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Spatiotemporal Dynamic Changes and Prediction of Wild Fruit Forests in Emin County, Xinjiang, China, Based on Random Forest and PLUS Model

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Abstract: As an important ecosystem, the wild fruit forest in the Tianshan Mountains is one of the origins of many fruit trees in the world. The wild fruit forest in Emin County, Xinjiang, China, was taken as the research area, the spatial and temporal distribution of the wild fruit forest was inverted using random forest and PLUS models, and the 2027 distribution pattern of the wild fruit forest was simulated and predicted. From 2007 to 2013, damage to the wild fruit forest from tourism and overgrazing was very serious, and the area occupied by the wild fruit forest decreased rapidly from 9.59 km^2 to 7.66 km^2. From 2013 to 2020, suitable temperatures and reasonable tourism management provided strong conditions for the rejuvenation of wild fruit forests. The distance of the center of gravity of the wild fruit forest increased, and the density of distribution of the wild fruit forest in the northwest direction of the study area also increased. It is predicted that the wild fruit forest in the study area will show a steady and slowly increasing trend in places far away from tourist areas and with more complex terrain. It is suggested that non-permanent fences be set up as buffer zones between wild fruit forests, ensuring basic maintenance of wild fruit forests, limiting human disturbance such as overgrazing, and reducing the risk of soil erosion.

Keywords: wild fruit forest; random forest algorithm; spatiotemporal distribution; overgrazing; tourism

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1. Introduction

In recent years, global climate change, overgrazing, rapid development of tourism, insect pests, plant diseases [1,2], and other factors have threatened the ecological environment of wild fruit forests and the distribution of tree species [3]. This has resulted in a sharp decline in wild fruit forest communities, with severe obstacles to population regeneration. Many wild apples (*Malus sieversii*), wild apricots (*Armeniaca vulgaris var. ansu* (Maxim.) Yü et Lu), and wild hawthorns (*Crataegus songorica K. Koch.*) are found only in the mountainous regions of Central Asia, including southern Kazakhstan, eastern Uzbekistan, Kyrgyzstan, Tajikistan, Turkmenistan, and the Xinjiang Uygur Autonomous Region of China [4]. Among them, the Xinjiang wild apple (*Malus sieversii*) is included in China's list of priority protected species and is a nationally protected plant. It naturally inhabits mountainous areas in western Xinjiang at altitudes ranging from 1000 to 1800 m and is widely found in the Tianshan Mountains in the Ili Prefecture and the Tarbagatai and Barluk Mountains in the Tacheng region of Xinjiang [5].

Due to the poor quality of the wild fruit forest, those fruits have a sour taste and low aesthetic degree and yield, so they cannot be sold or consumed as a fruit. However, the wild fruit forest in the Tianshan Mountains of Xinjiang has unique advantages in adaptability and stress resistance. It is an important area of distribution of the natural gene pool in

China's economic fruit tree resources, and also an important wild germplasm resource in Xinjiang, China [6]. There are 58 species of wild fruit trees in Xinjiang; among them, the wild apple is the most important constructive species, with 84 types. It is a rare natural gene treasure trove of apples in the world and an important germplasm gene pool for studying the genetic diversity and gene evolution of temperate fruit trees worldwide. The Xinjiang wild apples in the wild fruit forest are of great significance for improving the quality of modern economic fruit trees, screening excellent varieties, and molecular genetic breeding [7]. Wild fruit forests are not only precious strategic biological resources but also play an important role in maintaining ecological balance, protecting water sources, wind-breaking, and sand-fixing. As a reserve gene pool, the Tianshan wild fruit forest once gradually shrank; therefore, it is necessary to save and protect the wild fruit forest in the Tianshan Mountains.

Remote sensing technology has been widely applied in forest resource surveys and landscape pattern analyses of ecosystems. Multisource remote sensing satellite data has substantial application value in aspects such as spatiotemporal distribution of forests [8,9], dynamic changes in forests [10], and forest landscape patterns [11,12]. With the gradual maturity of data mining and deep learning methods, many machine learning methods have been closely integrated with land use/cover classification [13,14], enhancing precision and demonstrating considerable advantages for information interpretation [15]. In setting and optimizing parameters for land use/cover change models, a multitude of machine learning algorithms, such as convolutional neural networks, spatiotemporal convolutional networks, and the Random Forest (RF) algorithm, have been integrated and applied [16,17]. Among these, RF, a classic and mature machine learning algorithm, stands out for its evident advantages in the supervised classification of remote sensing data [18,19]. To predict changing trends in land use/cover, scholars have utilized models such as the patch-generating land use simulation (PLUS) model to investigate the spatial distribution of land cover and forecast future changes. Predictive models can simulate future ecological land changes at a regional level. A comprehensive approach is necessary to advance the development, utilization, protection, and management of land resources, and strengthening ecological spatial control is essential for constructing a secure and harmonious ecological environment protection pattern. Compared to other models, the PLUS model can achieve higher precision and simulate various scenarios, demonstrating the advantages of large-scale and multi-land-class comprehensive simulations. Moreover, the PLUS model has been proven to have excellent applicability in arid and semi-arid regions, subtropical humid and semi-humid area regions [20,21], and the simulation results have substantial reference value [22].

The emergence of high-resolution remote sensing images has brought unprecedented opportunities to forestry remote sensing. However, high-resolution remote sensing images still face difficulties in identifying tree species in the forestry field, resulting in low classification accuracy. Therefore, the combination of high-resolution images with appropriate machine learning methods and prediction models could provide the possibility for improving the accuracy of forestry information interpretation. To support the effective protection and management of wild fruit tree resources in Xinjiang, we aimed to investigate the spatiotemporal distribution trends of wild fruit forests in Emin County from 2007 to 2020 using satellite images and field measurements. Additionally, we performed a simulation to predict the future spatial distribution of wild fruit forests in the study area. This study quantitatively analyzed the current situation and changing trends of wild fruit forests, providing reliable data and reasonable measures for the protection of wild fruit forests, which can promote the protection and sustainable utilization of wild fruit forests effectively.

2. Materials and Methods

2.1. Study Area

Emin County is located northwest of the Xinjiang Uyghur Autonomous Region in China and is surrounded by mountains on three sides. The county's mountainous area surpasses its plains area, with agricultural land and grassland distributed vertically along the mountains. The region has a temperate continental climate with distinct seasons: substantial temperature variations in spring, short and hot summers, rapid cooling in autumn, and long cold winters with frequent cold air activity. The average annual temperature is 5.5 °C, with frost occurring throughout the year and 195 days without absolute frost. Abundant sunlight, with a total annual sunshine duration of 2784.6 h, meets the needs of crop growth. The average annual precipitation is 441.2 mm, which is unevenly distributed and characterized by more precipitation in the northeast and less precipitation in the southwest, with more precipitation in the mountains and less precipitation in the plains. The soil types in the study area are brown calcic soil and meadow brown calcic soil, with high organic matter content. The brown calcic soil area is dominated by soil with organic matter content of about 10–20%, the humic acid is the main component of humus. The soil water under the forest is the seasonal leaching type, with the loess parent material containing $CaCO_3$. The organic matter in the tidal soil has a stronger selenium-enriched ability than the brown calcium soil [23].

