

Article

Integrating Cloud Computing and Landscape Metrics to Enhance Land Use/Land Cover Mapping and Dynamic Analysis in the Shandong Peninsula Urban Agglomeration

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Abstract

Accurate land use/land cover (LULC) maps generated through cloud computing can support large-scale land management. Leveraging the rich resources of Google Earth Engine (GEE) is essential for developing historical maps that facilitate the analysis of regional LULC dynamics. We implemented the best-performing scheme on GEE to produce 30 m LULC maps for the Shandong Peninsula urban agglomeration (SPUA) and to detect LULC changes, while closely observing the spatio-temporal trends of landscape patterns during 2004–2024 using the Shannon Diversity Index, Patch Density, and other metrics. The results indicate that (a) Gradient Tree Boost (GTB) marginally outperformed Random Forest (RF) under identical feature combinations, with overall accuracies consistently exceeding 90.30%; (b) integrating topographic features, remote sensing indices, spectral bands, land surface temperature, and nighttime light data into the GTB classifier yielded the highest accuracy (OA = 93.68%, Kappa = 0.92); (c) over the 20-year period, cultivated land experienced the most substantial reduction (11,128.09 km²), accompanied by impressive growth in built-up land (9677.21 km²); and (d) landscape patterns in central and eastern SPUA changed most noticeably, with diversity, fragmentation, and complexity increasing, and connectivity decreasing. These results underscore the strong potential of GEE for LULC mapping at the urban agglomeration scale, providing a robust basis for long-term dynamic process analysis.

Keywords: land use/land cover (LULC); cloud computing; machine learning; landscape pattern; Shandong Peninsula urban agglomeration



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1. Introduction

Since LULC mirrors the socio-economic, cultural, and environmental priorities of any given region, the rapid generation of high-precision LULC data is of great significance for regional sustainable development [1,2]. Remote sensing data coupled with machine learning techniques has revolutionized traditional land surveys, enabling regular, large-scale monitoring of LULC through the transformation of raw digital images into useful semantic information [3,4]. Simultaneously, multiple LULC datasets from diverse remote sensing sources have emerged, covering regions, countries, and even the entire globe [5,6]. Conducting quantitative analysis of LULC changes based on these existing products can save the time and effort required to independently generate classification maps. However,

comparative assessments show that variations in class definitions, algorithms, and minimum mapping units across LULC datasets introduce biases and uncertainties in regional consistency and accuracy, thereby affecting the accurate representation of actual LULC status [7–10]. Moreover, the limited temporal coverage and comparability of existing LULC datasets directly impact the subsequent outcomes in target-specific studies related to LULC change, particularly those focusing on agriculture [11], urbanization [12], and ecological restoration [13].

Independent mapping, with classifiers and features selected according to specific objectives and local conditions, can reduce reliance on existing LULC datasets with discontinuous updates and overcome the limitations of uncertain product release cycles. This approach still holds a practical and flexible advantage in producing historical and regularly updated maps while minimizing classification uncertainty [14]. Classifiers exhibit unique strengths across different application scenarios, making it challenging to identify a universally optimal classifier. Comparative studies in Dali County [15], the uMngeni river catchment [16], and Tehran [17] have shown that RF, being less prone to overfitting, outperformed classifiers such as Support Vector Machines and Artificial Neural Networks. However, relatively few studies have explored the usability of GTB for LULC mapping, despite its potential as a competitive alternative. By enriching features, classifiers gain improved decision-making capacity during training, which allows them to detect subtle differences among LULC classes. Multispectral bands, remote sensing indices, and other auxiliary data are extensively integrated into the classification training process to capture comprehensive LULC information or to target specific classes [18,19]. Understanding the relative contribution of these features to classification performance, would help clarify strategies for optimized multi-feature fusion.

The emergence and continued development of cloud computing platforms for geographic remote sensing data processing have provided powerful help for conducting autonomous online LULC classification, drawing increasing attention from researchers [20,21]. Thanks to the Java and Python Application Programming Interfaces (APIs) and parallel processing capacity provided by the high-performance computing platform GEE, researchers have easy access to seamlessly integrate multi-source datasets for the development of customized geospatial processing workflows for different tasks [22,23]. When dealing with large-scale region mapping that involves data-intensive and complex classification processes, GEE offers a resource-efficient and technologically supportive environment [24]. It alleviates the challenges of decentralized data acquisition, limited storage constraints, long processing cycles, and high computational demands typically faced by traditional stand-alone software processing that relies on locally downloaded remote sensing data. Consequently, GEE-based LULC mapping has become an indispensable tool for advancing research on regional sustainability and human-earth interaction, with applications ranging from nature reserves to the continental scale [25–29]. With ongoing breakthroughs in global satellite remote sensing and the expanding capabilities of GEE, it is imperative to develop fit-for-purpose classification frameworks that integrate multiple data sources to tap into the potential of GEE for LULC mapping. Nevertheless, systematic evaluations of multi-source data fusion and the synergies among diverse features and classifiers, including the parallel ensemble RF classifier and the sequential optimization GTB classifier, remain scarce, particularly at the urban agglomeration scale.

Landscape pattern is regarded as the spatial manifestation of LULC, reflecting the arrangement and combination of heterogeneous landscape elements [30]. High-precision maps provide a solid foundation for examining LULC changes, while their integration with landscape metrics for dynamic analysis has been a research emphasis [31,32]. To analyze the spatial variability of landscape patterns over a large area, the equally spaced grid

method reduces computational burden and accelerates analysis, while still yielding reliable results, as opposed to the moving window approach. However, both methods impose requirements on the spatial extent, since overly large grids or window radii can oversimplify landscape patterns and result in considerable information loss [33,34]. The inflection-point method and semivariogram analysis are widely employed to determine the extent, and the applicability of each method has been validated in spatial variability studies [35–37]. However, the combined advantages of these two methods remain underexplored and merit further development.

The SPUA, a core component of China's urbanization strategy, experienced an increase in its permanent resident urbanization rate from 43.50% to 66.48% between 2004 and 2024 [38,39]. This rapid urban population growth directly accelerated land urbanization and reshaped landscape patterns, evident in early-stage green-gray conversions during urban expansion and later efforts to safeguard cultivated land and restore vegetation [40,41]. This study aims to utilize the GEE cloud computing platform to develop an efficient and reliable classification scheme and to analyze the spatio-temporal dynamics of LULC and landscape patterns in the SPUA from 2004 to 2024. Specific objectives were (a) to evaluate the performance of RF and GTB classifiers under varying feature input conditions and determine which is preferred; (b) to examine the effects of different features on the classification accuracy and which feature combination leads to peak accuracy; and (c) to investigate the dynamic process of LULC change from the perspectives of spatio-temporal characteristics, transitions, and the evolution of landscape patterns using the optimal extent.

2. Materials and Methods

2.1. Study Area

Geographically, the SPUA lies on the eastern coast of China and within the river–sea junction of the Yellow River Basin, extending between 34°22′–38°24′ N and 114°47′–122°43′ E (Figure 1). The 2017 expansion of the SPUA brought its coverage to the entirety of Shandong Province, now consisting of 16 cities, headed by two core cities of Jinan and Qingdao, spanning roughly 155,800 km². Nearly 65.56% of the SPUA is dominated by plains, with the lowest elevation in the Yellow River Delta being less than 10 m [42]. The SPUA has a high level of urban–rural integration and is an important economic growth pole in China. In 2023, it recorded a per capita GDP of 90,771 yuan and achieved a gross regional product exceeding 9.20 trillion yuan, accounting for about 7.30% of the national GDP.

