

Research Article

A Multi-Temporal Land Cover Analysis of Kathmandu Using Google Earth Engine and ENVI: A Comparative Study of SVM and RF Algorithms

Bhuwan Singh Bisht^{1,*} , Nabaraj Subedi¹ , Gaurav Bisht² , Amit Yadav² 

¹Land Management Training Center, Dhulikhel, Nepal

²Department of Geomatics Engineering, Kathmandu University, Dhulikhel, Nepal

Abstract

Rapid urbanization and land cover change have emerged as major environmental concerns in developing regions, particularly within the Kathmandu District of Nepal. This study aims to analyze multi-temporal land cover changes and compare the performance of two machine learning algorithms—Support Vector Machine (SVM) and Random Forest (RF)—across two platforms: Google Earth Engine (GEE) and ENVI. Sentinel-2 satellite imagery from 2017, 2020, and 2023 was utilized to classify four major land cover classes (water, bareland, built-up, and vegetation) using supervised classification techniques. Preprocessing included cloud masking, filtering, and subsetting, while training samples were generated from high-resolution Google Earth Pro and Copernicus Sentinel imagery. Accuracy was assessed using user's accuracy, producer's accuracy, overall accuracy, and the Kappa coefficient derived from confusion matrices. Results indicate a steady increase in built-up areas (from 24.75% in 2017 to 37.06% in 2023) and bareland, alongside a marked decline in vegetation. The RF algorithm in GEE achieved the highest performance with an overall accuracy of 98.43% and Kappa coefficient of 0.9773 in 2023, demonstrating strong stability across all years. SVM, while slightly less consistent, achieved 97.6% user accuracy and 98.8% producer accuracy for the water class in 2023, outperforming RF in that category. ENVI-based SVM models attained an overall accuracy of 91.96% and Kappa coefficient of 0.8862, performing well for vegetation but showing slightly lower robustness than RF in GEE. In conclusion, the integration of cloud-based (GEE) and desktop (ENVI) remote sensing platforms with machine learning algorithms proved highly effective for large-scale urban monitoring. The findings highlight rapid urban expansion and vegetation loss in Kathmandu and offer valuable insights for sustainable urban planning and environmental management.

Keywords

Land Cover Change, Google Earth Engine (GEE), ENVI, SVM, RF, Urban Expansion

1. Introduction

Background

Land cover refers to the physical surface of the Earth—such as vegetation, water, and built-up areas—while

land use indicates human activities like agriculture or urban development [1]. Changes in land cover are largely driven by population growth, urbanization, and deforestation [2, 3].

*Corresponding author: geo.bhuwan@gmail.com (Bhuwan Singh Bisht)

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Urbanization is one of the most significant land cover changes globally, with projections showing the urban population will rise to 6.7 billion by 2050 [4]. Despite covering a small land area, cities contribute over 70% of global CO₂ emissions [5]. Nepal is also urbanizing rapidly, ranking among the top ten fastest urbanizing countries [6], with major drivers including infrastructure growth and deforestation [7].

Remote sensing (RS) plays a vital role in monitoring these changes, offering timely and large-scale observation capabilities. Modern platforms like Google Earth Engine (GEE) allow cloud-based processing of satellite data and integration of spectral indices for accurate classification [8]. Alternatively, desktop-based tools like ENVI provide powerful classification methods, including Support Vector Machine (SVM), and are widely used in high-resolution image analysis [9].

This study compares GEE and ENVI platforms using Sentinel-2 imagery to classify land cover changes in Kathmandu

(2017-2023). The performance of Random Forest (RF) and Support Vector Machine (SVM) algorithms is evaluated to assess their effectiveness in detecting urban growth and vegetation loss, providing insights for sustainable land management.

2. Research Methodology

2.1. Study Area

The study area of the project is chosen to be the Kathmandu district which is shown in Figure 1. It lies in the extent of approximately 27°35'00"N to 27°48'00"N and 85°12'00"E to 85°40'00"E. Being the capital of the country, it has a high population density, due to which urbanization is at its peak in this district. Hence, analyzing the overall land cover change pattern is necessary here.

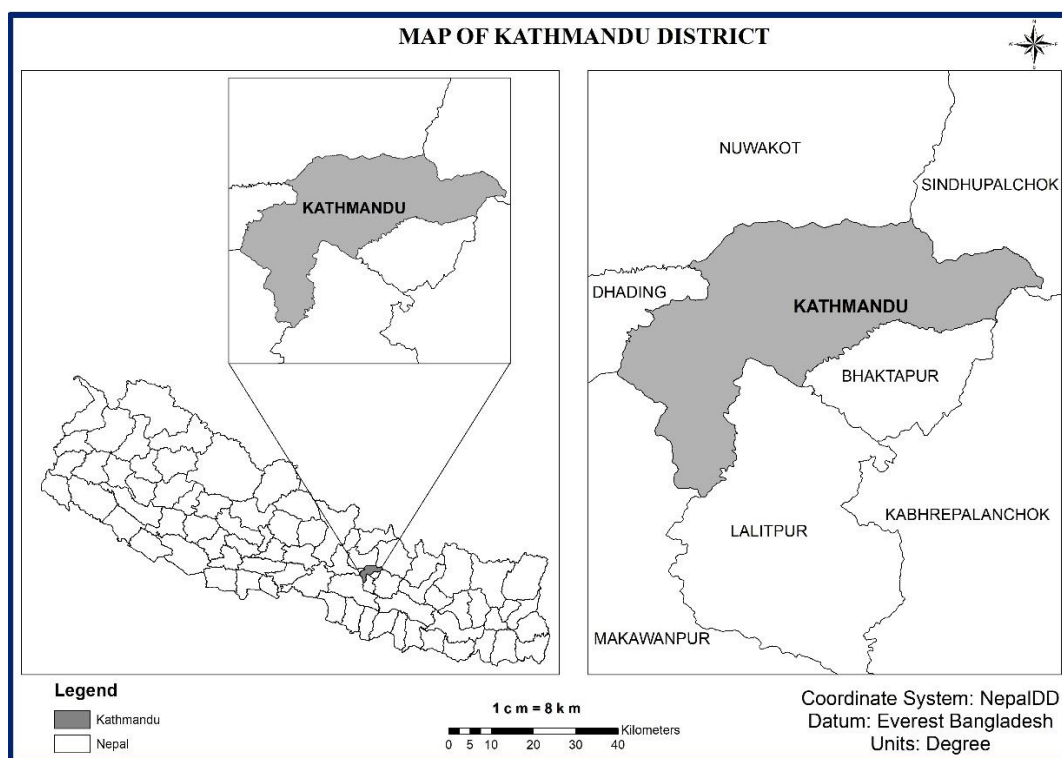


Figure 1. Study Area.

2.2. Methodology

The flowchart shows in Figure 2 outlines the methodological steps taken for land use/land cover (LULC) classification

of the Kathmandu district using temporal Sentinel images from 2017, 2020, and 2023.

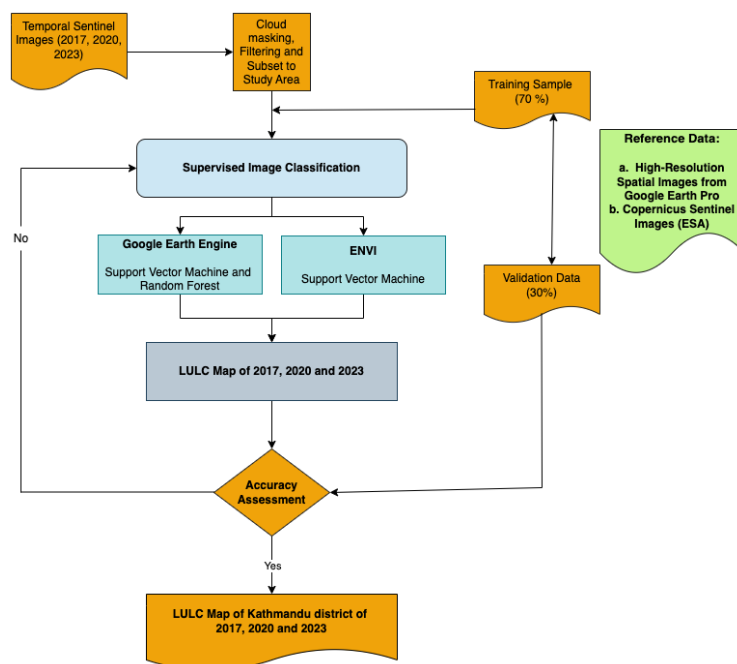


Figure 2. Working methodology.