Emin County is rich in natural vegetation and mountainous wild flora and fauna. Wild fruit forests in Emin County are primarily located in the southeast (80°47′–83°58′ E, 43°20′–46°21′ N). They are dominated by wild apples (*Malus sieversii*) and also include wild hawthorns (*Crataegus songorica K. Koch.*) and wild bird cherries (*Prunus padus* L.). Most of the wild fruit forests in the study area grow on the shaded or semi-shaded slopes of mountainous regions at an altitude from 900 m to 1930 m because their habitat is warm and humid, with stripy, blocky, and discontinuous distribution, and appear in various mountain systems with great discontinuity. The distributions of wild fruit forests show the strict selectivity of microclimates and the characteristics of primitive residual communities. In 2021, our team found that the average stand density of wild fruit forest in the study area was 355 trees $\cdot$ hm^{-2}, the average tree height was 7.6 m, the average basal diameter was 27.8 cm, and the total density of the soil seed bank was 10.20 grains $\cdot$ m^{-2}.

The construction of a wild fruit forest scenic area within the research area, covering 50 km^2, has been prompted by the rise in tourism. This scenic area is a comprehensive tourist destination that emphasizes vacationing, leisure, and sightseeing, featuring activities such as skiing, hiking, and fruit picking. Scientific research, hiking adventures, self-driving tours, and cultural and sports tourism have also been conducted (Figure 1).

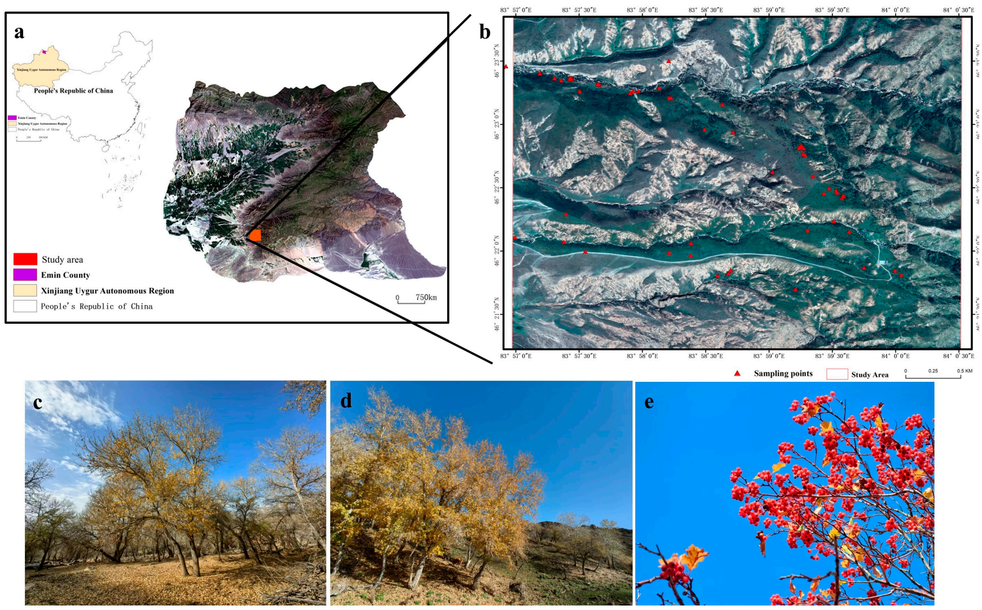

Figure 1. Schematic diagram of the study area. (**a**) Represents the geographical location of the study area in China. (**b**) Represents a satellite image of the study area and sample points. (**c**–**e**) Wild fruit forests mixed with other trees, wild apples, and wild hawthorn, respectively.

2.2. Data Sources

We utilized QuickBird (QB), Gaofen (GF), and advanced land observing satellite (ALOS) data. QuickBird remote sensing images were obtained from 12 September 2007, with a geographical range of 83°57′00″–84°0′00″ E and 46°21′00″–46°24′00″ N and a spatial resolution of 0.6 m (panchromatic band) and 2.4 m (multispectral band). High-resolution satellite imagery was obtained from China's Gaofen satellites from 17 September 2013 and 17 July 2020, with a spatial resolution of 2 m (panchromatic band) and 8 m (multispectral band). Emin County administrative vector digital elevation model (DEM) data were obtained from ALOS, with a spatial resolution of 12.5 m. Additional data were obtained from the Xinjiang Statistical Yearbooks from 2006 to 2021. We also conducted field measurements, including GPS location, wild fruit forest plot surveys, and tree species distribution. A total of 68 regular plots and 102 irregularly shaped areas were surveyed. The regular quadrats were 30 m × 30 m, covering wild apples (*Malus sieversii*), wild hawthorns (*Crataegus songorica K. Koch.*), wild bird cherries (*Prunus padus* L.), and mixed forests of wild fruit trees and other trees (such as poplar and birch). The crown width and quantity of wild fruit trees and other trees were measured, forming a foundation for the interpretation and validation of wild fruit forests.

2.3. Data Preprocessing

To ensure the accuracy of information identification and interpretation, radiometric correction, geometric correction, image overlay, and cropping were conducted as preprocessing steps using ENVI 5.3 software. The multispectral band has a strong spectral resolution and rich spectral information, but the spatial resolution cannot fully express the spatial details. The spectral resolution of the panchromatic band is weak, whereas the spatial resolution is strong. Therefore, to obtain images with high spatial detail performance and good spectral characteristics, the multispectral band and high spatial resolution panchromatic band were superimposed and fused to improve image accuracy. In this study, the principal component analysis (PCA) transform fusion method was used to enhance images from 2007, 2013, and 2020. The obtained images displayed the spectral characteristics of the original images with greater detail and clarity [24].

2.4. Random Forest Algorithm

Machine learning and deep learning algorithms have found extensive applications in the classification of satellite imagery [18,25], with RF being a classical model among many machine learning approaches.

The RF algorithm is a tree-based model that incorporates numerous classification and regression decision trees. This methodology delivers faster and more reliable classification results without greatly increasing computational demands. It has been widely employed in various research domains, including image classification, and is considered to exhibit excellent performance in the presence of numerous features, demonstrating robust noise resistance and achieving high classification accuracy. The RF model combines the outcomes of multiple decision trees trained on samples, and the final classification result is determined by a majority vote from these trees. This approach mitigates overfitting issues and effectively enhances the generalization capability of the classifier [26]. First, using the bootstrap method with replacement, samples were randomly drawn for the training set, with each extraction comprising approximately two-thirds of the total. The remaining one-third was reserved for estimating the internal training error. Subsequently, individual decision trees were generated for each bootstrap sample, and these trees were amalgamated to form a classification forest. Finally, the collective results of all decision trees were integrated using a voting strategy [27].

2.5. Precision Evaluation Principle

The results of remote sensing classification need to verify and evaluate the classification accuracy using some indicators. In this study, under the premise of a suitable classification algorithm, the most important thing is that we collected a large number of information sample data for wild fruit forests and non-wild fruit forests in the field; 70% of the samples were used as the region of interest in the classification process, and 30% of the information samples were used to verify the results after classification. Confusion matrix was used to evaluate the accuracy of information extraction, including the calculation of producer accuracy (PA), user accuracy (UA), overall accuracy (OA), and Kappa coefficient (KC) to obtain accurate results of image classification.

