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Identifying Terrestrial Landscape Character Types in China

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Abstract: Landscape character assessment (LCA) is a widely used tool that integrates natural, cultural, and perceptual attributes to identify and portray landscape. In this study, we used the LCA method to identify the landscape characteristics of China at the national scale. Furthermore, we applied cultural and landscape structural factors along with spatial transmission to improve the identification system. First, we incorporated all the parameters in the assessment. We selected 15 landscape character factors from four factor types including nature, culture, spatial geographic co-ordinates, and landscape structure. These parameters were analysed using multilevel overlay and spatial connection tools in ArcGis 10.2, which resulted in 2307 landscape description units (LDUs). Second, the spatial structure properties of the LDUs were determined using a semivariogram and the moving window method in ArcGis 10.2 and Fragstats 4.2 software, respectively. Third, for visualisation, we applied the principal component analysis (PCA) using the SPSS software and elbow and k-means clustering methods using MATLAB to determine 110 landscape character types (LCTs) of China's entire terrestrial landscape. Finally, we determined 1483 landscape character areas through semiautomatic segmentation and manual visual correction using eCognition. Based on the unique characteristics of the entire terrestrial landscape of China, a set of ideas and methods for the overall identification of LCTs was proposed. Our findings can be used to optimise territorial spatial planning and landscape protection and management, and promote multiscale land-use studies in China.

Keywords: China; cluster analysis; landscape character areas (LCAs); landscape character assessment (LCA); landscape structure; landscape character types (LCTs)

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1. Introduction

Landscape character is a relatively consistent and distinguishable pattern of elements determined by the identification of landscape resources [1]. Landscape character can promote a better understanding of landscape resources [2] and help avoid the homogeneous evolution of the landscape that leads to the loss of uniqueness and a sense of place [3,4]. Identifying landscape characteristics, mapping their types, making judgments based on landscape character assessment (LCA), specific development, and utilisation methods are accepted core methods of landscape characterisation in Europe [5–8]. These approaches provide information for research on the landscape, territorial planning, and land management [9], and provide a basic framework for the systematic monitoring and assessment of landscape changes [3,7,10–12].

In recent decades, China's rapid economic development, large-scale urbanisation, and agricultural intensification have changed and deformed the structure of several natural landscapes, resulting in the gradual alienation and loss of cultural landscapes. Thus, the landscape faces the risk of sameness. Since 2019, China has introduced relevant policies to promote the use of 'national territory' as a carrier for the construction of an ecological civilisation [13,14]. These policies emphasise the overall planning of all regional and elemental resources to achieve sustainable development [15], and landscapes have received considerable attention and considered vital resources. LCA is applied in China to address both risk and development and provide special support for the planning of territorial spaces [13]. In recent years, many scholars have conducted studies on LCA [16,17]; however, a complete and systematic LCA method is still lacking. Existing studies mostly focus on provinces, cities, and rural areas that are delineated by administrative regions [16–20], while national-scale studies are absent.

Multidisciplinary studies on landscape character have resulted in the identification and classification of various methods with different emphases. Simensen et al. [21] categorised these methods into ensemble, automatic segmentation, and parametric methods. The ensemble method is an intuitive and interpretive method [1,21], which is conducive for comprehensive identification [16] as it can directly obtain landscape character types (LCTs) and landscape character areas (LCAs) in a top-down approach; however, it requires strong comprehensive thinking, abstraction, and application of expert knowledge and judgment, and it is subjective and difficult to replicate [3,22]. The automatic segmentation method is highly dependent on machines for image processing and segmentation and are commonly used for LCA over large areas (e.g., at the national and transnational scales) [11] and has the advantages of rapid identification and objective and accurate boundary demarcation. It is mostly used for research on the classification of LCAs. However, this method requires a prior definition of key variables [23,24] and does not involve factors such as cultural attributes [25]. The parametric method is based on geographic information systems (GIS) and statistical methods that can classify and cluster landscape samples [5,10,26], choose the detailed characteristics of landscape elements to reflect more comprehensive relationships among landscape elements, and produce perfect recognition results while reducing the influence of human subjectivity [3]. However, this method cannot directly access LCAs, and grid plaques must be integrated for interpretation. The GIS approach has been used as a tool for the large-scale assessment of LCA [1], and ensures consistency at the national scale, while manual techniques at finer scales capture local subtleties [10].

Notably, combining a top-down holistic approach and bottom-up clustering analysis can accurately identify LCTs [16]. Comparisons revealed that the three LCA methods implemented at the transnational and national scales focused primarily on biophysical features to determine landscape character factors (LCFs), whereas human factors were mainly based on land use/cover [3,11,27]. A majority of these studies are based on the perspective of landscape composition and thus cannot reflect the overall appearance of landscape characters. To address this issue, Belgian researchers introduced landscape structure factors (LSFs) [5]; however, the scale effect of landscape structure has not yet been clearly defined.

Our study describes a refined framework combing the ensemble, automatic segmentation, and parametric methods for efficient and flexible identification of LCTs. We considered the entire terrestrial landscape of China as our study area and introduced the spatial distribution types of Chinese settlements based on the contextual characteristics of the country. We constructed a basic ArcGIS information database by performing a structural attribute analysis of the landscape description units (LDUs) and by scientifically calculating the scale transitivity of landscape structure using the quantitative statistical method. The overall process is shown in Figure 1. Our study was aimed at improving the selection of index factors and analysing the structural configuration at the LCA stage and establishing a systematic method to create an overall, comprehensive, and relatively objective classification system of LCTs that is suitable for China. Additionally, our aim was to fill the gap in the current literature on China's LCA at the national scale. Our results can provide a reliable reference for feature identification in provinces and cities at the mesolevel.

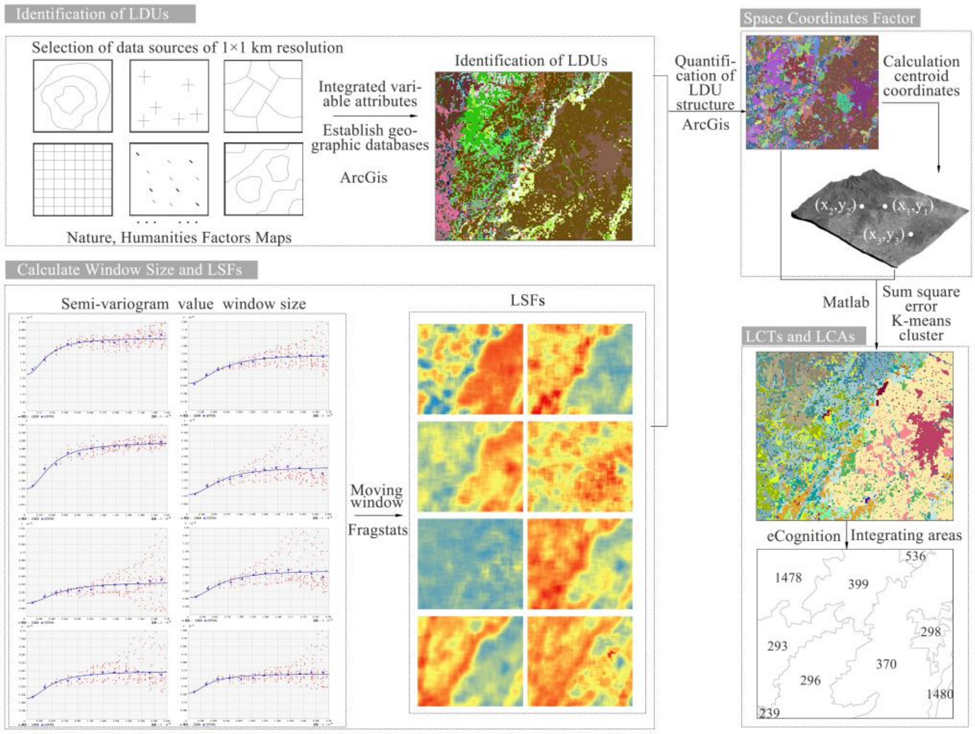


Figure 1. Flowchart depicting the process used to determine China's terrestrial landscape character types and identify landscape character areas.