1) Data Acquisition:

The process begins with the acquisition of temporal Sentinel images for the years specified. The images were derived using the Google Earth Engine Data Catalog. The following Table 1 specifies the image characteristics:

Table 1. Satellite Image Characteristics.

Year	Satellite Image
2017	Sentinel-2 level-1C (Mean of Jan. 1 to Dec. 30)
2020 and 2023	Sentinel-2 level-2A (Mean of Jan. 1 to Dec. 30)

2) Preprocessing:

These images undergo preprocessing, which includes cloud masking to remove cloud-covered areas that can obscure the view of the Earth's surface [10], filtering to enhance image quality, and subsetting to the study area to focus on the region of interest.

3) Training Sample Selection:

Concurrently, a training sample, which constitutes 70% of the reference data, is selected to train the classification algorithms. This training data is derived from High-resolution spatial images from Google Earth Pro and Copernicus Sentinel images provided by the European Space Agency (ESA). The polygon-to-point feature in QGIS was used to develop the training sample for each class. Table 2 presents approximately 1,282 training samples categorized into four land cover classes: Water, Bareland, Built-up, and Vegetation. The spatial distribution of these samples is visually represented in Figure 3.

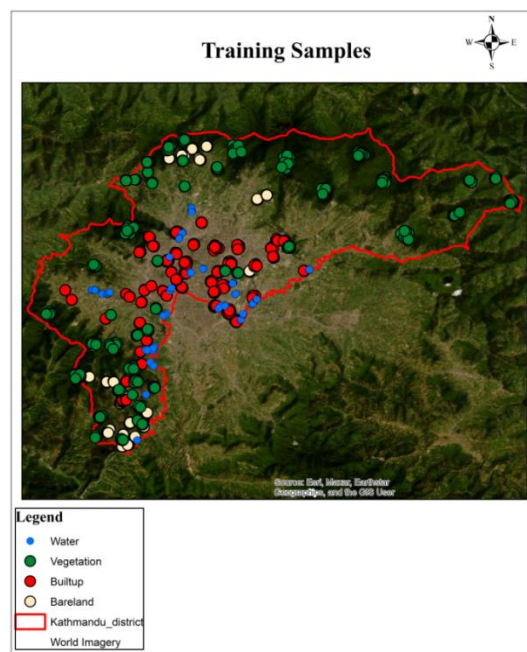


Figure 3. Training Samples.

Table 2. Number of sample points developed for each class.

Class	Number of training sample points
Water	412
Bareland	420

Class	Number of training sample points
Built-up	430
Vegetation	420

4) Supervised Image Classification:

The prepared Sentinel images are then subjected to supervised image classification, a process where the satellite images are classified using training sets for each defined class [11].

Two platforms are utilized for classification:

- 1) Google Earth Engine (GEE) uses both the Support Vector Machine (SVM) and Random Forest (RF) algorithms for classification.
- 2) ENVI, which employs only the SVM algorithm for classification.

5) LULC Maps Creation:

Using the results from the SVM and RF algorithms in GEE, and the SVM algorithm in ENVI, LULC maps for the years 2017, 2020, and 2023 are created.

6) Accuracy Assessment:

An accuracy assessment is then performed to evaluate how well the classified LULC maps match real-world conditions. This is achieved by comparing the classified data against validation data, which is the remaining 30% of the reference data not used in training [12]. Accuracy metrics including producer's accuracy, user's accuracy, overall accuracy, and the kappa coefficient are calculated from the confusion matrix [13, 14].

7) Final LULC Maps:

If the accuracy assessment yields satisfactory results, the final LULC maps for the Kathmandu district for the years 2017, 2020, and 2023 are accepted and finalized.

3. Results and Discussions

The study aimed to perform a supervised classification of 4 land use/landcover classes in the Kathmandu district using Remote Sensing Imageries of the year 2017, 2020, and 2023. Across the study, two platforms have been used: Google Earth Engine, and ENVI. Two algorithms: Support Vector Machine (SVM) and Random Forest (RF) have been used across and inter-platform for classification. Hence, this section aims to describe the overall output obtained which includes:

- a. Land use/ landcover maps of three periods: 2017, 2020, and 2023, and the distribution of each class of the landcover.
- b. Accuracy Assessment of Classification Algorithms across platforms.
- c. Comparative analysis of the performance of Classification algorithms across and inter-platform.

3.1. Land Use/ Landcover Map (Visual Inspection) and Distribution of Each Class of the Landcover

The Table 3 shows the percentage of area covered by various land use/land cover classes in the Kathmandu district for the years 2017, 2020, and 2023 and graph distribution of area of each class during study period is shown in Figure 4.

The LULC classification results were generated using SVM and RF algorithms in the Google Earth Engine platform, and the SVM algorithm in ENVI, for the years 2017, 2020, and 2023. Figures 5-7 illustrate the LULC maps classified using the SVM algorithm in GEE, Figures 8-10 present the classification results obtained from the RF algorithm in GEE similarly Figures 11-13 display the LULC maps derived using SVM in ENVI. The trends across the years and algorithms can be summarized as follows:

- 1) Water: The area classified as water has fluctuated in GEE using SVM, with a decrease from 2017 to 2020 and then an increase in 2023. However, the RF algorithm shows a more significant increase over time. In ENVI, the SVM algorithm estimates the water coverage relatively stable with a slight decrease by 2023.
- 2) Bareland: There's a noticeable increase in the area classified as bareland in GEE using SVM, suggesting either actual land cover change or variability in classification accuracy. The RF algorithm shows an initial increase followed by a decrease in 2023. In ENVI, the SVM estimates indicate an increase until 2020 and a slight decrease in 2023.
- 3) Builtup: The area classified as built-up land displays a small increase from 2017 to 2020 in GEE using SVM, followed by a slight decrease in 2023. The RF algorithm shows a more consistent increase in built-up areas until 2020 and a slight decrease in 2023. ENVI's SVM shows a substantial increase over the years, suggesting a considerable expansion in built-up areas or a difference in classification sensitivity between platforms.
- 4) Vegetation: All platforms and algorithms show a decrease in the area classified as vegetation. This trend is most pronounced in the GEE SVM data, which shows a significant drop by 2023. The RF algorithm shows a less dramatic decrease, maintaining a higher percentage of vegetation in 2023 compared to SVM in GEE. ENVI's SVM algorithm also indicates a substantial decrease in vegetation over the years, aligning with the trend observed in GEE.

Overall, the RF algorithm in GEE seems to depict less volatility in classifying land use/land cover changes across the years, which might indicate its robustness or differing sensitivity to changes in the landscape. The SVM algorithm, whether in GEE or ENVI, shows more variation in the area percentages, which could be due to differences in algorithmic processing or actual changes in land cover. Notably, the decrease in vegetation and increase in built-up areas across all

platforms and algorithms could reflect urban expansion and the corresponding loss of green spaces in the Kathmandu district [15]. The choice of platform and algorithm may im-

pact the precision of land cover classification, highlighting the importance of selecting the appropriate tool for specific analysis goals.

Table 3. Distribution of each class of the landcover using RF and SVM across GEE and ENVI.

