

# Assessment of land dynamics transformation into tea plantations using support vector machine

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## ABSTRACT

Precisely monitoring land use dynamics and spatial distributions is essential for sustainable development and long-term land management. Tea is one of the leading beverage crops cultivated in Bangladesh, expanding rapidly in northern districts and forcing land use change. This study aims to decipher the expansion of tea cultivation and land dynamics transformation to tea land areas in the northern region of Bangladesh by using Landsat 5 TM and Landsat 8 OLI/TIRS surface reflectance images. The supervised support vector machine (SVM) method was used for classification purposes, resulting in three classified maps for the years 2004, 2013 and 2022, having overall accuracies of 91.43 %, 98.67 %, and 98.48 % and kappa coefficients of 89.51, 98.37, and 98.13, respectively. The images were classified into six land use classes: agriculture, tea cultivation area, settlement, waterbody, bare land, and forest. Land transformation results reveal that overall tea land increased by 41.08 % from 2004 to 2022, experiencing a downward trend during 2004–2013, while from 2013 to 2022, a dramatic rise of 70.01 % (equal to 4683.60 ha) tea cultivation area was found in Panchagarh district. The bare land was among the most highly transformed land classes into tea plantations, followed by the forest area. This study provides evidence of transforming underutilized land class into a profitable land use practice, i.e., tea plantation. Thus, cutting-edge technologies would be imperative in land transformation detection for sustainable land management and policy implications for the sustainable development of small landholding livelihoods and the tea industry.

## 1. Introduction

Tea (*Camellia sinensis* L.), which offers medicinal advantages due to its antioxidant activity and higher concentration of gallate content, is one of the most popular beverages worldwide and is expanding more quickly than coffee (Lou et al., 2013a; Parida et al., 2023). After its discovery in China, tea rapidly expanded to Kenya, Indonesia, India, and Sri Lanka (Parida et al., 2023; Zhu et al., 2019), and now tea has expanded to >50 countries worldwide (Falla et al., 2021; Jahan et al., 2022). Bangladesh was initially exposed to tea in 1840 at Chittagong for scientific purposes (Hasanuzzaman, 2019; Jahan et al., 2022), and commercial tea cultivation began in 1854 at Malnicherra in greater Sylhet (Jahan et al., 2022; Prodhan et al., 2023; Saha et al., 2021). Currently, tea plant has been grown in three different geographical

locations since its initiation in Bangladesh, including the Surma Valley (Sylhet), the Halda Valley (Chittagong), and the Karatoa Valley (Panchagarh) (Hasanuzzaman, 2019; Jahan et al., 2022). Statistics for the year 2018 showed that tea has been cultivated in around 4.9 million hectares and produced around 5.96 million tons of dust tea (Parida et al., 2023; Zhu et al., 2019). Bangladesh ranks 12th among the tea-producing countries regarding production (Jahan et al., 2022) and 3rd in consumption worldwide (Rahman et al., 2020a). Bangladesh is an evergreen agriculturally based export-oriented country (Adnan et al., 2020; Prodhan et al., 2023; Rahman et al., 2020a; Saha et al., 2021) where tea has become a significant export product (Rahman et al., 2018; Saha et al., 2021), producing 1.89 % of the world's tea (Saha et al., 2021). Moreover, Bangladesh now has around 166 tea estates covering almost 116219 hectares of land, where about 61579 hectares are in greater

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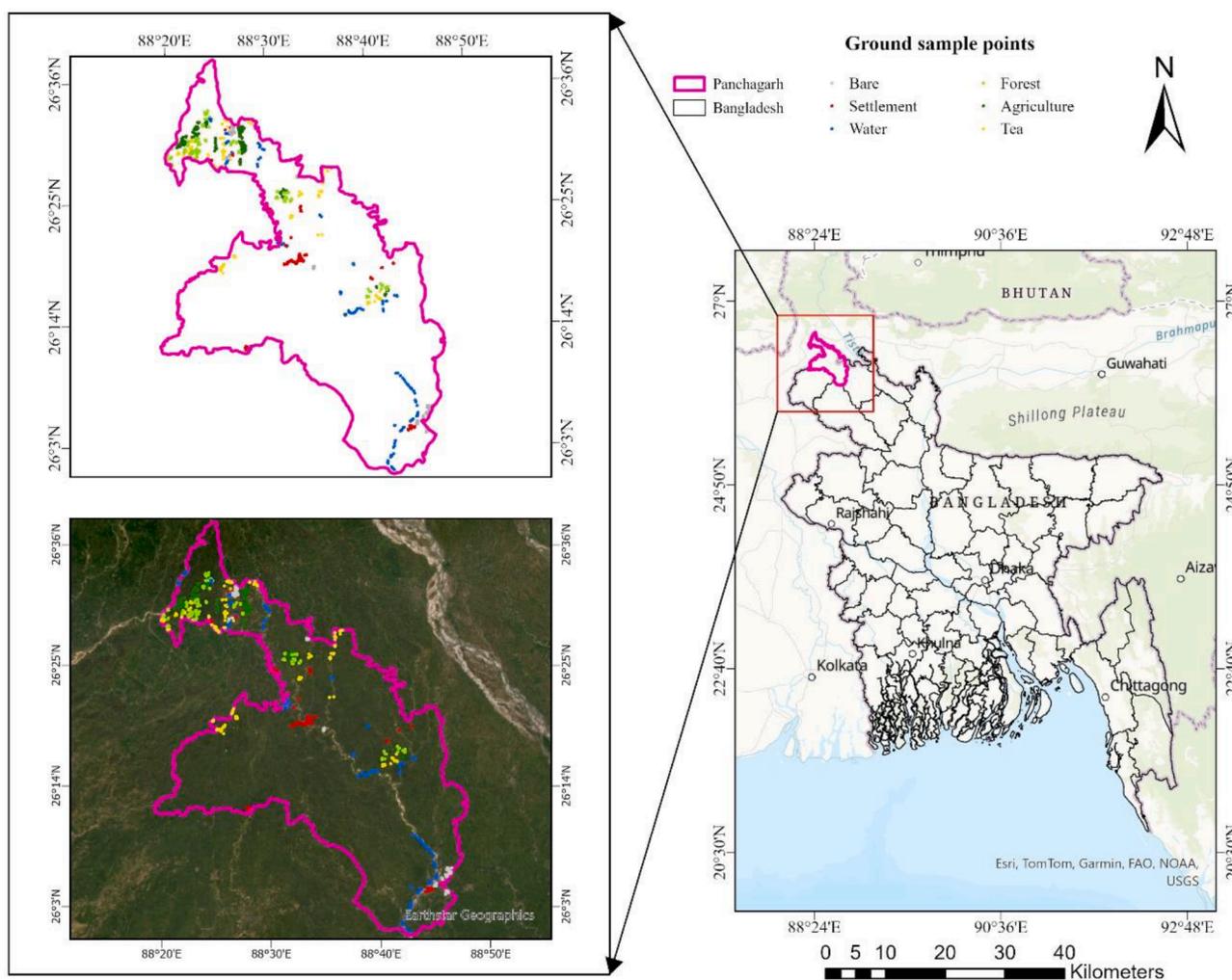


Fig. 1. Selected area of the study.

