

Article

Changes in Impervious Surfaces in Lhasa City, a Historical City on the Qinghai–Tibet Plateau

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Abstract: Impervious surface cover reflects the urban environment and urban expansion. Lhasa City is a historical city and one of the most populous on the Qinghai–Tibetan Plateau, and has been experiencing rapid urbanization in recent years. Analyzing the impervious surface distribution can reveal urban development characteristics and provide data for sustainable urban planning to protect the heritage. This study explored the spatial and temporal changes and expansion patterns of impervious surfaces in different zones of Lhasa City. Impervious surface maps (2014 and 2021) were extracted from Gaofen-1 images with a high spatial resolution (2 m) using an object-based image analysis method. Next, a gravity center, standard deviational ellipses and landscape indices were used to characterize impervious surface expansions in different zones. The result indicated that the impervious surface in Lhasa expanded from 51.149 km² in 2014 to 63.299 km² in 2021. The growth rates of impervious surfaces inside the Environmental Coordination zone were lower than in the zones outside. From 2014 to 2021, the impervious surface of Lhasa expanded in the southeast direction. Infilling and consolidation were the primary impervious surface development patterns. The expansion of the impervious surface was related to topography, population, and economic and policy factors.

Keywords: impervious surfaces; urban development; Qinghai–Tibetan plateau; landscape indices



Citation: Wang, S.; Tan, X.; Fan, F. Changes in Impervious Surfaces in Lhasa City, a Historical City on the Qinghai–Tibet Plateau. *Sustainability* **2023**, *15*, 5510. <https://doi.org/10.3390/su15065510>

Academic Editor: Baojie He

Received: 20 February 2023

Revised: 8 March 2023

Accepted: 18 March 2023

Published: 21 March 2023



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1. Introduction

Impervious surfaces are defined as materials that prevent water from infiltrating the soil, including parking lots, rooftops, roads, and sidewalks [1]. Impervious surface changes have been considered an efficient indicator for monitoring urban changes and play an important role in natural environment assessment [2–4]. The urbanization process of an area and the direction of urban expansion are reflected in the geometry, location, magnitude, and spatial pattern of impervious surfaces, as well as the ratio of pervious to impervious surfaces [5,6]. Increases in the area of impervious surfaces cause a variety of environmental problems, including water quality degradation [7], urban heat islands [8,9], and urban waterlogging [10]. As a result, the estimation and mapping of impervious surface areas is extremely important for diverse issues in environmental science that are central to global environmental changes and human–environment interactions, environmental management, and urban planning, including the construction of infrastructure and achieving sustainable development [5].

Impervious surfaces have already been widely used to explore spatial and temporal changes in urban development and to analyze urban environmental effects [11–13]. A variety of approaches have been employed to identify urban land use changes, including concentric rings [14], Moran’s I index [15], bands [16], transects [17], gravity center analysis and standard deviational ellipses (SDE) [4], as well as landscape indices [18,19]. Single

methods can be used to evaluate different aspects of urban dynamics, such as orientation and patterns. However, conducting these analyses alone cannot achieve a comprehensive understanding of the spatiotemporal heterogeneity of impervious surfaces in complex urban environments over extended time periods, such as at the decade scale. It is therefore important to investigate the expansion of urban impervious surfaces at various scales using methods in combination.

Much effort has recently been made to map impervious surfaces using remote sensing techniques. Major approaches over the past decade to impervious surface extraction include an impervious surface index, a support vector machine, a spectral mixture analysis, a decision tree model, a regression tree, a random forest (RF), an object-based image analysis (OBIA), and an artificial neural network. Among these approaches, many researchers have used the OBIA method to extract impervious surfaces from high-spatial-resolution images [20–22]. Rather than relying on individual pixels, this method uses nearby pixel groups (objects). These pixel groups can be segmented based on geometric, spectral, contextual, and textural information. This method can effectively reduce the spectral variation present in a variety of land cover types, thereby improving the precision of classification [23–25]. Numerous investigations have indicated that the OBIA method exhibits high efficiency and precision in revealing the distribution of impervious surfaces [26–28]. The nearest neighbor (NN) classifier is popular when performing the OBIA method; however, the NN classifier may be less effective with high-dimensional data due to issues related to feature correlation [29,30]. To reduce these limitations and enhance object-based classification accuracy, machine learning classifiers have attracted increasing research interests. Machine learning classifiers including the support vector machine, the classification and regression tree, and the RF have been reported to outperform most classifiers in many studies [23,31,32].

Since the beginning of the 21st century, Chinese cities have developed rapidly, and the urban geographical structure and spatial pattern have been continuously optimized and upgraded. The implementation of the “Western Development” strategy has significantly driven the urbanization development of the Qinghai–Tibet Plateau. Over the past 30 years, the Tibetan Autonomous Region has achieved rapid economic development with the support of national policies. Lhasa City is the capital of the Tibet Autonomous Region, with a history of over 1300 years. Lhasa City is a multifunctional urban center defined by the intersection between history and modernity. It is among the most populous cities on the Qinghai–Tibet Plateau and a center of Tibetan national and regional culture, with extremely elevated historical and cultural value and unique social and economic functions. The development status of Lhasa City is an important window to characterize the development level of the Tibet region, and the impervious surface can well represent the urban expansion and development trends. However, the ecological environment of the Qinghai–Tibet Plateau is extremely fragile and any human disturbance can easily change the ecological functions and ecosystem structures [33]. As a major human activity zone in the plateau, the land cover of Lhasa City experienced significant changes accompanied by urbanization [34,35]. The expansion of impervious surfaces in Lhasa City has changed the land surface temperature [36,37], eco-environmental quality [38], and riverine hydrological processes [39]. Furthermore, rapid urbanization has led to the rapid expansion of urban space, and the overall pattern and traditional features of many historical and cultural cities have been damaged during large-scale urban and rural construction [40–42]. Heritage conservation is an indispensable factor for sustainable development [43]. Balancing heritage conservation and urban development is very important in sustainable urban development plans [44]. This study is the first to analyze the impervious distribution of Lhasa City and heritage conservation areas with high spatial resolution images, which can reveal urban development characteristics and provide more precise fundamental data for sustainable urban planning to protect the heritage.