Platform/ Area of Class (%)	2017 SVM GEE	2020 SVM GEE	2023 SVM GEE	2017 RF GEE	2020 RF GEE	2023 RF GEE	2017 SVM ENVI	2020 SVM ENVI	2023 SVM ENVI
Water	1.74	0.88	2.36	2.49	2.66	5.52	3.14	3.18	3.11
Bareland	9.44	11.07	27.01	21.15	25.87	9.69	19.99	23.03	25.09
Builtup	24.75	26.36	24.55	26.88	25.75	23.12	22.84	33.76	37.06
Vegetation	64.07	61.69	46.08	49.48	45.73	61.67	54.03	40.03	34.73

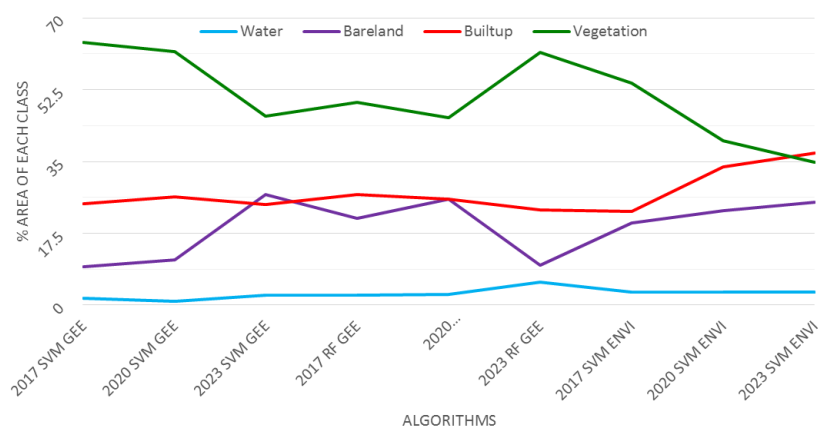


Figure 4. Graph showing the distribution of area of each class during the study period.

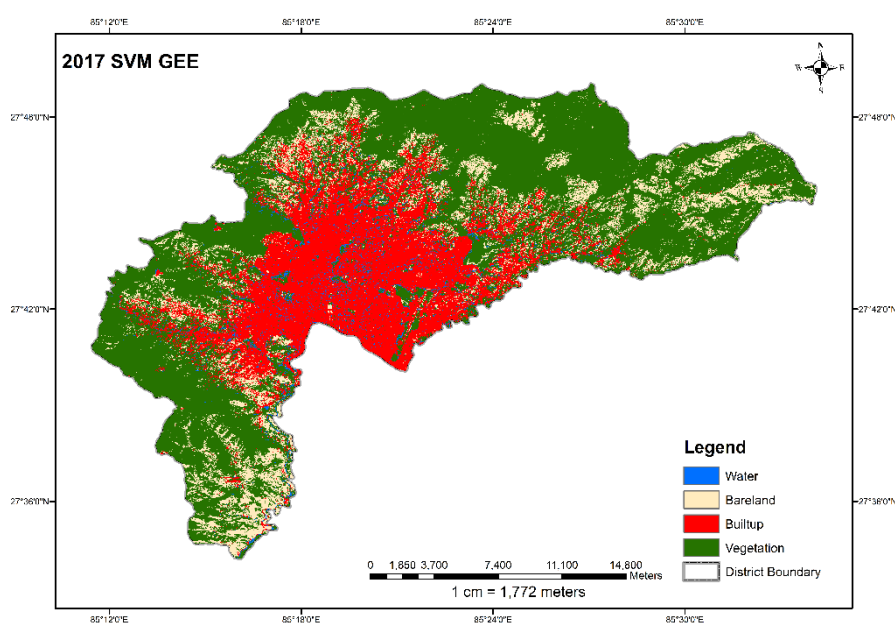


Figure 5. LULC map developed using SVM in GEE of year 2017.

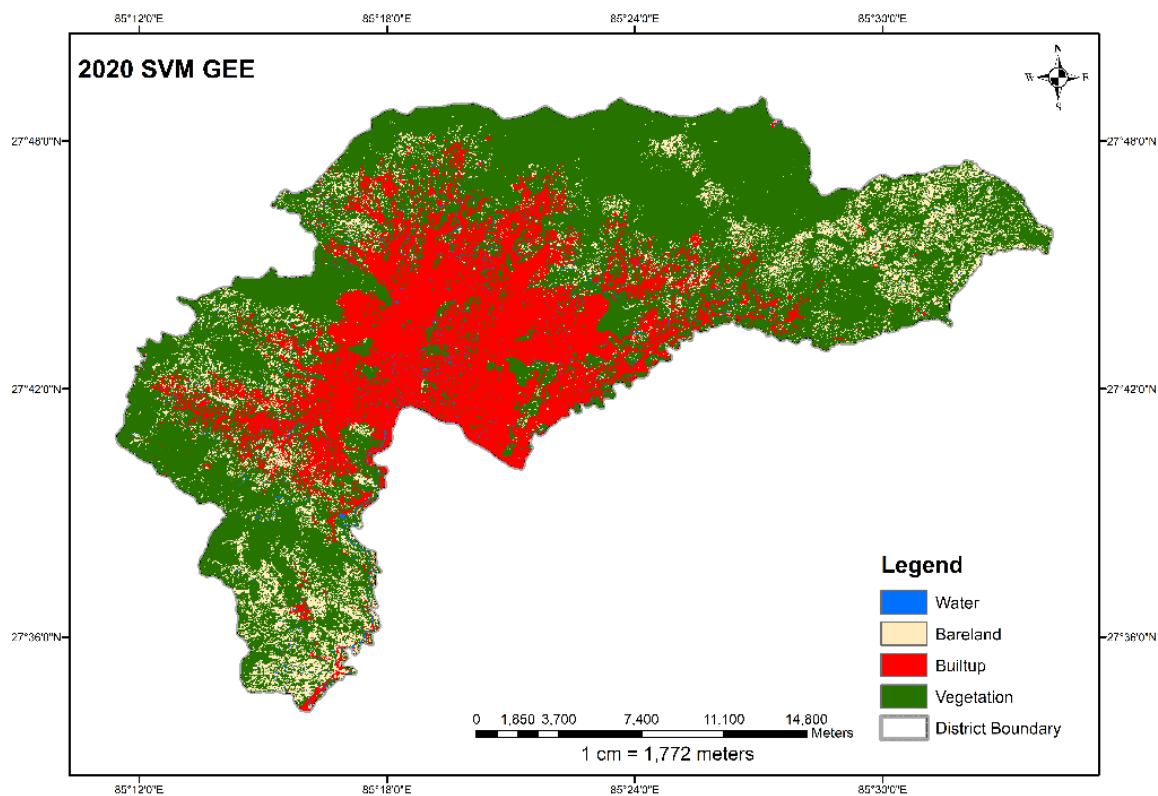


Figure 6. LULC map developed using SVM in GEE of year 2020.

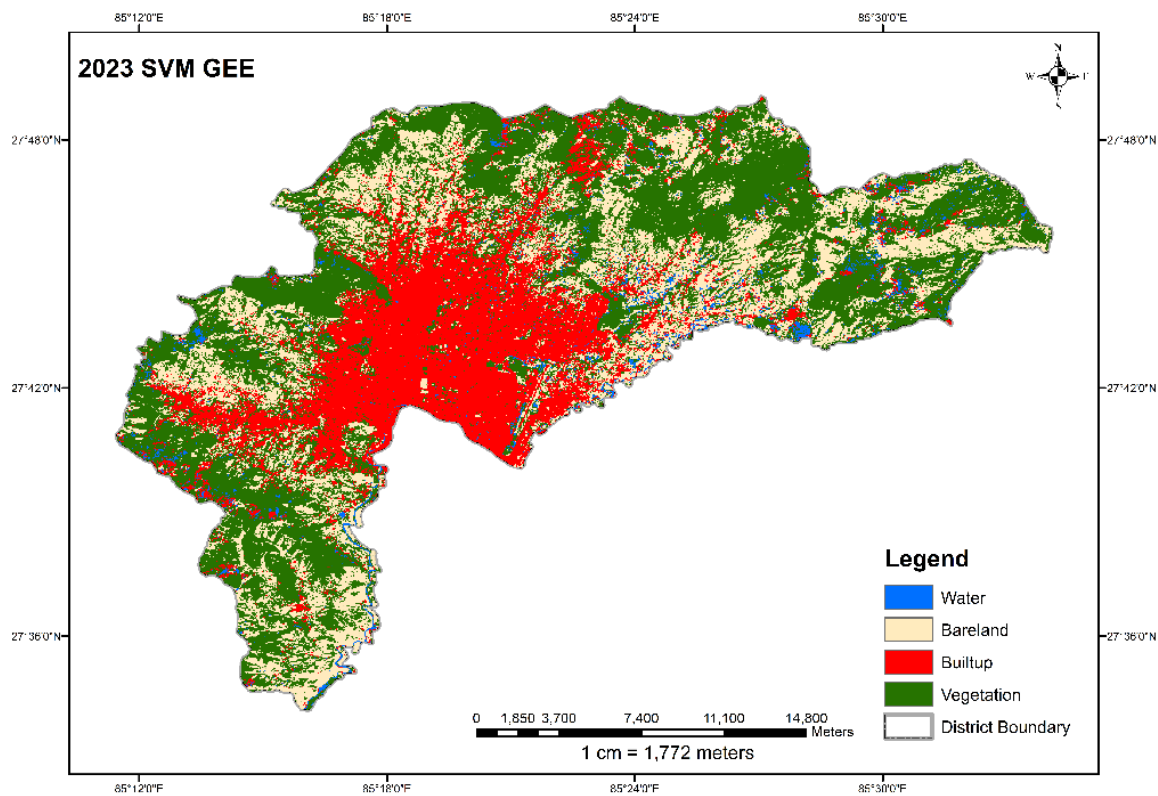


Figure 7. LULC map developed using SVM in GEE of year 2023.

