

Article

Assessing Spatiotemporal Dynamics of Poplar Plantation in Northern China's Farming-Pastoral Ecotone (1989–2022)

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Abstract

The farming-pastoral ecotone (FPE) of northern China serves as a critical ecological transition zone, in which poplar plantations significantly contribute to afforestation for large-scale ecological restoration projects. Due to concerns about sustainability, precise monitoring of the spatiotemporal dynamics of poplar plantations is needed, but systematic research is lacking. This study investigated the spatiotemporal dynamics of poplar plantation area and growth status from 1989 to 2022, taking the Anguli Nao watershed, a typical region in the FPE of northern China, as an example. Firstly, by utilizing satellite images and the random forest classification algorithm, the poplar plantation areas were well extracted, with a high accuracy over 93% and extremely strong consistency as demonstrated by a Kappa coefficient larger than 0.88. Significant changes in poplar plantation areas existed from 1989 to 2022, with an overall increasing trend (1989: 130.3 km², 2002: 275.9 km², 2013: 256.0 km², and 2022: 289.2 km²). Furthermore, the accuracy of our extraction method significantly outperformed six widely used global land cover products, all of which failed to capture the distribution of poplar plantations (producer's accuracy < 0.21; Kappa coefficient < 0.18). In addition, the analysis of vegetation growth status revealed large-scale degradation from 2002 to 2013, with a degradation ratio of 24.4% that further increased to 31.1% by 2022, satisfying the significance test via Theisl–Sen trend analysis and the Mann–Kendall test. This study points out the uncertainty of existing land cover products and risk of poplar plantations in the FPE of northern China and provides instructive reference for similar research.

Keywords: poplar plantation; farming-pastoral ecotone; remote sensing; spatiotemporal distribution; degradation



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1. Introduction

As the largest carbon sink in terrestrial ecosystems, forests play an irreplaceable role in mitigating climate change and ensuring ecological security [1–3]. However, the Food and Agriculture Organization (FAO) reports that, over the past 30 years, natural forests have continuously declined, with China alone losing about 22×10^4 km² [4,5]. Conversely, plantation forests expanded globally by 123×10^4 km² during the same

period [6], with China contributing significantly through large-scale ecological restoration projects like the Three-North Shelterbelt [7,8]. However, assessing the ecological benefits of plantation forests remains challenging. Spatially, there is a lack of high-precision monitoring of plantation distribution dynamics [9,10]. As a result, temporally, the long-term growth trends (e.g., degradation rates) of plantations are difficult to quantify [11]. Solving this scientific and practical problem is highly significant for optimizing ecological restoration project management, particularly in developing reasonable and sustainable strategies for the restoration of degraded forests [12]. This is particularly urgent in areas with concentrated plantation forests. The farming-pastoral ecotone (FPE) of northern China, a core area of the Three-North Shelterbelt project, plays a key role in carbon sink functions, ecological restoration, and environmental protection with large-scale afforestation [13–15]. However, recent studies indicate severe degradation of planted forests in this region. In Inner Mongolia, Shaanxi, and Hebei provinces, the areas of degraded forests exceeded 4000 km², posing a direct threat to the regional ecological security [16,17]. Accurately analyzing plantation distribution and growth trends is essential for evaluating ecological restoration projects and optimizing shelterbelt management strategies [10,18,19].

Optical remote sensing data, with long-term observation records and multispectral capabilities, has been widely used to map land cover types (including forests) and produce many global or regional products [9,20]. The advancement of machine learning algorithms, including random forest (RF) [21], support vector machine (SVM) [22], and deep learning (DL) techniques [23], has significantly improved land cover classification accuracy and efficiency. However, existing products still face significant challenges in practical applications. Low-resolution data, for example, the MODIS Land Cover product (500 m resolution), has time series advantages but struggles with spatial heterogeneity, often affected by mixed pixel effects [24,25]. High-resolution products like FROM-GLC 10 and WorldCover 10 (10 m resolution) improve spatial precision but lack sufficient time series data, limiting their ability to monitor plantation dynamics [26]. Some 30 m resolution products (e.g., GLC_FCS30 and GlobeLand30) balance temporal and spatial resolution to some extent but still face challenges in ecotone areas, like the FPE of northern China, with strong spatial heterogeneity [27]. A key challenge in this region is the spectral similarity between poplar plantations (*Populus simonii* Carrière)—the dominant forest type—and other non-forest vegetation, such as farmland and shrublands, causing confusion in traditional classification methods relying solely on spectral information.

Accurately assessing plantation forest degradation is crucial for evaluating ecological restoration project effectiveness [28]. Traditional ground surveys, using plot delineation and isotope tracing [29,30], precisely quantify local-scale degradation but are costly, are spatially limited, and lack temporal continuity, making large-scale monitoring challenging. Remote sensing technology has transformed degradation assessment. For regional-scale evaluation, Zhou et al. used MODIS NDVI time series to monitor plantation forests in Bashang region, Hebei province, China [31]. While effective in identifying growth and loss events, this approach lacked insight into gradual degradation. Recent advancements in optical remote sensing-based vegetation index time series analysis, utilizing methods such as univariate linear regression [32], Theil–Sen slope [33], and the Mann–Kendall test [34], have enabled the quantitative characterization of regional-scale degradation trends. However, existing satellite remote sensing studies analyze vegetation change broadly, without targeted assessments of specific vegetation types like poplar plantations [35–37].

This study was motivated by the hypothesis that poplar plantations in the Anguli Nao watershed—a typical region of the FPE in northern China—have undergone significant changes in spatial distribution and growth status between 1989 and 2022, which can be effectively monitored using remote sensing techniques and trend analysis. The primary

objectives were (1) to develop and validate a high-accuracy method for extracting poplar plantation areas by integrating multi-temporal Landsat imagery and the random forest (RF) classification algorithm, with its performance rigorously evaluated against six existing global land cover products, and (2) to assess the long-term growth status and degradation trends of poplar plantations as well as their contribution to vegetation greenness within plantation areas using Theil–Sen median trend analysis and the Mann–Kendall test based on long-term NDVI time series.