2. Materials and Methods

2.1. Research Area

China's terrestrial area covers approximately 9.6 million km^2, with over 23 provinces, four municipalities, and two special administrative and five autonomous regions. Fifty-six ethnic groups are widely distributed throughout the country. The contiguous land area runs for approximately 5500 km from north to south and 5200 km from east to west. The overall terrain has a high and low altitude in the west and east, respectively. The vast area of mountains and plateaus in China include the Tianshan, Gangdisi, and Hengduan mountains, North China Plain, middle and lower reaches of the Yangtze River Plains and Sichuan Basin, and parts of the Himalayas; the natural landforms are diverse, with substantial altitude differences. In addition, the country consists of several major climate types: the subtropical, temperate, and warm temperate climate zones. Notably, regional precipitation also varies considerably throughout China. In line with these factors and human resources, the country has diverse landscape resources and rich biodiversity.

2.2. Data Collection

Natural and biophysical attributes provide a factual background for the development of landscapes, society, and culture, which, in turn, provide an important basis for LCA. Thus, identifying LCTs is of great significance for determining the dynamic evolution of the landscape and optimising land management and planning [28,29].

Based on the accuracy and availability of data, we selected 15 LCFs from four factor types, namely, nature, culture, spatial geographic co-ordinates, and landscape structures. Among them, the natural factors included (1) altitude and topographic relief, which was measured by the Shuttle Radar Topography Mission (SRTM 4.1) with a digital elevation model (1 × 1 km resolution) using the ArcGIS 10.2 spatial analysis tool (http://srtm.csi.cgiar.org, accessed on 5 March 2021), and (2) climate zone obtained from the 'China Climate Type Figure' vectorised distribution map (http://map.ps123.net/, accessed on 5 March 2021), with a total of five climate zones.

The human factors included (1) land-use data obtained from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (http://www.resdc.cn/, accessed on 5 March 2021, 2018; 1 × 1 km resolution), and (2) the distribution of rural settlements obtained from the settlement division vector diagram in China [30] consisting of a total of 11 settlement divisions.

To comprehensively analyse landscape at the regional level and determine the structure of each LCT, eight commonly used indexes were selected from four aspects, namely, clustering and dispersion, density and difference, shape complexity, and diversity. The indexes applied were artificial intelligence (AI), contiguity mean (CONTIG-MN), landscape division index (DIVISION), area-weighted fractal dimension (FRAC-AM), land sustainability index (LSI), patch density (PD), Shannon's diversity index (SHDI), and Shannon's evenness index (SHEI). In addition, the boundaries of China's administrative map were downloaded from the BIGEMAP platform.

2.3. Research Methods

2.3.1. Identification of Landscape Description Units

We divided the LCFs into distinguishing factors with typical boundaries (altitude, topographic relief, and land use) and descriptive factors (settlement and climate). The latter factors were not used to delineate the LDU boundaries; instead, they were used to supplement the description.

We used a resolution of 1 × 1 km as the statistical unit for the following reasons: (1) this resolution is often used to analyse large-scale study objects [11] and national-scale character recognition [5,25,31], and (2) China's national-scale mapping mainly uses this resolution expansion [32–35].

To ensure the uniqueness of the calculation results of the distinguishing factors in the process of applying the spatial overlay technique in ArcGIS 10.2, the number theory was adopted to encode the classification of different LCFs. Moreover, to ensure that no number exceeded the upper limit of integer data, similar values were grouped to ensure the lowest possible variance within the groups. Thus, a dataset of the LCFs of the entire landscape of China was constructed. Table A1 (Appendix A, Table A1) illustrates the categorical attributes [36,37] and the number of variables considered in our study. The ArcGIS 10.2 platform was used to apply the spatial overlay technique. The spatial connection tool was used to extract the attribute values of the settlement and climate factors into the grid attribute table obtained after stacking, thus producing a database of five factors. Finally, with reference to the European Landscape Classification (LANMAP) method [11], the elimination tool was used to merge the patches of land that had an area of <10 km^2, along with adjacent surfaces that had the largest common boundary or areas, to identify the LDUs of China's entire territory.

2.3.2. Quantification of the Structure of Landscape Description Units

Landscape pattern is a concrete manifestation of the composition and spatial heterogeneity of perceptible landscape elements [38] that reflect the structural characteristics in relation to the biophysical, social, and cultural conditions. Notably, landscape patterns are important data required to determine the type of landscape characteristics [39,40]. The LSF is often used to make quantitative analyses of the structural characteristics of the landscape [41]. According to the overall structure of the LDU and to avoid redundancy, we applied the properties of the eight abovementioned LSFs (Appendix A, Table A2) while considering the operability of the units and the complexity of the spatial structure. Among them, AI and CONTIG-MN characterised the aggregation and dispersion of LDUs, DIVISION and PD characterised the fragmentation degree of spatial distribution, and LSI and FRAC characterised the complexity and regularity of shapes and reflected the degree of disturbance to the landscape. Meanwhile, SHDI and SHEI characterised the degree of heterogeneity and uniform distribution of the landscape, providing a thorough understanding of landscape diversity in the region. Considering that scale changes have different degrees of influence on the results of quantitative analysis of spatial structures [39,42,43], semivariograms are widely used to study landscape pattern scales [44–47]. Therefore, we used a semivariogram to identify the suitable study scales.

Semivariograms describe the distribution characteristics of elements by measuring the relationship between the degree of variation in the spatial attributes of two points and the distance between them [48]. The semivariogram curve contains four corresponding parameters: nugget value (C_0), partial abutment value (C), variable range (A_0), and abutment value (C_0 + C). Among these, the ratio of nugget value to abutment value [$C_0/(C_0 + C)$] is also called the basal effect, and it is used to conduct comparative analyses for different window sizes. A lower value of the degree of variation of the LSF indicates a higher spatial autocorrelation and a stable landscape pattern [49–51]. Previous studies have indicated that a stable $C_0/(C_0 + C)$ ratio can be identified as the characteristic scale of the landscape of the study area [52,53].

$$r(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(x_i) - z(x_i + h)]^2 \quad (1)$$

where the regional change amount, $z(x_i)$, is the measured value obtained at position x_i, $n(h)$ is the logarithm separated by h units in the vector direction, and $r(h)$ is called the semivariogram [54,55].