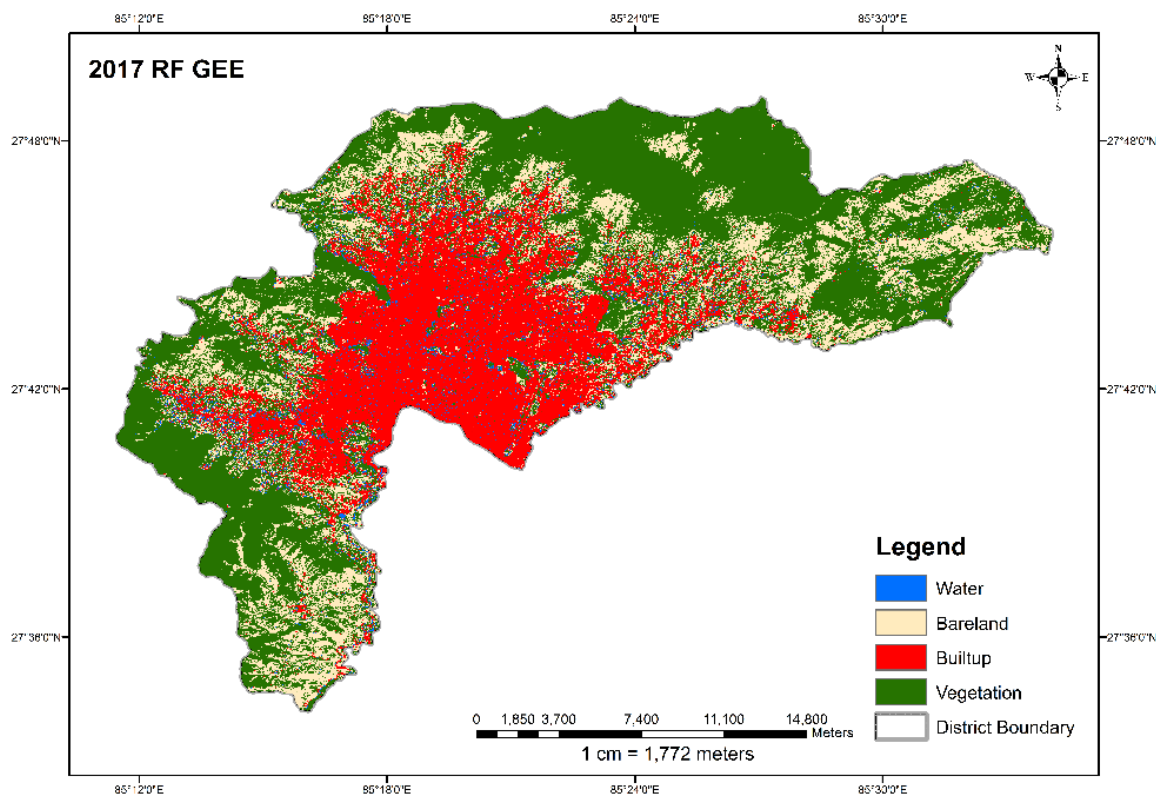


Figure 8. LULC map developed using RF in GEE of year 2017.

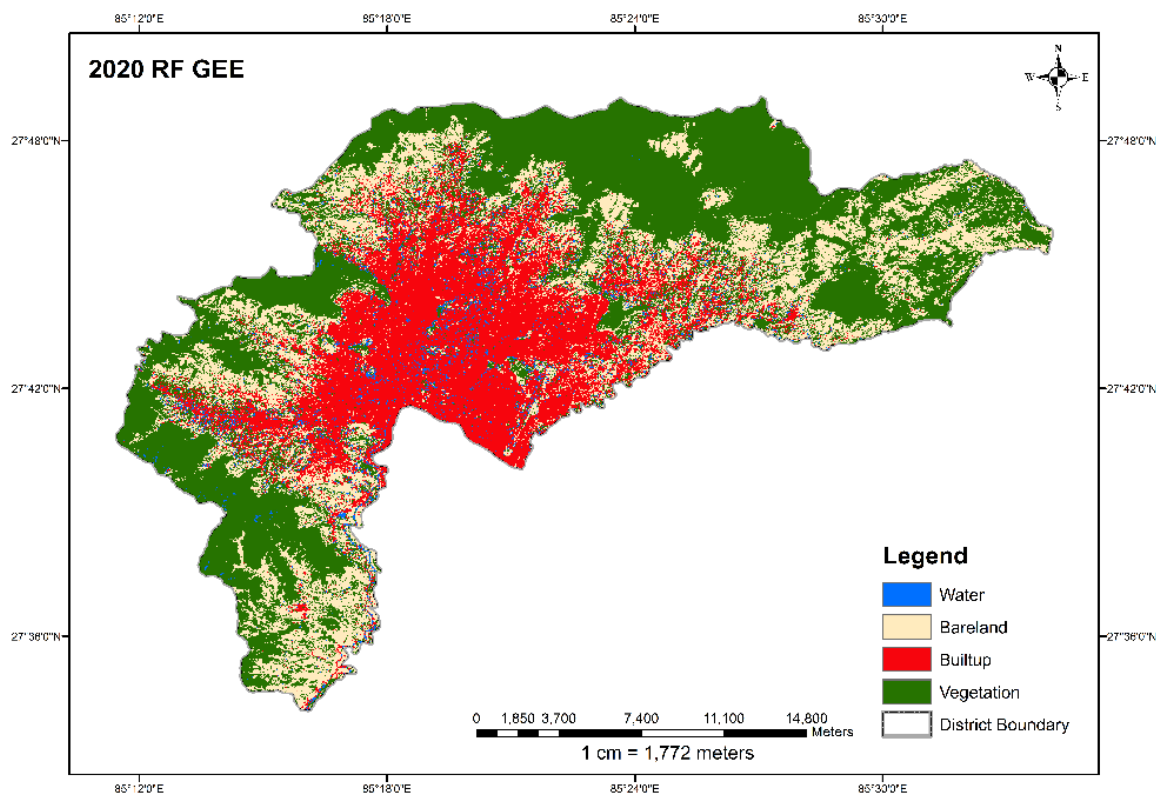


Figure 9. LULC map developed using RF in GEE of year 2020.