2. Materials and Methods

2.1. Study Area

The Anguli Nao Watershed, an endorheic watershed and a typical region of the FPE, is located in Zhangbei County, northern China (Figure 1). Geographically, it lies between 40°57′–41°31′ N and 114°15′–115°48′ E, with an area of 3421 km² and elevation ranging from 1310 to 2004 m a.s.l. It has a high-cold climate, with an average annual temperature of about 4 °C and annual precipitation of around 400 mm [38]. This area, adjacent to the Hunshandake Sandy Land, serves as a crucial ecological barrier, preventing sand carried by wind from moving southward into Beijing and Tianjin cities [39]. The Three-North Shelterbelt project has been implemented in this region since 1978, predominantly planting poplar trees. However, in recent years, environmental and human factors have caused widespread degradation and mortality of these poplar plantations [40]. Additionally, the area is confronting significant degradation of its lake and wetland ecosystems. Anguli Nao Lake, which was once the largest plateau inland lake in the Beijing–Tianjin–Hebei region, has been rapidly shrinking since 2000 and had completely dried up by 2004 [41]. The desiccation of the lake has resulted in severe destruction of the original wetland and lacustrine belt ecosystem, with the lake basin and surrounding flatlands gradually transforming into a saline-alkali desertification zone. These combined ecological and environmental characteristics make the Anguli Nao Watershed an ideal study area for monitoring poplar plantation distribution and assessing their growth dynamics.

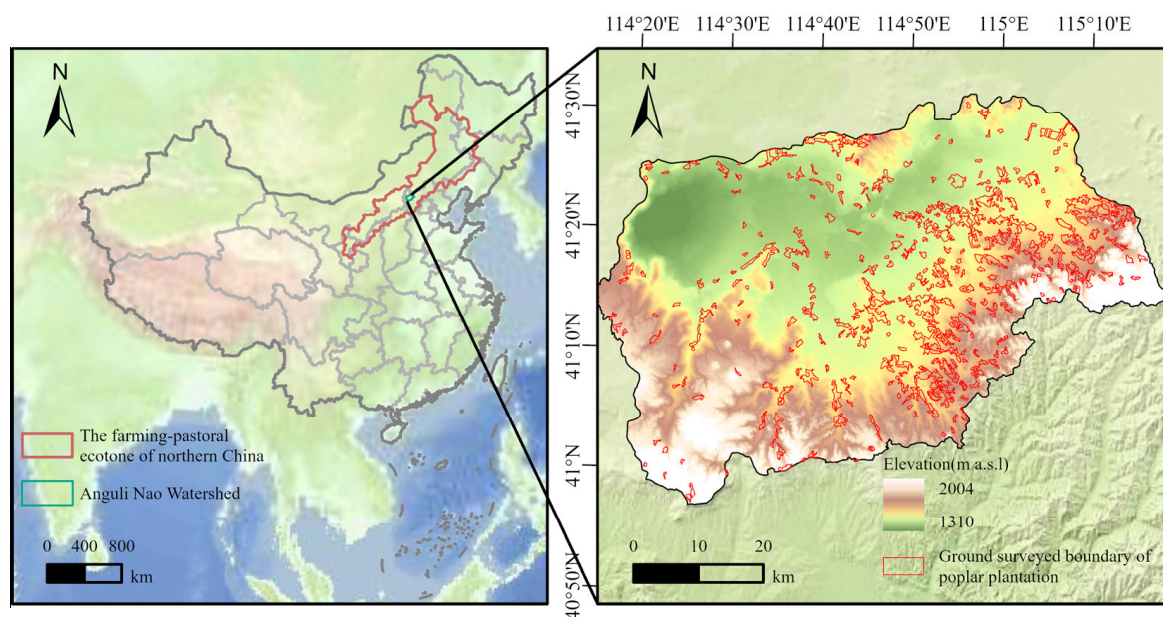


Figure 1. Location of the study area.

2.2. Data Collection

2.2.1. Satellite Images

(1) High-resolution RGB images

The Jilin-1 satellite, developed and launched by Chang Guang Satellite Technology Co., Ltd. (Changchun, Jilin, China), provides freely accessible global RGB images with a spatial resolution of 0.75 m in 2022. Sub-meter satellite RGB images for the long-term period were also additionally collected from Google Earth Pro software (7.1.8). These high-resolution RGB images guarantee the visual identification of poplar plantations, supporting the development of training and validation datasets for poplar extraction.

(2) Landsat image series

To extract long-term poplar distribution at nearly equal time intervals, Landsat images from 5 TM, 7 ETM+, and 8 OLI were obtained via the Google Earth Engine (GEE) platform [42]. Landsat 5 TM provided images from 1989 to 2012, while Landsat 8 OLI was used for 2013–2022 after Landsat 5 TM ceased operation. Blue, green, red, and near-infrared (NIR) bands from Landsat 5 TM and 8 OLI were used. Landsat 7 ETM+ shares the same spectral band as Landsat 5 TM but was excluded due to Scan Line Corrector (SLC) failure after May 2003, causing about 22% data loss [43]. However, since Landsat 5 TM and Landsat 8 OLI have different band widths, Landsat 7 ETM+ was used to standardize spectral indices: Landsat 8 OLI imagery, taken near the dates of Landsat 7 ETM+ images, was converted to match Landsat 7 ETM+ indices. This approach was then applied to Landsat 5 TM to minimize inconsistencies in long-term vegetation trend analyses [44]. The satellite images used in this study have a spatial resolution of 30 m and a temporal resolution of 16 days.

2.2.2. Ground Survey Data

During 2019 and 2020, the local government surveyed poplar forest boundaries in the Anguli Nao watershed (Figure 1). However, the survey overlooked internal forest degradation and sporadic poplars near roads, croplands, and buildings. Thus, this survey only provided a definition of poplar areas and could not be directly used to assess the accuracy of our remote sensing-based classification.

2.3. Extraction Method of Poplar Plantation Areas

2.3.1. Random Forest Classification

The classification of poplar plantation areas in the Anguli Nao watershed was conducted using the random forest (RF) algorithm, an ensemble learning method based on decision trees [45]. RF was selected due to its robustness with high-dimensional and heterogeneous data and its resistance to noise and overfitting. The RF algorithm constructs a large number of decision trees during training and makes a final prediction by taking the mode of the classes predicted by these individual trees [46]. The following sections describe the data, features, training, and validation procedures used specifically for the random forest classification of poplar plantations.