We used the moving window tool in Fragstats 4.2 to set the radius at the landscape level to 8, 10, 12, 14, 16, 18, 20, 22, and 24 km, combined with the semivariogram model that was set to an isotropic condition [25]. We then calculated the base effect of each LSF and obtained the line graphs, $C_0/(C_0 + C)$, for each window size (Figure 2). As shown in Figure 2, the spatial pattern reached a stable state at 14 km and the grid distribution of each pattern index can be calculated.

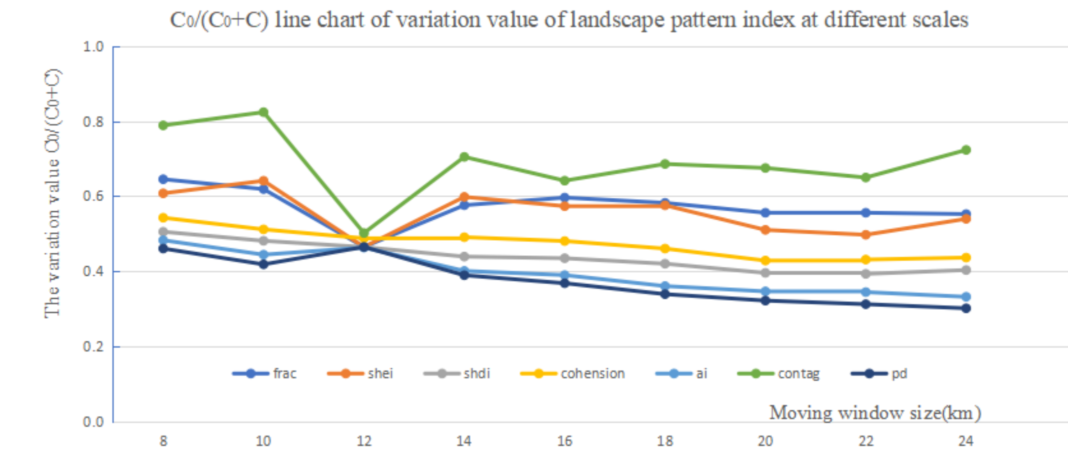


Figure 2. Line chart of variation value of landscape structure factors $C_0/(C_0 + C)$ for different window sizes.

2.3.3. Identification and Nomination of Landscape Character Types

As a multivariate statistical algorithm, principal component analysis (PCA) can achieve 'noise reduction' and 'redundancy' [56,57]. Furthermore, previous studies have proved that combining PCA with clustering algorithms can ensure data accuracy and streamlining [16,58]. After PCA, eight LSFs were fused and extracted into two independent variables and one mixed variable, explaining 84.581% of the data variation. Combined with the longitude and latitude of the grid centroid and the LDU database, 10 variables and 1.39 million landscape patches were determined.

The 10 LCFs included continuous and categorical variables. Since k-means cluster analysis can only be applied to continuous variables, one-hot encoding was introduced to convert the categorical variables in the LCFs into multiple dummy binary variables, which can be conveniently compared with other variables. The combination can intuitively reflect the influence of different attributes of the independent variables on the dependent variables, thus improving the accuracy of the model. Notably, if the dummy binary variable corresponded to a category, its value was set to 1; otherwise, it was set to 0 [59].

Because k-means clustering is a simple classic clustering algorithm used for unsupervised learning [60], it does not rely entirely on expert judgement and reduces the influence of human subjectivity [61]. Therefore, it is widely used in large-scale data clustering [62,63]. In this study, we used the elbow method to calculate the sum square error (SSE) value of the specified cluster. When the SSE value decreased sharply to a certain point and tended to be flat, that point was designated as the 'elbow point,' indicating the optimal K value [61,64]. The *SSE* value was calculated using the following equation:

$$SSE = \sum_{i=1}^{k} \sum_{p \in L_i} |P - q_i|^2, \tag{2}$$

where L_i is the i-th cluster, P is the sample point in L_i, q_i is the centroid of L_i (mean of all samples in L_i), and k represents the number of groups.

Since the sample size of our landscape (1.39 million landscape patches) was large, the similarity matrix exceeded the limit of computer memory. To address this issue, we randomly selected 100,000 samples from the original database. We calculated the cluster values and cluster centre points for these samples before calculating for the entire data set.

We used a juxtaposition method to create names for the LCTs. This method was also used in LANMAP [11]. The names of each LCT comprised five parts with respect to the landscape codes: the letters indicated land use, altitude, undulation, climate, settlement, and the numerical subscripts corresponding to the number of the factor classification (Appendix A, Table A1). Since the spatial structure factor was mainly used to analyse the complexity of the spatial configuration of LCTs, LSF was used as the subdivision type, distinguished by a number added at the end. To improve the comprehensibility of the LCTs map, we used the colour classification of the land-use type in China's urban land classification and planning and construction land standard. We combined the saturation changes to vividly portray and define similar and dis-similar character types to improve the application of the process, results, and achieve the visual display of different LCTs intuitively [5,65].

2.3.4. Regional Division of Landscape Characters

eCognition, an image segmentation technology, integrates automatic and supervised classification, manual editing, and object-based image segmentation. Notably, previous studies have indicated that it can intuitively and instantaneously identify character attributes and reduce the influence of subjective factors [66]. We used the LCT map, obtained by cluster analysis, as the eCognition image segmentation base map for the spatial distribution position and appropriate regional division of the LCTs (through the control variable method) to ensure information richness of LCFs. Then, we adjusted the three parameters (scale, shape, and compactness) to realize the automatic or semiautomatic segmentation of the LCTs, identify the LCAs, and adjust the boundaries by combining manual visual inspection and remote sensing images.

3. Results

3.1. Types of Landscape Characters and Regional Delineation

Using the spatial analysis of five LCFs, we finally identified 2307 LDUs and 1,438,518 patches. Each LDU had a unique number. As shown in Figure 3, the spatial pattern was stable at 14 km, which is the optimal research scale for an LDU structure. As shown in Figure 4, the eight LSF maps corresponded to a window size of 14 km. By integrating LDUs, LSFs, and the spatial geographic co-ordinate factors, and after performing PCA and clustering, we identified 110 LCTs (Figure 5). These LCTs were then ranked with respect to their land-use

(Appendix A, Table A3). For naming, we used the LSFs as a subdivision type, distinguished by placing a number at the end. For example, the 26th and 27th types of LCFs: woodland, middle altitude, middle topographic relief, subtropical monsoon climate, and southwestern rural settlement region, were consistent in both natural and human factors. However, there were differences in their spatial configuration; therefore, they were named $L_2A_2R_4C_3S_8$_1 and $L_2A_2R_4C_3S_8$_2, respectively.

