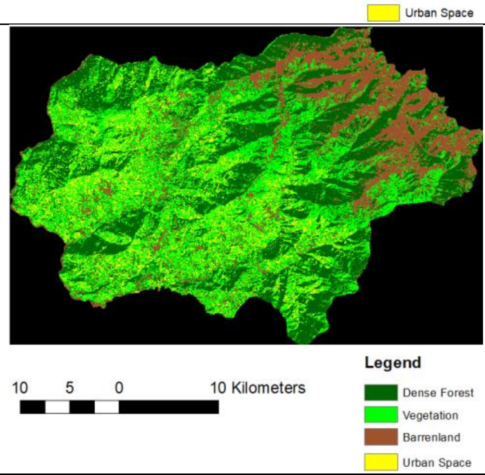
<tr><td>2023</td><td>
</td><td>
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Table 1 represents results obtained from the classification process.

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Estimation of Coverage of various classes

Pixel Coverage

Table 2 represents the total number of pixels classified into the various identifiable classes represented in table 1.

Table 2. Pixel coverage

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	446526	413325	138350	60783
2013	440093	414025	119524	84315
2015	437869	418716	121584	87749
2018	437577	416090	120024	92227
2023	430445	414359	120277	100837

Area Coverage

Table 3 represents the total area covered by the identified classes. This was estimated by multiplying the pixel coverage with resolution of the reference data.

Table 3. Area Coverage (represented in km2)

Year	Dense Forest	Vegetation	Barren Land	Urban spaces
2000	401.88	371.99	124.52	54.71
2013	396.9	372.63	107.57	75.89
2015	394.1	376.8	109.5	78.95
2018	393.82	374.48	108.02	83.01
2023	389.40	372.92	107.25	90.75

Graphical representation of temporal changes observed

Based on the quantifiable values represented in table 3, the increase and decrease in the classes can be represented as follows:

i) Figure 5 represents decrease in forest cover from approximately 401.88 km2 to 389.4 km2 from 2000 to 2023.

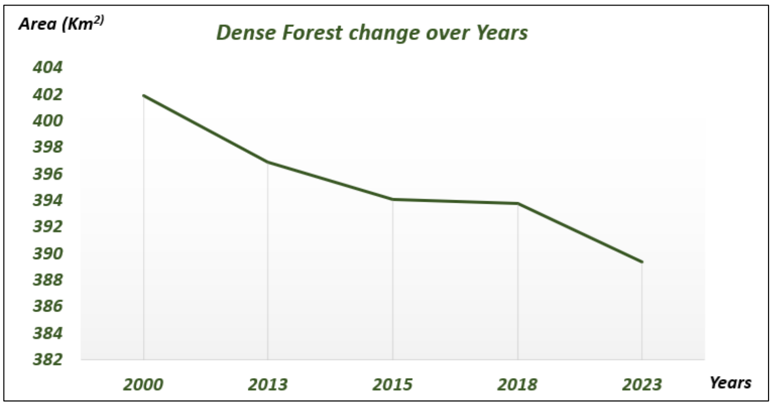

Figure 5. Forest Cover

ii) Figure 6 represents increase in vegetation cover from approximately 371.99 km2 to 372.99 km2 from 2000 to 2023.

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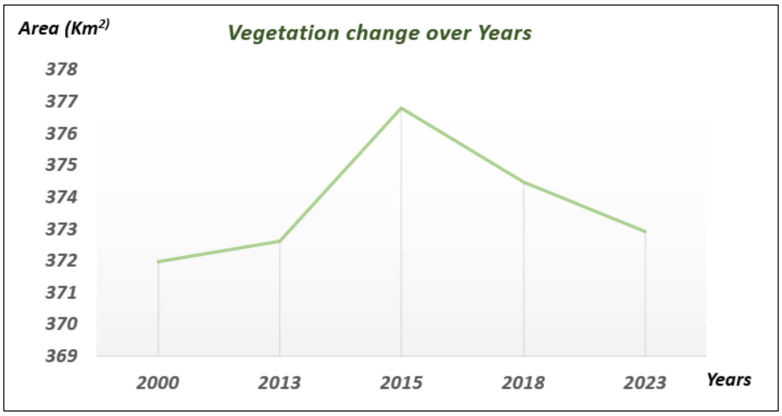

Figure 6. Vegetation Cover

iii) Figure 7 represents decrease in barren land cover from approximately 124.52 km2 to 107.25 km2 from 2000 to 2023.