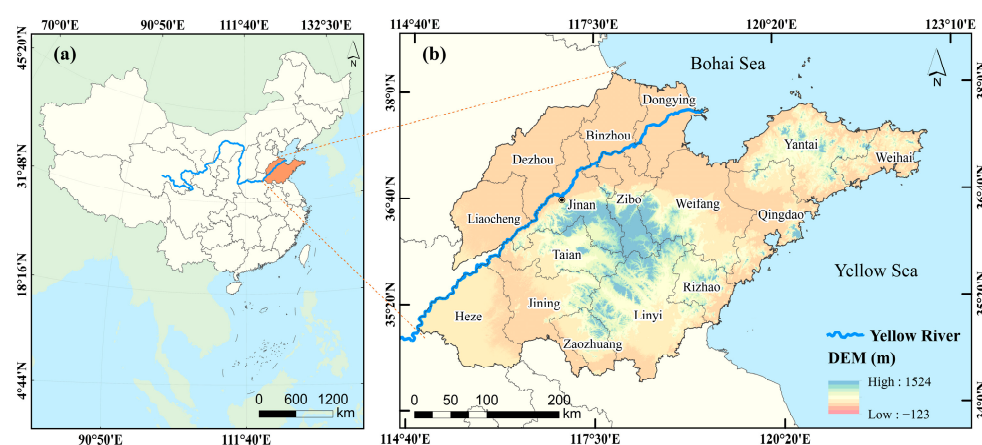


Figure 1. Geographic location of the study area: (a) the SPUA in China; (b) boundaries, cities, and digital elevation model (DEM) of the SPUA.

2.2. Data and Preprocessing

The datasets used include a series of Landsat TM/OLI images, NASA DEM, and nighttime light (NTL) data, all of which are available on GEE. The bands used are summarized in Table 1. The annual Landsat Surface Reflectance (SR) datasets utilized in this study were acquired at Level 2, indicating that the satellite images had undergone prior radiometric, geometric, and atmospheric corrections. To obtain high-quality, cloud-free images covering the SPUA, filtering criteria were applied: images from the vegetation growing season (April–October) and adjacent periods with cloud coverage below 22% were selected, followed by band median compositing. Additionally, the Landsat Top of Atmosphere (TOA) reflectance datasets, containing thermal infrared bands for land surface temperature (LST) retrieval, were also subjected to the same filtering conditions and processing workflow. To ensure classification accuracy, NTL data with mitigated saturation effects were reprojected to match the Landsat images, and raster data resolutions were unified at 30 m. Once the individual images were prepared, image retentions were performed to minimize subsequent data processing workloads by study area boundaries derived from the National Catalogue Service For Geographic Information website (<https://www.webmap.cn/main.do?method=index> (accessed on 10 April 2024)).

Table 1. Datasets and bands used in this study on GEE.

Dataset	Band	Year	Resolution
USGS Landsat 5 Level 2, Collection 2, Tier 1	SR_B1 (blue), SR_B2 (green), SR_B3 (red), SR_B4 (nir), SR_B5 (swir1), SR_B7 (swir2)	2004	30 m
USGS Landsat 5 TM Collection 2 Tier 1 TOA Reflectance	B6 (thermal infrared 1)	2009	
USGS Landsat 8 Level 2, Collection 2, Tier 1	SR_B2 (blue), SR_B3 (green), SR_B4 (red), SR_B5 (nir), SR_B6 (swir1), SR_B7 (swir2)	2014	
USGS Landsat 8 Collection 2 Tier 1 TOA Reflectance	B10 (thermal infrared 1)	2019	
		2024	
NASA 30m Digital Elevation Model [43]	elevation	2000	1000 m
Consistent and Corrected Nighttime Light Dataset from DMSP-OLS (1992–2013) v1 [44]	b1 (corrected nighttime light intensity)	2004	
		2009	
VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1	avg_rad (average DNB radiance values)	2014	463.83 m
		2019	
		2024	

To ensure comparability and adequately capture the spatial dynamics of LULC, we applied a consistent sampling strategy across all study periods. Initially, 1000 sampling points were randomly generated within the SPUA, and additional points were manually added in areas with high spatial heterogeneity. Each sample was visually interpreted with reference to sub-meter resolution historical imagery from Google Earth and the Shandong Province Geographic Information Public Service Platform, and assigned to one of six designated LULC classes (cultivated land, forest, grassland, water, built-up land, or unused land). In total, 6462 samples were collected for 2004, 2009, 2014, 2019, and 2024, averaging approximately 1292 per year. For 2024 specifically, 1233 samples were collected (Figure 2). The sample density was highest for cultivated land and lowest for unused land, reflecting the actual spatial distribution of LULC in the SPUA. Except for forest and grassland, all classes showed good spatial representativeness. The uneven distribution of forest and

grassland primarily stems from their clustered occurrence, which is strongly influenced by topography.

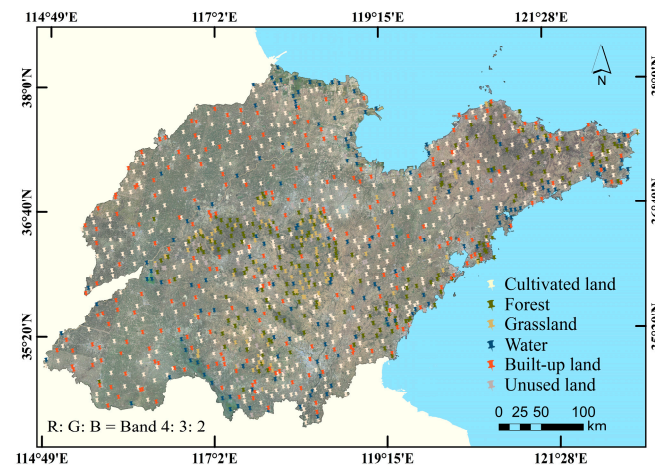


Figure 2. Spatial distribution of LULC classification samples in the SPUA for 2024.

2.3. LULC Mapping

2.3.1. Classifier Selection

Two similar tree-based machine learning classifiers available on GEE were compared for classification: RF and GTB. Both of them improve the overall accuracy and robustness by combining multiple decision trees, but the former and the latter are algorithms that employ decision trees with the ideas of bootstrap aggregation (bagging) and boosting, respectively. Random forest is composed of multiple independent decision trees, using a majority voting mechanism to enhance the accuracy and stability of the final prediction [45]. For GTB, the strategy is to optimize the prediction performance progressively by iteratively constructing new decision trees to gradually reduce the residuals of the preceding trees [46].

The number of decision trees was determined using 5-fold cross-validation within the previously reported sufficient range of 30–200 for LULC classification [47–50]. Both high and balanced performance were observed beyond ~100 trees for RF and ~140 for GTB, where Accuracy and Macro-F1 stabilized (see Figure A1, Appendix A). Considering the trade-off between classification performance and efficiency, we set this hyperparameter to 110 for RF and 160 for GTB. Meanwhile, the shrinkage parameter of the GTB classifier was set to 0.09. The remaining parameters were kept at their default values. In the `ee.Classifier.smileRandomForest` function, the number of variables per split was defined as the square root of the total number of variables. For the `ee.Classifier.smileGradientTreeBoost` function, a 0.70 sampling rate was applied for stochastic tree boosting, and LeastAbsoluteDeviation was selected as the loss function.

2.3.2. Feature Extraction and Combination

We constructed a feature set integrating six categories of information (Table 2). Landsat spectral bands were extracted, and remote sensing indices and texture features were generated to enhance the discrimination of target LULC classes based on spectral and spatial characteristics. Texture features were derived from the first principal component of annual median composite Landsat images, which accounted for over 60% of the spectral variance, using a gray-level co-occurrence matrix with a 3×3 sliding window. Topographic features, including elevation, slope, and aspect, were extracted from NASA DEM data. LST was retrieved using an established method based on the calculation of vegetation fraction and land surface emissivity [51]. NTL, a widely used indicator for tracking population

concentration, industrial production, and commercial activity, was utilized to capture socio-economic information.

Table 2. A feature set for classification.

Category	Feature	Number
Spectral bands	BLUE, GREEN, RED, NIR, SWIR1, SWIR2	6
Remote sensing indices	PGI, PMLI, NDVI, MNDWI, NDBI, BSI	6
Texture features	ASM, CONT, CORR, VAR, IDM, SAVG, ENT	7
Topographic features	ELEVATION, SLOPE, ASPECT	3
Land surface temperature	LST	1
Nighttime light	NTL	1

Note: The corresponding calculation formulas of all remote sensing indices are listed in Table A1 (Appendix A). In addition, ASM, CONT, CORR, VAR, IDM, SAVG, and ENT refer to the texture features of Angular Second Moment, Contrast, Correlation, Variance, Inverse Difference Moment, Sum Average, and Entropy, respectively.