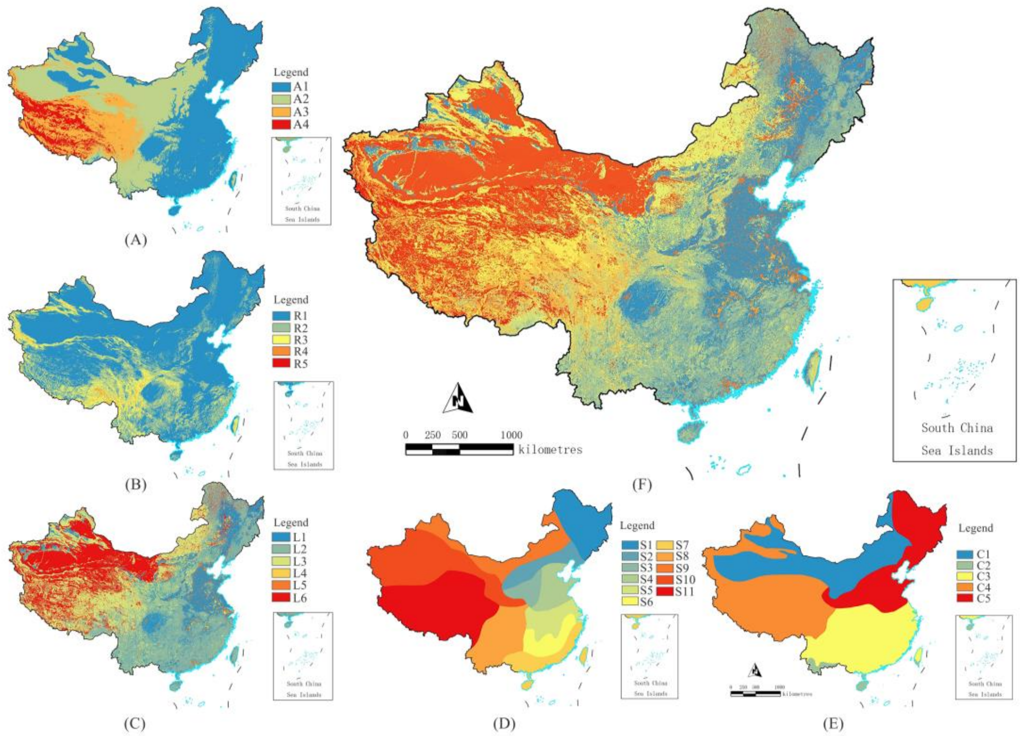


Figure 3. Attribute classification of natural and human factors and 2307 kinds of landscape description units: (**A**) altitude type classification, (**B**) topographic relief type classification, (**C**) land-use type classification, (**D**) settlement type classification, (**E**) climate type classification, and (**F**) showing 2307 kinds of landscape description units (LDUs).

We developed a base map consisting of the 110 LCTs for image segmentation using eCognition. We adjusted the scale parameters, regardless of the administrative boundaries, to an appropriate segmentation scale by combining satellite images and natural and human attributes (which were based on the image colour and shape). Notably, the weights of shape and tightness in the single-variable test homogeneity parameters were controlled. After several experiments, we deduced that there were appropriate classification results when scale, shape, and compactness were 80, 0.7, and 0.3, respectively. We identified 1483 LCAs by combining satellite images and LCTs after manual division and adjustment in ArcGIS 10.2 (Figure 6).

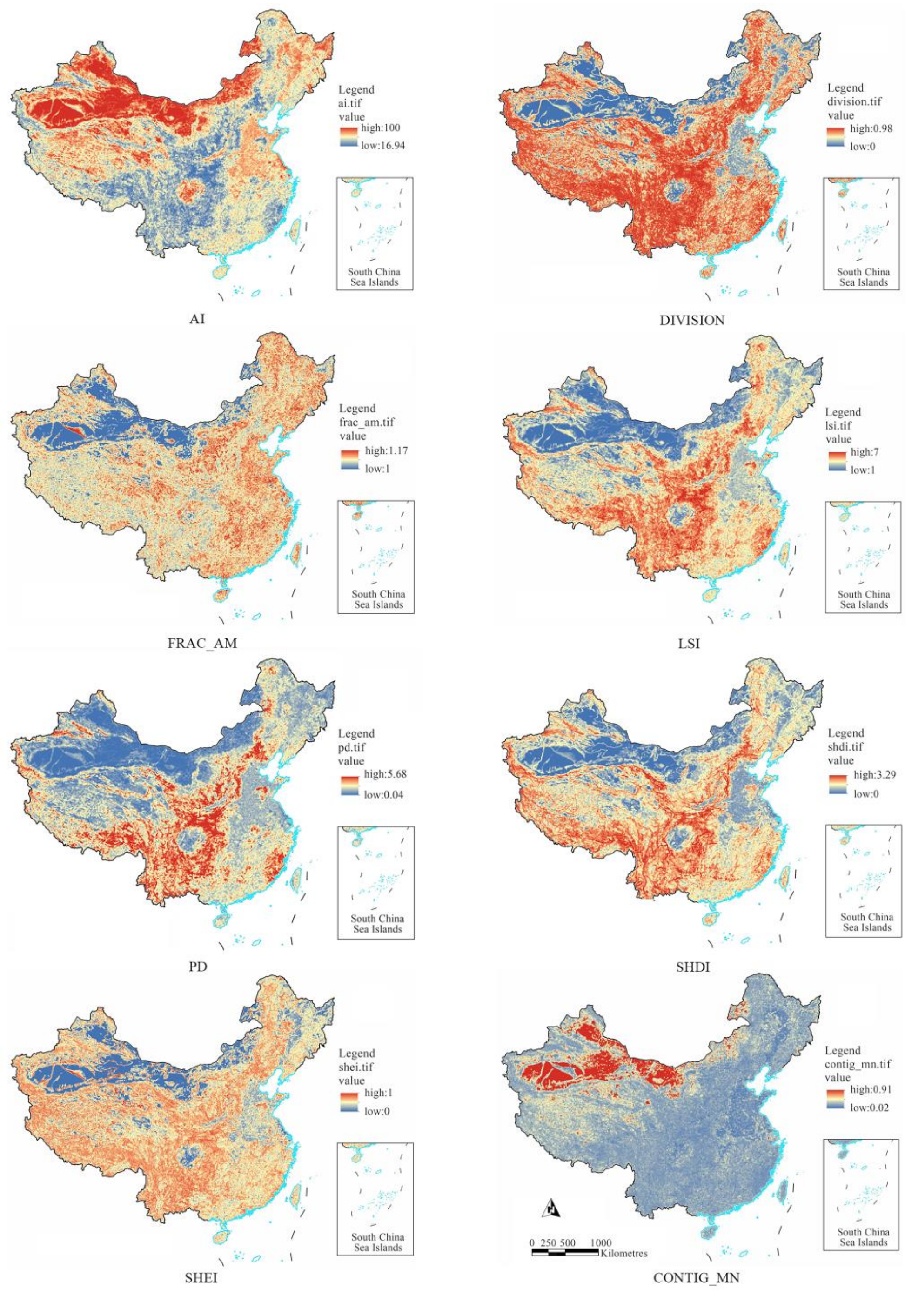


Figure 4. Eight landscape structure factors (LSFs) corresponding to a scale of 14 km.