2.3.2. Selected Years for the Extraction of Poplar Plantation Areas

Since poplar plantations change gradually, data can be analyzed at multi-year intervals. This study selected four representative years—1989, 2002, 2013, and 2022—to assess plantation conditions, based on both the availability of high-resolution reference imagery (e.g., Jilin-1 and Google Earth) and the difficulty of obtaining cloud-free Landsat imagery during key phenological periods as well as the need to meaningfully segment the entire study period from 1989 to 2022. Four remotely sensed and seasonal images were selected

for each representative year, aligning with key phenological stages (PS) (Table 1): leaf expansion (LE), rapid growth (RG), canopy closure (CC), and leaf fall (LF).

Table 1. Selected dates (mm.dd) for image acquisition at each representative year.

PS	2022	2013	2002	1989
LE	04.18	05.03	04.27	05.01
RG	05.20	05.19	05.29	05.17
CC	09.01	08.23	08.17	09.06
LF	11.01	11.11	10.12	10.08

2.3.3. Input Variables

(1) Variables of phenological characteristics

Phenological characteristics include intra-annual spectral band features and index features. The selected spectral features consist of red, green, blue, and NIR band reflectances. Based on poplar growth variations, four PSs (Table 1) were chosen, yielding 16 spectral band features. The Normalized Difference Vegetation Index (NDVI, Equation (1)), widely used for assessing vegetation growth and cover [47], was also selected for four PSs, yielding 4 spectral index features.

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \quad (1)$$

where ρ_R and ρ_{NIR} are the red and NIR band reflectances, respectively.

(2) Texture characteristics

Texture characteristics enhance land cover classification by addressing spectral limitations [48]. This study selected Landsat imagery from mid-to-late May for texture feature extraction, as this period represents a critical stage in the vegetation growth, characterized by rapid vegetation growth and the most distinct spectral differences. To extract texture information, principal component analysis was initially applied to the imagery based on four Landsat band reflectances (i.e., red, green, blue, and NIR). The principal components were computed using a covariance matrix. Texture features were calculated using the gray-level co-occurrence matrix (GLCM) method, employing a 3×3 pixel window and a step size of 1. Eight texture features were extracted: mean, variance, homogeneity, contrast, dissimilarity, entropy, second-order moment, and correlation. These eight features were derived for each of the three top principal components (accounting for over 99% of the cumulative variance), yielding 24 texture features.

2.3.4. Training and Validation Datasets

To train and validate the RF classifier, samples were collected through visual interpretation from Jilin-1 (2022), Google Earth (2002 and 2013), and Landsat 5/TM satellite (1989) RGB images. Figure 2 illustrates the selected training areas for 2022. Note that the collection in 1989 referred to the results in the other three years due to the relatively low spatial resolution. Each area was converted into points and matched with the Landsat imagery following [49]. A total of 47,026, 47,026, 36,016, and 83,688 pixels were collected in 2022, 2013, 2002, and 1989 for the training dataset, with 9670, 9670, 10,547, and 6036 pixels being the poplar, respectively. Taking the 2022 dataset, for example, the coverage rate of poplar at Landsat pixel scale was calculated by subdividing Landsat imagery (30 m resolution) using Jilin-1 high-resolution imagery (0.75 m resolution). Figure 3 shows a near-linear relationship between cumulative poplar area and coverage rate, ensuring accurate extraction while minimizing omission of poorly grown poplars. For the validation dataset, to consistently evaluate the accuracy of extracted poplar in this study and the other existing six land cover products, random selection of 400 pixels for each year, with about half of the pixels being

the poplar, was conducted using the ArcGIS software (10.8.1) (corresponding distributions are presented in Figure S1).

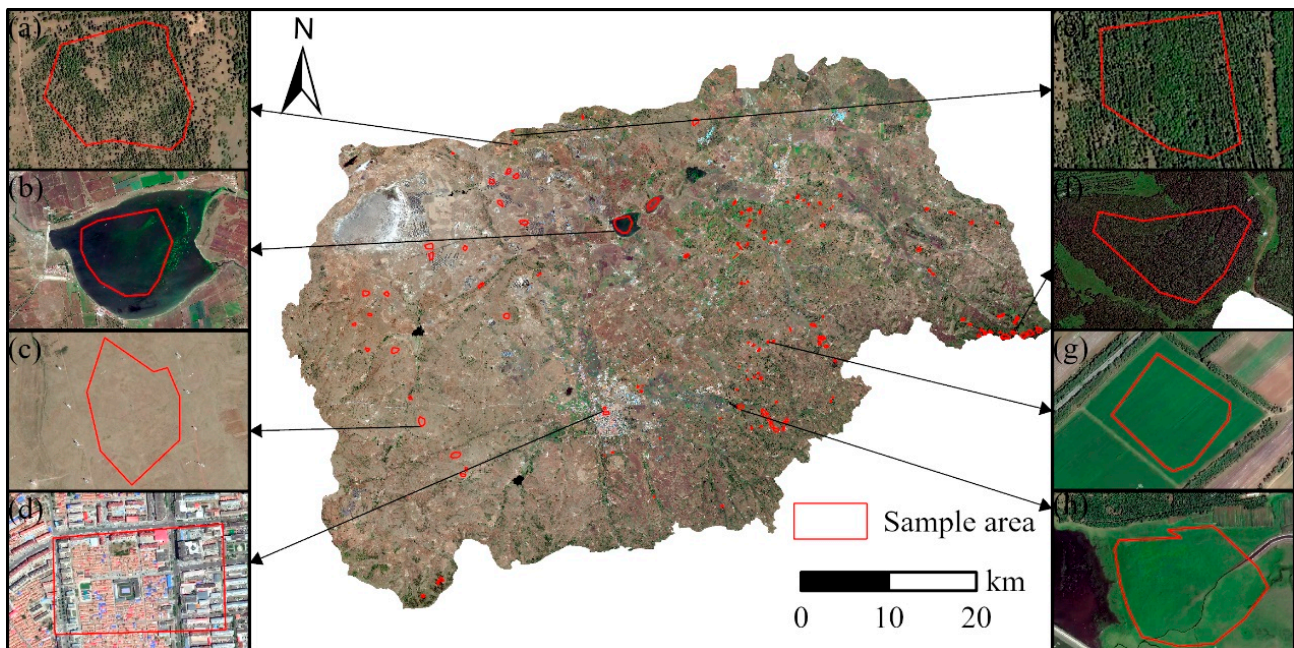


Figure 2. Types of selected samples in 2022 based on Jilin-1 satellite RGB image. (a) Poorly grown poplar plantation, (b) water body, (c) bare land, (d) artificial building, (e) well-grown poplar plantation, (f) *Pinus sylvestris* var. *mongolica*, (g) farmland, and (h) grassland.