Sylhet and Chittagong (Saha et al., 2021).

The Panchagarh district of Bangladesh has come under tea cultivation due to its suitable soil and climatic conditions and is one of the fourth major tea growing areas in the country (Rahman et al., 2020a). Since 2000, farmers have been interested in cultivating tea as a cash crop on the plain land of the sub-Himalayan district (Saha et al., 2021). After introducing organic tea by Kazi and Kazi Tea Company, tea cultivation rapidly expanded throughout the Panchagarh district (Prodhan et al., 2023). A feasibility study by the Bangladesh Tea Board shows that about 6000 hectares of land is available for tea cultivation in three sub-districts of Panchagarh (Saha et al., 2021; Sultana et al., 2014). It is also noteworthy that almost all suitable areas in Sylhet and Chittagong have already been saturated by tea cultivation (Rahman et al., 2018; Saha et al., 2021).

Globally, the tea-cultivating areas are increasing rapidly with their demands in the domestic and international markets (Kumar et al., 2013; Parida et al., 2023; Su et al., 2014; Wang et al., 2019). For the expansion of tea cultivation over the last several decades, the influence of market demands, as well as local factors, has been studied by researchers to disentangle the consequences of land transformation (Nasir and Shamsuddoha, 2011; Parida et al., 2023). Although the expansion of tea plantations has contributed to the development of the local economy, it has also caused various environmental issues. The expansion of tea cultivation considerably alters the land use and land cover (LULC), geographical structure, and species diversity. This alteration can result in diverse ecological impacts, including unexpected landslides,

diminished soil fertility, and erosion (Hailu et al., 2023; Alam et al., 2022; Obiahu and Elias, 2020; Dihkan et al., 2013; Parida et al., 2023), and the decline of forest cover may lead to disruption in the forest habitats (Teweldebrihan et al., 2023; Nad et al., 2022; Parida et al., 2023; Shimu et al., 2019). Therefore, it is crucial to regularly monitor tea areas and other surrounding land use dynamics to understand land use alteration and environmental issues. However, nowadays, the transformation of land dynamics into tea gardens has received special attention from the tea growers and stakeholders of the Panchagarh districts. Shawon (2023) reported an astonishing increase in tea cultivation and production in Panchagarh; however, land use classes transforming to tea plantations remain unexplored. Moreover, there is no clear information regarding the chronological expansion of tea cultivation areas in the northern districts; this information would be essential for the sustainable growth of the tea sector and associated stakeholders for sustainable land management.

The physical monitoring of a relatively large area is very laborious and time-consuming, while remote sensing technology can be a useful, effective, and convenient monitoring tool. In recent decades, remote sensing has been widely employed in the detection and analysis of tea plantations (Kalita et al., 2022; Phan et al., 2020; Prokop, 2018; Tang et al., 2020; Wei et al., 2019) and used for monitoring of other land use dynamics (Parida et al., 2023; Sahoo et al., 2022; B. Wang et al., 2019). The remote sensed data has a wide range of information, including spectral, temporal, and spatial, widely used in tea plantation mapping and change detection worldwide (Dihkan et al., 2013; Parida et al.,

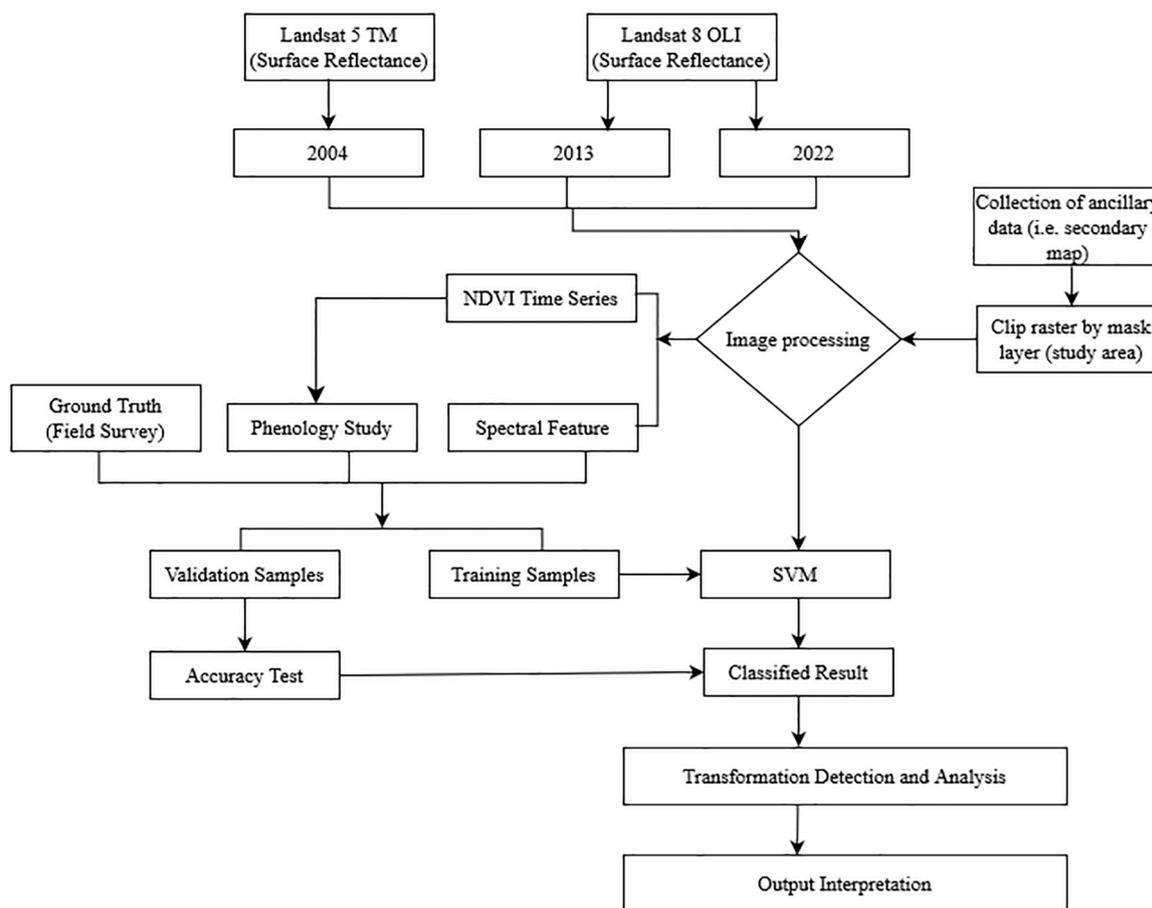


Fig. 2. Detailed workflow of the study.