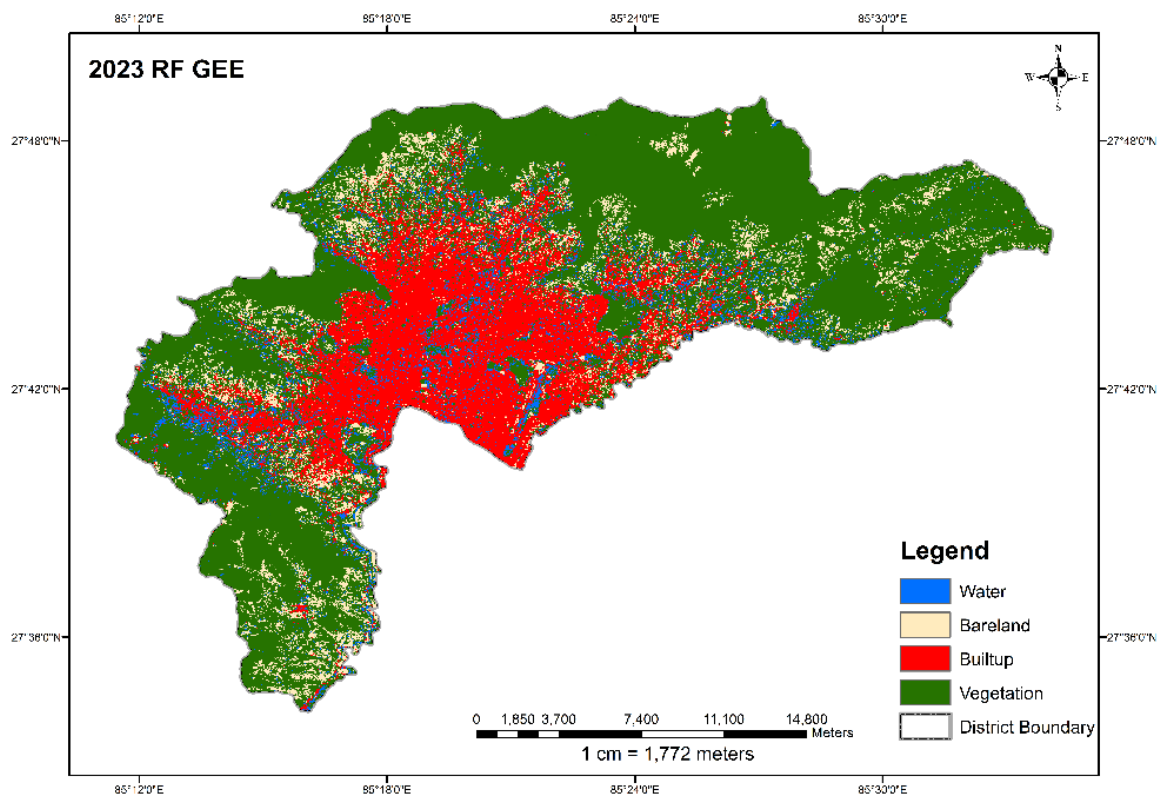


Figure 10. LULC map developed using RF in GEE of year 2023.

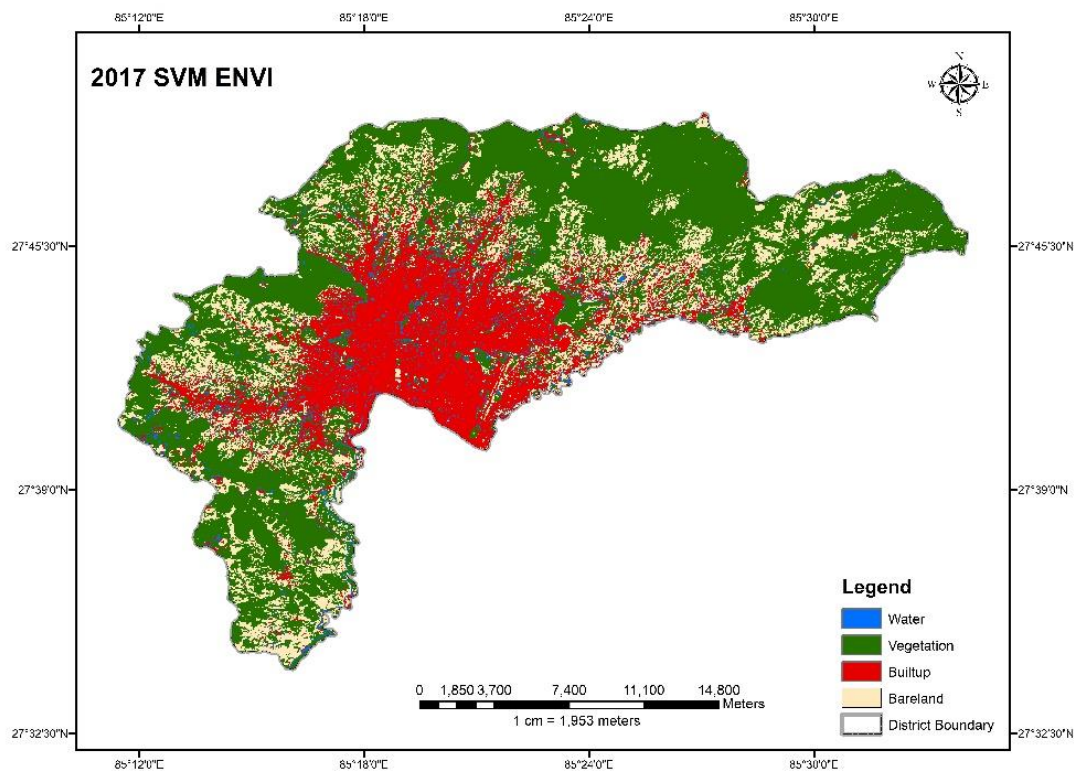


Figure 11. LULC map developed using SVM in ENVI of year 2017.

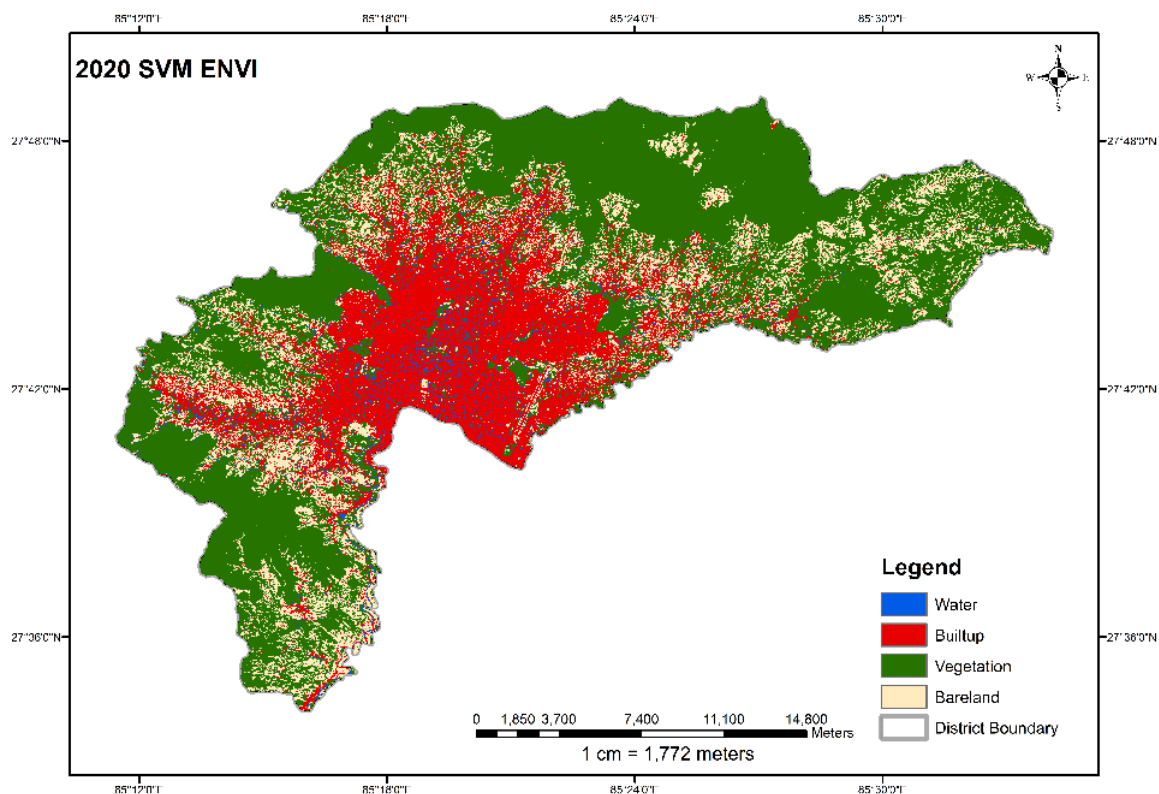


Figure 12. LULC map developed using SVM in ENVI of year 2020.