In this study, the Chengguan District of Lhasa City was used as the study area, and a variety of methods were adopted to perform a spatial and temporal analysis of its impervious surfaces in different zones from 2014 to 2021. The specific objectives of the

study are to (1) extract impervious surface maps using the OBIA method and analyze the spatial and temporal dynamics of impervious surfaces over the study period; (2) identify the expansion direction of impervious surfaces by gravity centers and the SDE method; and (3) explore the landscape pattern of impervious surfaces using the landscape indices of the city and heritage conservation areas.

2. Materials and Methods

2.1. Study Area and Data

2.1.1. Study Area

Lhasa has an average altitude of 3656 m and a population of 867,891, making it the one of the most populous cities on the Qinghai–Tibet Plateau. Lhasa is among the highest cities in the world. Since the mid-17th century, the city has been both the administrative and religious capital of Tibet and is home to numerous culturally significant Tibetan Buddhist sites, including the Norbulingka Palaces, Jokhang Temple, and Potala Palace. Chengguan District is found in the valley plain area where the Lhasa River flows. It has a plateau mountain climate. The rainy season occurs from July to September every year and it rains frequently at night. The unique geographical location gives the area an average annual sunshine duration of over 3000 h and it is known as the “Sunlight City”. The urbanization rate is 42.40% and the GDP is CNY 47.925 billion. In 2020, the resident population of Chengguan District was 473,586, accounting for 54.57% of the total population of Lhasa.

According to the “Regulations on Protection of Famous Historical and Cultural Cities of Lhasa,” the study area (Figure 1) was divided into five zones: the Central City zone (Chengguan District), the Environmental Coordination zone, the Historic zone, and two historical and cultural districts—Bakuojie zone and Caiyicun zone. Caiyicun is a historical and cultural district established in 2019.

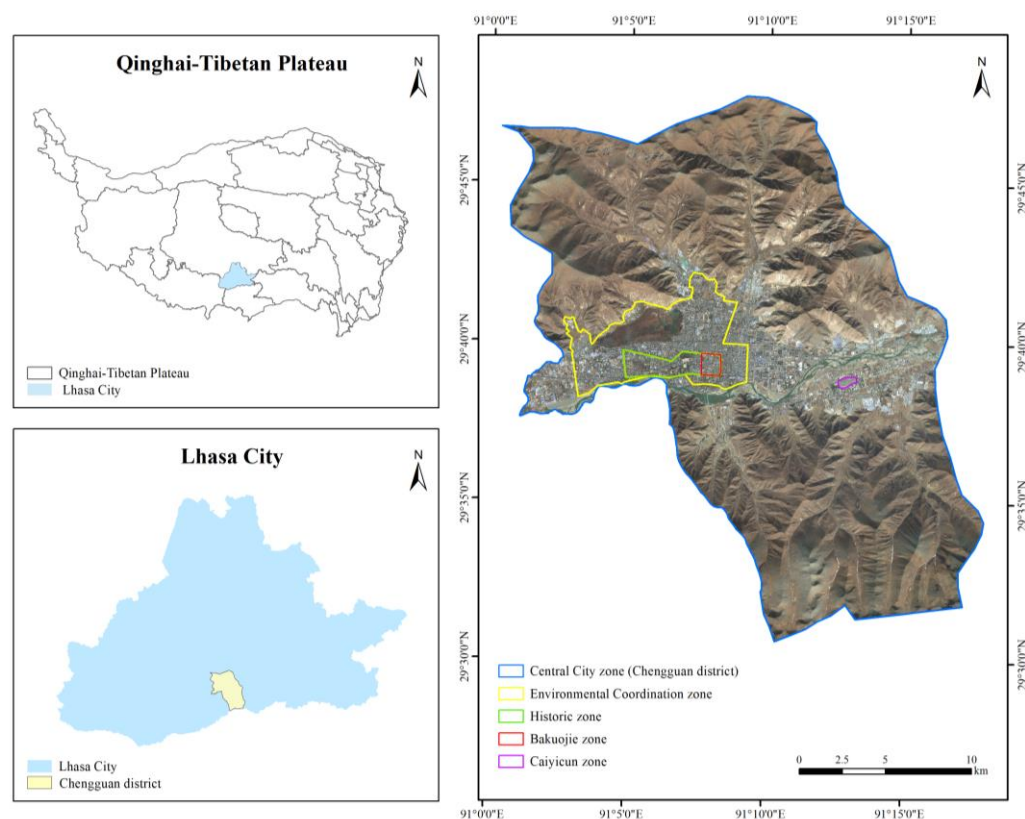


Figure 1. Study area.