2023; Ranjan and Parida, 2020). Moreover, medium spatial resolution (e.g. Landsat, MODIS, and Sentinel-2) which is captured at a scale of between 10- and 100-meters spatial distance has been intensively used (Izadi and Sohrabi, 2021; Srivastava et al., 2022) for land cover mapping because of their suitable geographic coverage, high temporal resolution, and availability (Li et al., 2015; Tang et al., 2020; Wang et al., 2019). Recent remote sensing studies advocate using data processing techniques due to their advantages over traditional supervised classification methods, such as maximum likelihood (Ahmad et al., 2013). Researchers have created diverse data processing techniques, including machine learning and deep learning algorithms (Chowdhury, 2024; Khatami et al., 2016; Rodriguez-Galiano et al., 2012; Wang et al., 2019; Weng, 2012; Zhang and Xie, 2012), but their uses are limited in tea land classification. Few studies have used both satellite data and machine learning algorithms to monitor tea plantations (Parida et al., 2023; Phan et al., 2020; Qu et al., 2022). However, various machine learning models, including Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT), and K-Nearest Neighbor (KNN), have been commonly used for land cover classification tasks. In this study, we selected SVM for its effectiveness in handling high-dimensional data and consistent performance in similar contexts (Basheer et al., 2022; TAATI et al., 2015; Dihkan et al., 2013; Maryantika and Lin, 2017). The study aims to detect the expansion of tea plantations and land use transformations in Panchagarh district using SVM.

## 2. Materials and methods

### 2.1. Study area

Panchagarh is one of the most highland regions in Bangladesh

geographically, considering it is in the lower basin of the Himalayas. Plentiful sand and stones are in the soil, giving it a unique composition. The district is located in the far north of Bangladesh between latitude 26°17' and 26°29' north and longitude 88°31' and 88°46' east (Raihan et al., 2020). The total area of the district is 1404.62 km<sup>2</sup>. Its sandy alluvial soil has a strong affinity with the soil of the old Himalayan basin. The northern part of the district has an underground layer of pebbles.

Panchagarh is well known for its tea industry nowadays, vital to the local economy. Currently, 246 tea gardens – 18 large estates, 13 medium-sized, and 215 small-scale gardens – located on >1815 acres in Tetulia and the surrounding district; over 7000 skilled and unskilled labors, mostly women, were temporarily employed. About 2300 workers, primarily women, work alone at the massive Kazi and Kazi Tea Estate in Tetulia. The estate has gained recognition in domestic and foreign markets while generating foreign exchange (Proadhan et al., 2023). The study area and respective spatial ground sample point used in this study are illustrated in Fig. 1.

### 2.2. Satellite data

The tea cultivation area was limited within the private sector and slowly expanded among small-scale farmers in the early 2000s. This study focused on disentangling the shift of land use change at the small growers' level; thus, it considers 2004 the initial stage for detecting tea cultivation areas. The detailed workflow for this study to detect and map tea plantations for 2004, 2013, and 2022 is outlined in Fig. 2. For preparing land use maps, Landsat 5 Thematic Mapper (TM) and 8 Operational Land Image (OLI) at a resolution of 30 m were utilized. The Landsat 5 data was used for 2004, whereas the Landsat 8 data was preferred for 2013 and 2022. Data was provided by an archive of the

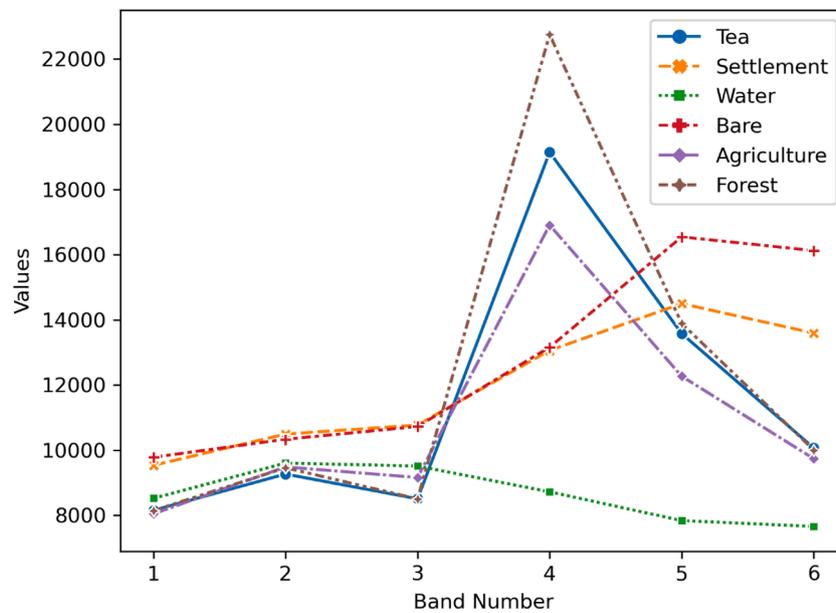


Fig. 3. Spectral profile of the selected features.

Earth Explorer that is freely downloadable. The cloud amount was kept under 5 % as an additional criterion to minimize the cloud effect. The Top of Atmospheric (TOA) data has significant limitations because of the rapid change in land cover and the sensitivity of the spectrum to atmospheric composition (Wang et al., 2020; Xia et al., 2023). Therefore, the Surface Reflectance (SR) data were used in this study. The images were collected for November for all the years considered in this study when not only the spectral and textural features are noticeable after trimming tea but also other crops, such as rice, out of the growing season. The sub-images covering the Panchagarh district were clipped from the original images.