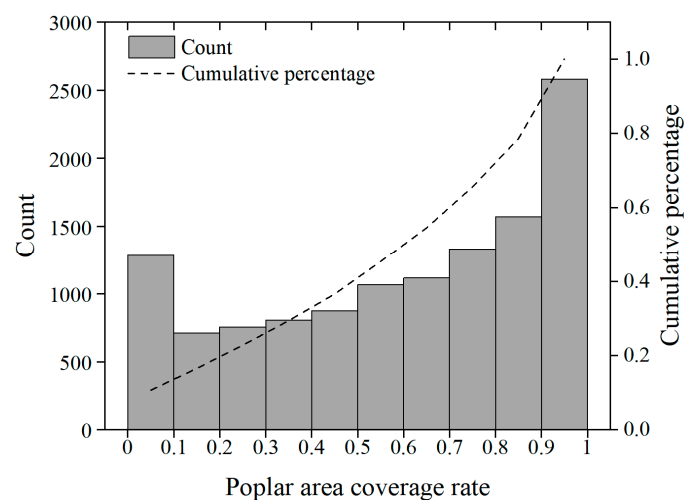


Figure 3. Cumulative percentage of poplar area coverage rate in the sample areas in 2022. The count indicates the number of Landsat pixels with 30 m resolution.

To account for environmental variability, the training and validation samples were intentionally collected across a wide range of site conditions, including variations in soil moisture (Figure S2a), elevation (Figure S2b), and planting density (Figure 2a,b). This sampling strategy ensured that the classifier was trained on representative spectral signatures of poplar plantations under heterogeneous environmental conditions, which is particularly important in the farming-pastoral ecotone.

2.3.5. Model Training and Implementation

The prepared training dataset (Section 2.3.4) and input variables (Section 2.3.3) were used to build the RF model. The RF model was trained on the training set and evaluated

using the validation set, with parameters of number of trees equal to 100 and feature numbers for each split determined as the square root of the total features. To explore the impact of texture features on classification performance, two different classification schemes were used: scheme 1 includes input variables of 16 spectral features and 4 vegetation index features; scheme 2 includes all variables in scheme 1 and 24 texture features.

2.3.6. Evaluation Matrices

The classification results were evaluated by producer's accuracy (PA, Equation (2)) and Kappa coefficient (Kappa, Equation (3)) based on the random selection of 400 pixels. PA reflects the extraction accuracy for only poplar pixels with a range of 0–1. Kappa represents the consistency of classification results for both poplar and non-poplar pixels, ranging from −1 to 1. Usually, Kappa can be divided into five groups to represent different levels of consistency between actual and extracted type of pixel: very low (<0.2), fair (0.2~0.4), moderate (0.4~0.6), substantial (0.6~0.8), and almost perfect (0.8~1.0). High PA and Kappa values are expected to obtain accurate poplar extraction.

$$PA = \frac{TP}{TP + FN} \quad (2)$$

$$Kappa = \frac{P_0 - P_e}{1 - P_e} \quad (3)$$

$$P_0 = \frac{TP + TN}{N} \quad (4)$$

$$P_e = \frac{(TP + FP) \cdot (TP + FN) + (TN + FP) \cdot (TN + FN)}{N^2} \quad (5)$$

where TP is the number of pixels correctly classified as belonging to the poplar, TN is the number of pixels correctly classified as belonging to the non-poplar, FN is the number of pixels that belong to the poplar but were incorrectly classified as non-poplar, FP is the number of pixels that belong to the non-poplar but were incorrectly classified as poplar, and N is the total number of pixels ($N = 400$).

To assess whether discrepancies in classification accuracy between the proposed methodology and global land cover products are statistically significant, McNemar's test was applied [50]. McNemar's test is a paired-sample test for 2×2 contingency tables (Table 2) and considers only the pixels where the two methods disagree.

Table 2. Definition of the contingency table for significance testing.

	Global Product Correct	Global Product Incorrect
Method correct	a	b
Method incorrect	c	d

The McNemar test statistic is calculated as follows:

$$\chi^2 = \frac{(b - c)^2}{b + c} \quad (6)$$

where b is the number of pixels correctly classified by the proposed method but misclassified by the global product and c is the number of pixels misclassified by the proposed method but correctly classified by the global product. The null hypothesis assumes that the two methods have equal classification accuracy. A p -value < 0.05 indicates a significant difference in classification performance between the two methods.

2.4. Existing High-Resolution Land Cover Products for Comparison

Six existing high-resolution land cover products were chosen to compare the extraction accuracy in the study area: FROMGLC10 [26], ESRIGLC10 [51], Worldcover10 [52], FROMGLC30 [26], GLC_FCS30 [53], and GlobeLand30 [54], with their parameters listed in the Table S1. None of these six global high-resolution land cover products classify specific tree species like poplar. Instead, they use broader categories such as forest land or forest types (e.g., broadleaf forest, coniferous forest, and mixed forest). Ground survey confirms that poplar dominates the study area's forests, while other species, like *Pinus sylvestris* var. *mongolica*, are sparsely distributed in the southern and southeastern parts of the study area. This species composition suggests that the forest distribution in the study area closely reflects poplar-dominated forests. Thus, although these products lack poplar-specific classifications, their forest classifications remain comparable to our extracted poplar distribution.

2.5. Analysis of Growth Trend Changes

2.5.1. NDVI Filtering and Interpolation

Mean NDVI of the growing season (April to October) was used to evaluate the vegetation growth status. Higher NDVI values indicate better growth. However, due to the uncertainties in the original NDVI data caused by cloud and other factors, Savitzky–Golay (SG) filtering and Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) interpolation methods [55,56] were employed to construct a daily NDVI data series for each year from 1989 to 2022.