Owing to their widespread use and proven effectiveness for target discrimination in mapping studies [52–54], spectral bands and remote sensing indices were integrated to form the baseline feature combination (C1) for classification. Feature combinations C2 to C5 were produced, where C2 added texture features to C1, C3 added topographic features to C2, C4 added LST to C3, and C5 added NTL to C4. We intended to examine the effect of stepwise addition of texture, topographic, LST, and NTL features on the classification accuracy of both classifiers by this strategy. In addition to testing different feature combinations, features with low contributions that exert little influence on the model were selectively removed based on importance ranking, leading to the construction of an optimized feature combination (C6).

2.3.3. Accuracy Assessment

The `ee.randomColumn()` function in GEE was used to randomly partition the sample points, allocating 70% of the samples for training and the rest for validation. The major metrics of the confusion matrix (Equations (1)–(4)), including the producer accuracy (PA), user accuracy (UA), overall accuracy (OA), and the kappa coefficient (Kappa), were used to evaluate the classification performance and validate the effectiveness of each classifier under different feature combinations.

$$PA = T_{ii} / T_{+i} \quad (1)$$

$$UA = T_{ii} / T_{i+} \quad (2)$$

$$OA = \sum_{i=1}^k T_{ii} / N \quad (3)$$

$$Kappa = (P_o - P_e) / (1 - P_e) \quad (4)$$

where T_{ii} is the count of correctly classified instances for LULC class i , T_{+i} is the count of actual instances for LULC class i , T_{i+} is the total number of instances predicted as LULC class i , N is the total number of instances, P_o is the observed accuracy, and P_e is the expected agreement by chance.

Apart from evaluating accuracy with metrics, we assessed the reliability of the SPUA classification by comparing our 2019 results with the annual China Land Cover Dataset (CLCD) [55] of the same year and the China's Land Use/Cover Dataset (CLUD) [56] of 2020. These two Landsat-derived datasets, as frequently used multi-period LULC products for China, differ in terms of temporal coverage and update frequency, with their latest versions overlapping only in 2023.

2.4. LULC Dynamics Analysis

2.4.1. Transitions of LULC

Dissimilarities in LULC at each time point relative to 2024 were quantified statistically by a transition matrix (Equation (5)), a widely accepted application of the Markov model that tabulates the relative change frequencies for all type transitions at two dates.

$$S_{ab} = \begin{pmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nn} \end{pmatrix} \quad (5)$$

where S_{ab} is the LULC class transfer area from the initial state a to the final state b and n denotes the total amount of LULC classes ($n = 6$).

2.4.2. Landscape Pattern Analysis

To better understand the spatial implications of LULC changes, we employed landscape-level metrics (Table 3) with the equally spaced grid method to capture the landscape patterns in the SPUA. Landscape metrics such as Shannon's Diversity Index (SHDI), Patch Density (PD), Splitting Index (SPLIT), Landscape Shape Index (LSI) and Contagion (CONTAG) are highly condensed information on LULC structure and spatial configuration, which are capable of spotlighting regional landscape diversity, fragmentation, complexity of distribution and shape, and connectivity characteristics, all calculated with the help of Fragstats 4.2 software.

Table 3. Landscape metrics at the landscape-level used in the study.

Metric	Formula	Unit	Explanation
SHDI	$SHDI = -\sum_{i=1}^m (P_i \times \ln P_i)$	\	Higher values indicate greater landscape richness.
PD	$PD = \frac{N_i}{A} (10,000) (100)$	No. per 100 ha	Higher values indicate a more uneven spatial distribution of different patch types.
SPLIT	$SPLIT = A^2 / \left(\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2 \right)$	\	Higher values indicate a more fragmented landscape.
LSI	$LSI = 25 \sum_{k=1}^m (e_{ik}) / \sqrt{A}$	\	Higher values indicate increased complexity in landscape shapes.
CONTAG	$CONTAG = \left[1 + \frac{\sum_{i=1}^m \sum_{k=1}^m \left[P_i \cdot \frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right] \cdot \left[\ln \left(P_i \cdot \frac{g_{ik}}{\sum_{k=1}^m g_{ik}} \right) \right] \right]}{2 \ln(m)} \right] (100)$	%	Higher values indicate stronger connectivity among landscape-dominant patches.

Note: m refers to the number of patch classes present in the landscape, n refers to the number of patches. P_i refers to the proportion of the landscape occupied by patch class i , N_i refers to the number of patches in the landscape of patch class i , A refers to the total landscape area (m^2), a_{ij} refers to the area (m^2) of patch ij , e_{ik} refers to the total length (m) of edge in landscape between patch classes i and k , and g_{ik} refers to the number of adjacencies between pixels of patch classes i and k based on the double-count method.

The equally spaced grid method involves partitioning the entire region into several equally sized, continuously arranged grids and calculating landscape metrics for each grid sequentially. The average patch size of the SPUA landscape was calculated to be approximately 0.27 km^2 over the study period. According to the empirical principle that the minimum analysis grid size should be 2–5 times the average patch size [57], even when the upper threshold value of 1.16 km was taken as the analysis scale in this study,

computational overload would be an inevitable dilemma. Therefore, to determine a larger scale, we combined the inflection-point method and the semivariogram model to identify the optimal spatial extent for calculating landscape metrics and to mitigate uncertainties associated with scale effects. Multi-level grids were created at scales ranging from 1.80 km to 23.40 km, based on previous findings that scale effects level off beyond 25 km [58,59]. The inflection point of the response curve was used to identify a preliminary scale interval, which was then subdivided for semivariogram fitting in GS+ 9.0 Geostatistics Software. Analysis was performed only for SHDI and PD, anisotropy-free metrics responsive to spatial scale, whereas SPLIT, LSI, and CONTAG were excluded because of their sensitivity to patch geometry and spatial arrangement [60,61]. The final extent of the SPUA landscape pattern analysis was determined by the criteria of a smaller Nugget/Sill ratio and a higher coefficient of determination (R^2) [62]. The formula for the semivariogram that reflects differences in regionalized random variable attributes with respect to spatial distance is as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad (6)$$

where $\gamma(h)$ represents the semivariogram, h is the spatial distance between samples, $N(h)$ is the number of sample pairs separated by lag h , and $Z(x_i)$ and $Z(x_i + h)$ are the attribute values of variables at locations x_i and $x_i + h$, respectively. The general technical flowchart of this study is depicted in Figure 3.

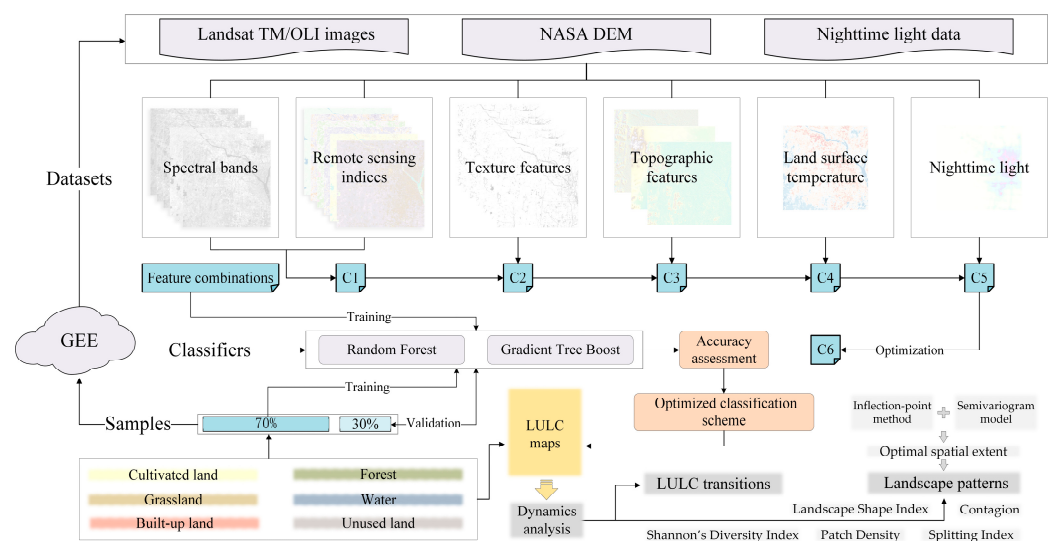


Figure 3. Technical flowchart of the study.