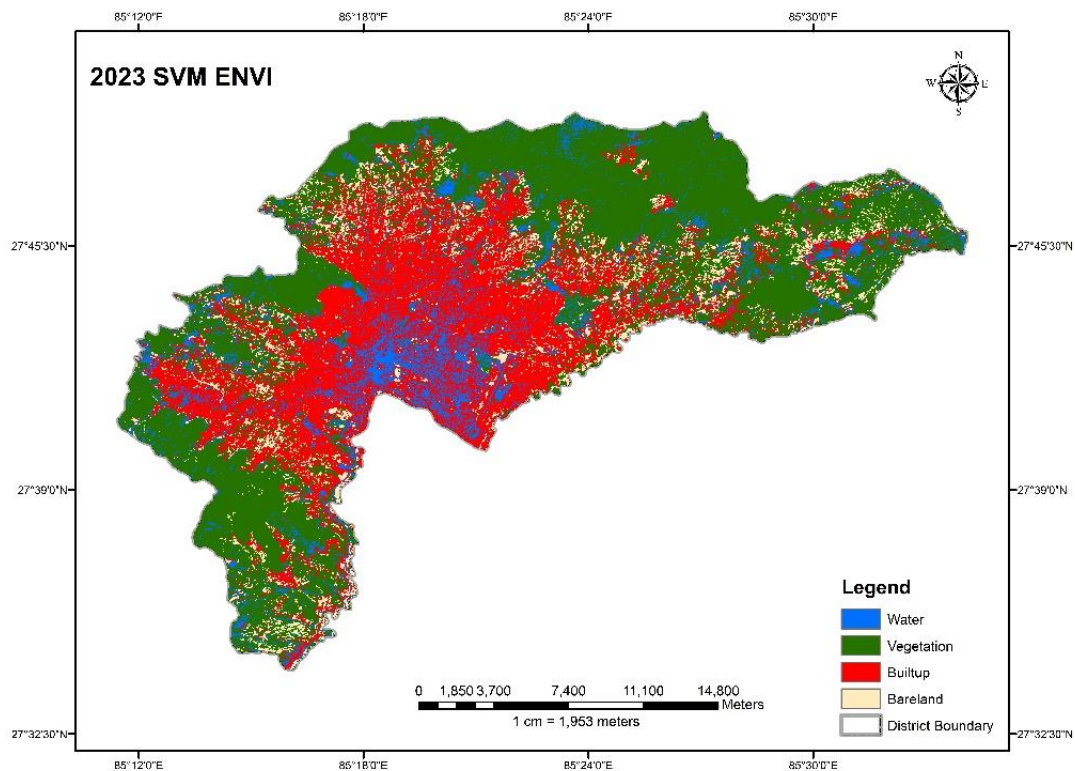


Figure 13. LULC map developed using SVM in ENVI of year 2023.

3.2. Accuracy Assessment Based on User and Producer Accuracy

The classification made using different algorithms does not always give perfect results, as errors may arise from spectrally similar classes, band correlation, or limitations in training data. An accuracy assessment of a classified image is therefore essential to evaluate the quality of information. The user's accuracy and producer's accuracy are two critical metrics in remote sensing that assess the correctness of classification from the perspectives of user reliability and map maker reliability, respectively [16, 17].

3.2.1. Analysis of User and Producer Accuracy of Support Vector Machine (SVM) Across GEE and ENVI

The [table 4](#) provides a comprehensive view of the performance of two satellite image processing platforms, Google Earth Engine (GEE) and ENVI, across different land cover classes (Water, Bareland, Built-up, Vegetation) within the Kathmandu district over three distinct years: 2017, 2020, and 2023. These results are derived using the Support Vector Machine (SVM) algorithm.

Table 4. User and Producer Accuracy across GEE and ENVI of various landcover classes.

Year	Platform	Type of accuracy	Water	Bareland	Built-up	Vegetation
2017	GEE	User Accuracy (%)	69.59	78.18	94.52	83.33
		Producer Accuracy (%)	88.88	83.41	92.00	78.76
	ENVI	User Accuracy (%)	93.75	82.84	82.99	82.72
		Producer Accuracy (%)	29.13	63.79	96.70	94.97
2020	GEE	User Accuracy (%)	76.19	77.14	92.42	80.95
		Producer Accuracy (%)	69.56	65.06	94.57	88.14
	ENVI	User Accuracy (%)	84.34	86.21	88.47	90.67
		Producer Accuracy (%)	54.26	83.96	94.62	95.22
2023	GEE	User Accuracy (%)	97.60	86.07	92.46	85.51
		Producer Accuracy (%)	98.80	72.34	95.74	91.85
	ENVI	User Accuracy (%)	77.57	96.47	89.58	94.66
		Producer Accuracy (%)	57.24	94.06	95.11	98.09

The *overall trend analysis* from 2017 to 2023, GEE demonstrates a notable improvement in accuracies for all classes. This is particularly evident in the water class where the user accuracy significantly increased from 69.59% in 2017 to 97.60% in 2023, and producer accuracy also rose from 88.88% to 98.80%. Such improvements indicate GEE's enhanced capability over time to correctly identify and classify water bodies, which could be crucial for hydrological studies and urban planning in the context of Kathmandu's rapid urbanization and environmental changes.

On the other hand, ENVI displayed varying patterns of accuracy. While there were improvements in certain classes such as bareland and vegetation, the most remarkable enhancement was seen in the vegetation class, where the producer accuracy increased from 94.97% in 2017 to 98.09% in 2023. ENVI's strength lies in its high consistency and reliability, particularly in complex vegetative classifications that

are crucial for environmental monitoring and urban green planning.

Comparing the two platforms, ENVI generally exhibited higher user accuracies across most classes, suggesting that from a user's perspective, the classifications are more reliable. However, GEE showed more consistent improvements in producer accuracies, particularly in the water and built-up classes, which points to GEE's increasing effectiveness as a tool for creating accurate land cover maps. In terms of class-specific observations, both platforms have their strengths. For instance, GEE's significant increase in accuracy for the water class by 2023 suggests its potential for reliable water resource management, which is critical for a district like Kathmandu that faces water distribution issues. For ENVI, the high accuracy in the vegetation class by 2023 underscores its utility in accurately delineating vegetative covers, which are vital for assessing urban heat islands and green space man-

agement. The built-up and bareland classes showed less dramatic changes over the years but maintained high accuracies, indicating both platforms' robustness in urban and bareland classification. Such accuracy is indispensable for urban planners and development agencies aiming to monitor and manage urban growth and land degradation, especially in a rapidly changing urban landscape like that of Kathmandu.

In conclusion, the analysis of the dataset highlights the evolving capabilities of GEE and ENVI in land cover classification using the SVM algorithm. Both platforms show particular strengths in different classes and years, which suggests that the choice of platform could be strategically made based on the specific needs of the project or the specific land cover class being studied. As both platforms continue to improve, they offer valuable tools for environmental monitoring, urban planning, and resource management in dynamic urban settings like Kathmandu.

tings like Kathmandu.

3.2.2. Analysis of User and Producer Accuracy of Support Vector Machine (SVM) and Random Forest (RF) in GEE

The [table 5](#) provided captures the user and producer accuracies for land use/land cover classification in the Kathmandu district over the years 2017, 2020, and 2023, conducted using Google Earth Engine (GEE). It compares the performances of two machine learning algorithms: Support Vector Machine (SVM) and Random Forest (RF). User accuracy reflects the probability that a land cover type classified on the map truly represents that category on the ground, while producer accuracy indicates the probability that a certain land cover type on the ground is correctly classified on the map.

Table 5. User and Producer Accuracy of Support Vector Machine (SVM) and Random Forest (RF) in GEE of various landcover classes.