2.1.2. Data Recourses and Preprocessing

Four images from 2014 to 2021 were acquired from the GF-1 satellite at the China Centre for Resources Satellite Data and Application (CRESDA) (<https://data.cresda.cn/>, accessed on 18 March 2023) and were selected to extract impervious surfaces. Table 1 lists the images used in this study. The images selected in the study had 2 m panchromatic and 8 m multispectral bands. The selected images were almost cloud-free, with good atmospheric conditions and high image quality.

Table 1. Remote sensing images of Lhasa.

Acquisition Date	Cloud Cover	Center Latitude and Longitude	Sensor
12 February 2014	0	91.0 E, 29.7 N	PMS
12 February 2014	1%	91.3 E, 29.6 N	PMS
5 February 2021	1%	91.1 E, 29.7 N	PMS
5 February 2021	1%	91.1 E, 29.4 N	PMS

Radiometric correction, geometric correction, image registration, and image mosaicking were used to preprocess the original remote sensing images in order to obtain remote sensing image data for the study area.

The GF-1 satellite imagery has four multispectral bands including blue, green, red, and near-infrared spectra [45]. Radiometric correction was applied to convert raw digital image data from satellite to apparent reflectance [46]. The FLAASH Atmospheric Correction Model was applied to the multispectral images to minimize the atmospheric effects. Next, geometric correction was applied using an RPC sensor model and the images were reprojected into the WGS84/UTM coordinate systems. The NNDiffusion pan-sharpening method was implemented to obtain a fused image with a spatial resolution from 8 to 2 m for multispectral bands.

2.2. Methods

The OBIA method for the extraction of impervious surfaces is composed of two main steps: image segmentation and object-based classification. The OBIA method was performed with eCognition Developer 9.0 software. Furthermore, an accuracy assessment was performed to evaluate the classification results. Figure 2 shows the workflow of the study.

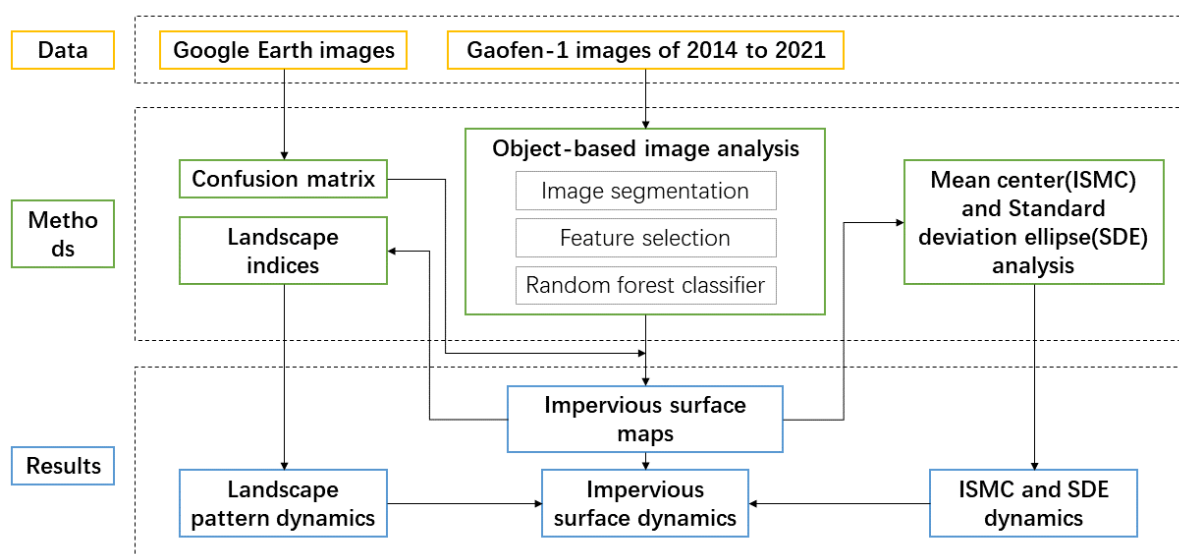


Figure 2. Workflow of this study.

2.2.1. Mapping Impervious Surfaces Image Segmentation

Image segmentation refers to the process of dividing an image into a group of adjacent pixels (objects) that exhibit similar spatial features, spectral information, and textual features [20]. The multiscale segmentation algorithm was used to generate segmented images. In the algorithm, scale is a key parameter which determines spectral variation within objects and their size. Greater scale values result in larger and heterogeneous objects. Furthermore, the shape and compactness parameter values are also important because they determine the weight of the color and the smoothness of segmented objects. Using different segmentation parameters leads to different results; thus, the generation of discernible image objects on the greatest possible scale can be accomplished through trial and error. In the present work, the three parameters (scale = 70, shape = 0.3, and compactness = 0.4) were chosen using an iterative experimental approach at different levels.

Feature Selection

The feature selection plays a key role in classification and can enhance the computational performance of classifiers by eliminating redundant information [47]. The Trimble eCognition software provides various sets of feature options; besides image statistics, many remote sensing indices, including the normalized difference water index (NDWI) and normalized difference vegetation index (NDVI), are an option that can improve the classification results. Moreover, the perpendicular impervious surface index (PISI) is used as a feature in the OBIA method because of its good performance in mapping impervious surfaces in high spatial resolution images with great accuracy [28]. Experiments were performed during the feature selection step to determine the appropriate statistics, and the most widely used features including the shape and texture (derived from the grey-level co-occurrence matrices (GLCM)) were also extracted, including the homogeneity, dissimilarity, entropy, and correlation, while spectral statistics (mean value and brightness) were defined for the classifier.