3. Results

3.1. LULC Classification

3.1.1. Performance of Classifiers Under Feature Combinations

Figure 4 presents the LULC mapping results produced by RF and GTB classifiers, offering valuable insights into the relative contributions of each feature combination. Visual analysis revealed that, within Area I, both classifiers reliably identified water across all feature combinations. In Area II, the combination of C1 and C2 struggled to separate grassland from cultivated land, and it was not until the addition of topographic features in C3 that the differentiation of forest, grassland, and cultivated land in highly vegetated areas was substantially enhanced. The inclusion of LST in C4 and NTL in C5 was instrumental in correctly identifying built-up land and differentiating it from unused land, with only minor differences observed between the results in Area III.

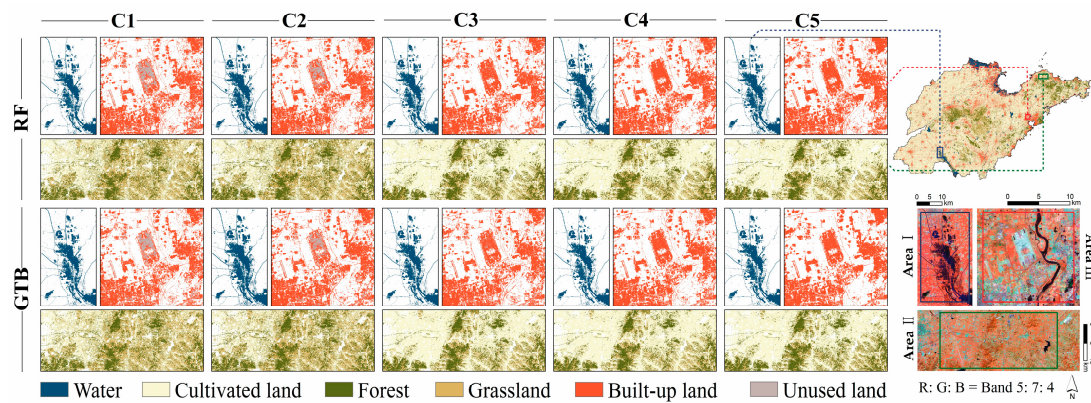


Figure 4. Comparison of mapping results of RF and GTB classifiers across different feature combinations in the SPUA reference areas.

The differences between classifications generated by RF and GTB were elaborated with statistical analysis, with OA and Kappa values mentioned in Table 4. As for the RF classifier, classification accuracy increased incrementally by 0.07%, 2.33%, 0.57%, and 1.06% with the sequential addition of texture features, topographic features, LST, and NTL. The model trained with the complete set of 24 features (C5) had the highest accuracy, with OA for 92.20% and Kappa for 0.90. With regard to the GTB classifier, classification accuracy generally improved with the addition of features, but followed by a slight decrease, with its highest accuracy being achieved by C4 (OA = 93.22%, Kappa = 0.91). The addition of topographic features (C3) provided the most significant OA improvement (2.27%) for GTB compared to the other features. The maximum accuracy difference between GTB and RF occurred at C2, with GTB surpassing RF by 2.15%. This difference diminished as topographic features, LST, and NTL were gradually incorporated. Nevertheless, GTB was prioritized for SPUA LULC mapping, given its consistent advantage of at least 1.00% across all feature combinations.

Table 4. Comparison of RF and GTB classification accuracies with different feature combinations.

Feature Combination	RF		GTB	
	OA	Kappa	OA	Kappa
C1	88.17%	0.85	90.30%	0.87
C2	88.24%	0.85	90.39%	0.88
C3	90.57%	0.88	92.66%	0.90
C4	91.14%	0.89	93.22%	0.91
C5	92.20%	0.90	93.20%	0.91

3.1.2. Optimization of Feature Combinations

Findings from the importance score ranking revealed that the SLPOE (0.074) and ELEVATION (0.072) of topographic features, NDVI (0.069) and PMLI (0.068) of remote sensing indices, and the spectral band BLUE (0.062) strongly influenced the classification (as depicted in Figure 5). Notably, the cumulative contribution of texture features to the classification was merely 0.048. Among them, SAVG had the highest contribution of 0.012, yet this value still lagged behind any feature from other categories. Texture features also led to only marginal improvements in classification accuracy (<0.10%), indicating that their impact was considerably weaker than that of the other features. Although including NTL in GTB-C5 slightly reduced OA (0.02%), its relatively high importance score justified retaining it in the model. Consequently, texture features were deemed optional, and the optimal feature combination (C6) was established by retaining all features except these.

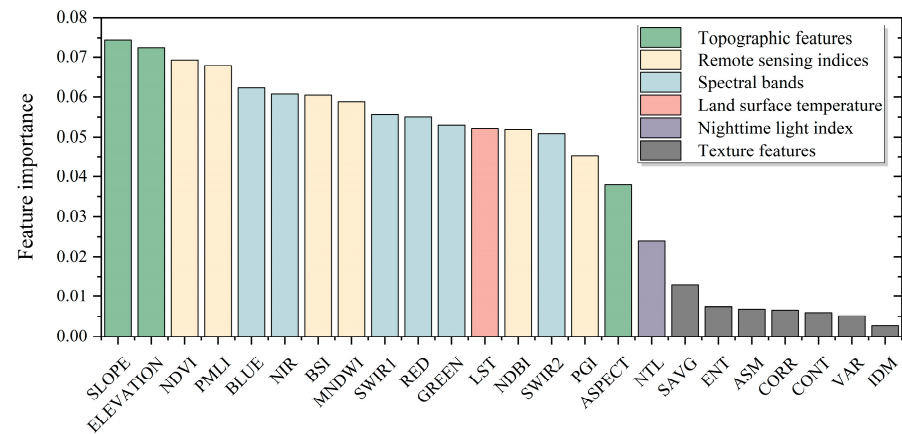


Figure 5. Ranking of feature importance scores.

3.1.3. Classification Assessment and Comparison

Schemes RF-C5, GTB-C4, and GTB-C6 effectively classified all classes at thresholds of $\geq 80.00\%$ for both UA and PA, as displayed in Figure 6. The misclassification of cultivated land and built-up land led a lower OA for RF-C5 compared with GTB-C4. In addition, GTB-C4 performed sub-optimally than GTB-C6 in identifying certain LULC classes, such as forest, water, and built-up land. Accordingly, GTB-C6 was determined as the final classification scheme, delivering robust accuracy across the majority of classes, with OA and Kappa values 0.46% and 0.01 higher than those of GTB-C4, respectively. Using this optimized scheme on GEE, OAs for the study period ranged from 91.02% in 2014 to 93.68% in 2024 (see Table A2 in Appendix A).

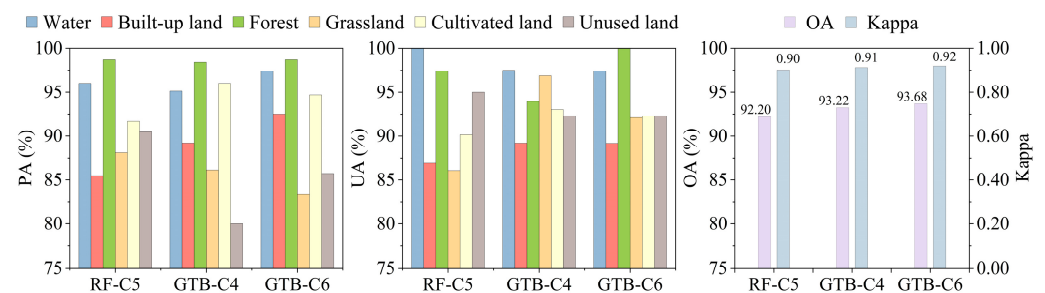


Figure 6. Comparative evaluation of the RF-C5, GTB-C4, and GTB-C6 classification schemes.