### 2.3. Ground reference data

More precise reference data and an appropriate method are prerequisites for satellite image classification (Qu et al., 2022). This study combined imagery observations (spectral features) and field investigations to determine the reference points. We randomly obtained ground reference data using field investigations with a handheld GPS receiver in the point-positioning mode in Panchagarh in 2022. Garmin 70S GPS tool was used to collect field data. The spectral characteristics of the original bands of the remote sensing images record the reflectance intensity of different ground objects (Qu et al., 2022; Upadhyay and Kumar 2018). By analyzing the different spectral characteristics of these objects, it is possible to distinguish vegetation, water, and other types of ground objects (Peña-Barragán et al., 2011; Qu et al., 2022). Fig. 3 shows the spectral profile of all investigated classes for different spectral bands. The six original bands in the Landsat data were selected for classification: blue, red, green, NIR, SWIR1, and SWIR2. Tea trees and natural forests show substantial spectral similarities; therefore, in addition to the original spectral features, phenological characteristics were also considered in this study.

The phenological characteristics helped to identify vegetation features that specifically helped to separate tea plantations. To analyze the phenological characteristics of the vegetation, we calculated the time series of NDVI and then made a composite band from all the NDVI of the respective year.

### 2.4. Classification method and analysis

After extensive field investigation, six broad land cover classes were

established before the classification stage: tea, waterbody, bare land, agriculture, settlement, and forest. Based on the defined class, we collected a total of 1050 (150 for each class) points for the classification process to train the machine learning model and post-classification and evaluation of the classification accuracy (Shooshtari et al., 2020; Rahimi-Ajdadi and Khani, 2021). The collected ground reference points were randomly divided into three different training-testing separations: 20 %–80 %, 50 %–50 %, and 70 %–30 %. Results in Table A1 show that the 50 %–50 % split generally outperformed other ratios, except for the 2022 dataset, where 70 %–30 % performed better. However, this may risk overfitting due to the larger training set. Therefore, we opted for the 50 %–50 % split for further classification maps generation, as it provides a more balanced approach across all datasets.

This study used a non-parametric SVM with a radial basis function (RBF) kernel to pixel-wise classify the satellite images. The Grid-SearchCV with 10-fold cross-validation from Python's scikit-learn library is used to tune the SVM hyperparameters. The cost parameter (C) was optimized over a range of 1 to 15, with a step size of 1. For gamma, we selected the 'scale' option, which automatically adjusts gamma based on the input data. This combination provided robust performance across the datasets and helped prevent overfitting. The details of parameter C and gamma are shown in Table A1. We chose the RBF kernel because it effectively handles non-linearly separable data by mapping it to higher dimensions, making it well-suited for our classification task. The detection of land transformation into tea gardening was then analyzed using Python programming languages. Additionally, ArcGIS 10.8 was used for map representation, and Python with Microsoft Excel was used for graphical visualization.

### 2.5. Accuracy assessment

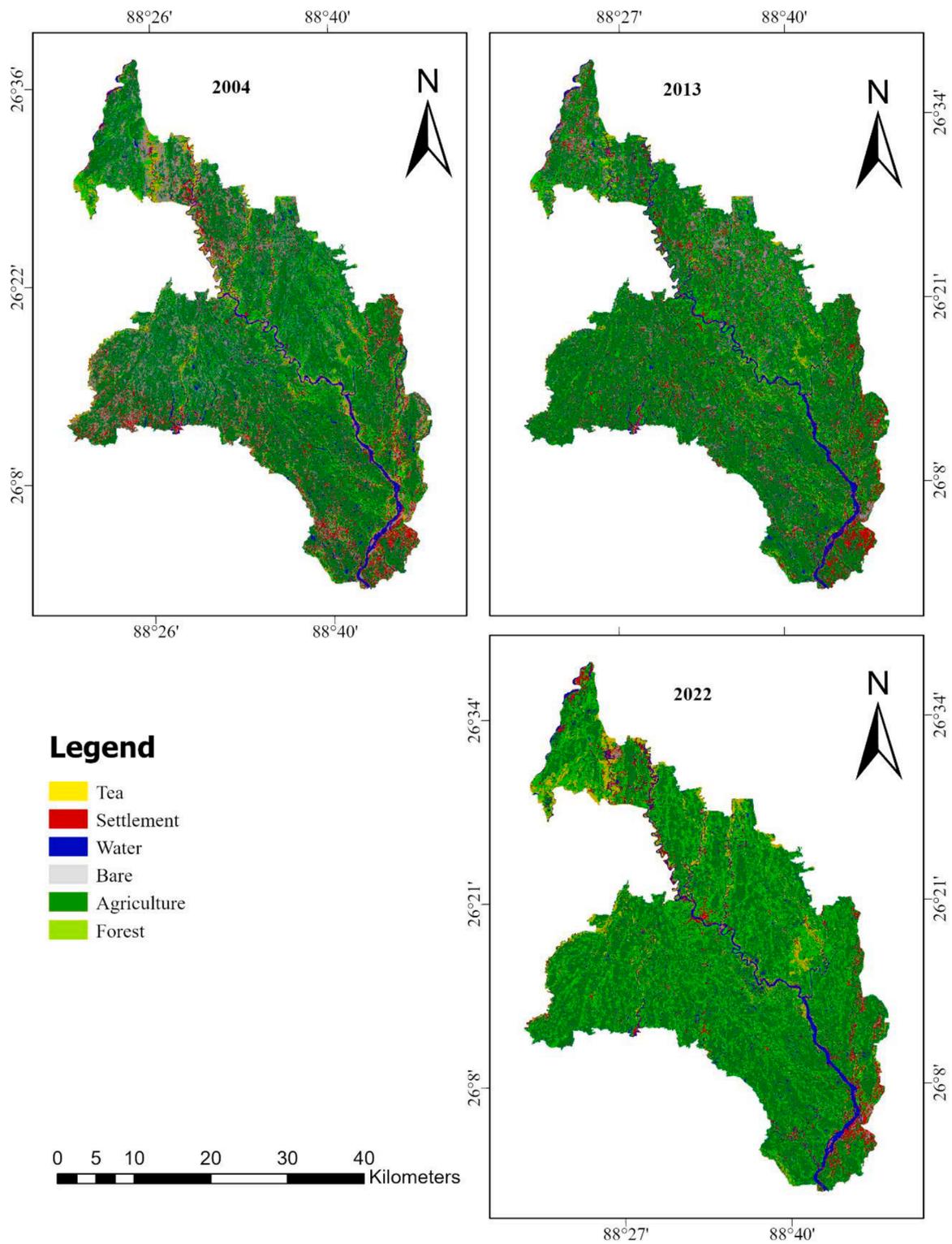
The classification accuracy was demonstrated to see how well the classified results matched the actual ground scenario. The training samples not involved in the classification process (another 50 % of the collected reference data) were used to calculate classification accuracy. A confusion matrix was produced to determine the accuracy of the classification model. Kappa coefficient, overall accuracy, and F1 score were calculated as performance measures metrics. (Maryantika and Lin, 2017; Rahimi-Ajdadi and Khani, 2021; Zheng et al., 2016).