2.5.2. Trend Analysis

The Theil–Sen median trend analysis (Equation (6)), a robust method for trend analysis [57–59], was used to calculate the trend magnitude of the NDVI time series from 1989 to 2022 by estimating the median slope (β) of all pairwise comparisons in the series. Compared to ordinary least squares (OLS) regression, this method demonstrates greater resilience in handling outliers and noise.

$$\beta = \text{Median}\left(\frac{x_j - x_i}{j - i}\right) \quad j > i \quad (7)$$

where β represents the median of all data slopes ($\beta > 0$ signifies an increasing trend of NDVI, while $\beta < 0$ indicates a decreasing trend) and x_i (or x_j) corresponds to the data for the i th (or j th) year in the time series from 1989 to 2022 ($j > i$). To determine significance of trend, the Mann–Kendall test was applied to assess whether a monotonic upward or downward trend exists in the time series:

$$\text{sgn}(x_j - x_i) = \begin{cases} +1 & x_j > x_i \\ 0 & x_j = x_i \\ -1 & x_j < x_i \end{cases} \quad (8)$$

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (9)$$

$$\text{VAR}(S) = \frac{n(n-1)(2n+5)}{18} \quad (10)$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{VAR}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\text{VAR}(S)}} & S < 0 \end{cases} \quad (11)$$

where the sign function, $\text{sgn}(x_i - x_j)$, takes the values +1, 0, or −1, indicating whether the subsequent observation is greater than, equal to, or less than the preceding observation, respectively. The variance of the S statistic, $\text{VAR}(S)$, is then adjusted by accounting for tied values within the series, resulting in the Z statistic, which is used to assess the significance of the trend. n represents the number of data points in the time series. The combination of the Theil–Sen estimator (β) and the Mann–Kendall test (Z) provides a robust framework for trend analysis. The final trend classification was determined by integrating the trend magnitude (β) and statistical significance ($|Z| > 1.96$ at the 95% confidence level), with the following criteria:

$|Z| > 1.96$ with $\beta > 0$ indicates significant improvement, and $|Z| \leq 1.96$ with $\beta > 0$ indicates slight improvement. $|Z| > 1.96$ with $\beta < 0$ indicates severe degradation, and $|Z| \leq 1.96$ with $\beta < 0$ indicates slight degradation. $\beta = 0$ indicates stability. In addition, the trend analysis was based on the complete annual NDVI time series from 1989 to 2022, ensuring that both long-term trajectories and inter-annual deviations were captured.

3. Results

3.1. Extraction Accuracy of Poplar Plantation

Table 3 shows the statistical results of extracted poplar plantation areas by this study using PA and Kappa for both schemes, with confusion matrices in Table S2. While scheme 2 performed better, both achieved high accuracy (PA > 0.80) and extreme high consistency between actual and extracted poplar plantations (Kappa > 0.8). This confirms the RF classification method as an effective approach for extracting poplar plantations, with texture features enhancing classification performance. Figure 4 shows poplar distribution across four years based on scheme 2. Most of the planted poplar were in the eastern and southeastern Anguli Nao watershed. Generally, from 1989 to 2022, there was a generally increasing trend of poplar plantation area (1989: 130.3 km², 2002: 275.9 km², 2013: 256.0 km², and 2022: 289.2 km²).

Table 3. Classification results for two schemes in 1989, 2002, 2013, and 2022.

Year	PA		Kappa	
	Scheme 1	Scheme 2	Scheme 1	Scheme 2
2022	0.829	0.950	0.800	0.895
2013	0.847	0.933	0.826	0.905
2002	0.927	0.958	0.875	0.880
1989	0.945	0.970	0.925	0.935

3.2. Comparison with Existing Land Cover Products

Although the years of land cover products range from 2017 to 2022, major poplar and forest areas likely remained stable over six years [60]. Thus, comparing their distributions with ground survey data from 2019 to 2020 is reasonable. Figure 5 shows extracted poplar from this study, forests from six products, and ground surveyed poplar boundaries. Existing products failed to capture the spatial pattern of forests (including poplar), while fortunately, this study's extraction aligned well. Additionally, the extracted poplar map by this study obviously reflected the sporadic poplar near roads, cropland, buildings, and others, which were not considered in the ground survey. Moreover, Figure S3 intuitively presents examples of obvious misclassification of poplar growing in clusters

with large areas by existing products. Quantitatively, the proportions of poplar or forest to the ground-surveyed boundaries of poplar were 57.96%, 1.74%, 17.19%, 1.13%, 7.32%, 2.51%, and 3.11% for products of this study, GlobeLand30, WorldCover10, ESRI GLC10, FROM-GLC10, FROM-GLC30, and GLC_FCS30, respectively. Note that the ground survey did not regard internal forest degradation, explaining the lower proportion of 57.96% by this study.

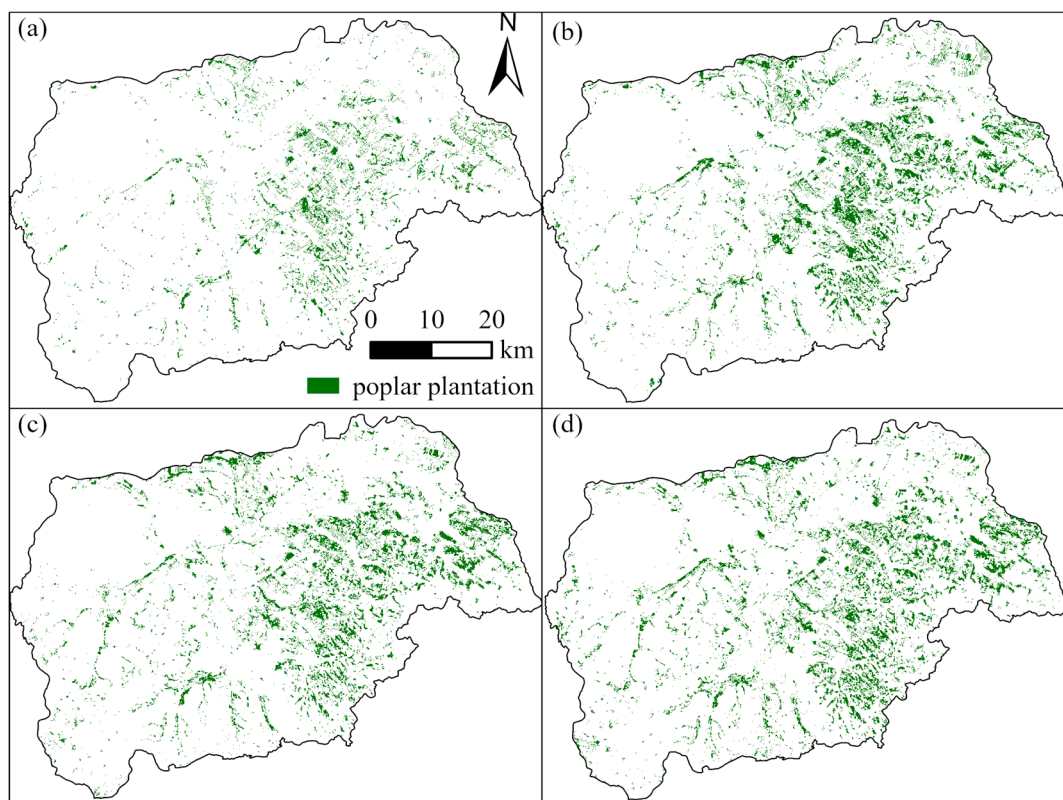


Figure 4. Extracted poplar plantation distribution in the Anguli Nao watershed in 1989 (a), 2002 (b), 2013 (c), and 2022 (d).