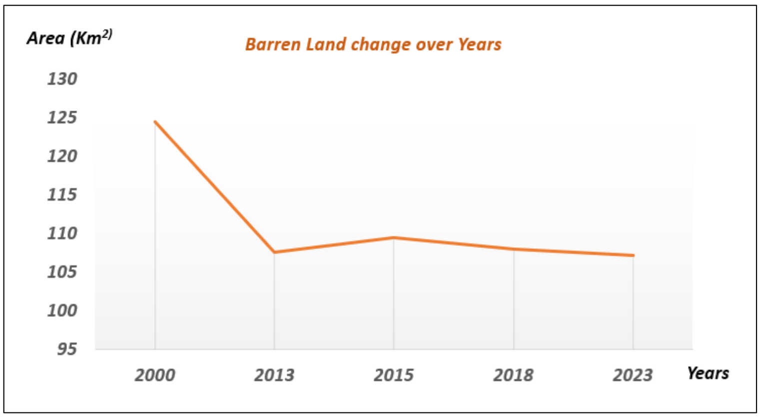

Figure 7. Barren Land Cover

iv) Figure 8 represents increase in urban coverage from approximately 54.71 km2 to 90.75 km2 from 2000 to 2023.

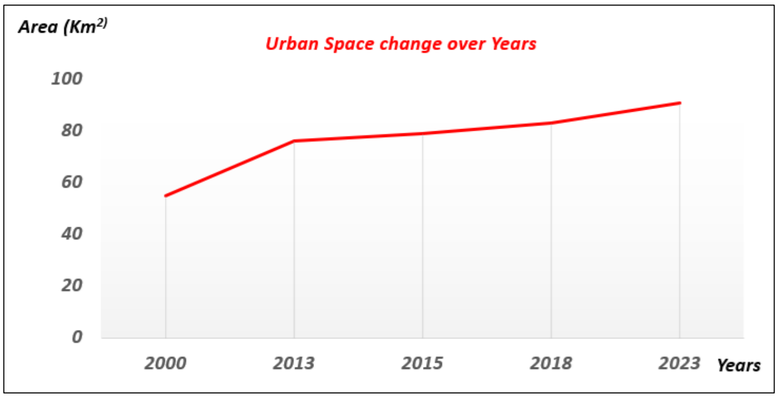

Figure 8. Urban Cover

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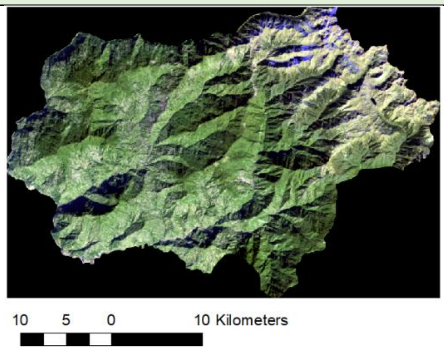
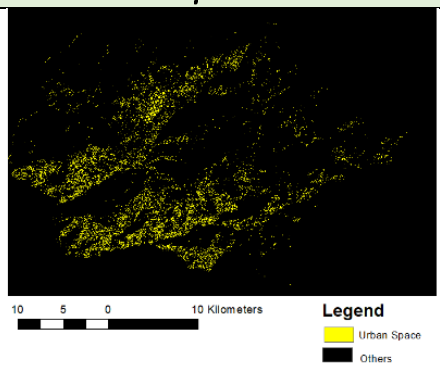
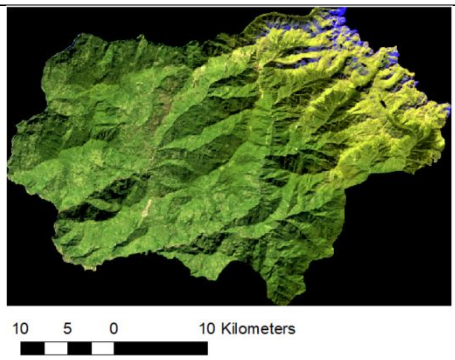
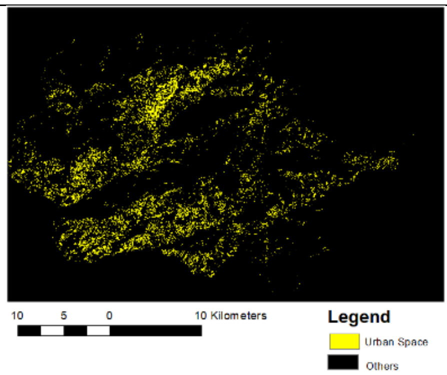
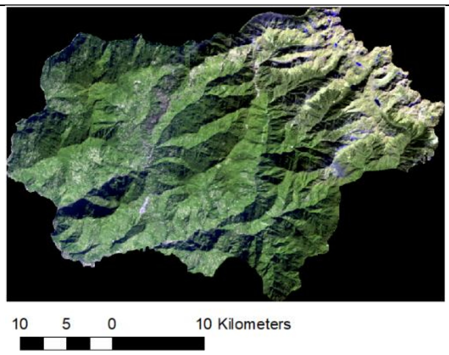
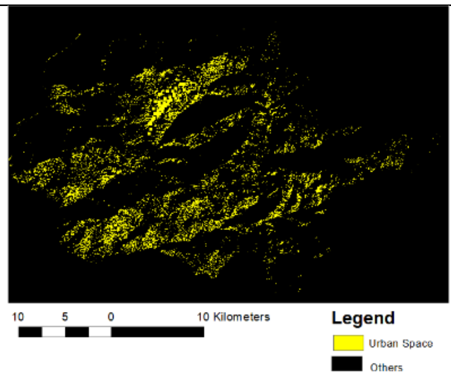
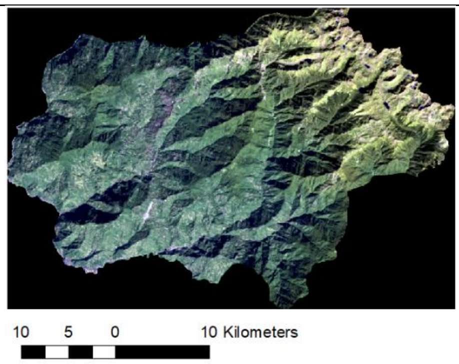
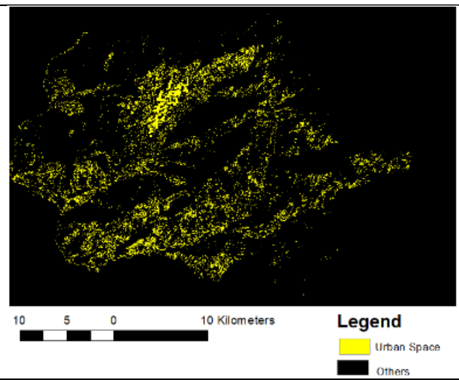
Table 4. Urban cover