The equations used for accuracy assessment for the  $k$  number class are as follows-

**Table 1**

The classification accuracies of selected features in respected years when 50 %–50 % training testing data were used.

Year	C	gamma	OA %	Kappa	F1 (weighted) %	F1 (each class) %					
						Water Body	Settlement	Bare	Forest	Agriculture	Tea
2004	14	0.00162	92.00	90.21	91.99	99.33	95.36	96.69	75.52	97.99	79.75
2013	14	0.00130	98.48	98.13	98.47	99.67	99.34	100.00	95.36	96.60	98.68
2022	14	0.00121	98.29	97.90	98.29	99.67	95.42	95.95	98.68	98.65	100.00



**Fig. 4.** LULC of Panchagarh of three different years.

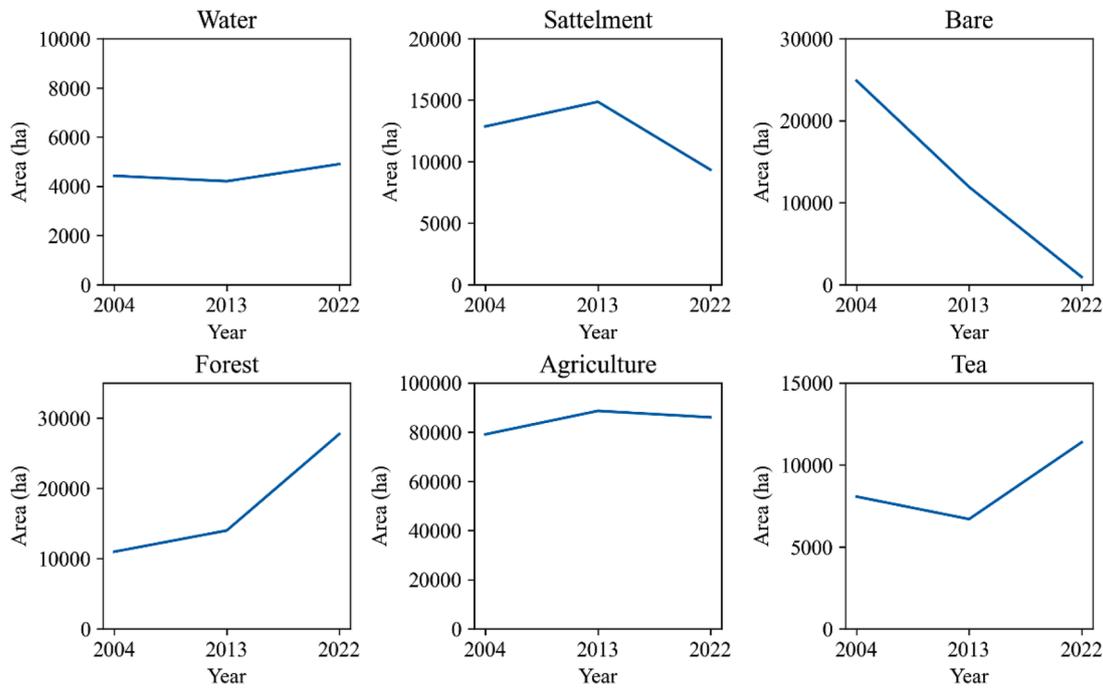


Fig. 5. Changes in the areas of the land classes over the years.

**Overall Accuracy (OA):**

$$OA = \frac{\text{Total Correct Predictions}}{\text{Total Predictions}} \text{ or } OA = \frac{\sum_{i=1}^k (TP_i + TN_i)}{\sum_{i=1}^k (TP_i + TN_i + FP_i + FN_i)}$$

Where,  $TP_i$ ,  $TN_i$ ,  $FP_i$ , and  $FN_i$  denotes True Positive, True Negative, False Positive, and False Negative, respectively, for class  $i$ . The overall accuracy represents the proportion of correctly classified instances across all classes.

Kappa Coefficient ( $\kappa$ ):

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

where  $P_o$  is the observed accuracy (i.e., overall accuracy) and  $P_e$  is the expected accuracy, calculated as:

$$P_e = \frac{1}{N^2} \sum_{i=1}^k (TP_i + FP_i)(TP_i + FN_i)$$

The Kappa coefficient adjusts for agreement by chance, providing a more robust evaluation of the classifier’s performance.

F1 Score (for each class  $i$ ):

$$F1_i = \frac{2 \times \text{Precision}_i \times \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i}$$

Where:

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i}, \text{ Recall}_i = \frac{TP_i}{TP_i + FN_i}$$

Weighted-average F1 Score:

$$F1_{\text{weighted}} = \sum_{i=1}^k \frac{TP_i + FN_i}{N} \times F1_i$$

Where  $N$  is the total number of instances across all classes.

**3. Results**

**3.1. Spatiotemporal maps and classification accuracy**

The classification accuracy results (Table 1) showed that the overall accuracies were 91.43 %, 98.67 %, and 98.48 %, and the kappa coefficients were 89.51, 98.37, and 98.13 for 2004, 2013, and 2022, respectively. A comparison of the classified maps using SVM during 2004–2022 revealed an overall increase in the tea area over time (Fig. 4). The tea expansion was especially significant for the time frame of 2013–2022, which is 6689.97 ha to 11,373.57 ha. In the study area, maximum land was allotted for the agricultural sector, which remained almost constant throughout the study period (Fig. 5& Table A2); however, the bare land area plummeted during the same period from 24,860.97 ha to 925.02 ha (Figs. 5& 6). The tea area in 2004 was 6.31 % (8062.02 ha) of the total land of Panchagarh district, which increased to 8.35 % (11,373.57 ha) in 2022 (Fig. 5). The results also indicated that the increasing rate of tea area between 2013 and 2022 has been more remarkable, with an increase of 4683.60 ha. It is noteworthy that over the 18 years, bare land experienced a decrease of 95.99 %. Bare land, with its rapid reduction in 2004–2013, decreased from 26569.08 ha to 1062.81 ha, i.e., 25506.27 ha of bare land was converted to other land categories, and most of the areas were converted to tea cultivation areas.