2.6. Centroid Migration Model

The centroid migration model was used to capture spatial changes in the position of wild fruit forests. Using standard deviation ellipses for directional distribution and a planar centroid model, the position of the wild fruit forest centroid and directional distribution of the centroid at different time periods were computed. Consequently, an analysis was conducted of the centroid displacement and migration rate in a geographical two-dimensional space across different time intervals, revealing the spatial transition processes of the wild fruit forest [28,29]. The formula for the planar centroid calculation model is as follows:

$$X = \frac{\sum_{i=1}^{n} (A_i \times X_i)}{A} \tag{1}$$

$$Y_j = \frac{\sum_{i=1}^{n} (A_{ji} \times Y_{ji})}{A_j} \tag{2}$$

X_j represents the X-coordinate value of the centroid of land use/cover type j, Y_j represents the Y-coordinate value of the centroid of land use/cover type j, A_{ji} is the type i area within land use/cover type j, X_{ji} is the average X-coordinate value within the range corresponding to type i in land use/cover type j, Y_{ji} is the average Y-coordinate value within the range corresponding to type i in land use/cover type j, and A_j is the total area of land use/cover type j.

2.7. Patch-Generating Land Use Simulation Model

The PLUS model is a land use/cover simulation prediction model that was developed by the High-performance Spatial Computational Intelligence Lab at the China University of Geosciences [30]. Compared with other land use/cover prediction models, the PLUS model can better utilize the land expansion analysis strategy (LEAS) and explore changes in different land cover types.

The PLUS model has a good reflection in transformation analysis and pattern analysis; therefore, the model has a strong ability to analyze the changes in each feature at a certain period of time. The PLUS model includes random seed generation and threshold-decreasing mechanisms. The calculated development probability can better simulate land use/cover change. The simulation results can support planning policies to achieve sustainable development. This model integrates a LEAS and a cellular automata model based on multitype random patch seeds. It adopts a multitype random patch-seeding mechanism based on the descent threshold, which is realized by calculating the overall probability [31].

The PLUS model is based on the evolution of various types of land-use patches. By using the LEAS (Land Expansion Analysis Strategy) and CARS (Cellular Automata model of multitype Random Forest) functions in the model, it can analyze the causes of land use changes in the study area and simulate the changes of each type of patch level land accurately [32]. Compared with other models, the results of the PLUS model have important reference value because it can simulate more scenarios with higher accuracy. The model is as follows:

$$P_{i,k}^{d=1,t} = \left\{ \begin{array}{ll} P_{i,k}^{d=1} \times (r \times u_k) \times D_k^t, \Omega_{i,k}^t = 0 \; and \; r < P_{i,k}^{d=1} & \\ P_{i,k}^{d=1} \times \Omega_{i,k}^t \times D_k^t, \rightarrow all & all \; other \end{array} \right\} \tag{3}$$

where r is a random value ranging from 0–1; $P_{i,k}^{d=1,t}$ is the development probability from pixel i to land type k; $P_{i,k}^{d=1}$ represents the growth probability of land type k at the cell level I; d = 0 indicates that the land type k is converted to other land types and d = 1 means that other land types are converted to land type k; U_k is the threshold value for producing new land-use patches for land use type k; D_k^t represents the adaptive inertia coefficient; and $\Omega_{i,k}^t$ is the neighborhood weight of k.

The characteristics of land use change can be well demonstrated by the Markov chain analysis method in the PLUS model. In addition, the Markov chain analysis method is also a common method for predicting the area change of various land use types. It can intuitively describe the trend of land use change in the study area from one period to another, and use this as a criterion to predict future change trends [21]. The equation is as follows:

$$S_{t+1} = P \times S_t \tag{4}$$

$$P = \begin{pmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{pmatrix} \tag{5}$$

$$P_{ij} \in [0,1), \sum_{i=1}^{n} P_{ij} = 1, i, j = 1, 2, \cdots, n \tag{6}$$

where P represents the transfer matrix of land use type; S_t and S_{t+1} are the land use status of the current and future period in the study area, respectively; and n is the land use type.

The specific parameters of the PLUS model are set as follows: the size of the neighborhood window is defaulted to 3 in the CARS module and the size of the neighborhood weight is determined by the expansion of each land type [33].

3. Results

3.1. Spatiotemporal Distribution of Wild Fruit Forests

In this paper, the principal component analysis (PCA) transform fusion method is used to enhance the images from 2007, 2013, and 2020, and the obtained images can better display the spectral characteristics of the original images. The red wave and near-red wave information, which are most sensitive to vegetation information in the multi-spectral band, are assigned to other bands and the high-resolution panchromatic band image is stretched to replace the first principal component band to achieve inverse conversion and complete image fusion. Fusion can reduce or suppress the problems of incompleteness and interpretation errors that may occur when interpreting wild fruit forest information. It can maximize the utilization of various information provided by the image, facilitating the identification and extraction of information on wild fruit forests in the image. The gray-level co-occurrence matrix extraction method of adding textural features can effectively improve the separation degree of the region of interest [34] and lay a good foundation for the information interpretation of wild fruit forests. When establishing the interpretation mark, we selected a gray-level co-occurrence matrix that is widely used to extract texture structures [35]. The gray-level co-occurrence matrix was used to count the number of occurrences of the same pixel value in the image area or specified calculation window. The texture feature effect was used to statistically analyze the classified images and extract statistical parameters that could describe the relevant texture information. Based on the principal component transform, the pixel offset distance was set to 1 pixel, the offset direction was 45°, and the texture feature image was obtained using a 3 × 3 window scale.

In computer interpretation, these important information samples become an important basis for verifying accuracy. Based on the combination of field investigation and remote sensing data, land use/cover types were divided into six categories: wild fruit forest (including wild apples (*Malus sieversii*), wild hawthorns (*Crataegus songorica K. Koch.*) and wild bird cherries (*Prunus padus* L.), other trees (non-wild fruit forest trees such as birch (*Betula* L.), poplar (*Tacamahaca*), and willow (*Salix*)), shrubs, grassland, bare soil, and construction land (including roads, yurts, and buildings). Fieldwork and computer interpretation are equally important. In the field, a large amount of sample information was collected from wild fruit forests and other types of ground objects, and the region of interest (ROI) was recorded. The RF algorithm was used to interpret the remote sensing data for the study area from 2007, 2013, and 2020 to determine the spatial distribution characteristics of wild fruit forests (Figure 2 and Table 1). Using data collected during fieldwork, the information interpretation map of the wild fruit forests was verified and its accuracy was evaluated. The Kappa coefficient was greater than 0.80, laying a good foundation for subsequent research.