RF Classifier

RF is a widely used ensemble learning method that has been used effectively for classification to solve a range of pixel- and object-based tasks owing to its processing speed, accuracy, and robustness [48–51]. The main concept underlying the RF algorithm is the creation of a decision forest constructed from a multitude of decision trees (DT) classifiers trained based on various bootstrap sub-samples from the original dataset [52]. For unknown samples, class labels are predicted based on majority voting after combining the outputs of all individual trees [52–54]. Each DT utilizes approximately two-thirds of the training samples selected using the bootstrapping technique, while the remaining one-third samples are used for out-of-bag error estimation.

Accuracy Assessment

High-resolution images obtained from Google Earth imagery for 2014 and 2021 were utilized for the evaluation of the accuracy of the impervious surface map. Five hundred verification points were randomly selected for each year. The confusion matrix method was applied for the extraction of the following four accuracy indicators: overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and overall kappa coefficient [55].

The OA is the proportion of correctly classified pixels from the total accuracy assessment pixels. The PA refers to the probability that a certain land cover of an area on the ground is correctly classified and represents the omission error. The UA refers to the proportion of correctly classified pixels within the image and represents the commission error. The kappa coefficient is a statistical measure used to test interrater reliability [56].

2.2.2. Impervious Surface Mean Center Analysis and Standard Deviation Ellipse

The gravity center [57], assigned as the impervious surface mean center (ISMC), was applied to determine the direction of urban expansion based on impervious surface maps from 2014 to 2020. The coordinates of the ISMC are calculated as the following equation:

$$\begin{cases} \bar{x} = \frac{\sum_{i=1}^n x_i}{n} \\ \bar{y} = \frac{\sum_{i=1}^n y_i}{n} \end{cases} \quad (1)$$

where x and y are the longitude and latitude coordinates of the ISMC, respectively; x_i and y_i are the coordinates of the i th grid in the impervious surface map; and n is the grid number of the impervious surface map.

Determining the spatial patterns of a city facilitates the comprehension of the development direction and degree of urbanization [58]. Therefore, SDE were applied to illustrate the spatial expansion of urbanization. Based on the impervious surface images, four SDE parameters were calculated: the mean center, long and short axis, and azimuth angle. The mean center and the azimuth angle were determined to capture the urbanization change direction of the entire region [50,51]. The mean center of the SDE was the previously calculated ISMC. The azimuth of the SDE is calculated as the following equations:

$$\tan \theta = \frac{(\sum_{i=1}^n \tilde{x}_i^2 - \sum_{i=1}^n \tilde{y}_i^2) + \sqrt{(\sum_{i=1}^n \tilde{x}_i^2 - \sum_{i=1}^n \tilde{y}_i^2)^2 - 4(\sum_{i=1}^n \tilde{x}_i \tilde{y}_i)^2}}{2 \sum_{i=1}^n \tilde{x}_i \tilde{y}_i} \quad (2)$$

$$\begin{cases} \tilde{x}_i = x_i - \bar{x} \\ \tilde{y}_i = y_i - \bar{y} \end{cases} \quad (3)$$

where x_i and y_i are the deviations of the i -th grid center and the ISMC for the x - and y -axis, respectively. The standard deviations, σ_x and σ_y , for the x - and y -axis, respectively, are calculated as follows:

$$\begin{cases} \sigma_x = \sqrt{\frac{2 \sum_{i=1}^n (\tilde{x}_i \cos \theta - \tilde{y}_i \sin \theta)^2}{n}} \\ \sigma_y = \sqrt{\frac{2 \sum_{i=1}^n (\tilde{x}_i \sin \theta + \tilde{y}_i \cos \theta)^2}{n}} \end{cases} \quad (4)$$

The long and short axis and azimuth angle describe the direction and range of impervious surface distributions. The ratio of the long axis to the short axis reflects the clustering or dispersion degree of the impervious surface. A greater value of the ratio demonstrates stronger orientational effects of the impervious surface. By contrast, a ratio of 1 reflects no directional trend of the data. In this work, variation of the SDE of the impervious surface helped to identify whether the spatial distribution of the impervious surface was elongated and showed a particular direction of the impervious surface.

2.2.3. Analysis of the Changes in Landscape Indices

Landscape indices quantitatively reflect the configuration and composition of urban landscapes [13,59]. In the present study, the impervious surfaces expansion degree was calculated based on these indices. The analysis was performed with FRAGSTATS 4.2 software using an eight-neighbor rule. Five landscape indices were adopted to characterize the impervious surface changes which are commonly used in the study of urban expansion and its environmental impacts. These landscape indices were the number of patches (NP), patch density (PD), mean patch size (MPS), largest patch index (LPI), landscape shape index (LSI), and aggregation index (AI) (Table 2).

Table 2. Landscape indices used in the study.