Using the 400-pixel validation dataset from 2022, PA and Kappa were calculated for six existing products, and the differences in classification performance between the proposed method and each existing product were further tested for statistical significance using McNemar's test (Table 4). Consistent with the above result, all existing products obtained very poor performance, particularly for product ESRI GLC10. Combining Tables 3 and 4 and Figures 5 and S3, it was demonstrated that the existing six products cannot reflect the forest (including poplar) distribution in the Anguli Nao watershed, while fortunately, this study provided a reliable approach based on the RF algorithm to extract poplar distribution.

3.3. Spatiotemporal Changes in Poplar Plantation Areas

Figure 6 shows the land cover transitions over three periods (1989–2002, 2002–2013, and 2013–2022), with corresponding statistical results in Figure 7. From 1989 to 2002, newly planted poplar (167.31 km²) far exceeded degraded areas (21.7 km²), increasing total plantation area from 130.3 to 275.9 km². A similar trend occurred from 2013 to 2022, with plantation expansion from 256.0 to 289.2 km². However, from 2002 to 2013, degradation (83.37 km²) surpassed new plantations (63.42 km²), reducing total area to 256.0 km². Figure 6 shows that both plantation and degradation mainly occurred in the central watershed, particularly from 2002 to 2013, while the eastern regions remained stable. In the most eastern regions, the planted poplar had almost no occurrence of degradation.

Additionally, the newly replanted poplar area during the period of 2002–2013 on completely degraded land of poplar during the period of 1989–2002 was 4.68 km², accounting for 21.57% of the total completely degraded poplar area (21.7 km²), while these values were 22.52 km² and 27.01% by comparing the areas during the period of 2013–2022 with those during the period of 2002–2013. Moreover, the completely degraded poplar during the period 2002–2013 from the newly planted poplar during the period of 1989–2002 was 58.27 km², accounting for 34.83% of the total newly planted poplar area (167.31 km²), while these values were 19.52 km² and 30.79% by comparing the areas during the period of 2013–2022 with those during the period of 2002–2013.

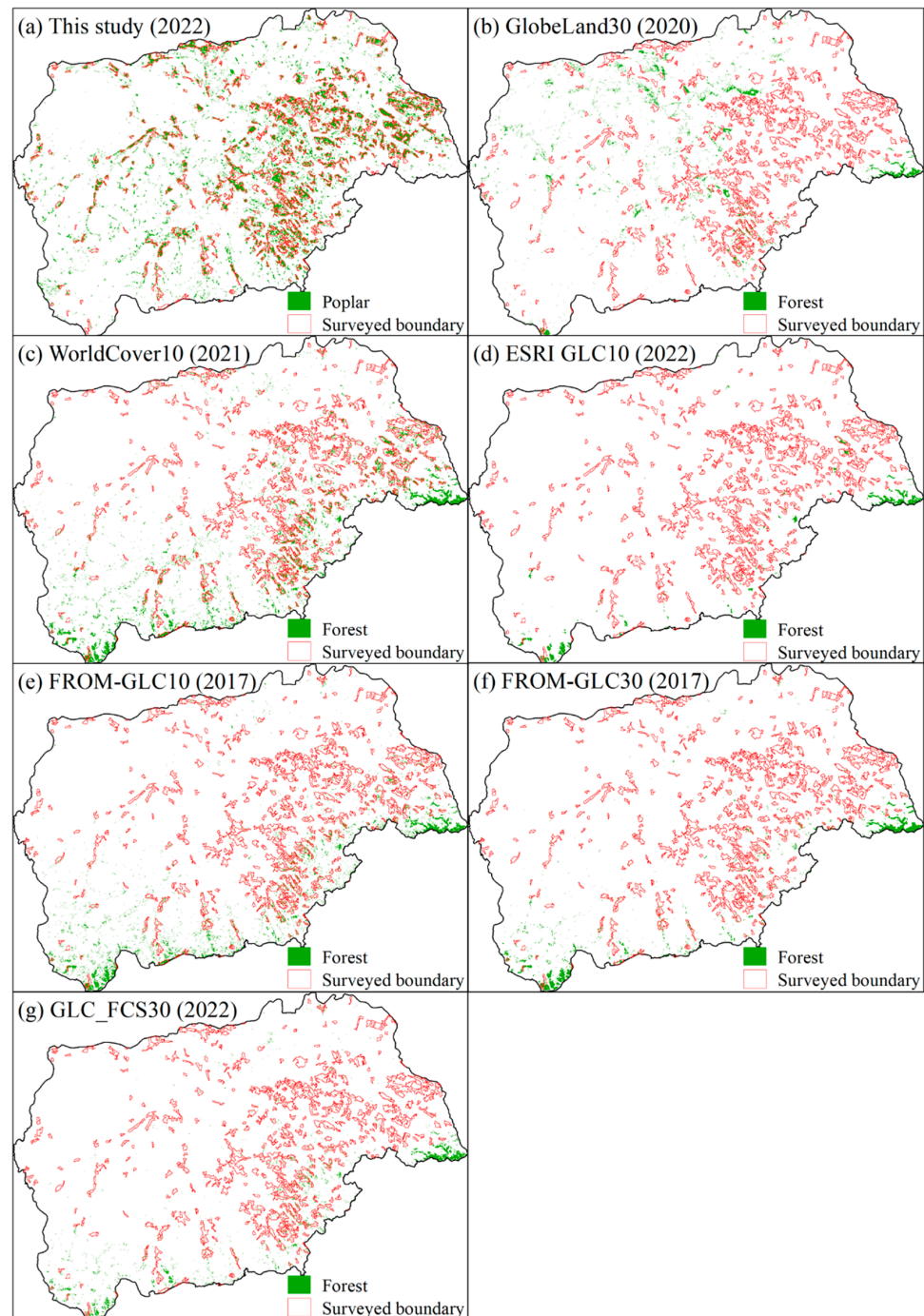


Figure 5. The ground-surveyed boundaries of poplar and poplar or forest distribution of different products.