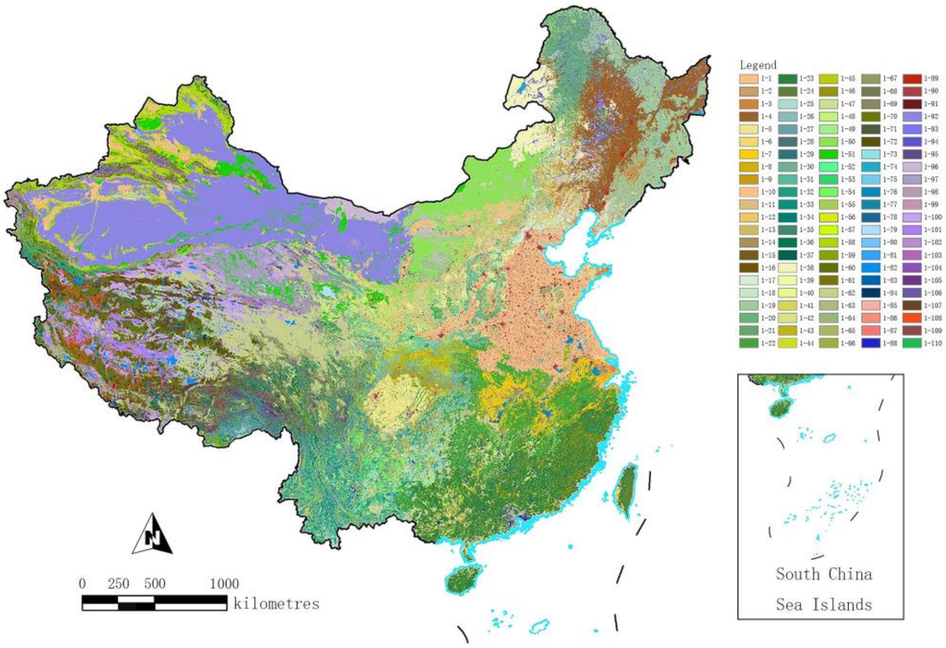


Figure 5. Map of 110 landscape character types (LCTs) across China at a scale of 1 × 1 km.

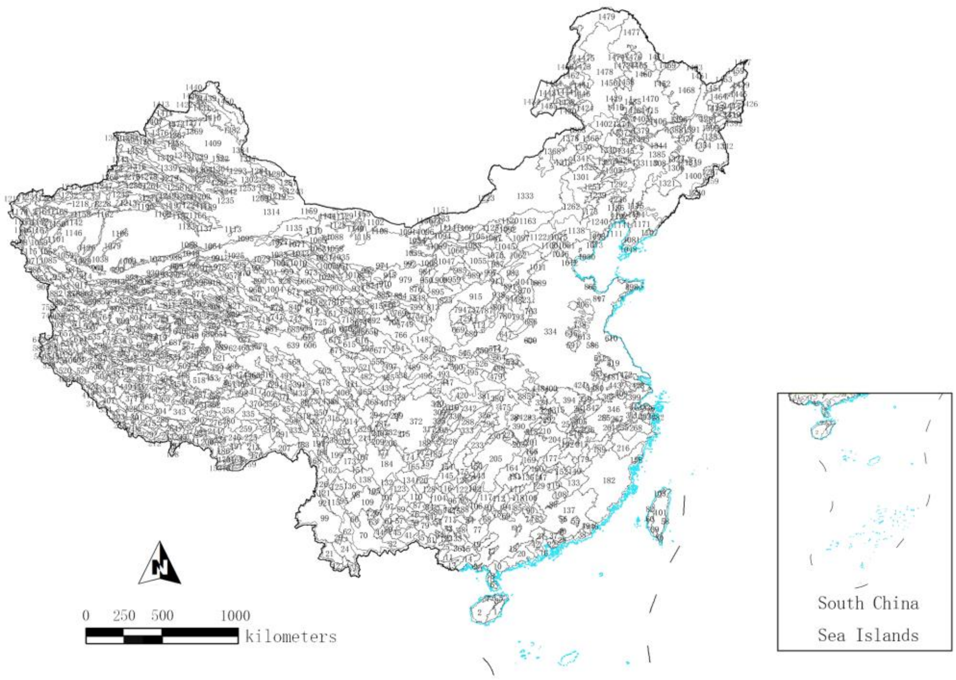
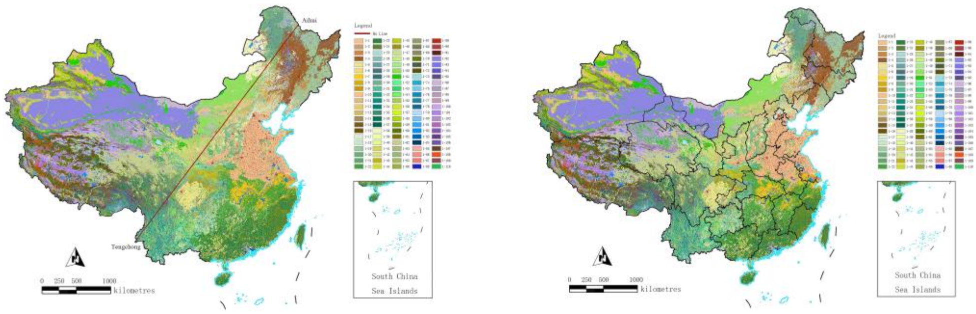


Figure 6. Combined artificial adjustment of the regional map of 1483 landscape character areas (LCAs) in China.

3.2. Spatial Distribution Characteristics of Landscape Character Types

In our study, we identified 110 LCTs across China. Spatially, LCTs existed across all administrative regions, and there were substantial differences in the LCTs in the north–south and east–west geographic locations. Furthermore, the LCTs of adjacent administrative regions were similar.

By considering the Aihui–Tengchong Line (Hu line), which divides China's population density and urbanisation level (Figure 7A), we deduced that the richness of LCTs was negatively correlated with China's population density and economic development. Notably, our results also revealed that the LCTs west of the Hu Line were rich and distinct from each other and were portrayed as independent areas on the map. The area east of the Hu Line demonstrated a high degree of economic development; moreover, in large areas, the LCTs were intertwined, and the homogeneity of the region was obvious.



(**a**) (**b**)

Figure 7. Landscape character types (LCTs) maps superimposed on (**a**) Hu Line and the (**b**) and administrative boundaries of China.

China's provincial administrative boundaries (Figure 7B) indicated that the administrative region having the most abundant LCTs was Sichuan Province (64 categories), followed by the Tibet Autonomous Region (62 categories) and Qinghai Province (57 categories); all these areas were located in Southwest China. Since these areas border each other, they are suitable for integrated protection and planning and management across administrative boundaries. Additionally, Sichuan Province was the administrative region with the most LCTs per unit area. It is located in the transition zone between the second and third steps of altitude in China and has rich landform types. Furthermore, the province has a pleasant climate, and several ethnic minorities have created a variety of natural and cultural tourism regions in this area.