**3.2. Land transformation analysis**

In a certain period, the land classes may lose their land in some places, while in others, they may gain new lands. The results of land transformation (Fig. 7& Table A3) showed the amounts of land converted to and from tea plantations. In 2004–2013, there was a reduction in tea areas, and about 4277.97 ha of tea area was converted to agricultural land, which was the highest among all the land types to which tea lost its area; however, the forest highly contributed to tea plantations in the same interval (Fig. 7a). In contrast, the 2013–2022 interval portrayed the opposite scenario of 2004–2013 where the agricultural land was highly transformed into tea plantations (Fig. 7b). The overall land transformation scenarios during the 18 years indicated that the agricultural land remained more or less unchanged, whereas the significant

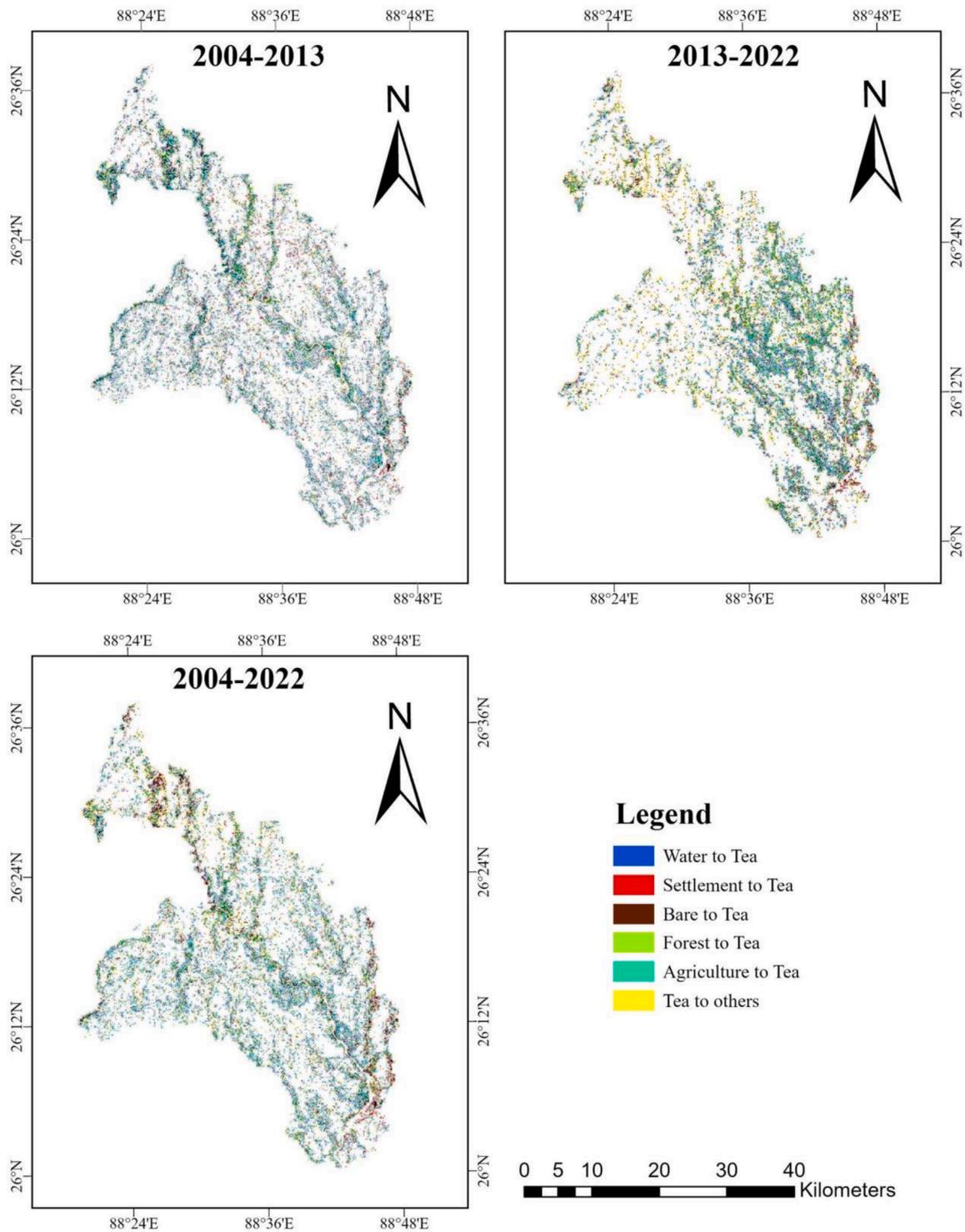


Fig. 6. Maps showing shifts of land classes to tea gardens during 2004–2022.

amount of bare land and forest was transformed to tea plantations (Figs. 7c and 8). Indeed, the two period i.e. 2004–2013 and 2013–2022, showed different patterns in land use types in terms of tea area and agricultural land increase and reduction, especially tea coverage significantly decreased during 2004–2013 but increased substantially during 2013–2022 (Fig. 9).

#### 4. Discussion

##### 4.1. Performance of the classification method

The accuracy of a classification is calculated to evaluate the performance of the classification method. Kappa values ranging from 0.81 to 1.00 denote an almost perfect match between the classified and reference data in the classification systems (Islam et al., 2018; van Vliet et al., 2011), and most importantly, non-parametric methods like machine learning usually offer greater accuracy (Chundu et al., 2024). The