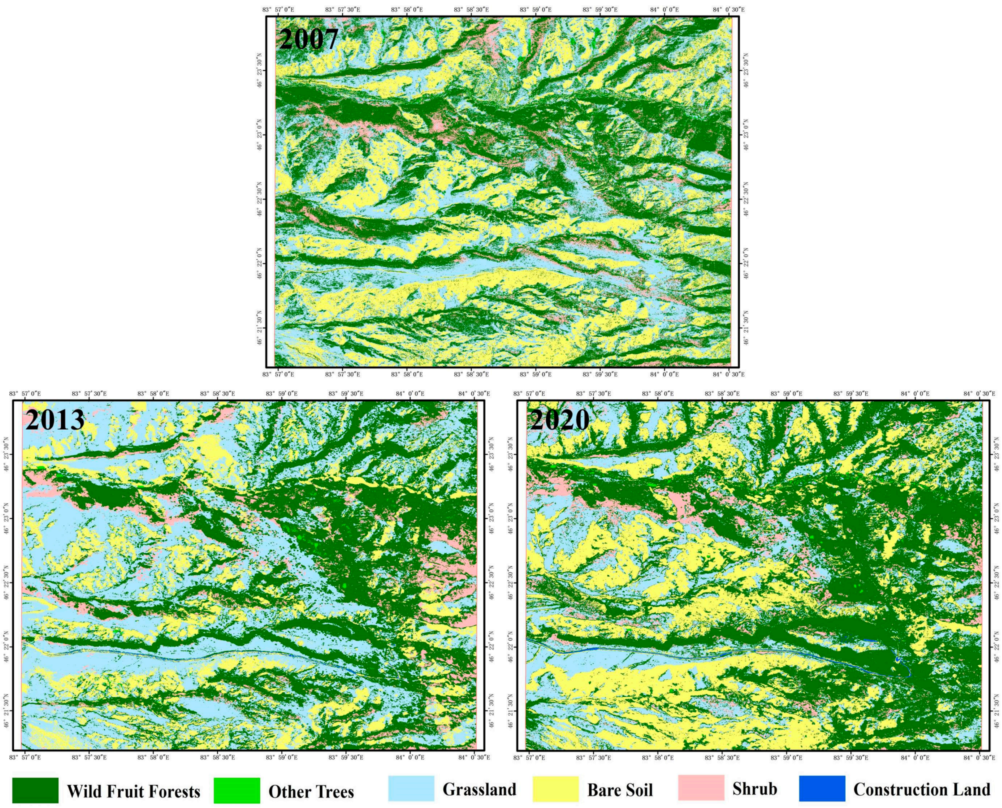

Figure 2. Classified images of the study area.

Table 1. Statistical table of land use/cover change from 2007 to 2020.

	Year	Wild Fruit Forest	Other Trees	Grassland	Bare Soil	Shrub	Construction Land
Area/km^2	2007	9.59	0.37	8.33	6.39	1.68	0.007
	2013	7.66	0.06	11.79	5.37	1.25	0.25
	2020	10.73	0.08	6.59	7.03	1.84	0.11
Proportion/%	2007	36.36	1.14	31.8	24.3	6.37	0.022
	2013	29.04	0.23	44.7	20.35	4.74	0.94
	2020	40.67	0.30	24.98	26.65	6.97	0.42
Total change area/km^2	2007–2013	−1.93	−0.24	−0.43	3.41	−1.04	0.222
	2013–2020	3.07	0.02	5.34	−4.76	−3.53	−0.14
K/%	2007–2013	−2.88	−11.43	−3.66	5.81	−2.32	113.26
	2013–2020	5.73	4.76	61.03	−5.77	−9.39	−8

From 2007 to 2020, the wild fruit forest area first decreased and then increased. In the context of serious damage to the ecological environment of wild fruit forests in Xinjiang, the distribution of wild fruit forests in different regions has suffered from different degrees of decline [3,36]. Wild fruit forests in Emin County were affected, resulting in a substantial decrease in the area occupied by wild fruit forests between 2007 and 2013. The construction land area initially increased sharply and then decreased slowly. Although this area accounted for a small proportion of the total land area, it exhibited a high degree of dynamic change, and the area occupied by construction land increased by 113.3% from 2007 to 2013. During this time, the social economy developed rapidly and the ecotourism industry expanded. To explore the economic value of wild fruit forest tourism, Emin County increased the development and utilization of wild fruit forests and built scenic tourism spots with wild fruit forests as a theme. Tourist attractions such as ski resorts, Mongolian yurts with Xinjiang characteristics, and field camps prompted the local government to increase its investment by continuously increasing the layout of artificial landscapes in wild fruit forest scenic spots and constructing public facilities such as roads and parking lots. Frequent human activities and alterations in the fragile ecological landscape imposed pressure on the survival of wild fruit forests, seriously hindering their renewal.

The disorderly development of tourism, overgrazing, invasion of alien species, and the spread of pests and diseases will lead to a reduction in the area occupied by wild fruit forests. For example, The Buprestid Beetle was introduced to Xinjiang with apple seedlings in 1993. Due to a lack of natural enemies, it quickly propagated and destroyed a large number of wild fruit forests. The area occupied by other trees (such as poplar, birch, and willow) continued to decrease, from 0.37 km^2 in 2007 to 0.08 km^2 in 2020. This was related to the slow natural regeneration of trees. Between 2007 and 2013, the harvesting of poplar and other trees increased during the process of expanding grazing land, which contributed to the sharp decrease in the area occupied by other trees.

However, between 2013 and 2020, the development of tourism gradually became rationalized, and the local government's construction of a forest culture constantly improved. After 2018, Emin County improved the protection of wild fruit forest resources, erected fences to maintain the area of distribution of wild fruit forests, effectively prevented grazing by cattle and sheep in wild fruit forests, reduced damage from anthropogenic activities, controlled the occurrence of pests and diseases, and adopted artificial renewal measures. These measures achieved positive results in the protection of wild fruit forests. The area occupied by wild fruit forests increased by 3.07 km^2 between 2013 and 2020.

The comprehensive dynamic attitude increased from 1.42% to 2.37%, and the stability of the pattern change of land use/cover in the study area decreased. The slow increase in the area occupied by wild fruit forests is mainly due to the achievements of human protection. The reasonable development of the tourism industry, artificial cultivation, biological control, and other measures effectively protected and restored wild fruit forests. There were reports that the conversion from construction land, grassland, and bare soil to wild fruit forests, especially from grassland to wild fruit forests, was also one of the reasons for the increase in the area occupied by wild fruit forests. Although the protection of wild fruit forests increased, dynamic changes in grassland and bare soil became more intense, resulting in a slight increase in the comprehensive dynamic degree of change in the study area.

3.2. Spatial and Temporal Transfer of Wild Fruit Forests

Using the results of the wild fruit forests, spatial transfer changes in wild fruit forests were calculated. The combination of the Sankey diagram and spatial distribution map (Figures 3 and 4) shows the intensity of mutual transformation between wild fruit forests and other land use/cover types and clarifies the spatial distribution of wild fruit forest transformation. Figure 5 shows the changes in social and natural factors affecting wild fruit forests in the study area.