An LSF can effectively reflect the composition and spatial configuration of the landscape structure and it is a classic method to describe landscape patterns and their changes [67]. Among the eight indexes considered in our study, AI represents the degree of aggregation and dispersion of patches in the spatial distribution of the landscape; the higher the value of this index is, the higher the degree of aggregation is. On a national scale, Xinjiang, Inner Mongolia, northeastern Heilongjiang, northern Tibet, and Chengdu Plain in central Sichuan demonstrated the highest agglomeration of LDUs, followed by central Tibet, Shandong, Jiangsu and Shanghai, Yunnan, northern Sichuan, and Shaanxi. In contrast, the agglomeration degree in Shanxi was low. The SHDI, LSI, DIVISION, and PD indexes characterised the patch diversity, shape complexity, segmentation degree, and patch density of the landscape, respectively. These four indexes demonstrated similar trends with respect to their spatial distribution, but there were still differences in their peaks and some properties of spatial structure. The values were low in the Tarim and Junggar basins and western Inner Mongolia in Xinjiang, and high in southern Tibet, Yunnan, Sichuan, Gansu, Hebei, and other regions. However, the strengths and weaknesses of these spatial distribution trends differed considerably, and there are prominent differences in regions such as the Altun Mountains in Xinjiang. The SHEI index characterised the uniformity of landscape patches; the higher the value, the more even the distribution of the LCT. As shown in Figure 5, the spatial trends of the SHEI and SHDI indexes portrayed similarity. However, the trends of the former are more average, and there are differences in some regions, such as Qinghai and Tibet, which have higher SHEI and lower SHDI values. The trends in Qinghai and Tibet are different because the proportion of LCTs in these areas is average, and the number of types is small. Meanwhile, CONTIG-MN represented the coherence of patches within the LDU, and its spatial trend was unique, portraying high aggregation in Xinjiang and Inner Mongolia, followed by Tibet, and low and uniform coherence values in other regions.

3.3. Description of Landscape Character Areas

As shown in Figure 6, the top three LCAs for the largest areas of terrestrial China are summarised below:

LCA No. 1314: Located in the Xinjiang Autonomous Region of northwest China, this area covers 7.60% of China. The hilly desert landscape, with sparse vegetation and wide views, is adjacent to the Tianshan Mountains and Qilian Mountains and shows only a few signs of human activities. It belongs to the 'northern rural settlements' category.

LCA No. 334: Located in Hebei, Shandong, Jiangsu, and Henan, the area accounts for 5.73% of the land surface of China. This is a low-elevation area with a flat terrain and expansive views. It mainly comprises cultivated land, including a large expanse with a regular geometric texture, and built-up areas occur only sporadically. Human habitation shows a scattered distribution, including the rural settlements of the Great Wall in the north and the North China Plain in the south. Settlement patches are mainly distributed along roads and on both sides of the river.

LCA No. 1333: Located northeast of the Inner Mongolia Autonomous Region, this area accounts for 2.17% of China's terrestrial surface. This region occupies a medium elevation area, supports important grasslands, offers wide views, and is rich in geological, mineral, animal, and vegetation resources. Human occupants are mainly nomadic pastoralists, and the habitation type belongs to the northern rural settlements category.

4. Discussion

In this study, we introduced settlement zoning, which is widely recognized, as a cultural factor for identifying terrestrial LCTs in China. Settlement zoning was classified into 11 regional types from the perspective of structure, economic function, and relationship with the natural environment [30] to reflect the diversity in physical geography and social and cultural differences underlying the spatial structure, density, and housing form of the rural settlements in the country [68–70]. Notably, the only cultural factor used by the European LCA is land-use [11]. Land tenure, field size and pattern, farm type, and settlement mode are mentioned in the LCA method used in the United Kingdom. However, these indicators are used in a detailed scale, and only settlement patterns are used in large-scale research [1]. In addition, we have tried to introduce ethnic elements, but the 'Hanization' of ethnic minorities in China is widespread. Moreover, the population of each ethnic group is dispersed over large areas, and these groups have small settlements and staggered living patterns [71]. Our study highlights the fact that ethnic factors are more suitable for consideration in studies conducted at the meso- and microscales, and a large amount of statistical analysis is still needed to obtain the spatial distribution characteristics of ethnic minorities within each region. In terms of selection of LCFs, we prefer the visibility of landscape that is affected by data accuracy, and hence, we chose altitude, topographic relief, and land-use as distinguishing factors, and climate and settlement as descriptive factors. We also considered vegetation coverage and other regionally common data with the objective of covering the entire territory of China to arrive at broad patterns rather than fine details [1]. Vegetation cover and other data will show more interesting results at the regional scale.

In previous landscape classification studies, the selection of factors was mostly based on natural and physical factors of landscape composition [22,31]. In addition to introducing settlement factors, our study demonstrates that LCFs depend on the composition of elements (natural and human) and should also include structural features [28,29,40,72]. This, to a certain extent, creates a sharp distinction between different patches of the same landscape and reflects the interaction between man and different elements of nature. At the same time, the existence of culture has geographical characteristics, and there are potential cultural connections in adjacent areas. However, due to the nonspatial characteristics of landscape composition and structure, there may be LDUs with the same composition and structure in different regions in a large range of research objects, but their cultural attributes are different. The cultural factors that can be obtained at the same scale covering China are limited by data availability and accuracy. We solved this problem using the spatial co-ordinates of grid centroid points of supplementary LDUs in the clustering calculation.

Since the structure of landscape patches is a relatively fixed composition system, the main difference and core concern of transmission at different scales lie in the more significant granularity and amplitude effects [73]. Notably, generalised structural properties result in false perceptions of landscape features at different scales [42,43], which may hinder the accuracy of the LCA results. Therefore, we used the semivariogram to analyse the relationship between the granularity and amplitude of the landscape structure and the study object [52] and calculated the window size corresponding to the spatial attribute reaching a stable state; this was used to quantify the structural characteristics of different objects at different scales and provide scientific and objective calculation methods. Results showed that the optimal window size for the calculation of the LSF was 14 km, which reflected the unique spatial characteristics of landscape patches in China on a national scale. Furthermore, this window size is similar to the one chosen by Li and Qi [35] and Zou, Wang, and Bai [34] in their studies related to the global landscape structure in China.

With respect to terrestrial China, a comparison of the landscape structure and composition revealed that land-use type had a significant impact on the AI, SHDI, LSI, PD, and DIVISION values. The AI was high in cultivated and unused land and low in forest land and grassland; in these areas, the values of DIVISION, LSI, PD, and SHDI were also high. At the same time, there were differences in the structural trend of cultivated and unused land. Concerning AI aggregation, the AI value of unused land in the northwest region was significantly higher than that of the cultivated land in the central and eastern regions. This was because other land types were scattered among the cultivated land due to the influence of the natural geographical environment and the intensity of development and utilisation. Furthermore, among the types of cultivated land, there were also differences in the LSPs of the Chengdu Plain, the North China Plain, and the middle and lower reaches of the Yangtze River. We believe that this is related to the altitude, fluctuation, climate, and settlement type of the area, indicating that the landscape was the result of the long-term interaction of natural abiotic, biotic, and human activities, creating a terrain that people perceived as distinctive [9,74,75]. Notably, for this region, the composition is not only determined by land-use but also by other driving factors, such as biophysical factors, landscape structural characteristics, and human attributes (e.g., settlements) [28,40]. Several scholars have carried out quantitative analyses on landscape patterns from the perspective of land-use type [34,76,77]. Our study provides a new perspective for landscape structure analysis. Furthermore, our results revealed that the spatial distribution trends of diversity (SHDI) and fragmentation (PD and DIVISION) were highly consistent and are important for defining fragmentation and diversity thresholds of landscape structures in future studies.