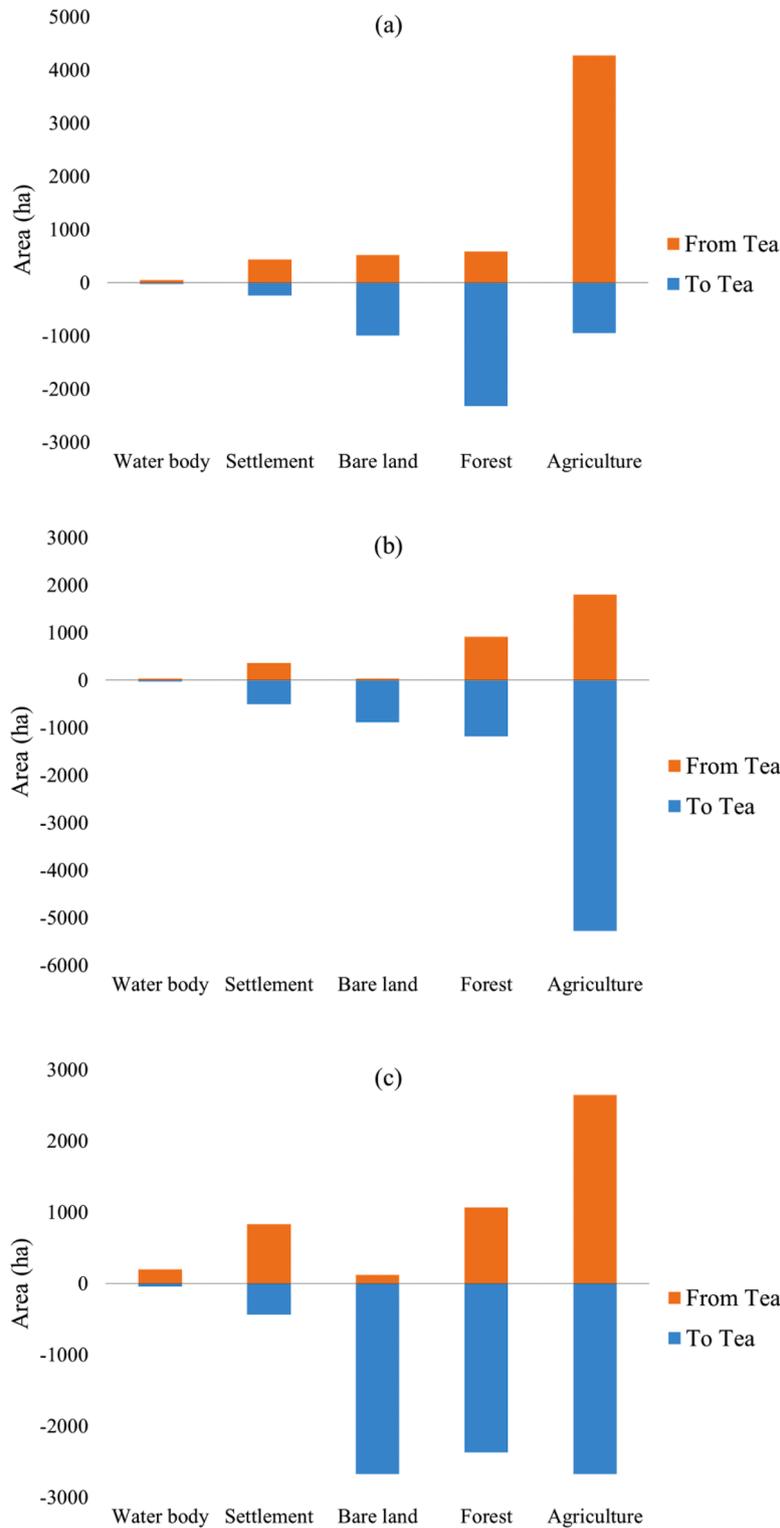


Fig. 7. Land transformation to tea and from tea (a) 2004–2013, (b) 2013–2022, (c) 2004–2022.

accuracy assessment results of this study indicated that the classification method performed satisfactorily and detected tea plantations and land classes that almost matched the reality on the ground, which helped to decipher the transformation of land types into tea gardens.

#### 4.2. Land transformation and tea area expansion

Agriculture, forest, and settlement were the main land use types in

the study area during the past 18 years. Since 2000, the farmers of the Panchagarh district have been getting interested in tea plantations, and the land use types of the district have been changing; mainly, the land dynamics have been transforming into tea plantations to a great extent. The present study analyzed tea areas and changes in land use types from 2004 to 2022, wherein in 2004, the tea area was 6.31 % of the total area of the Panchagarh district. This data implies that tea consumed the other land use types that existed before 2004 and has expanded to 8.35 % of

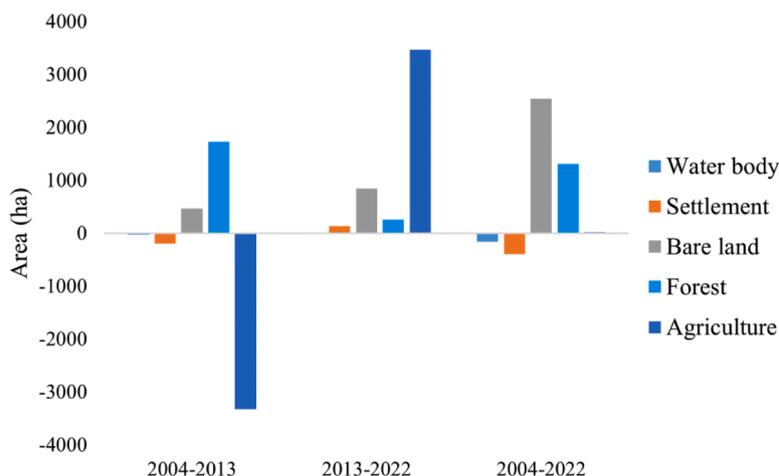


Fig. 8. The net contribution of each land class to tea plantation.

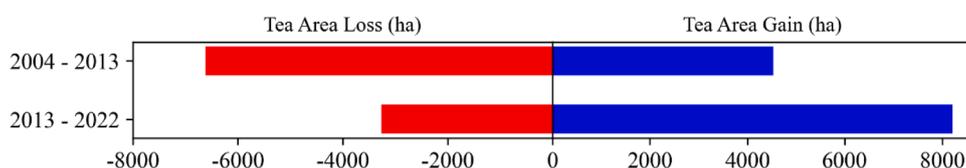


Fig. 9. Total tea area gain and loss over the study period.

the district areas in 2022. Before conducting this study, it was hypothesized that tea might be consumed mainly on agricultural lands; however, this study revealed the real scenario and found that the uncultivated areas, such as bare land, were mostly converted into tea plantations. However, there was an interchange among the land use types, including tea area transformation to other land use types, other land use types of transformation to tea plantations, and inter-transformation among the land use types other than tea plantation area. For instance, during 2004–2013, about 17.02 % tea area reduction was seen from 2004 (Fig. 9). A reduction of tea land areas was also detected in Iran (Rahimi-Ajdadi and Khani, 2021). This might be because some older tea gardens were entirely cut down to establish new gardens or there was an absence of adequate tea leaf processing industries. As observed, the findings of land transformation to tea and from tea were not obtained directly from the algebraic summation of increases together or losses together from the consecutive period because of the interchange between two periods so that some losses in one period were increased in another vice-versa.