Year	Algorithm	Type of accuracy	Water	Bareland	Built-up	Vegetation
2017	SVM	User Accuracy (%)	69.59	78.18	94.52	83.33
		Producer Accuracy (%)	88.88	83.41	92.00	78.76
	RF	User Accuracy (%)	85.71	95.32	97.20	98.46
		Producer Accuracy (%)	85.71	97.14	98.58	95.52
2020	SVM	User Accuracy (%)	76.19	77.14	92.42	80.95
		Producer Accuracy (%)	69.56	65.06	94.57	88.14
	RF	User Accuracy (%)	98	94.44	98.47	99.23
		Producer Accuracy (%)	98	98.83	99.22	97.01
2023	SVM	User Accuracy (%)	97.60	86.07	92.46	85.51
		Producer Accuracy (%)	98.80	72.34	95.74	91.85
	RF	User Accuracy (%)	95	98.93	98.46	98.57
		Producer Accuracy (%)	95	98.93	97.70	99.28

From the data presented, there is a general trend of increasing accuracy over time for both algorithms, which suggests improvements in algorithmic performance, training data quality, or perhaps advancements in the satellite imagery resolution. When evaluating which algorithm performs better, one must look at both user and producer accuracies across all classes.

SVM Algorithm:

- 1) The SVM user accuracy shows an upward trend in all categories, with the most significant increase noted in the water class from 69.59% in 2017 to 97.60% in 2023.
- 2) The producer accuracy for SVM also increases for the water and built-up classes, with a slight decline in bareland from 83.41% in 2017 to 72.34% in 2023.

Random Forest (RF) Algorithm:

- 1) RF consistently shows high user accuracy across all classes, with the highest in the vegetation class, increasing slightly from 98.46% in 2017 to 99.28% in 2023.
- 2) Producer accuracy for RF is similarly high and improves or maintains its high levels across the years, especially notable in bareland (97.14% in 2017 to 98.93% in 2023) and built-up classes (98.58% in 2017 to 99.22% in 2023).

Overall Performance:

- 1) For water classification, SVM shows a remarkable improvement and exceeds RF's performance in 2023.
- 2) In bareland classification, RF consistently outperforms

SVM.

- 3) In the built-up class, both algorithms show high accuracies, but RF has a slight edge, especially in producer accuracy.
- 4) For vegetation, RF demonstrates very high user and producer accuracies throughout and would be the preferred algorithm.

Considering the user and producer accuracies for each land cover type, the RF algorithm generally yields better results than the SVM algorithm, providing particularly high accuracies for the built-up and vegetation classes. The RF algorithm's robust performance makes it a suitable choice for land cover classification tasks in the Kathmandu district, especially when the highest level of accuracy is required [18]. The SVM algorithm, while showing notable improvements in the water class, tends to be outperformed by RF in the majority of the classes and years [19]. Beyond accuracy, however, other factors such as computational efficiency, robustness to overfitting, and ease of implementation may also influence the choice of algorithm for practical applications.

3.3. Comparative Analysis of the Performance of Classification Algorithms Across and Inter-Platform

The overall accuracy indicates the proportion of correctly classified instances out of the total instances. The kappa coefficient, on the other hand, is a more robust measure as it accounts for the agreement occurring by chance, with values closer to 1 indicating strong agreement between the classified data and the reference data [20, 21].

Here, the SVM is used in GEE and ENVI, while RF is used in GEE only. So, the performance of SVM in both platforms is compared. Similarly, the performance of two algorithms: RF and SVM in GEE is also compared.

3.3.1. Comparison of SVM Across ENVI and GEE

The table 6 outlines the overall accuracy and kappa coefficient of land use/land cover classifications performed in Google Earth Engine (GEE) and ENVI using the Support Vector Machine (SVM) algorithm for the years 2017, 2020, and 2023.

Table 6. Overall Accuracy and Kappa Coefficient of SVM across ENVI and GEE.

Year	Platform	Overall Accuracy	Kappa Coefficient
2017	GEE	85.73	0.7847
	ENVI	83.2	0.7501
2020	GEE	84.05	0.7671
	ENVI	88.53	0.8358
2023	GEE	88.97	0.8389
	ENVI	91.96	0.8862

From the values provided, it's evident that there is an increasing trend in both overall accuracy and the kappa coefficient over the years for land cover classifications performed in both GEE and ENVI. GEE shows a starting overall accuracy of 85.73% with a kappa coefficient of 0.7847 in 2017, which slightly decreases in 2020 before rising again to 88.97% with a kappa coefficient of 0.8389 in 2023. ENVI, starting at a lower overall accuracy of 83.2% with a kappa coefficient of 0.7501 in 2017, shows a consistent increase in both metrics, reaching an overall accuracy of 91.96% and a kappa coefficient of 0.8862 in 2023. Figure 14 illustrates the changes in overall accuracy of the SVM classifier across GEE and ENVI, while Figure 15 presents the corresponding Kappa coefficient trends.

Considering the data, ENVI demonstrates a stronger performance over the assessed years, ending with the highest

overall accuracy and kappa coefficient in 2023. The consistent upward trend in ENVI's metrics suggests an improvement in classification efficacy, possibly due to enhancements in the algorithm's application within the platform, improved processing capabilities, or better tuning of the SVM parameters specific to ENVI's processing environment.

While both platforms have improved their land use/land cover classification capabilities over the years, ENVI has produced better results overall compared to GEE when using the SVM algorithm, as evidenced by the higher overall accuracy and kappa coefficient in the most recent year analyzed, 2023. These metrics suggest that ENVI may offer a more precise and reliable classification, making it a preferable choice for such tasks, at least within the parameters of this study.

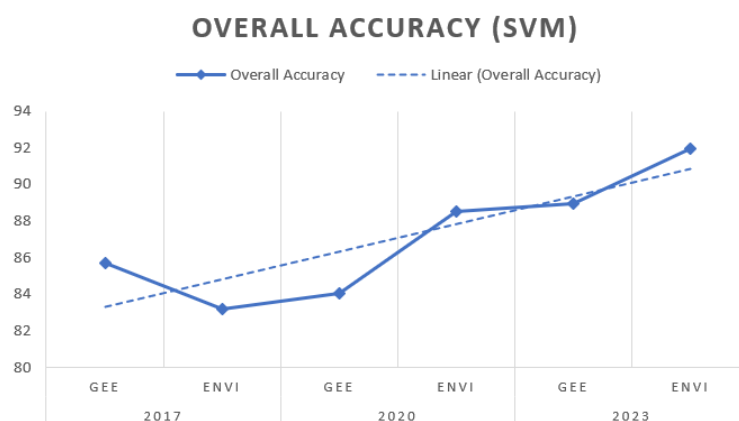


Figure 14. Graph showing overall accuracy of SVM across GEE and ENVI.

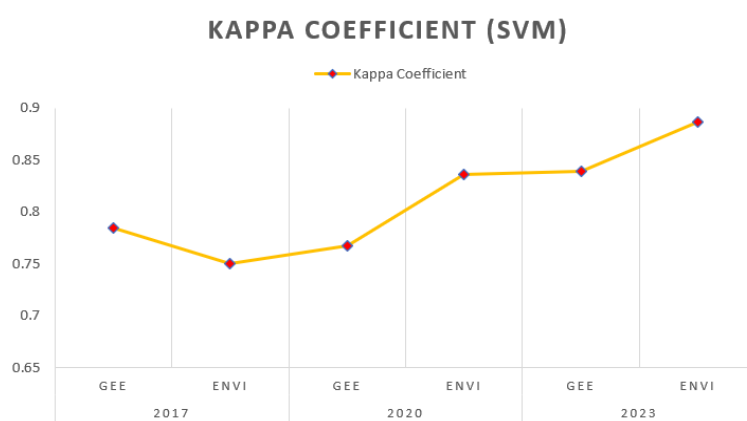


Figure 15. Graph showing Kappa coefficient of SVM across GEE and ENVI.

3.3.2. Comparison of SVM and RF in GEE

The Table 7 provides the overall accuracy and kappa coefficient for land use/land cover classification using two algorithms—Support Vector Machine (SVM) and Random Forest (RF)—in Google Earth Engine (GEE) for the years 2017, 2020, and 2023.

As mentioned earlier, the overall accuracy is a straightforward measure of the proportion of correct predictions, including both true positives and true negatives, out of all predictions. The kappa coefficient, on the other hand, accounts for the agreement that may occur by chance, where a value of 1 indicates perfect agreement and a value of 0 represents no better agreement than chance [22].

Table 7. Overall Accuracy and Kappa Coefficient of SVM and RF in GEE.