To evaluate the effectiveness of different research methods, we compared the shortcomings of the ensemble, automatic segmentation, and parametric methods. We considered the parameter method as the main method of LCA and selected the detailed character of landscape elements to reflect on the more comprehensive combination of relationships of LCFs [5]. In addition, we introduced the automatic segmentation method to quickly and objectively divide the LCAs and reduced the subjective impact of human interpretation [66]. Finally, we supplemented the expert knowledge and judgment of the ensemble method to correct and verify the LCAs [3]. Compared with satellite images, we found that the accuracy of LCTs and LCAs obtained using this method provided better results. Our research provides a systematic and logical approach for LCA, and the developed system can be applied to other countries and regions. We performed cluster value calculation using the elbow method to solve the a priori definition of the number of clusters [25,26], which are considered unavoidable defects [5,78]. Furthermore, by comparing k-prototype, affinity propagation, second-order clustering, and k-means clustering algorithms, we deduced that the k-means clustering algorithm had high efficiency in processing large samples and effects [62,63].

Our study has two major limitations, which are as follows: (1) The completeness and availability of cultural history and socioeconomic data are limited as only a selection of factors for cultural attributes were considered. (2) As the scale of the study area is extremely large, manual field correction was almost impossible to implement. The LCA of the national-scale region was mainly based on satellite images for manual verification. Therefore, future studies must consider different cultural factors while exploring and expanding their zoning types, such as language, place-name, ethnic elements, historical memory, and so on. Additionally, with the improvement of computer software technology and the optimisation of the popularisation rate, research results can be shared on the public participatory GIS platform in the later stages, thus promoting extensive and easy-to-understand popular scientific studies. Strengthening public participation can further supplement the national LCA results, thereby strengthening the landscape character and collecting and preserving interpretations of landscapes by the people, which can be used to supplement social and cultural elements.

5. Conclusions

Guided by the value of neutrality, we selected nature, culture, spatial geographic co-ordinates, and landscape structure to identify LCTs across China. Thus, we filled the gap in the literature regarding the identification of LCTs at the national scale against the current background of China's territorial and spatial planning. Notably, our study has constructed a system for China's terrestrial LCA using an approach that combines the ensemble, automatic segmentation, and parametric methods. This system provides a comprehensive and relatively objective classification of LCTs, which can serve as a reference at the mesoscale. Furthermore, through data processing, statistical clustering, automatic image segmentation, and manual correction, we improved the LCA system and provided a solution for the transmission of landscape structure. These data can be further supplemented and optimised at the meso- and microlevel in future research, which can evolve into a multilevel nested landscape management and protection system at the national, regional, and local scales. Additionally, our study can provide a scientific basis and support for national land-space planning and cross-administrative regional development, protection, enhancement, and management strategies.

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Appendix A

Table A1. Thirty-one landscape characteristic factors.

Categories	Subcategories	Digital Number	Landscape Code
Altitude	Low <1000 m	59	A1
	Middle 1000–3500 m	61	A2
	High 3500–5000 m	67	A3
	Extremely high >5000 m	71	A4
Land use/cover	Farmland	2	L1
	Woodland	3	L2
	Grassland	5	L3
	Water	7	L4
	Construction land	11	L5
	Unused land	13	L6
Topographic relief	Plain <30 m	17	R1
	Hills 30–200 m	19	R2
	Small topographic relief 200–500 m	23	R3
	Middle topographic relief 500–1000 m	29	R4
	High topographic relief >1000 m	31	R5
Climate	Temperate continental climate	37	C1
	Tropical monsoon climate	41	C2
	Subtropical monsoon climate	43	C3
	Plateau alpine climate	47	C4
	Temperate monsoon climate	53	C5
Settlement	Northern China Rural Settlement Region	73	S1
	Great Wall Rural Settlement Region	79	S2
	Loess Plateau Rural Settlement Region	83	S3
	North China Plain Rural Settlement Region	89	S4
	Middle-Lower Yangzi River Rural Settlement Region	97	S5
	South Yangzi River Hill Areas Rural Settlement Region	101	S6
	Southeast Coastal Rural Settlement Region	103	S7
	Southwest Rural Settlement Region	107	S8
	Northern Rural Settlement Region	109	S9
	Northwestern Rural Settlement Region	113	S10
	Qinghai-Xizang (Tibet) Rural Settlement Region	127	S11

Table A2. Landscape structure factor and its structural meaning.

Index	Theoretical Extent	Meaning
Aggregation index (ai)	$0 \leq AI \leq 100$	The degree of aggregation or dispersion of LCTs.
Contiguity index_Mean (contig_mn)	$0 \leq CONTIG \leq 1$	The degree of coherence of the same LCT patches.
Landscape division index (division)	$0 \leq DIVISION \leq 1$	The degree of fragmentation of the distribution of LCT.
Fractal dimension index_Area-weighted mean (frac_am)	$1 \leq FRAC \leq 2$	The shape complexity of the LCTs at the spatial scale.
Landscape shape index (lsi)	$LSI \geq 1$	The complexity or regularity of the shape of the LCT.
Patch density (pd)	$PD > 0$	The degree of fragmentation of LCTs.
Shannon's diversity index (shdi)	$SHDI \geq 0$	Indicates the heterogeneity of LCTs and emphasises the contribution of scarce patch types to information.
Fractal dimension index_Area-weighted mean (frac_am)	$1 \leq FRAC \leq 2$	The shape complexity of the LCTs at the spatial scale.
Shannon's evenness index (shei)	$0 \leq SHEI \leq 1$	Indicates whether there are obvious dominant types in the landscape and the degree to which each patch type is evenly distributed in the landscape.

Table A3. Nomenclature of 1 km * 1 km scale LCTs.