However, it is noteworthy that during the 18 years from 2004 to 2022, tea expanded significantly in the Panchgarh district. This rapid expansion of tea gardens might be due to the congenial geographical and environmental conditions (acid soil and higher altitude) that ensured higher leaf yields from tea plantations (Li et al., 2012). Initially, the leading business corporations were investing in tea cultivation, but the pick of tea areas during 2013–2022 was due to the small landholders shifting from conventional land use to tea cultivation. This transformation was due to increasing market demand and higher returns from tea cultivation than traditional agriculture. Guo and Min researched to elucidate the change in tea gardens and explore the factors responsible for the changes (Guo and Min, 2023), and Lou et al. (2013) investigated the transformation of frost to tea gardens with the help of remote sensing and GIS.

Though bare land was highly transformed into tea plantations, forest areas were also significantly consumed by tea plantations. A similar study was conducted in Eastern Himalayan Piedmont in West Bengal, India and found a significant reduction in the forest area transformed into tea plantations (Prokop, 2018). Deforestation in the initial stage of

tea plantations was observed in Asam and Darjeeling Himalayan (Weatherstone, 2008). Moreover, deforestation was commonly found in establishing oil palm, rubber, cocoa, and banana in Southeast Asia, Central Africa and South America (Ajonina et al., 2014; Wannitikul, 2005; Miyamoto, 2006; Miyamoto et al., 2014).

This land transformation process can be explained by the following theories: the land is a complex of human social production, life, and environmental factors (Guo and Min, 2023), and land use types of change is a process of reallocating limited land resources among various uses. Therefore, in the context of global change (such as soil and environment), cost-benefit ratios and market demand have been forcing us to think about transforming functional land use type to a new one, such as a new crop or other land use dynamics. This change mechanism may not always be positive but sometimes negative. For instance, the present study revealed that tea area expansion had raised a significant concern for the surrounding communities because tea area expansion resulted in the reduction of other functional land use dynamics such as cropland, forest, and water bodies.

## 5. Conclusion

Our study highlighted the utilization of RS-GIS-based approaches in detecting land use change dynamics. This study found a chronological expansion of tea cultivation areas; bare land and forest areas were the primary land classes transformed into tea plantations. This might be predicted that the initial transformation of bare lands into tea plantations was owned by the private commercial groups, and slowly, this transformation reached small-scale growers' level. Most importantly, the agricultural land underwent fewer changes, i.e., it remained almost constant. Overall, the tea area has been noticeably expanding daily, and these findings would be helpful to policymakers in making appropriate decisions on land management to conserve croplands and other functional land use types. Therefore, satellite-derived accurate information on the dynamics of land use types and significant changes in tea plantations is required to assess environmental change, land management, and planning.

**Policy implications**

The fallow lands of the adjacent districts might be brought under tea cultivation; however, careful steps are needed when transforming forest areas into tea cultivation areas. The transformation of forest areas to tea cultivation might negatively impact the area’s biodiversity and local climatic conditions. In this connection, farmers need to be encouraged in planting shade trees in tea plantations, this approach might have a positive effect on the environment of the study area. Moreover, establishing backward linkage industries linked to tea cultivation, processing, and marketing would be necessary for the sustainable development of the tea sector of northern Bangladesh.

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**CRedit authorship contribution statement**

**Md Sahadat Hossan:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Masud Ibn Afjal:** Writing – original draft, Visualization,

**Appendix**

**Table A1**

The classification accuracies and SVM parameter of selected features in respected years when different training testing data were used.

Year	Ratio	C	gamma	OA (%)	Kappa	F1 (weighted) %	F1 (each class) %					
							Water Body	Settlement	Bare	Forest	Agriculture	Tea
2004	50–50	14	0.00162	92.00	90.21	91.99	99.33	95.36	96.69	75.52	97.99	79.75
	70–30	14	0.00161	90.16	87.96	90.20	98.99	93.48	95.56	71.91	96.63	76.09
	20–80	3	0.00159	87.62	84.86	87.07	98.09	92.24	94.02	94.44	94.44	74.39
2013	50–50	14	0.00130	98.48	98.13	98.47	99.67	99.34	100.00	95.36	96.60	98.68
	70–30	3	0.00128	98.09	97.66	98.09	100.00	100.00	100.00	93.48	94.25	98.90
	20–80	14	0.00129	98.10	97.67	98.10	98.95	98.36	98.33	95.90	97.44	98.77
2022	50–50	14	0.00121	98.29	97.90	98.29	99.67	95.42	95.95	98.68	98.65	100.00
	70–30	13	0.00120	99.36	99.22	99.36	100.00	98.88	98.90	98.90	98.88	100.00
	20–80	13	0.00172	97.02	96.37	97.03	97.90	93.06	94.56	98.35	98.33	99.16

**Table A2**

Area of the selected land use types of Panchagarh district (areas in hectares).

Year	Water	Settlement	Bare	Forest	Agriculture	Tea
2004	4421.43	12,856.41	24,860.97	10,966.5	79,077.87	8062.02
2013	4200.66	14,860.8	11,904.84	13,986.63	88,602.3	6689.97
2022	4898.16	9336.78	925.02	27,713.34	85,998.33	11,373.57

**Table A3**

Inter-transformation between tea and other land use types (areas in hectare).

Land Dynamics	2004–2013		Net conversion to tea	2013–2022		Net conversion to tea	2004–2022		Net conversion to tea
	To Tea	From Tea		To Tea	From Tea		To Tea	From Tea	
Water body	19.08	52.20	–33.12	24.84	37.62	–12.78	43.11	201.42	–158.31
Settlement	237.42	436.59	–199.17	498.87	370.44	128.43	432.81	834.93	–402.12
Bare land	991.62	526.50	465.12	880.20	40.68	839.52	2669.13	125.37	2543.76
Forest	2317.05	592.11	1724.94	1176.03	917.46	258.57	2369.88	1064.79	1305.09
Agriculture	948.15	4277.97	–3329.82	5277.78	1807.92	3469.86	2672.01	2648.88	23.13

Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Md.Faruq Hasan:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Md.Abu Hanif:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

**Declaration of competing interest**

We hereby declare that no known conflicts of interest are associated with this manuscript. All named authors have read and approved the manuscript, and no other individuals have met the authorship criteria but have not been included. All have unanimously approved the order of authors listed in the paper.

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## Data availability

Data will be made available on request.

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### Further reading

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