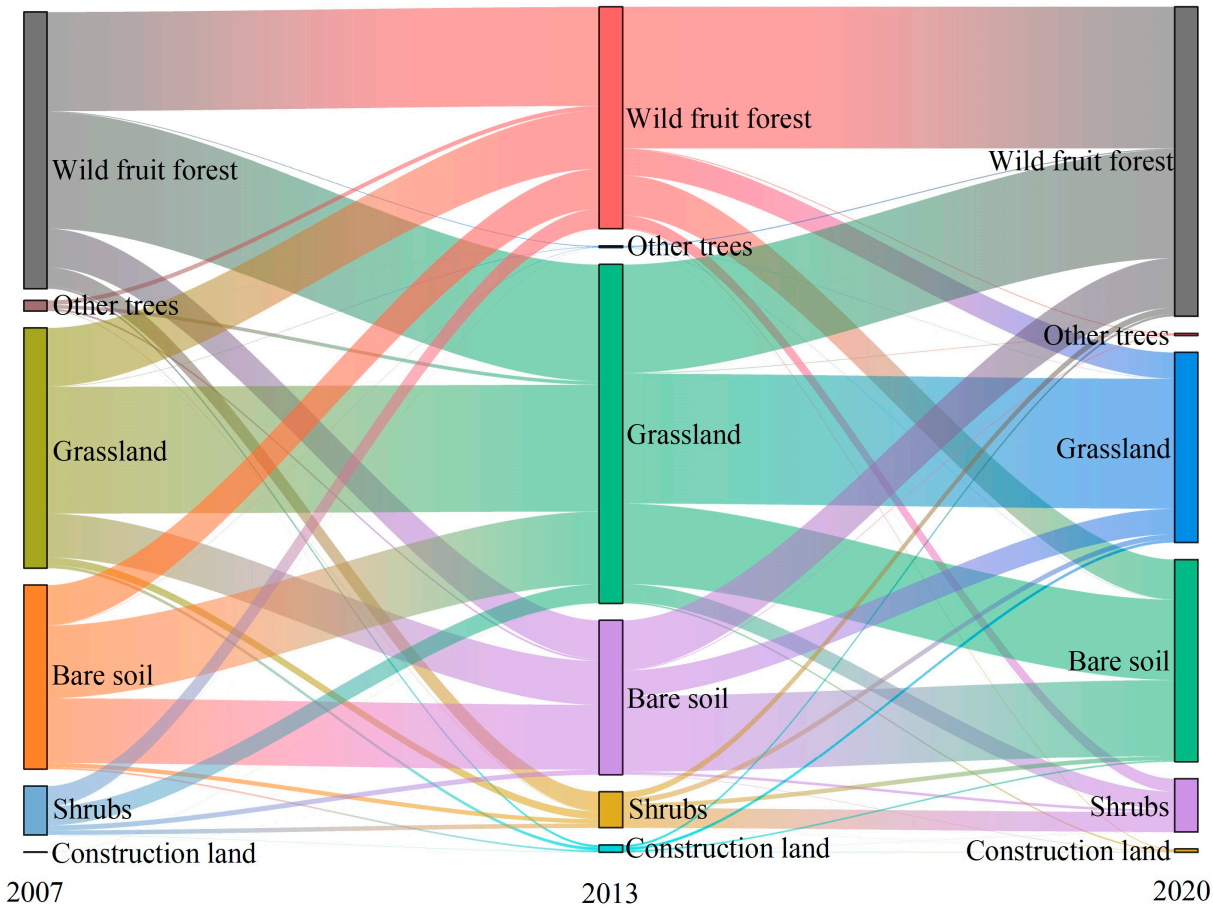

Figure 3. Transformation between wild fruit forests and other land features from 2007 to 2013 and from 2013 to 2020.

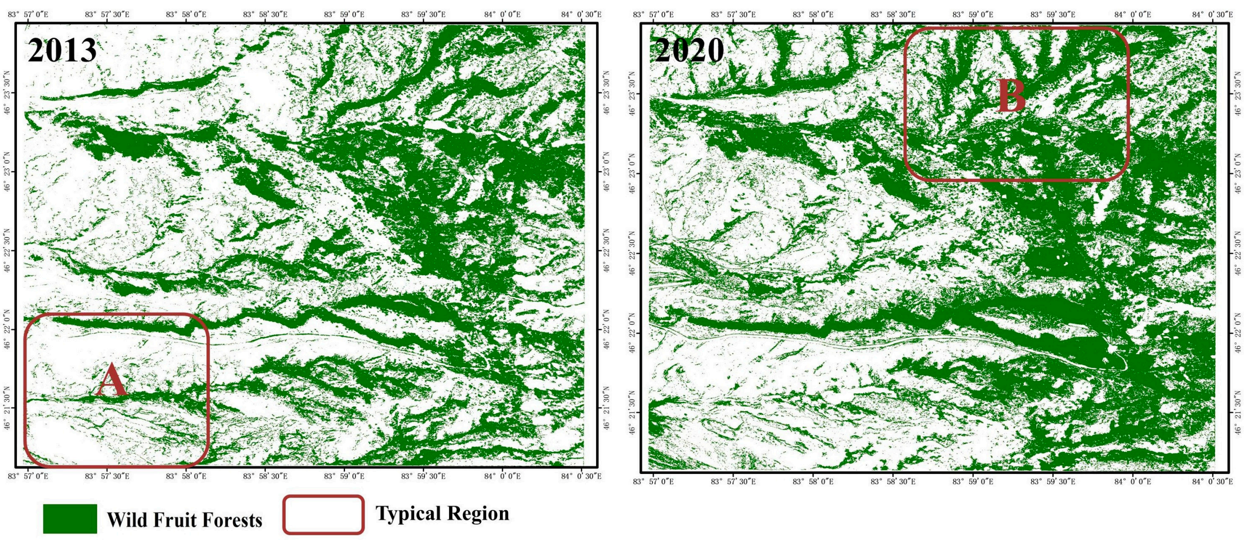

Figure 4. Typical areas of spatial distribution changes in wild fruit forests.

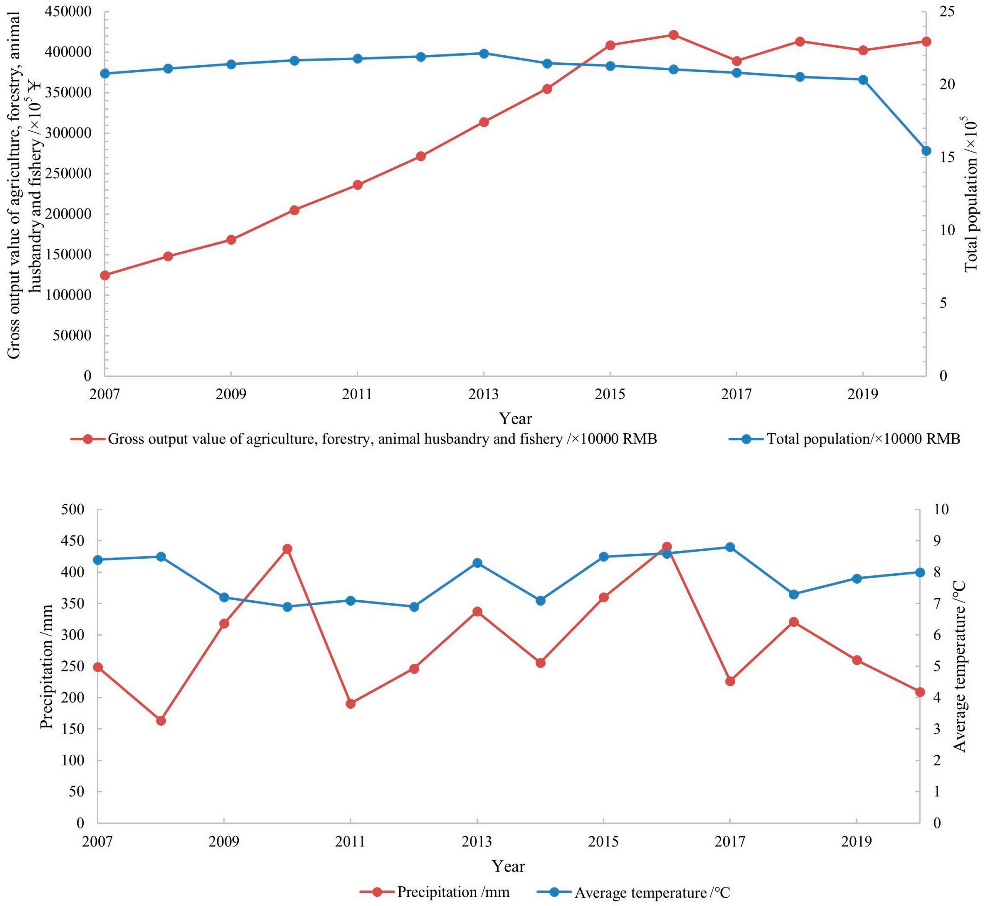

Figure 5. Changes in the main natural and human driving factors between 2007 and 2020.