Years	*Input Image*	*Classified Output identifying Urban Sprawl*
2000		
2013		
2015		
2018		

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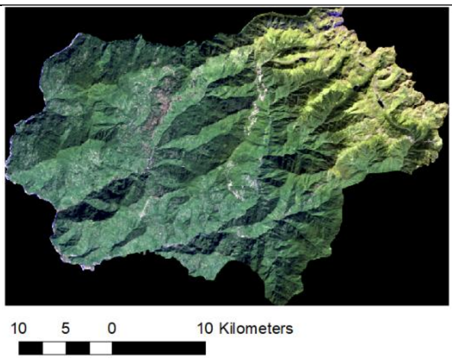

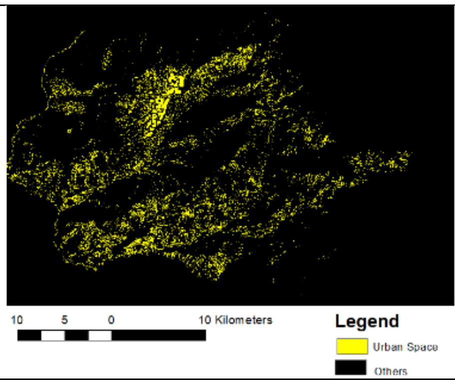

Accuracy Assessment

The accuracy assessment was performed using the ERDAS Imagine 14 module. Random points were selected for classification based on distribution parameters, using stratified sampling. A total of 400 random points were chosen, with a minimum of 60 points for each class. The image class for each point in the sample was automatically recorded. The viewer was utilized to determine the reference class for each point. After entering the reference class for each sample point, Imagine was used to create the error matrix and calculate accuracy estimates. The reference data used for this assessment was the Google Earth map, with the classes considered being Vegetation, Barren land, and Urban space. Represented in table 5 is the results achieved from accuracy assessment.

Table 5. Accuracy Assessment

Year	Average User Accuracy	Average Error of Commission	Average Producer Accuracy	Average Error of Omission	Average Kappa Value	Overall Classification Accuracy
2000	***91.05%***	***8.95%***	***93.06%***	***6.94%***	***0.8627***	***91.25%***
2013	***90.67%***	***9.33%***	***91.82%***	***8.2%***	***0.8575***	***92.75%***
2015	***90.07%***	***10.03%***	***90.99%***	***9.1%***	***0.8483***	***91.00%***
2018	***90.60%***	***9.4%***	***93.72%***	***6.3%***	***0.8738***	***93.25%***
2023	***90.07%***	***9.9%***	***90.99%***	***9.1%***	***0.8483***	***91.00%***

CONCLUSION

East District is the most populated district in the entire state of Sikkim, India, as it is at the center of state administrative, educational, commercial, cultural, industrial, and social affairs. The state capital city is also located in East District. The district has a well-established road network, ensuring connectivity with other districts and neighbouring states. The availability of promising work opportunities, economic prosperity, and a better quality of life are some of the crucial factors that have resulted in an unprecedented influx of aspiring populations from the adjacent districts and states. This rapid surge has created an escalated demand for residential provisions to accommodate an increasing population, a reliable supply of commodities and resources to cater to their daily needs, efficient water and waste management solutions, and an uninterrupted power supply to ensure continuous operations.