The final LULC maps were further validated through comparison with two major LULC change datasets (CLCD and CLUD) and cross-referenced against Landsat-8 OLI image slices of the SPUA. As shown in Figure 7, the present classification correlates well with both datasets while providing superior detail. In contrast, CLCD and CLUD occasionally misclassify grassland as cultivated land or cultivated land as built-up land, leading to an underestimation of grassland or an overestimation of built-up land.

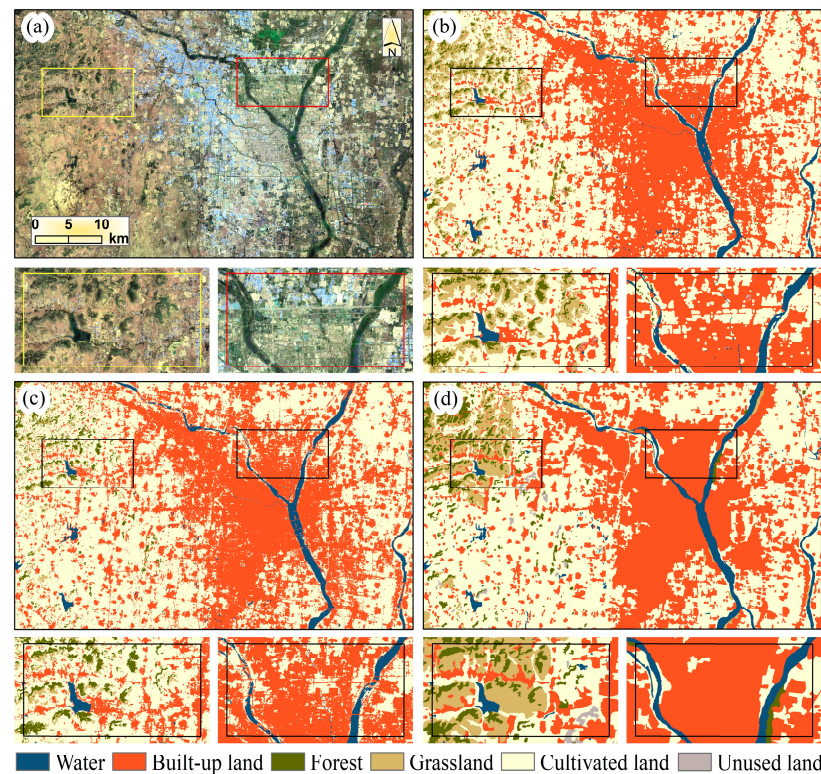


Figure 7. LULC classification results in representative SPUA zones compared against two public datasets: (a) true-color Landsat-8 OLI image (2019); (b) classification results from this study (2019); (c) CLCD (2019); and (d) CLUD (2020).

3.2. Spatio-Temporal Dynamics of LULC

3.2.1. LULC Change and Conversion Analysis

Cultivated land remained the most extensive LULC class in the SPUA, covering over 60% of the study area (Figure 8), but exhibited a gradual downward trend throughout the period 2004–2024, with a total loss amounting to 11,128.09 km² (7.14% of the SPUA). In contrast, built-up land expanded by 9677.21 km², increasing in proportion from 12.46% to 18.67%, with notable spatial growth exemplified by the megacities of Jinan and Qingdao. Forest and grassland were primarily distributed in the hilly and mountainous areas of the central, southern, and eastern regions. Between 2004 and 2024, the forest expanded steadily from 3.98% to 6.32%, with notable growth typified by the eastern region. Grassland area decreased from 7.32% in 2004 to 6.00% in 2019, followed by a partial recovery to 6.45% by 2024. The total proportion of water remained essentially stable at around 4%, with its spatial distribution largely confined to the northern and southern regions. Unused land accounted for only 0.21% of the total area in 2024, representing a 0.89% reduction compared with 2004.

Leveraging “from-to” information, Figure 9 illustrates the LULC transition areas between class pairs for the periods 2004–2024, 2009–2024, 2014–2024, and 2019–2024, as derived from the transition matrix. By 2024, 12,548.19 km² of built-up land originated from previously cultivated land. Although only a small proportion of built-up land was converted to other classes, the largest share was converted back into cultivated land. Between 2004 and 2024, 4643.66 km² of built-up land was lost, of which 3496.40 km² was converted into cultivated land. Moreover, over the entire study period, grassland and forest restoration from the reduction in cultivated land amounted to 1867.77 km² and 2154.49 km², respectively. From 2019 to 2024, newly created unused land mainly came from cultivated

land (75.18 km²) and built-up land (61.32 km²), whereas over the 20 years, it primarily came from cultivated land (100.02 km²) and grassland (101.31 km²).

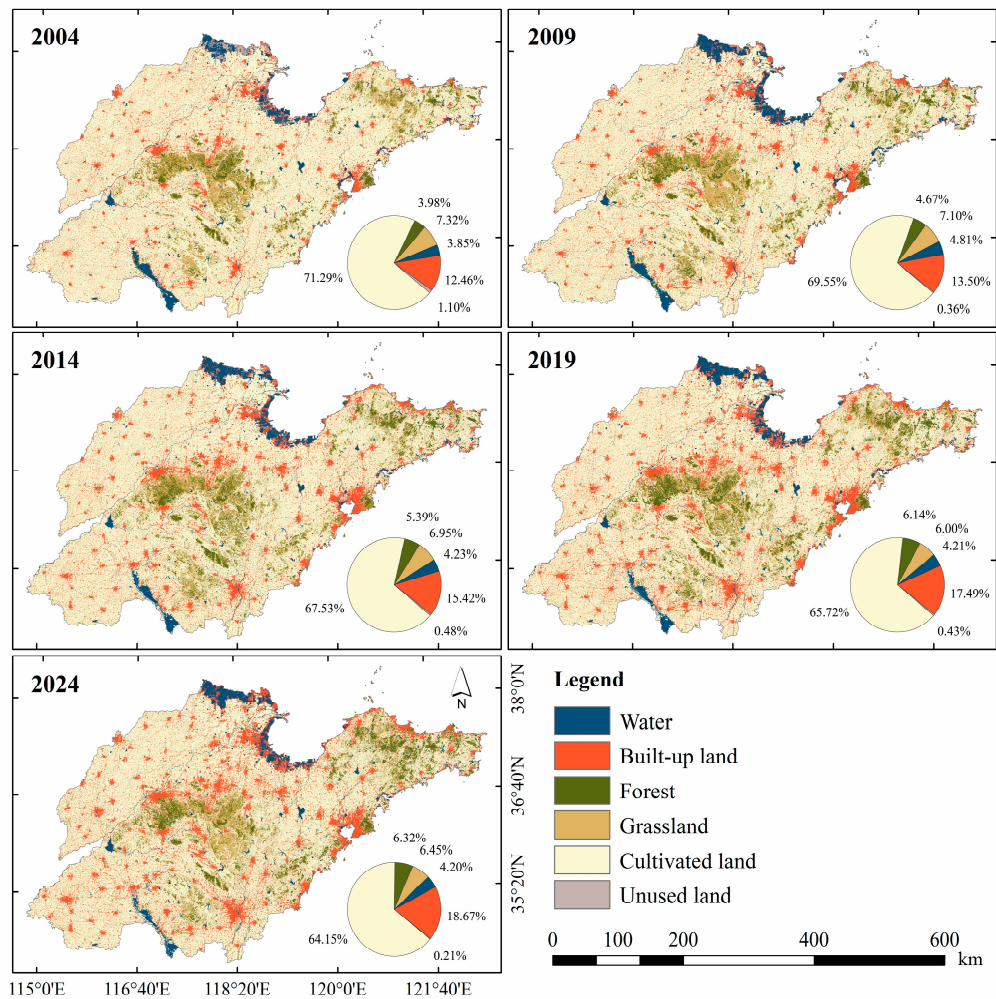


Figure 8. Dynamics of LULC spatial distribution in the SPUA between 2004 and 2024.