Landscape Indices	Calculation and Description
Number of patches (NP)	$NP = n_i$ where n_i is the number of patches in the landscape of patch type i .
Mean patch size (MPS)	$MPS = \frac{\sum_{i=1}^n a_i}{n}$ where n refers to the number of patches and a_i is the area of patch i .
Largest patch index (LPI)	$LPI = \max(a_{ij}) / A \times 100$ where a_{ij} refers to the area (m^2) of patch ij .
Landscape shape index (LSI)	$LSI = 0.25E / \sqrt{A}$ where E is the total length (m) of the edge between patch types i and k in the landscape; this includes the entire landscape boundary and some or all background edge segments that involve patch types i .
Aggregation index (AI)	$AI = \left[\sum_{i=1}^n (g_{ii} / \max g_{ii}) P_i \right] \times 100$ where g_{ii} is the number of like adjacencies (joins) between pixels of patch type i based on the single-count method and $\max g_{ii}$ refers to the maximum number of like adjacencies (joins) between pixels of patch type i based on the single-count method. P_i is the proportion of landscape comprising patch type i .

3. Results

3.1. Impervious Surface Changes and Accuracy Assessment

The result of the accuracy assessment is presented in Table 3. In 2014, the OA and kappa coefficient of the impervious surface map were 96.60% and 89.41%, respectively. In 2021, these values were 95.80% and 89.37%, respectively. As such, the results were considered reliable and could be used for further analyses.

Table 3. Confusion matrix for the impervious surface mapping.

2014		Google Earth Images			
Classified results	Classification	Impervious surface	Non-impervious surface	Sum	User's accuracy
	Impervious surface	92	9	101	91.09%
	Non-impervious surface	8	391	399	97.99%
	SUM	100	266	500	
	Producer's accuracy	92.00%	97.75%		
	OA	96.60%			
		KAPPA	89.41%		
2021		Google Earth Images			
Classified results	Classification	Impervious surface	Non-impervious surface	Sum	User's accuracy
	Impervious surface	125	12	137	91.24%
	Non-impervious surface	9	354	363	97.52%
	SUM	134	366	500	
	Producer's accuracy	93.28%	96.72%		
	OA	95.80%			
		KAPPA	89.37%		

The impervious surface maps for 2014 and 2021 are shown in Figure 3. Table 4 displays the impervious surface areas in different zones. In the Central City zone, the impervious surface area rose from 51.15 km² in 2014 to 63.30 km² in 2021, for an overall increase rate of

23.75% and a change rate of 1.74 km²/a. This indicates a clear expansion of impervious surfaces in Lhasa from 2014 to 2021. The added impervious surface was most concentrated in the southeast of the Central City zone. The impervious surfaces increasing rates in the Central City and Caiyicun were higher than in other zones. Furthermore, the Bakuojie zone had the highest impervious coverage in both 2014 and 2021. Moreover, impervious surface coverage of the Historic and Caiyicun zones were similar in 2014, while impervious surface coverage of the Caiyicun zone were much higher than the Historic zone in 2021.