Serial Number	Landscape Code	Area Percentage (%)	Serial Number	Landscape Code	Area Percentage (%)
1-1	$L_1A_1R_1C_1S_{10}$	0.9912	1-56	$L_3A_2R_3C_3S_8$_2	0.1882
1-2	$L_1A_1R_1C_1S_2$	0.4983	1-57	$L_3A_2R_4C_3S_8$	0.0311
1-3	$L_1A_1R_1C_5S_1$_1	0.8502	1-58	$L_3A_2R_1C_4S_{10}$	2.5549
1-4	$L_1A_1R_1C_5S_1$_2	0.2943	1-59	$L_3A_2R_3C_4S_{11}$	0.209
1-5	$L_1A_1R_1C_3S_6$	1.7655	1-60	$L_3A_2R_3C_4S_{10}$	0.66
1-6	$L_1A_1R_1C_3S_7$	0.8299	1-61	$L_3A_2R_4C_4S_{11}$	1.2264
1-7	$L_1A_1R_1C_3S_5$	1.5249	1-62	$L_3A_3R_1C_4S_{11}$	4.2387
1-8	$L_1A_1R_2C_3S_7$	0.3936	1-63	$L_3A_3R_2C_4S_{11}$_1	1.2107
1-9	$L_1A_1R_2C_3S_8$	0.7315	1-64	$L_3A_3R_2C_4S_{11}$_2	0.7532
1-10	$L_1A_2R_1C_1S_2$	5.7585	1-65	$L_3A_3R_2C_4S_{11}$_3	0.9384
1-11	$L_1A_2R_1C_5S_3$	0.9316	1-66	$L_3A_3R_3C_4S_{10}$	0.3671
1-12	$L_1A_2R_2C_3S_8$	0.9143	1-67	$L_3A_3R_3C_4S_{11}$_1	0.4491
1-13	$L_1A_2R_3C_3S_8$_1	0.1975	1-68	$L_3A_3R_3C_4S_{11}$_2	0.8617
1-14	$L_1A_2R_3C_3S_8$_2	0.1735	1-69	$L_3A_3R_4C_4S_{11}$	0.1134
1-15	$L_1A_2R_4C_3S_8$	0.0124	1-70	$L_3A_4R_2C_4S_{11}$	2.4811
1-16	$L_1A_3R_2C_4S_{11}$	0.0677	1-71	$L_3A_4R_3C_4S_{11}$_1	0.4293

Table A3. *Cont.*

Serial Number	Landscape Code	Area Percentage (%)	Serial Number	Landscape Code	Area Percentage (%)
1-17	$L_2A_1R_1C_1S_2$	1.0025	1-72	$L_3A_4R_3C_4S_{11}$_2	0.2449
1-18	$L_2A_1R_1C_1S_{10}$	0.1623	1-73	$L_4A_1R_1C_5S_2$	0.0981
1-19	$L_2A_1R_1C_5S_1$_1	3.0789	1-74	$L_4A_1R_1C_5S_1$	0.2433
1-20	$L_2A_1R_1C_5S_1$_2	1.5621	1-75	$L_4A_1R_1C_5S_4$	0.4337
1-21	$L_2A_1R_1C_5S_3$	0.7715	1-76	$L_4A_1R_1C_3S_5$_1	0.292
1-22	$L_2A_1R_1C_3S_5$	2.8842	1-77	$L_4A_1R_1C_3S_5$_2	0.2174
1-23	$L_2A_1R_1C_3S_7$	4.8023	1-78	$L_4A_1R_1C_3S_7$	0.4169
1-24	$L_2A_1R_3C_3S_7$	0.6338	1-79	$L_4A_2R_1C_1S_9$	0.1574
1-25	$L_2A_2R_1C_3S_8$	1.4807	1-80	$L_4A_2R_1C_4S_{10}$	0.118
1-26	$L_2A_2R_3C_3S_8$_1	0.805	1-81	$L_4A_2R_3C_4S_{11}$	0.0519
1-27	$L_2A_2R_3C_3S_8$_2	1.3185	1-82	$L_4A_3R_1C_4S_{11}$	0.724
1-28	$L_2A_2R_3C_4S_{10}$	0.0545	1-83	$L_4A_4R_3C_4S_{10}$	0.1684
1-29	$L_2A_2R_4C_4S_{11}$	0.237	1-84	$L_4A_4R_2C_4S_{11}$	0.0554
1-30	$L_2A_3R_1C_5S_1$	0.3932	1-85	$L_5A_1R_1C_1S_2$	0.2905
1-31	$L_2A_3R_1C_5S_{10}$	0.855	1-86	$L_5A_1R_1C_1S_{10}$	0.0864
1-32	$L_2A_3R_1C_3S_7$	0.3581	1-87	$L_5A_1R_1C_3S_5$	0.4385
1-33	$L_2A_3R_1C_3S_8$	1.6915	1-88	$L_5A_1R_1C_3S_7$	0.2978
1-34	$L_2A_3R_1C_4S_{10}$	0.0725	1-89	$L_5A_1R_1C_5S_1$	0.2288
1-35	$L_2A_3R_3C_4S_{11}$	0.9679	1-90	$L_5A_1R_1C_5S_4$	0.7722
1-36	$L_2A_3R_2C_4S_{11}$	0.6626	1-91	$L_5A_2R_1C_5S_3$	0.2017
1-37	$L_2A_4R_2C_4S_{11}$	0.2609	1-92	$L_6A_1R_1C_1S_{10}$	11.9268
1-38	$L_3A_1R_1C_1S_9$	1.3274	1-93	$L_6A_1R_1C_5S_1$_1	0.4567
1-39	$L_3A_1R_1C_5S_3$	0.4226	1-94	$L_6A_1R_1C_5S_1$_2	0.593
1-40	$L_3A_1R_1C_5S_1$	0.2525	1-95	$L_6A_1R_1C_3S_5$	0.0344
1-41	$L_3A_1R_1C_1S_2$	0.3639	1-96	$L_6A_2R_1C_1S_9$	0.9843
1-42	$L_3A_1R_1C_1S_9$	0.6308	1-97	$L_6A_2R_2C_1S_{11}$	1.6022
1-43	$L_3A_1R_1C_3S_5$	0.1284	1-98	$L_6A_2R_3C_4S_{10}$	0.2345
1-44	$L_3A_1R_1C_3S_7$	0.2421	1-99	$L_6A_2R_4C_1S_{10}$	0.0142
1-45	$L_3A_1R_2C_3S_8$	0.3587	1-100	$L_6A_3R_1C_4S_{11}$	2.0671
1-46	$L_3A_1R_1C_3S_7$	3.307	1-101	$L_6A_3R_2C_4S_{11}$_1	1.2224
1-47	$L_3A_2R_1C_5S_3$	0.7049	1-102	$L_6A_3R_2C_4S_{11}$_2	0.6958
1-48	$L_3A_2R_2C_5S_{10}$	1.067	1-103	$L_6A_3R_2C_4S_{10}$	0.3492
1-49	$L_3A_2R_3C_5S_{10}$	0.1692	1-104	$L_6A_3R_3C_4S_{11}$_1	0.2397
1-50	$L_3A_2R_1C_1S_2$	3.4231	1-105	$L_6A_3R_3C_4S_{11}$_2	0.2681
1-51	$L_3A_2R_1C_1S_1$	1.6981	1-106	$L_6A_3R_4C_4S_{10}$	0.0582
1-52	$L_3A_2R_2C_3S_8$_1	0.3156	1-107	$L_6A_4R_1C_4S_{11}$	0.2097
1-53	$L_3A_2R_2C_3S_8$_2	0.3491	1-108	$L_6A_4R_2C_4S_{11}$	0.1414
1-54	$L_3A_2R_2C_3S_8$_3	0.3961	1-109	$L_6A_4R_3C_4S_{11}$	0.5169
1-55	$L_3A_2R_3C_3S_8$_1	0.287	1-110	$L_6A_4R_3C_4S_{10}$	0.7028

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