This sudden rise in demand has led to the abnormal and unplanned proliferation of concrete structures in the district; moreover, Sikkim falls into Zone IV of the seismic map, i.e., a zone with very high seismic activity. Therefore, the state government has imposed a strict reservation on the vertical scaling of the construction activities, which has resulted in the creation of low-density leap frogged establishments along the length and breadth of the district. Such unexpected turns of events have adversely affected the health of the district. Some of the pertinent problems faced by the district include an unprecedented influx of population, an escalated demand for supplies and resources, a continuous increase in concrete structures, a rapid decrease in open spaces, an inflated cost of living, and behavioral changes due to cultural exposure and exchanges. This has, in fact, disturbed and distorted the state's ecology, demography, biodiversity, natural cycles, climate, and social and cultural wellbeing to unimaginable proportions.

This research initiative was planned and executed to classify prominent LULC classes within the East District's district boundary, track changes in these LULC classes over time using Landsat data from 2000, 2013, 2015, 2018, and 2023, evaluate their accuracy, conduct statistical comparisons of these changes, pinpoint prominent hotspots and trends in sprawl, and recommend necessary reformative measures.

Classification was performed on the Landsat data using a Supervised Approach, selecting the Maximum Likelihood Classifier. The classifier was selected based on its capability to handle miscalculation probabilities and computation ease. Various metrices for determining accuracy were implemented such as UA, PA, EC, EO, Kappa Coefficient and OA and the overall classification accuracy was estimated at 91.25%, 92.75%, 91.00%, 93.25% and 91.00% respectively for the different years.

The outcomes of the classification have revealed the following temporal developments in the East district of Sikkim over the last 23 years (i.e. between 2000 and 2023):

- The urban area has increased by approximately 65.86% covering a ground area of approximately 90.75 km2 in 2023 compared to that of 54.71 km2 in 2020. This progression has happened mainly at the cost of agricultural and forest land. High intensity of development was observed in between 2000 to 2013.
- The forest cover has decreased by approximately 31.05% covering a ground area of approximately 389.4 km2 in 2023 compared to that of 401.88 km2 in 2020.
- The vegetation has increased by approximately .25% covering a ground area of approximately 372.92 km2 in 2023 compared to that of 371.99 km2 in 2020.
- The barren has decreased by approximately 13.86% covering a ground area of approximately 107.25 km2 in 2023 compared to that of 124.52 km2 in 2020.

The involved agencies can adopt some reformative measures to slow down the spread of sprawl.

- Plan and devise strategies to decentralize state administrative, educational, and commercial operations from Gangtok by relocating establishments to open spaces in the opposing peak. This would not only allow for off-shedding of relentless stress but also allow for uniform growth leading to sustainable development essential for the preservation of ecology and biodiversity. It would also help in the effective and efficient management of the prevailing traffic crisis by facilitating cross-border movement and rising inflation. Strengthening the IT infrastructure and using the latest technological solutions would allow for bridging the space divide.
- Create new smarter zones to broaden development opportunities.
- Protect and preserve green spaces, this is the only way forward to safeguard our vanishing biodiversity and ecology. Conceive strict regulatory policies for the prevention of allotment and use for commercial or personal benefits.
- Protect and preserve open spaces. Due to social, cultural, and professional commitments, citizens in this fast-paced world face extreme stress and mental distress from the environment, making recreational places crucial for maintaining sound health.
- Promote community engagement in conceiving ideas for building better and smarter cities. Organize public meetings, focused discussion sessions, surveys, and forums for open discussions to enable planners to build an understanding of the community's needs and expectations.
- Identify vacant, aged, underutilized, or unused establishments, revitalize them, and promote their adaptive use. Plan multipurpose establishments with provisions for residential, commercial, and recreational spaces.
- Devise a mechanism for monitoring influx and impose strict administrative reservations on it.
- Develop and promote avenues of public conveyance, including overhead ropeways, shared buses, and shared vehicles. Organize awareness programs motivating people to make use of the same.
- Incentivize sustainable living and provide subsidies and privileges for sustainable practices.
- Design courses in the curriculum of school, college, and university education promote sustainable practices and planning.

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Data availability: The data generated or analysed during this study are included in this published article and its supplementary information files.

Declarations: The authors confirm that this article is original research and has not been published or presented previously in any journal or conference in any language (in whole or in part). Consent to participate is not applicable.

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