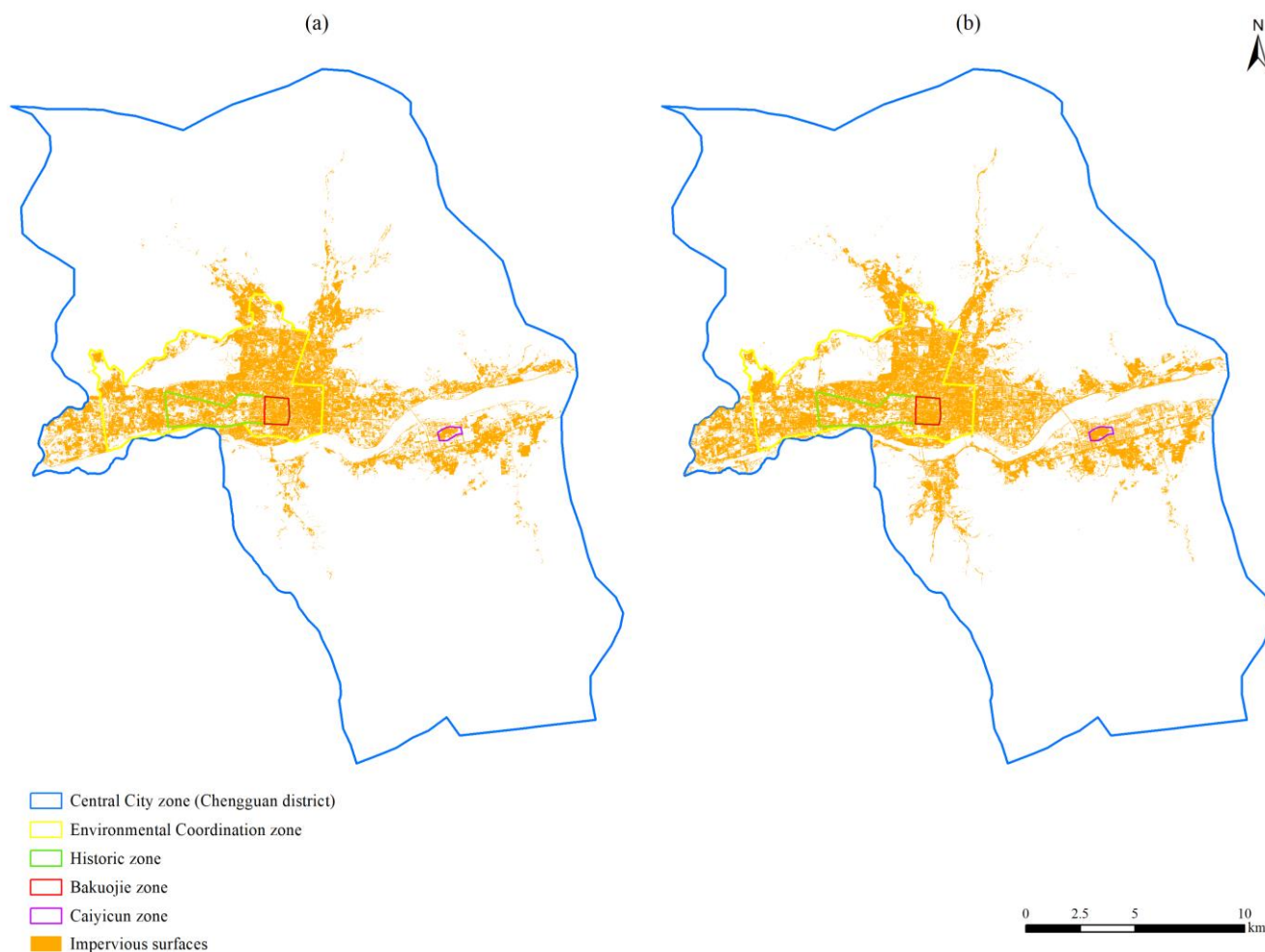


Figure 3. Impervious surface maps of (a) 2014 and (b) 2021.

Table 4. Impervious surface area changes in different zones of 2014 and 2021.

Zone	Impervious Surface Area (km ²)		Impervious Surface Coverage		Increase Rate
	2014	2021	2014	2021	
Central City zone	51.149	63.299	9.975%	12.345%	23.755%
Historic zone	4.506	4.642	65.575%	67.554%	3.017%
Environmental Coordination zone	23.827	24.973	55.800%	58.485%	4.812%
Bakuojie zone	1.150	1.199	83.967%	87.532%	4.246%
Caiyicun zone	0.328	0.404	67.434%	83.050%	23.157%

3.2. Spatial and Temporal Analysis of ISMC and SDE

To illustrate the barycenter changes during urban development, the ISMCs of the entire area were identified based on an impervious surface map. The ISMC of the entire area in 2014 and 2021 is displayed in Figures 4 and 5. In 2014, the ISMC was located at 91.146° E, 29.662° N, and moved to 91.148° E, 29.660° N in 2021. The changes in ISMC revealed

the direction expansion. Over time, the impervious surfaces throughout the entire area expanded in a southeast direction. This suggested that the direction for urban expansion was towards the southeast.

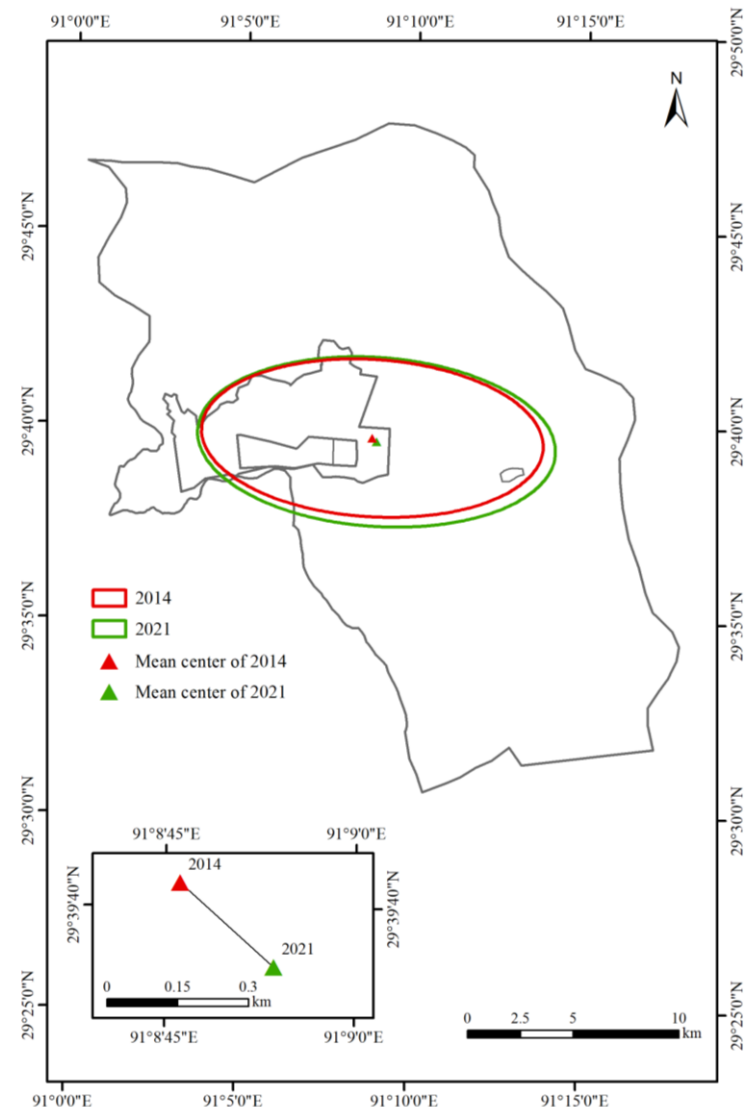


Figure 4. Standard deviational ellipses (SDEs) of impervious surfaces of 2014 and 2021.