Between 2007 and 2020, the changes in the spatial and temporal distribution patterns of wild fruit forests in the study area were attributed to the comprehensive influence of social and natural factors. To date, tourism still has negative effects on wild fruit forests in this area.

As shown in Figures 3–5, region A and region B were selected as typical regions with relatively severe dynamic changes in wild fruit forests during the study period, and the mutual transformation between wild fruit forests and various land use/cover types in typical change areas was further analyzed. From 2007 to 2013, the wild fruit forest area decreased and was mainly converted into grassland and bare soil. Within region A, the distribution of wild fruit forests was reduced considerably. This region is close to the tourist areas, and the continuous expansion of ski resorts has attracted many tourists. Consequently, human interference has intensified, resulting in the destruction of nearby wild fruit forests. Simultaneously, the region is close to rural Hoggilt, where the gradual increase in animal husbandry output value and demand for water and forage resources has likely contributed to the reduction in the area occupied by wild fruit forests. Grassland was the main land use/cover type from 2007 to 2013. Precipitation in 2007 and 2013 was 249.1 mm and 337.4 mm, respectively. Higher precipitation promotes grassland growth. Simultaneously, a large wild fruit forest area was transformed into grassland, which was an important reason for the relative increase in the grassland area in 2013. Mutual transformation between bare soil and grassland occurred, and the wild fruit forest area converted into bare soil was as high as 1.34 km^2. Although the area occupied by construction land was very small, its increase was very high, and its impact on grassland, bare soil, and wild fruit forests was relatively large. The wild fruit forest area converted into construction land was 0.08 km^2, accounting for 30.4% of the construction land area in 2013, which shows that the damage to wild fruit forests caused by construction was serious.

The sharp decline in wild fruit forests is mainly due to the combined results of human activities and natural factors. The sharp decline in wild fruit forests is mainly due to the combined results of human activities and natural factors. In order to protect wild fruit forests, effective measures need to be taken, including strengthening the construction of nature reserves, controlling pests and diseases, and limiting overgrazing and development. Climate change and other crises have led to a sharp loss of genetic diversity in wild fruit trees.

Between 2013 and 2020, the spatial distribution of wild fruit forests was relatively stable and land use changes were weak. The conversion of grassland and bare soil to wild fruit forests led to an increase in the total area of wild fruit forests, and the bare soil area converted into wild fruit forests was 0.33 km^2 more than that of wild fruit forests converted into bare soil, accounting for 4.3% of the total area of wild fruit forests in 2013. The transformation between shrubs and grasslands was also relatively frequent, the distribution of other trees was relatively stable, and the transformation into various types of land cover was very weak. From 2013 to 2020, the impact of the tourism industry was addressed by dismantling resort facilities in scenic spots, repairing original roads, and planning grazing areas to reduce construction land. For example, region B showed a considerable increase in the distribution of wild fruit forests. Precipitation in Emin County fluctuated, but the overall trend showed a slight increase. Precipitation, soil surface moisture content, and altitude are important factors influencing the distribution of different types of wild fruit forests [37]. Appropriate temperatures provided strong conditions for the rejuvenation of wild fruit forests. Most importantly, region B is far from grazing and tourist areas. The terrain is complex and changeable, with occasional wild animals, such as boars. Almost no human or agricultural interference was observed. In addition, in recent years, local protection and artificial cultivation of wild fruit forests have provided favorable conditions for the renewal and rejuvenation of wild fruit forests. The increasing awareness of the importance of wild fruit forests has played a positive role in promoting the implementation of environmental protection and ecological restoration. The government's conservation and health regulation project for the degraded ecosystem of wild fruit forests has effectively curbed the ecological degradation of wild fruit forests, resulting in a slow increase in the area occupied by wild fruit forests [38].

3.3. Shift in the Center of Gravity of the Distribution of Wild Fruit Forests

The shift in the direction and distance of the center of gravity of the wild fruit forests quantitatively expresses the direction of their spatial and temporal distribution and the degree of centripetal force. The characteristics of the spatial distribution and law of change over time were explored by studying the transfer distance and angle of the wild fruit forest area (details are shown in Table 2 and Figure 6).

Table 2. Statistical table of centroid migration distance and angle of wild fruit forests from 2007 to 2020.

Year	Centroid Point Coordinates (x, y)	Transfer Distance/km	Transfer Angle and Direction/°	Center of Gravity Migration Speed/km/year
2007	(83°58′54.97″ E, 46°22′31.41″ N)	/	/	/
2013	(83°58′34.34″ E, 46°22′26.35″ N)	/	/	/
2020	(83°58′19.18″ E, 46°22′28.58″ N)	/	/	/
2007–2013	/	0.17	W by S 11°	0.03
2013–2020	/	0.33	W by N 7°	0.04

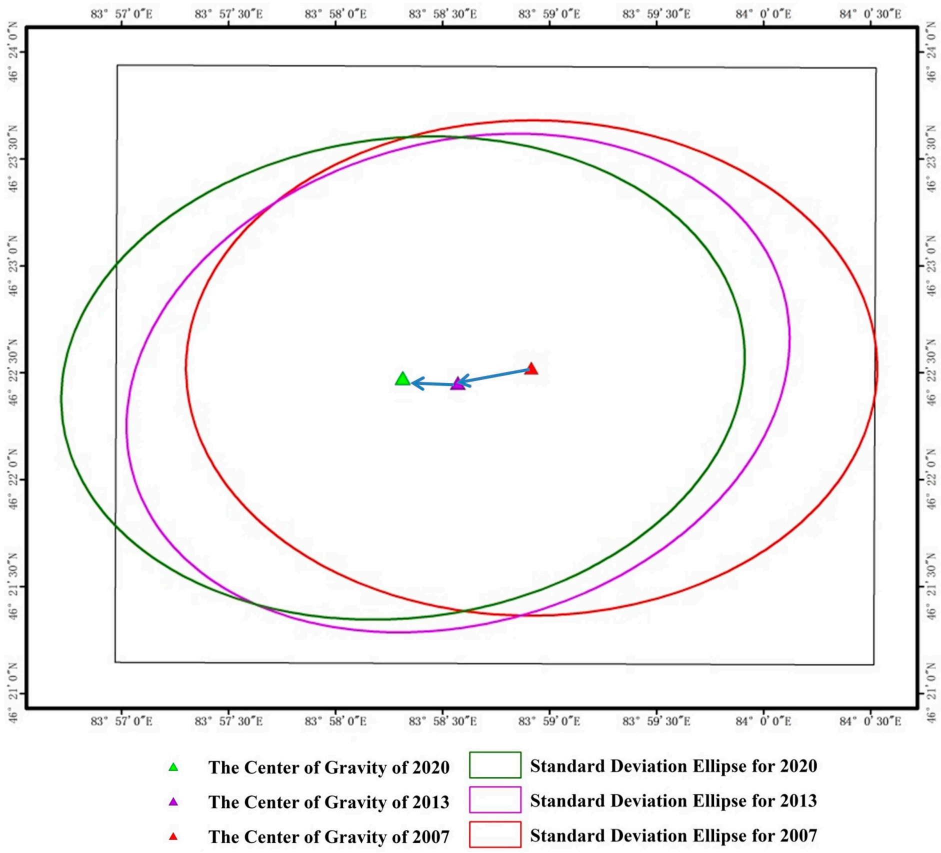

Figure 6. The centroid migration diagram of the wild fruit forest.