Table 4. Classification accuracy of existing products based on the 400-pixel validation dataset. *p*-value indicates the significance level of the differences in classification performance between the proposed method and each existing product through McNemar’s test.

Product	Year	PA	Kappa	<i>p</i> -Value
WorldCover10	2021	0.201	0.177	<0.001
ESRI_GLC10	2022	0.000	−0.005	<0.001
FROM_GLC10	2017	0.101	0.086	<0.001
FROM_GLC30	2017	0.030	0.010	<0.001
GLC_FCS30	2022	0.020	0.015	<0.001
GlobeLand30	2020	0.025	−0.005	<0.001

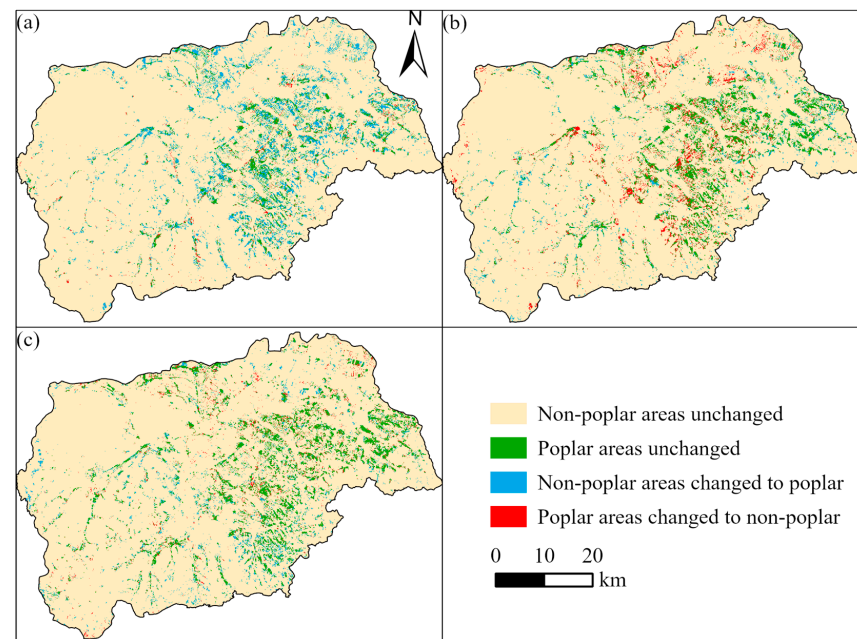


Figure 6. Spatial changes in land cover types between poplar plantations and non-poplar plantations over three periods: (a) 1989–2002, (b) 2002–2013, and (c) 2013–2022.

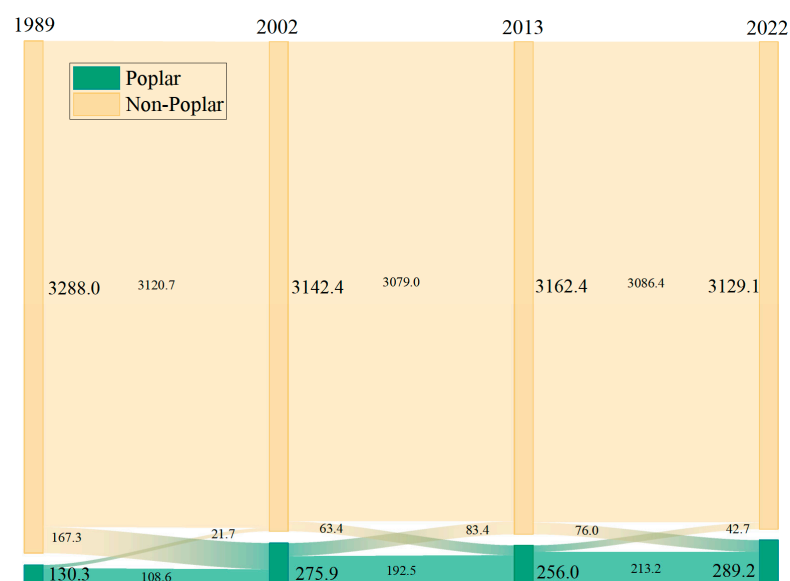


Figure 7. Quantitative statistic of land cover change between years. Unit: km².

3.4. Spatiotemporal Changes in Vegetation Growth Status

The analysis was conducted using the full annual NDVI dataset (1989–2022), which allowed us to detect both gradual trends and short-term anomalies related to climatic or management events. For the whole watershed, Figure 8a highlights significant spatial differences in vegetation growth, with stronger growth in the southeast and weaker growth in the northwest. Higher NDVI values were mainly in the eastern and southern regions, where artificial plantations (e.g., poplar and *Pinus sylvestris* var. *mongolica*) were concentrated, demonstrating their role in ecological improvement. In contrast, lower NDVI values appeared in the northwest and urban areas of Zhangbei County. Over the long term (1989–2022), 97.1% of the watershed improved, with only 1.9% experiencing degradation (Figure 8b). During 1989–2002, although the significantly and slightly improved areas accounted for 62.6% and 4.4%, respectively, widespread degradation was also observed (29.8%), particularly in the south and north (Figure 8c). From 2002 to 2013, the degraded area declined to 23.4%, shifting to central and western areas, while improvement was notable in the south and north (71.7%) (Figure 8d). During 2013–2022, vegetation improved significantly (82.4%), with 24.0% showing strong recovery, mainly in the southwest and northeast, though 13.7% of the central and northern areas degraded (Figure 8e). These results indicated a continuous improvement of vegetation growth status.