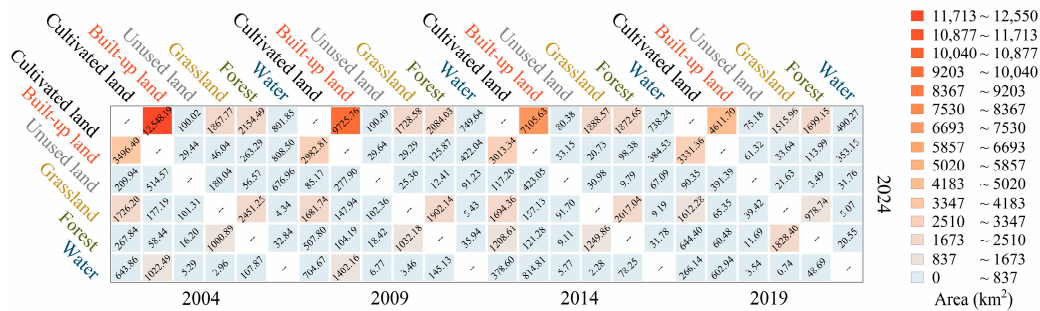


Figure 9. Area transitions between pairs of LULC classes from each time point to 2024.

The most active LULC transitions in the SPUA, involving the conversion between cultivated land and built-up land, were further examined from a city-level perspective (Figure 10). Over the longest temporal span of 20 years, Linyi experienced the largest net loss of cultivated land (1426.51 km²), whereas Dezhou had the smallest net loss (76.93 km²). In the most recent period (2019–2024), 12 cities experienced a net loss of cultivated land due to the expansion of built-up land, with the exception of Qingdao, Jining, Weihai, and Zaozhuang. Specifically, Qingdao recorded the largest net gain of cultivated land (94.62 km²), while Dongying showed the largest net loss (373.72 km²).

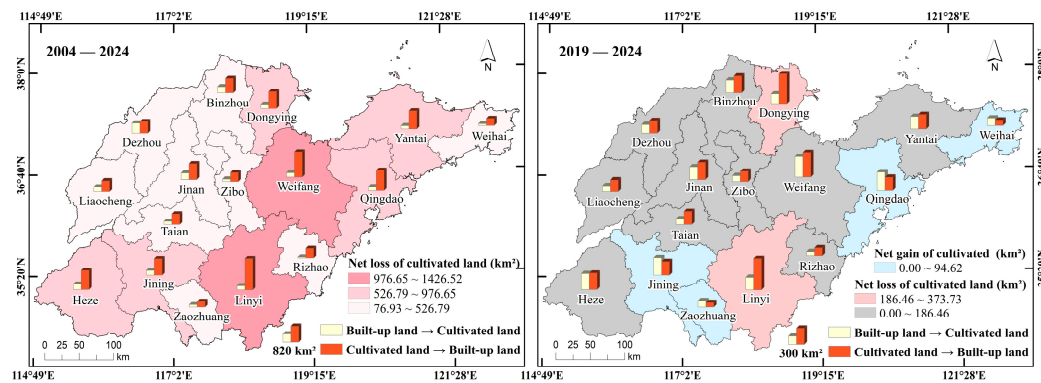


Figure 10. Spatial distribution of city-level net changes in cultivated land from conversions with built-up land in the SPUA over the long-term (2004–2024) and recent (2019–2024) periods.

3.2.2. Spatio-Temporal Trends of in Landscape Patterns

The first noticeable inflection point in the response curve appeared between 1.80 km and 9.00 km (Figure 11). Table 5 further presents the semivariogram model parameters for SHDI and PD across seven extents within the examined range. Because the exponential model reliably fitted SHDI across all scales, nugget values could be validly compared. The nugget values fluctuated downward with increasing scale from 1.80 km to 6.60 km, reaching a minimum at 6.60 km, and then increased again at larger scales. This suggests that scales smaller than 6.60 km tend to over-fragment the original patch structure, whereas larger scales may underrepresent local landscape features. At 6.60 km, both SHDI (5.82%) and PD (23.04%) reached their lowest Nugget/Sill ratios (<25%), indicating the regularity of landscape pattern variation was not obscured by localized stochastic noise and that spatial variation was more clearly reflected. In addition, SHDI achieved a high goodness of fit ($R^2 = 0.945$), and PD performed best ($R^2 = 0.893$) at this scale. Therefore, 6.60 km was identified as the ideal scale for robust landscape pattern analysis in the SPUA.

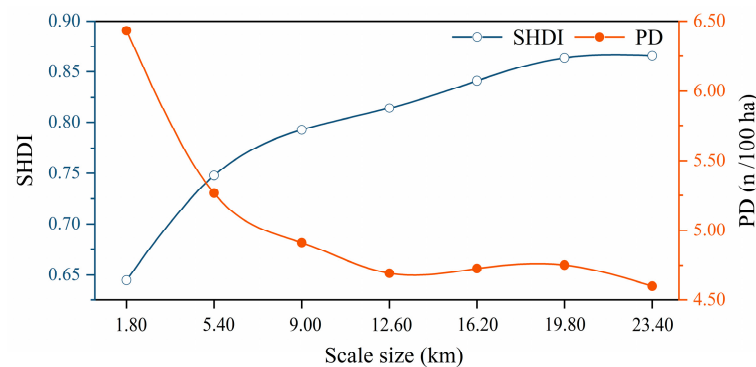


Figure 11. Response curves of landscape metrics (SHDI and PD) to different spatial extents.

The kriging interpolation visualization provides detailed representation of landscape metrics at the selected optimal extent (Figure 12). Over the past two decades, areas with lower SHDI values (<0.43) have contracted, while regions with higher PD values ($\geq 9.65/\text{km}^2$) have expanded across the SPUA, both reflecting increased landscape heterogeneity. Spatial clustering and variability were most apparent in the central and eastern regions, where the distribution of PD, SPLIT, and LSI further suggests accelerated patch fragmentation, greater landscape diversity, and increasingly complex, irregular patch shapes, especially since 2014. When viewed in conjunction with Figure 8, the results show that the northwestern region has maintained good continuity of cultivated land as the dom-

inant landscape, accompanied by a steady rise in both CONTAG values and the expansion of high-value areas ($\geq 77.95\%$).

Table 5. Semivariogram parameters of SHDI and PD at different spatial extents.

Metric	Scale Size (km)	Nugget	Sill	Nugget/Sill (%)	R ²	Best Model
SHDI	1.80	7.50×10^{-3}	0.094	7.98	0.706	Exponential
	3.00	7.00×10^{-3}	0.090	7.78	0.771	Exponential
	4.20	7.50×10^{-3}	0.092	8.07	0.938	Exponential
	5.40	6.90×10^{-3}	0.093	7.39	0.945	Exponential
	6.60	5.30×10^{-3}	0.091	5.82	0.945	Exponential
	7.80	7.90×10^{-3}	0.085	9.26	0.932	Exponential
	9.00	8.10×10^{-3}	0.092	8.81	0.947	Exponential
PD	1.80	11.77	35.01	33.62	0.848	Spherical
	3.00	8.17	25.46	32.09	0.845	Exponential
	4.20	6.91	20.96	32.97	0.865	Exponential
	5.40	4.33	17.27	25.07	0.847	Exponential
	6.60	5.54	24.04	23.04	0.893	Spherical
	7.80	3.59	14.51	24.74	0.884	Exponential
	9.00	5.27	20.26	26.01	0.883	Spherical