Year	Algorithm	Overall Accuracy	Kappa Coefficient
2017	SVM	85.73	0.7847
	RF	96.50	0.9496

Year	Algorithm	Overall Accuracy	Kappa Coefficient
2020	SVM	84.05	0.7671
	RF	98.40	0.9770
2023	SVM	88.97	0.8389
	RF	98.43	0.9773

Overall Trend:

SVM: The accuracy for the SVM algorithm shows a slight decrease from 85.73% in 2017 to 84.05% in 2020, followed by an improvement to 88.97% in 2023. The kappa coefficient follows a similar trend, indicating an initial decline followed by a recovery.

RF: The Random Forest algorithm presents a remarkably high level of accuracy, starting at 96.50% in 2017 and slightly improving to 98.43% in 2023. The kappa coefficient is also very high, starting at 0.9496 and remaining consistently high, reaching 0.9773 in 2023.

Overall Performance:

The RF algorithm consistently outperforms the SVM in terms of both overall accuracy and kappa coefficient. The

RF's kappa coefficients are significantly higher, suggesting a strong agreement beyond chance in its classification outcomes. The Random Forest algorithm is the superior performer for land use/land cover classification in Google Earth Engine, as indicated by its consistently higher overall accuracy and kappa coefficients.

The RF algorithm demonstrates robustness and reliability, making it the preferred choice for analysts and researchers

conducting such classifications within GEE. This trend suggests that RF's method of using multiple decision trees and the ensemble approach contributes to a more accurate and stable classification performance over the SVM's method of finding a hyperplane to separate different classes. Figure 16 illustrates the changes in overall accuracy of the SVM classifier across GEE and ENVI, while Figure 17 presents the corresponding Kappa coefficient trends.

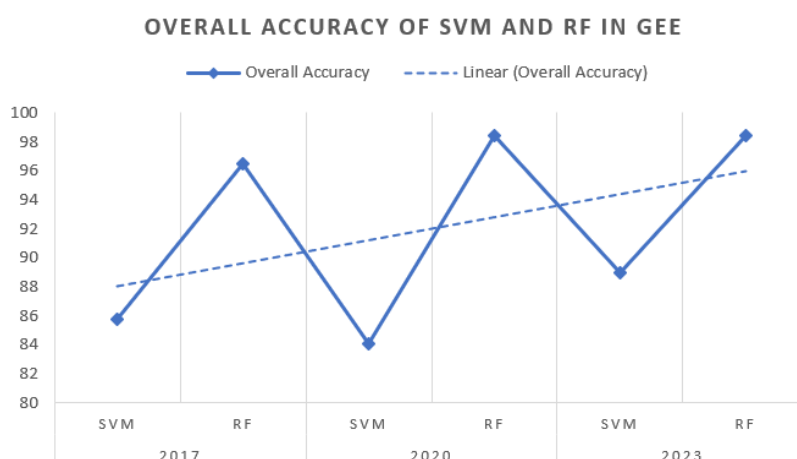


Figure 16. Graph of overall accuracy of SVM and RF in GEE.

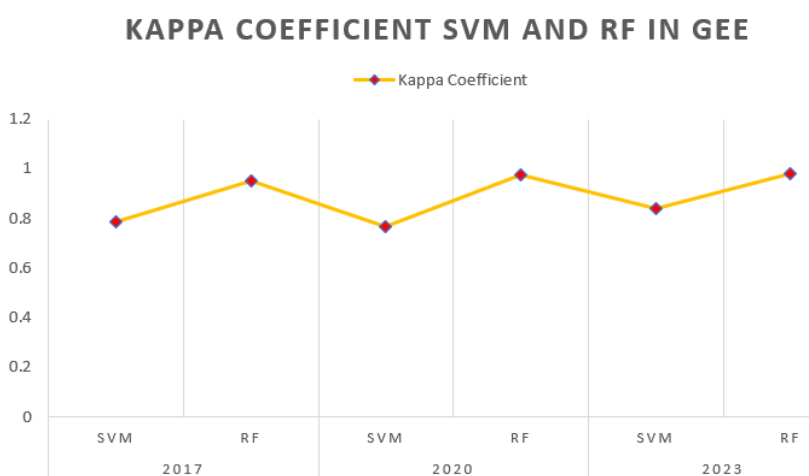


Figure 17. Graph of Kappa coefficient of SVM and RF in GEE.

4. Conclusion

The analysis performed is based on the supervised classification of land use and landcover in the Kathmandu district using Remote Sensing Imageries from 2017, 2020, and 2023 offers significant insights into the dynamics of urban and environmental changes over the studied period. Utilizing both Google Earth Engine (GEE) and ENVI platforms, with Support Vector Machine (SVM) and Random Forest (RF) algo-

rithms, the study meticulously evaluates the distribution and transition of land cover classes including water bodies, bareland, built-up areas, and vegetation.

A notable finding from the study is the variable change in the area of water bodies across different platforms and algorithms. In GEE, the SVM algorithm shows fluctuating levels while RF depicts a steady increase, suggesting possible improvements in algorithmic sensitivity or actual environmental changes. Specifically, the RF algorithm in GEE demonstrated an increase in water coverage from 2.49% in 2017 to 5.52% in

2023. The ENVI platform maintained a relatively stable representation of water bodies, with a slight decrease from 3.14% in 2017 to 3.11% in 2023. This indicates the critical role of selecting appropriate algorithms and platforms based on specific environmental features to enhance classification accuracy.

Another crucial result involves the increasing trend in built-up areas, particularly highlighted in the ENVI platform, which saw an increase from 22.84% in 2017 to 37.06% in 2023, indicative of rapid urban expansion within the district. The study also points out the decline in vegetation cover across all platforms and algorithms, echoing the challenges posed by urban sprawl and its impact on green spaces. The consistent decrease in vegetation could have significant implications for urban heat management and environmental sustainability in Kathmandu.

The comparative analysis of classification performance across different platforms and algorithms reveals varying strengths. For instance, the RF algorithm in GEE demonstrated less variability and generally higher accuracy in classifying land cover changes, suggesting its robustness. Meanwhile, the SVM algorithm showed higher sensitivity, which could be advantageous in certain analytical contexts but might also introduce variability.

In terms of accuracy assessment, both user and producer accuracies were evaluated to gauge the reliability of the classification. Notably, RF exhibited consistently high accuracies across the study period, making it a reliable choice for detailed land cover analysis, particularly for critical applications such as hydrological studies and urban planning. The RF algorithm in GEE showed remarkable improvements in user accuracy for the water class, from 85.71% in 2017 to 98.93% in 2023, and in producer accuracy from 85.71% to 98.93% over the same period. On the other hand, SVM's performance varied but showed improvement over time, highlighting advancements in algorithmic efficiency or training data quality.

Abbreviations

BOA	Bottom of Atmosphere
CART	Classification and Regression Trees
DEM	Digital Elevation Model
DL	Deep Learning
EO	Earth Observation
ESA	European Space Agency
GEE	Google Earth Engine
GIS	Geographic Information System
IA	Intensity Analysis
L1C	Level 1C (Top of Atmosphere Sentinel-2 data)
L2A	Level 2A (Bottom of Atmosphere Sentinel-2 data)
LC	Land Cover
LULC	Land Use and Land Cover
ML	Machine Learning
NDVI	Normalized Difference Vegetation Index
PB	Pixel Based

RF	Random Forest
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SNIC	Simple Non-Iterative Clustering
SVM	Support Vector Machine
TOA	Top of Atmosphere

Author Contributions

Bhuwan Singh Bisht: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Validation, Visualization

Nabaraj Subedi: Project administration, Supervision

Gaurav Bisht: Investigation, Writing – original draft

Statements and Declaration

We declare that we have no financial or non-financial competing interests that could have influenced the research presented in this manuscript. This study did not receive any specific funding from public, private, or non-profit organizations. Both authors contributed equally to the conceptualization, methodology design, data processing using Google Earth Engine and ENVI, analysis, interpretation of results, and writing of the manuscript. The remote sensing datasets used in this study consist of Sentinel data obtained from the European Space Agency (ESA) and were accessed through the publicly available Google Earth Engine platform. Additional processed data supporting the findings are available from the corresponding author upon reasonable request. Ethics approval and consent to participate are not applicable. Consent for publication is also not applicable.

Conflicts of Interest

The authors declare no conflicts of interest.

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