The standard deviation ellipse of the distribution of wild fruit forests quantitatively expresses the dynamic evolution of the spatial distribution of wild fruit forests through the long and short axes, shape index, and other indicators. During the study period, the deviation of the center of gravity in wild fruit forests was small, the distribution was relatively stable, and the spatial difference fluctuation was weak. The standard deviation elliptic shape indexes of wild fruit forests in 2007, 2013, and 2020 were 0.95, 0.82, and 0.92, respectively, showing a trend of first decreasing and then increasing. From 2007 to 2013, the distribution of wild fruit forests tended to be along the long axis, and the center of gravity of wild fruit forests migrated to the southwest, with a cumulative deviation of 0.17 km annually. Indicating that the spatial distribution of wild fruit forests tended to exhibit a longitudinal distribution from north to south. The center of gravity migration speed was 0.03 km/yr, which was relatively slow. The long axis of the standard deviation ellipse of the wild fruit forest increased and the short axis decreased, indicating that the spatial distribution of wild fruit forests showed a trend of contraction in the east–west direction and expansion in the north–south direction. From 2013 to 2020, the distribution of wild fruit forests tended to be along the short axis, and the spatial distribution tended to be circular. The spatial distribution characteristics changed little, and the spatial pattern of wild fruit forests developed toward the direction of uniformity. During this period, the center of gravity of wild fruit forests shifted by 0.33 km. Compared to that in the previous seven years, the distance of the center of gravity of the wild fruit forests increased and the degree of non-equilibrium of the spatial distribution increased, indicating that the high-density area of the spatial distribution of the wild fruit forests pointed in the northwest direction. The migration rate of the center of gravity was 0.04 km/yr and remained very slow. The distribution of wild fruit forests showed a contracting trend in the north–south direction. The short half-axis of the standard deviation ellipse increased and the distribution range of the wild fruit forests in the east–west direction showed an expanding trend.

3.4. Prediction of Future Spatial Distribution of Wild Fruit Forests

The PLUS model was used to predict the area of distribution of wild fruit forests. In order to verify the reliability of the model, firstly, based on the probability of land use/cover transfer between 2007 and 2013, the land use/cover demand of wild fruit forests in the study area in 2020 was predicted using the land use/cover data for 2007 and 2013 as the base period. The range of neighborhood weight parameters is 0–1; the closer the value is to 1, the higher the stability of the land use/cover type and the weaker the transfer ability. The appropriate neighborhood weight parameters were selected according to the changes in the proportions of areas occupied by various ground objects; the land use/cover data and development probability atlas for 2003 and 2013 were input in the module and the simulation prediction map for the spatial and temporal distribution of wild fruit forests in 2020 was obtained. Then, the spatial distribution data for wild fruit forests predicted by the PLUS model and interpreted by the Gaofen satellite in 2020 were tested and compared. The prediction results of the PLUS model have a good degree of fit with the classification results interpreted using the Gaofen data in 2020 and meet the needs of further prediction. This proves that the PLUS model has good applicability for the prediction of the spatial and temporal distribution of wild fruit forests.

Based on the spatial distribution data for wild fruit forests from 2007, 2013, and 2020 in the study area, combined with DEM, slope, and slope direction data, the suitability probability of different land use/cover types was calculated and the neighborhood weights of each land type were set to simulate and predict the distribution of wild fruit forests in 2027. Using ArcScene 10.6 software supplemented by an ALOS DEM with a spatial resolution of 12.5 m, the elevation, slope, slope direction, node elevation, and contour lines of the study area were extracted (Figure 7). Multiple layers were integrated to realize the drawing of the three-dimensional spatial distribution map of wild fruit forests in 2027 (Figure 8).

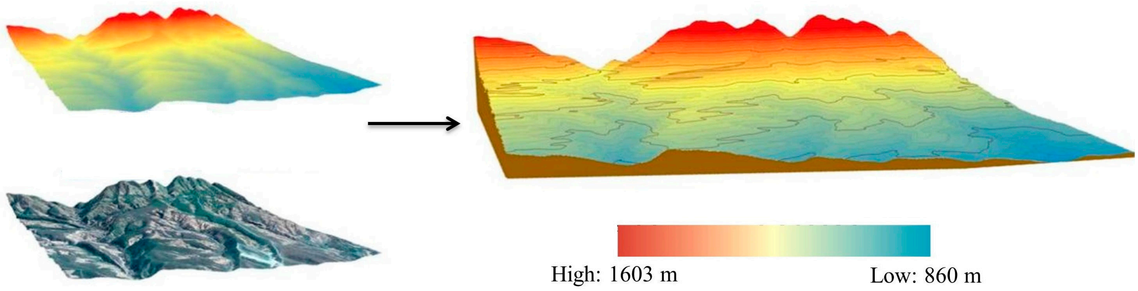

Figure 7. 3D topographic map of the study area.

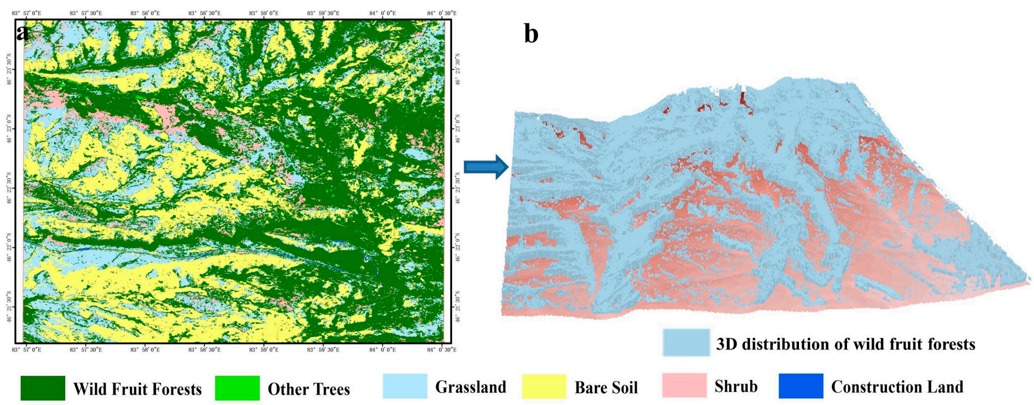

Figure 8. 3D map of wild fruit forest prediction for 2027. (**a**) Represents the spatial distribution map of wild fruit forests in 2027. (**b**) Represents the 3D map of wild fruit forest in 2027.