The SDE were applied to determine the orientation and spatial and temporal development trends of impervious surfaces. The SDE of impervious surfaces in 2014 and 2021 are shown in Figure 4. According to Figure 4, the impervious surface presents an obvious orientation and direction. Between 2014 and 2021, the azimuth increased from 93.634° to 94.053° (Table 5), showing that the impervious surface expansion was oriented from west to east. The long and short axis, and their ratio of the SDE represented the clustering or dispersion degree of impervious surfaces. If the ratio is close to 1, the expansion of the impervious surface does not have a certain principal. The ratio was 2.172 and 2.119 in 2014 and 2021, respectively, indicating that the impervious surface had a significant distinct direction. The long axis increased from 8108.17 to 8493.82 m and the short axis increased from 3732.33 to 4009.02 m. This indicates a dispersion trend of impervious surfaces in both directions.



Figure 5. Landscape indices of impervious surface of different zones in 2014 and 2021.

Table 5. Parameters of the standard deviational ellipses (SDE) of 2014 and 2021.

Year	Long Axis (m)	Short Axis (m)	Orientation (°)	Long Axis/Short Axis
2014	8108.176	3732.333	93.634	2.172
2021	8493.819	4009.020	94.053	2.119

3.3. Landscape Indices of Different Zones

The landscape indices for the five zones in 2014 and 2021 are shown in Figure 5.

NP increased in the Central City zone but decreased in the other four zones. The Bakuojie and Caiyicun zones had the lowest NP in 2014 and 2021. The MSP in all four

zones increased, with no obvious change in the Central City zone. The Central City zone had the lowest MSP. The LPI increased in the Central City zone, while no obvious changes were observed in other zones. The Central City zone had the lowest LPI and the Bakuojie zone had the highest LPI. This indicated that the dominance of impervious surfaces clearly increased only in the Central City zone. The LSI declined in the five zones, demonstrating that the spatial pattern of the impervious surfaces was simplified and regularized. AI increased in the five zones, indicating that as the impervious surface expanded, the impervious surface agglomerated. The Bakuojie and Caiyicun zones had the lowest LSI and relatively high AI compared to the other zones. This indicates that the impervious surfaces in the Bakuojie and Caiyicun zones have strong connectivity and simple shapes.

4. Discussion

4.1. Expansion of Impervious Surface

The results indicated that the impervious surface experienced clear expansion in Lhasa. However, the analysis results demonstrated that the impervious surface in different zones of Lhasa underwent different growth patterns.

From 2014 to 2021, the growth rates of impervious surfaces in the Central City and Caiyicun zones were 23.755% and 23.157%, respectively. The growth rates in the Historic, Environmental Coordination, and Bakuojie zones, which are inside the Environmental Coordination zone, were 3.017%, 4.812%, and 2.233%, respectively. This indicates that the expansion area was mainly outside the Environmental Coordination zone. The impervious surface covered most areas in the Historic zone, Environmental Coordination zone, and Bakuojie zone in 2014. With the continuous expansion of the urban areas, the available lands for construction reduced; therefore, the expansion area and expansion rate were limited. Moreover, because Lhasa is one of the National Famous Historical and Cultural Cities in China, new construction and expansion activities in conservation zones are limited. Therefore, the expansion rate and areas in the Historic, Environmental Coordination, and Bakuojie zones are lower than those in the Central City and Caiyicun zones.

The ratio of the long axis to the short axis of the impervious surface SDE showed that there was a clear direction in the distribution of impervious surfaces. Changes in the long and short axes showed that the impervious surfaces exhibited a dispersion trend. Between 2014 and 2021, the shift of the ISMC showed that the impervious surfaces expanded toward the southeast throughout the entire region. Chengguan District is a valley plain distributed from west to east. The topography makes urban development have a clear direction. The impervious surface distribution also showed a west-to-east trend. The newly added impervious surfaces were mainly located in the Najin zone, which is southeast of Lhasa. The expansion direction was consistent with the urban planning requirements of the city. With the expansion of the city, according to the Overall Urban Plan for Lhasa (2009–2020) [60], the government has actively developed the new urban area to ease the pressure coming from the central district and balance the preservation of historic towns and the rapid development. As a result, the ISMC has shifted toward the southeast.

4.2. Landscape Pattern Changes of Impervious Surface

In the Central City zone, the values of NP and LPI showed a clear increasing trend, indicating that the impervious surface had an obvious expansion and the dominance of impervious surfaces became more prominent. This is caused by economic development, population growth, and urban expansion. In the other four conservation zones, the values of NP showed a decreasing trend and the LPI showed no obvious changes. Owing to the limited impervious surface expansion in these zones, the dominance of the impervious surface did not exhibit an obvious change. In addition, the decreased values in mean patch size indicated that most of the added patches were connected to previous impervious surface patches, meaning that the expansion of the impervious surface was organized. This indicates that infilling and consolidation was the impervious surface development pattern

inside these areas. With the increase in impervious surfaces, landscape fragmentation decreased. The low LSI value suggests that the spatial shape of the impervious surface became increasingly regular, and the expansion of the impervious surface was orderly. The high AI value means that with the increase in impervious surfaces, the distribution of impervious surfaces became increasingly concentrated, and the degree of aggregation increased. Since 2013, a series of regulations have been released to protect the old city and promote the sustainable development of Lhasa [61–63]. In the conservation zone, the regions are well planned, especially in the Bakuojie and Caiyicun zones. The Bakuojie and Caiyicun zones had the lowest NP and strongest connectivity of impervious surfaces. In these zones, the spatial shape of impervious surfaces was regular, and the landscape inside the areas became more stable, regular, and aggregated.