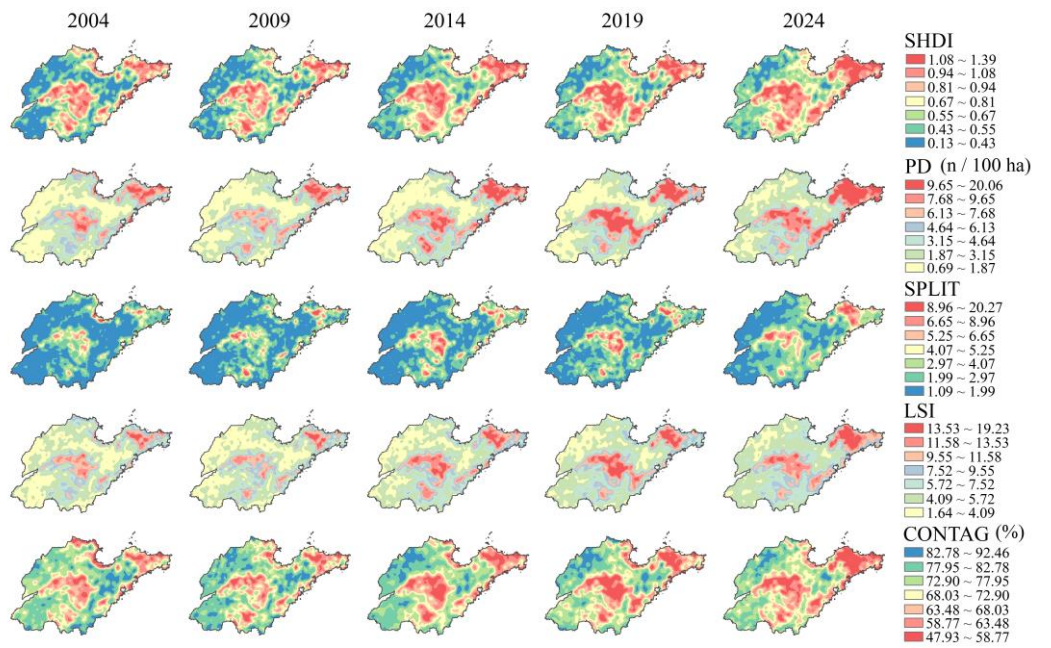


Figure 12. Spatio-temporal changes in landscape patterns of the SPUA (2004–2024).

4. Discussion

Working with the inherent RF and GTB classifiers of the GEE cloud computing platform, the overall accuracy fluctuated around 90% across feature combinations. It shows that even without considering feature optimization, the two machine learning classifiers boast outstanding abilities to effectively handle numerous datasets and complex non-linear relationships when mapping out LULC, which is consistent with previous studies that have conveyed GTB and RF were resilient in classification [63,64]. However, the GTB classifier, which harnesses the strengths of multiple weak learners, consistently surpassed the RF classifier by a slight advantage of 1.00–2.15% in overall accuracy with equal input features. Studies carried out by Tesfaye and Breuer [65] and Orieschnig et al. [66] likewise reported a roughly 1.00% higher overall accuracy for GTB compared to RF. For vegetated areas,

although a satisfactory spatial distribution of cultivated land could be better processed from GTB, it cannot be ignored that RF presents a particular sensitivity in woodland identification, as evidenced by the thematic categorization study of urban forests conducted by Jeong and Park [67].

The feature combination that fused spectral bands, remote sensing indices, topographic features, LST, and NTL was found to be both sufficient and effective for LULC mapping, employing the GTB classifier. Each feature category tested contributed differently to the classification. Topographic features, especially slope and elevation, proved to be critical for classification, consistent with the findings of Safaei et al. [68] and Sankalpa et al. [69]. These static characteristics stood out as key features in distinguishing cultivated land from forest and grassland, which can largely be attributed to the restrictive effects of high altitude and steep slopes on vegetation habitats, human settlement, and agricultural activities [70]. Although LST was used rarely in classification in previous studies, it provided valuable discriminatory power in improving classification precision, which aligns with the findings of Guddeti et al. [71], as a series of case studies have shown the distinct thermal signatures among LULC classes [72–74]. Conversely, the Landsat-derived texture features contributed minimally and provided less critical information, and were ultimately excluded without any reduction in accuracy. Cheng et al. [75] similarly reported the limited effectiveness of Landsat texture for mapping. Furthermore, Tassi and Vizzari [76] found that texture features derived from 30 m Landsat images underperformed compared to those from higher-resolution 10 m Sentinel images, attributing the discrepancy to the coarser spatial resolution of Landsat. In the present study, the limited utility of texture features may additionally stem from the dominance of flat, cultivated landscapes across much of the SPUA, with areas of complex topographies and heterogeneous land composition being relatively sparse and localized. However, in regions featuring varied and rugged terrain, texture features from Landsat may still provide valuable spatial-structural information for map generation [77].

As the leading driving force behind the urban and rural regional growth of China, growing urban agglomerations have undoubtedly brought great economic opportunities and facilitated resource flows. However, such developments have exacerbated the conflict between the scarcity of land resources and the diversification of land use demand, while causing drastic LULC changes. Over the past two decades, the SPUA experienced rapid growth in built-up land, with 12,548.19 km² of new urban area resulting from the conversion of cultivated land. It is comparable to the tight situation of occupied cultivated land for construction in neighboring developed urban agglomerations. The major LULC conversions in the Yangtze River Delta urban agglomeration from 1990 to 2010 [78] and in the Beijing-Tianjin-Hebei urban agglomeration from 1980 to 2015 [79] similarly involved cultivated land being converted to built-up land, with areas of 11,713.06 km² and 13,279.14 km², respectively. However, as a “leader” in national agricultural development, the SPUA plays a crucial role in safeguarding Chinese food security, warranting greater attention to the decline of its cultivated land. In the most recent five-year period, significant spatial differences emerged in the reciprocal conversion between cultivated land and built-up land. Cities such as Qingdao and Jining experienced relatively low pressure on cultivated land from built-up land expansion, whereas Linyi and Dongying were subjected to much higher pressure. Consequently, strengthening monitoring at the municipal level provides an entry point for implementing effective land management strategies that balance cultivated land protection, urban development, and ecological conservation. These strategies should strictly enforce the red line for the protection of cultivated land, limit the expansion of built-up land, and regulate both the spatial extent and intensity of new development to mitigate the adverse impacts of urban expansion on cultivated land.

The appropriate extent for SPUA landscape pattern analysis was set successfully through a combination of the inflection point method with quantitative semivariogram modeling. This hybrid method employed the inflection-point approach to rapidly identify candidate extent sizes, providing a defined range for semivariogram calculations rather than leaving the extent selection without clear constraints, while reducing the uncertainties associated with applying the inflection-point method alone. Though much smaller than the empirically determined 30 km size in a region of Jilin Province [80], the 6.60 km scale adopted in this study was close to the 5.40 km maximum optimal scale identified for Shanghai City, ascertained from semivariogram experimental tests [81], allowing for a more detailed presentation of the landscape patterns. Moreover, topographic factors exert a significant impact on shaping landscape patterns. Landscape pattern analysis revealed that the hilly areas in the central and eastern SPUA consistently persisted as extreme-value concentrations for all metrics. This pattern is primarily attributable to the significant topographic fluctuations and heterogeneity of these mountainous regions, which gave rise to a mosaic of landscapes with uneven spatial distributions. Limited landscape continuity in such areas contributes to higher landscape diversity. Furthermore, these regions exhibited a marked shift between the pre-2014 and post-2014 periods, characterized by increasing diversity and fragmentation along with decreasing connectivity. These changes may be potentially associated with large-scale afforestation activities, which included accelerated afforestation of barren mountains in key mountainous and hilly areas of central-southern and eastern SPUA, through a three-year afforestation campaign launched in 2014 [82], the “Green All Over Qilu, Beautiful Shandong” Land Greening Action in 2017 [83], and the accelerated territorial greening action in 2020 [84].

In this study, multi-year LULC maps of the SPUA were produced by a pixel-based approach with an optimized classification scheme on GEE. Nevertheless, there were still limitations. While this study focused on comparing and selecting classifiers and feature combinations, it did not explicitly evaluate sample size thresholds or address class imbalance, both of which are equally critical for robust classification. Future studies could address these issues by adopting more rigorous stratified sampling and class-balancing techniques, which would improve sample adequacy and representativeness, thereby enhancing classification robustness. In addition, this study emphasized harnessing features that better capture the natural traits of LULC, ensuring consistency with the first-level classification system of CLUD. However, coarse-resolution remote sensing images cannot fully detect the intrinsic characteristics and spatiotemporal rhythm of human activities, which can be captured more effectively by socio-economic datasets such as points of interest (POI) and trajectory data. POI data can directly map the socio-economic functions of land parcels through their functional and locational tags, while trajectory data can indirectly infer residential or commercial uses based on temporal patterns, thereby improving the accuracy of urban LULC identification. For future research, enriching the feature set by integrating these datasets with NTL on GEE may substantially enhance the refinement and comprehensiveness of LULC classification, enabling the subdivision of built-up land into functional categories such as residential, commercial, and transportation.