The PLUS model uses different scenarios to simulate and predict land use/cover, which can assist decision-makers in identifying a sustainable land use model for future development [39]. Moreover, the simulation accuracy of the PLUS model is higher than that of other models that have commonly been used in previous research, and the simulation results can better support sustainable development planning. Using this method, we predicted that the area occupied by wild fruit forests will increase between 2020 and 2027. In 2027, the area occupied by wild fruit forests is predicted to be 11.9 km^2, accounting for 44.9% of the total land area, followed by bare soil with an area of 7.39 km^2, accounting for 28.0%. The areas occupied by other trees, shrubs, and grasslands showed a decreasing trend, while the area occupied by construction land showed little change.

4. Discussion

4.1. Model Accuracy and Uncertainty

From a spatial perspective, compared with other traditional models such as CLUE-S, ANN-CA, and Logistic-CA, the FLUS (Future Land Use Simulation) model has significant accuracy advantages at regional, continental, and even global scales [33]. From a time series perspective, PLUS is more advantageous than FLUS in simulating historical land use changes [30]. The PLUS model was used to simulate and predict the spatial distribution and area of wild fruit forests in the study area in 2027. To test the accuracy of the model, the spatial distribution of wild fruit forests in 2020 was predicted using the distribution data for wild fruit forests from 2007 to 2013. The results showed that the prediction results for the distribution of wild fruit forests in 2020 fitted well with the classification results based on high-resolution data. This demonstrated that the model has good applicability in the study area and is suitable for predicting the spatial distribution of wild fruit forests in 2027. However, certain factors led to some uncertainties in the results of the PLUS prediction model. These factors include the use of nonlinear land use/cover and environmental meteorological factor data to drive the PLUS model, the differences in spectral parameters between the QuickBird and Gaofen satellite data, and the nonlinear changes in the center of gravity of the wild fruit forests and transfer of land use/cover during the study period. Additionally, the trend of the increase in the area occupied by wild fruit forests from 2013 to 2020 likely influenced the prediction of the distribution of wild fruit forests in 2027. These sources of uncertainty should be addressed in future studies. If hyperspectral technology is used as auxiliary data in future research, greater progress will be made in interpretation accuracy and universality, and the verification algorithm will be optimized via comprehensive error conduction and convergence cross-mapping so as to ensure the accuracy of wild fruit forest interpretation on a large scale.

4.2. Distribution Prediction and Protection Suggestions for Wild Fruit Forests

Due to the relic species from the Tertiary period, the Xinjiang wild apple (*Malus sieversii*) has characteristics with important scientific research and protection value. It was on the verge of extinction in 2000 [40]. Wild fruit forests exhibited a weak growth trend from 2013 to 2020. It is predicted that although wild fruit forests will show an increasing trend from 2020 to 2027, the increase will be relatively small, at only 0.7 km^2, with an average annual increase of only 0.1 km^2. The slow growth of the wild fruit forest area indicates that protection must be further strengthened. Awareness of the protection of wild fruit forests should be further promoted among local residents and tourists. The local government should also actively invest in the establishment of artificial fences, delineate pastoral and non-pastoral areas, and delineate core areas for the renewal and revitalization of wild fruit forests to prevent damage from cattle, sheep, and other pests to the core areas occupied by wild fruit forests. Reasonable grazing can effectively prevent livestock from damaging the regeneration of wild fruit forests, thereby changing the spatial distribution and quantity of wild fruit forests and effectively reducing the adverse effects of tourism development on wild fruit forests. Through the combined effects of rational grazing and artificial maintenance, we can promote a win–win situation between the development of animal husbandry and the ecological protection of wild fruit forests.

The stability of the spatial distribution pattern of wild fruit forests in the research area depends not only on the harmonious development of land use/cover and sustainable resource utilization but also on the comprehensive effects of the ecological environment, climate change, and human activities. With the continuous development of the social economy, the degree of land use/cover change is increasing, and human development and the unreasonable use of land resources may exacerbate the irrationality of resource distribution. Therefore, increasing the protection of wild fruit forests is necessary to stabilize and optimize the area and spatial structure of wild fruit forests in the research area so that future land use/cover changes are in an optimized state with a more stable development trend. There is an urgent need to strengthen investment in the concepts of forest culture, forest tourism, and ecological civilization and to promote harmonious development between humans and nature.

At present, the protection measures for wild fruit forests still need to be improved, and the establishment of special protection zones for wild fruit forests is also very rare [41]. Although local governments have vigorously developed tourism, its development and construction are based on protecting the regional ecological environment. It is suggested that sightseeing areas should be delineated in wild fruit forest scenic spots, and a fence should be set up as a barrier between the wild fruit forest and the tourist area to realize the basic maintenance of the wild fruit forest and limit human interference. A fence is the most commonly used effective measure for restoring forests and grasslands and has achieved good ecological and environmental benefits in the world, such as in the Tibetan Plateau [42], Inner Mongolia [43], and Australia [44], and also undoubtedly provides an effective idea for the protection of wild fruit forests. However, a fence has dual characteristics, and a long-term or permanent fence will have a negative effect on ecological restoration [45]. Therefore, we suggest that the local governments adopt transitional and non-permanent fence measures to enclose wild fruit forests surrounding grasslands for a short period of time and create favorable conditions for their natural recovery.

5. Conclusions

From 2007 to 2020, the area occupied by wild fruit forests in Emin County first decreased and then increased. Between 2007 and 2020, strong interference from human activities had a negative impact on the renewal of wild fruit forests and the area decreased considerably. Wild fruit forests were converted into construction land, accounting for 30.4% of the total construction land in 2013. The center of gravity of wild fruit forests shifted slightly, and the spatial distribution of wild fruit forests showed an expansion trend in the north–south direction and a contraction trend in the east–west direction.

Between 2013 and 2020, the spatial distribution of wild fruit forests was relatively stable, and suitable temperatures and reasonable tourism management provided favorable conditions for the revitalization of wild fruit forests. The shift in the distance of the center of gravity of the wild fruit forests increased, and the high-density area of the spatial distribution of the wild fruit forests pointed northwest.

A variety of environmental meteorological factors have nonlinear characteristics that drive the PLUS prediction model; additionally, there are differences in spectral parameters between different satellite data and these factors lead to errors and uncertainties in the prediction model. The spatial distribution results of wild fruit forests in 2020 obtained using the random forest algorithm and the PLUS prediction model are highly correlated, which fully proves the reliability and applicability of the PLUS model to wild fruit forest information interpretation.

It is predicted that between 2020 and 2027, wild fruit forests will show a stable and slowly increasing trend. Wild fruit forests are expected to reach a coverage area of 11.6 km^2 by 2027. It is suggested to install non-permanent fences as buffer zones between wild fruit forests and tourist areas while developing characteristic tourism, limiting human disturbance such as overgrazing in order to maintain the sustainable development of wild fruit forests.

Combining multi-band technology with hyperspectral technology, especially UAV hyperspectral technology, is expected to greatly improve the accuracy of wild fruit forest information classification. Additionally, we will focus on the quantitative verification of the prediction model in the future. Algorithms such as causal reasoning and cross-convergence mapping provide verification ideas for the accuracy of the prediction model, which will also make an effective reference for the classification and prediction of wild fruit forest information on regional and even global scales.

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