4.3. Driving Forces of Impervious Surface Expansion

Previous studies have shown that topography is an important factor restricting urban expansion and influencing development patterns [12,64]. The distribution of the impervious surfaces indicated that the urban space of Lhasa is restricted by the surrounding mountains.

Population and economic growth are the driving forces of urban development [65–67]. Generally, rapid population and economic growth are accompanied by significant ISA expansion. With the implementation of the “Western Development” strategy and the “One Belt and One Road” initiative, the economy of Lhasa has developed rapidly. In addition, urbanization accelerates population and economic growth [68].

The population of Lhasa increased from 6.56×10^5 in 2014 to 8.68×10^5 in 2021, with an increasing rate of 32.32%. Population has always been an active factor in urban formation and has an important impact on urban development [69]. The population growth in cities leads to increasing demands for housing, infrastructure such as roads, water conservancy, and electricity, as well as public service facilities for education, employment, medical care, and entertainment. The construction of new buildings and facilities occupied a large amount of land and resulted in the increase in impervious surfaces.

The gross domestic product (GDP) of Lhasa increased from CNY 34.74 billion in 2014 to CNY 74.18 billion in 2021. As a historical city and a popular tourism destination, Lhasa City has developed tourism and service industries. In 2014, the total GDP of Lhasa was CNY 34.745 billion, and the primary, secondary and tertiary industries were CNY 1.294 billion, 12.775 billion, and 20.676 billion, respectively. In 2021, the total GDP of Lhasa was CNY 74.184 billion, and the primary, secondary and tertiary industries were CNY 2.445 billion, 27.808 billion, and 43.931 billion, respectively [70,71]. The proportion of secondary and tertiary industries increased from 96.27% in 2014 to 96.70% in 2021. The rapid development of the secondary and tertiary industries led to an expansion in industrial land and service facilities, resulting in an increase in impervious surfaces. In addition, the development of secondary and tertiary industries and better services attracted more people to migrate to the city and further increase the area of impervious surfaces.

Policy is another important factor influencing urban development patterns. According to the Overall Urban Plan for Lhasa [60], the functions of the Central City should be optimized and the historic buildings should be well protected. This policy proposed the future expansion layouts of Lhasa: renovate the old city zones to improve the efficiency of space utilization; establish new urban cores and promote the development of the surrounding areas of the old city zones; and increase the connection between the new urban areas and the old city zones, to form a polycentric urban structure. Furthermore, with the implementation of the “Regulations on the Protection of the Old Town of Lhasa” [61], the “Regulations on the Protection of the Ancient Village of Lhasa” [62], and the “Historic and Cultural City Protection Plan for Lhasa” [63], the government put much effort into protecting the old city. At the same time, the impervious surfaces in the Central City zone tended to be saturated; thus, the increasing rates of saturation within the Environmental Coordination zone were lower than in the Central City and Caiyicun zones. Moreover, the government has made environmental protection a priority together with pursuing

high-quality development for the city [72] and balancing rapid urbanization and ecological protection. Farmland and ecological land were protected by policies, which also resulted in an infilling and consolidation growth pattern of impervious surfaces in Lhasa City.

5. Conclusions

In this study, the impervious surface maps of 2014 and 2021 were extracted by an OBIA method using Gaofen-1 images of Lhasa. This work utilized a variety of complementary methods to characterize and analyze the spatial and temporal changes in the impervious surfaces in different zones of Lhasa. The main findings are as follows:

1. The impervious surface area in Lhasa grew significantly from 51.149 km² in 2014 to 63.299 km² in 2021, with an overall increase rate of 23.75% and change rate of 1.74 km²/a. The Environmental Coordination, Historic, and Bakuojie zones, which are inside the Environmental Coordination zone, had increasing rates of 3.017%, 4.812%, and 4.246%, respectively. The Caiyicun zone, which is outside the Environmental Coordination zone, had an increasing rate of 23.16%.
2. Between 2014 and 2021, the shift of the ISMC revealed that the impervious surfaces of Lhasa expanded toward the southeast. The changes in SDE showed that the impervious surface distribution had a clear direction; the impervious surface expansion was oriented from west to east, and the impervious surfaces had an observable dispersion trend.
3. In general, the landscape pattern in Lhasa City tends to be orderly, aggregated, and regularized. In the Central City zone, the impervious surface with an obvious expansion and dominance became more prominent. In the other four conservation zones, the dominance of impervious surfaces did not change significantly. Infilling and consolidation were the primary impervious surface development patterns in these areas. With the expansion of the impervious surface, the landscape in Lhasa City tended to be stable, regular, and aggregated, especially in the Bakuojie and Caiyicun zones.

The findings of this study will improve the understanding of the spatial and temporal variation in urban expansion and provide a foundation for the analysis of its environmental effects as well as an exploration of its driving factors. In addition, these results will help decision-makers to formulate urban planning policies and provide a reference for further research in this area.

Author Contributions: Methodology, software, validation, visualization, writing, S.W.; resources, data curation, X.T.; conceptualization, supervision, F.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by “The National Social Science Fund of China” grant number “21AMZ011” And “The Major Cultivation Fund for Philosophy and Social Sciences of South China Normal University” grant number “ZDPY2206”.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

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