5. Conclusions

The study highlights the capability of the GEE cloud computing platform to integrate information from diverse datasets and accelerate machine learning processes in the cloud, enabling highly effective and accurate LULC mapping of large-scale areas. The SPUA-wide LULC maps spanning 2004 to 2024 were generated using the GTB classifier, which incorporates spectral bands, remote sensing indices, topographic features, LST, and NTL, and reported overall accuracies above 91.02%. This enables an in-depth examination of

the spatio-temporal changes in LULC and landscape patterns. The following conclusions are drawn:

GTB proved superior to RF, with an OA advantage of at least 1.00%, underscoring its potential to classify LULC accurately even without feature optimization. It is a viable alternative to the commonly employed RF, offering superior performance for handling the spatial heterogeneity associated with complex urbanizing environments, as demonstrated in the SPUA.

Topographic features had the greatest positive impact on classification among all the features examined, improving the OA of classifiers by 2.27% to 2.33%. By excluding Landsat-derived texture features, the optimized feature combination outperformed the best unoptimized combinations, achieving a minimum overall accuracy improvement of 0.46%.

Cultivated land is the dominant yet vulnerable landscape in the SPUA, covering over 60% of the area and showing a declining trend since 2004, primarily driven by its conversion to built-up land.

The 6.60 km × 6.60 km extent optimally facilitates characterization of landscape patterns in the SPUA. The central and eastern regions have exhibited marked increases in landscape diversity and fragmentation, while connectivity has declined, particularly since 2014.

The main contribution of this study lies in proposing a practicable solution for assisting in generating reliable and adaptable LULC maps on GEE using a machine learning model with optimal features, particularly for regions with similar conditions. Further study could drive progress by incorporating socio-economic datasets beyond NTL to construct a more comprehensive classification framework for finer functional differentiation of LULC classes.

Author Contributions: Conceptualization, L.C. and J.X.; methodology, J.X.; software, L.M.; validation, G.T. and T.Z.; formal analysis, J.X.; data curation, T.Z., G.T. and L.M.; writing—original draft preparation, J.X.; writing—review and editing, L.C.; visualization, J.X. and L.C.; supervision, L.C. and T.Z.; funding acquisition, L.C. and J.X. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The raster datasets used for mapping during this study are openly available from the Earth Engine’s public data catalog at <https://developers.google.com/earth-engine/datasets/catalog>, accessed on 28 November 2024.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

LULC	Land use/land cover
GEE	Google Earth Engine
SPUA	Shandong Peninsula urban agglomeration
GTB	Gradient Tree Boost
RF	Random Forest
APIs	Java and Python Application Programming Interfaces
DEM	Digital elevation model

NTL	Nighttime light
SR	Surface Reflectance
TOA	Top of Atmosphere
LST	Land surface temperature
PGI	Plastic Greenhouse Index
PMLI	Plastic-mulched Landcover Index
NDVI	Normalized Difference Vegetation Index
MNDWI	Modified Normalized Difference Water Index
NDBI	Normalized Difference Built-up Index
BSI	Bare Soil Index
ASM	Angular Second Moment
CONT	Contrast
CORR	Correlation
VAR	Variance
IDM	Inverse Difference Moment
SAVG	Sum Average
ENT	Entropy
PA	Producer accuracy
UA	User accuracy
OA	Overall accuracy
Kappa	Kappa coefficient
CLUD	China's Land Use/Cover Dataset
CLCD	China Land Cover Dataset
SHDI	Shannon's Diversity Index
PD	Patch Density
SPLIT	Splitting Index
LSI	Landscape Shape Index
CONTAG	Contagion
R ²	Coefficient of determination
POI	Points of interest

Appendix A

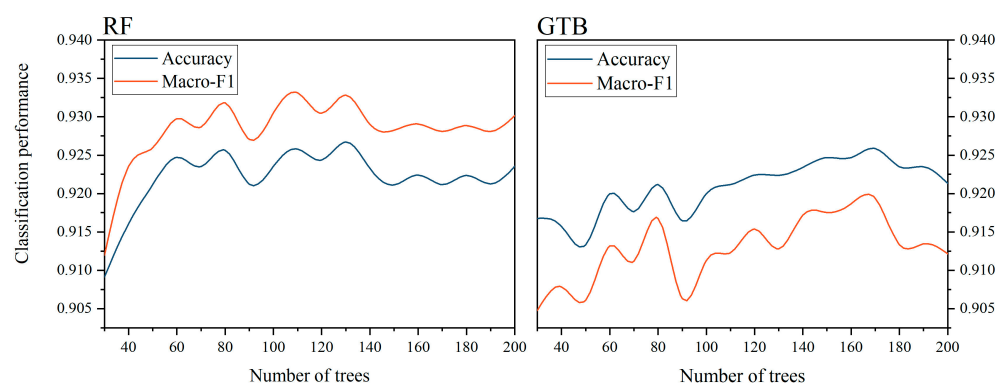


Figure A1. Variation in Accuracy and Macro-F1 of RF and GTB with tree numbers under 5-fold cross-validation.

Table A1. Formulas used for calculating remote sensing indices.

Remote Sensing Index	Formula
Plastic Greenhouse Index (PGI)	$\frac{BLUE \times (NIR - RED)}{1 - (BLUE + GREEN + NIR) / 3}$
Plastic-mulched Landcover Index (PMLI)	$\frac{SWIR1 - RED}{SWIR1 + RED}$
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - RED}{NIR + RED}$
Modified Normalized Difference Water Index (MNDWI)	$\frac{GREEN - SWIR1}{GREEN + SWIR1}$
Normalized Difference Built-up Index (NDBI)	$\frac{SWIR1 - NIR}{SWIR1 + NIR}$
Bare Soil Index (BSI)	$\frac{SWIR1 + RED - NIR - BLUE}{SWIR1 + RED + NIR + BLUE}$

Table A2. Assessment of classification accuracies for SPUA LULC maps over 2004–2024.

Year	User\Reference Class	Cultivated Land	Forest	Grassland	Water	Built-up Land	Unused Land	PA (%)	UA (%)	OA (%)	Kappa
2004	Cultivated land	130	0	3	3	8	1	97.01	89.66	92.55	0.90
	Forest	0	49	0	0	0	0	96.08	100.00		
	Grassland	3	2	41	0	0	1	89.13	87.23		
	Water	0	0	0	34	0	0	91.89	100.00		
	Built-up land	1	0	1	0	59	2	88.06	93.65		
	Unused land	0	0	1	0	0	10	71.43	90.91		
2009	Cultivated land	142	1	4	0	9	1	96.60	90.45	92.93	0.91
	Forest	0	80	1	0	0	0	96.39	98.77		
	Grassland	0	1	50	0	0	1	90.91	96.15		
	Water	2	1	0	49	0	1	94.23	92.45		
	Built-up land	3	0	0	2	43	1	82.69	87.76		
	Unused land	0	0	0	1	0	17	80.95	94.44		
2014	Cultivated land	138	0	4	0	9	0	93.24	91.39	91.02	0.88
	Forest	1	62	3	0	0	0	98.41	93.94		
	Grassland	1	1	48	0	1	0	87.27	94.12		
	Water	0	0	0	44	1	1	95.65	95.65		
	Built-up land	6	0	0	2	48	3	81.36	81.36		
	Unused land	2	0	0	0	0	15	78.95	88.24		
2019	Cultivated land	148	0	3	2	11	1	95.48	89.70	91.89	0.89
	Forest	0	61	0	0	0	0	96.83	100.00		
	Grassland	2	2	36	0	0	0	82.31	90.00		
	Water	0	0	0	57	0	0	93.44	100.00		
	Built-up land	4	0	0	1	55	4	82.09	85.94		
	Unused land	1	0	0	1	1	17	77.27	85.00		
2024	Cultivated land	107	0	5	0	4	0	94.69	92.24	93.68	0.92
	Forest	0	76	0	0	0	0	98.70	100.00		
	Grassland	1	1	35	1	0	0	83.33	92.11		
	Water	0	0	0	37	1	0	97.37	97.37		
	Built-up land	5	0	2	0	74	2	92.50	89.16		
	Unused land	0	0	0	0	1	12	85.71	92.31		

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