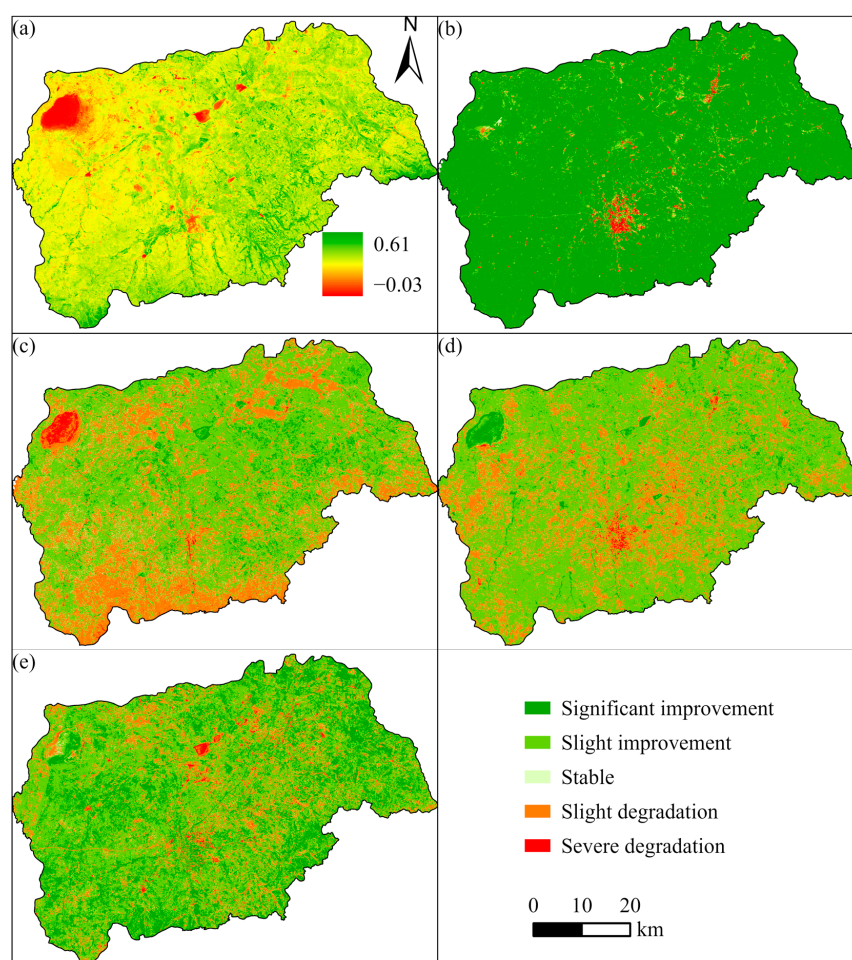


Figure 8. Spatial distribution for multi-year mean NDVI of growing season (a) and change trend in mean NDVI of growing season for four periods: (b) 1989–2022, (c) 1989–2002, (d) 2002–2013, and (e) 2013–2022.

Figure 9 illustrates temporal segmentation of the poplar planting areas, highlighting unchanged, increased, or decreased cover, overlaid with NDVI change trends. Statistical results in Figure 10 show that, in regions where poplar increased, 92.0%, 92.3%, and 88.0% exhibited NDVI improvement in 1989–2002, 2002–2013, and 2013–2022, confirming poplar's ecological benefits. In unchanged areas, 74.0%, 72.0%, and 61.7% showed improvement for three periods, respectively, while degradation increased from 21.4% (1989–2002) to 31.1% (2013–2022), particularly in central and western regions. In areas of poplar loss, degradation occurred in 60.2%, 41.2%, and 32.0%, while NDVI improvement reached 34.5%, 53.2%, and 61.6% over the three periods, respectively. This suggested some degraded poplar areas were converted into other forests or grasslands, leading to NDVI improvement despite poplar loss.

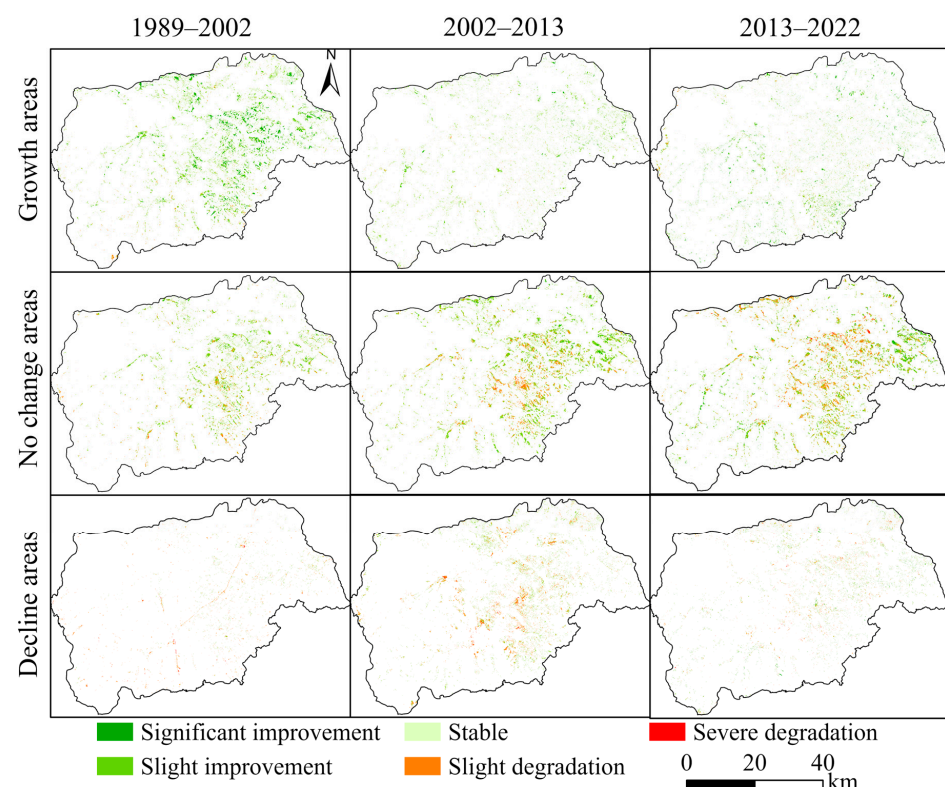


Figure 9. Spatial change trends in mean NDVI in poplar plantation areas in the Anguli Nao watershed for three periods. Growth areas: the type of pixels was changed by the newly planted poplar from other land cover types; No change areas: the type of pixels was still the poplar; and Decline areas: the type of pixels was transferred into other land cover types from poplar.

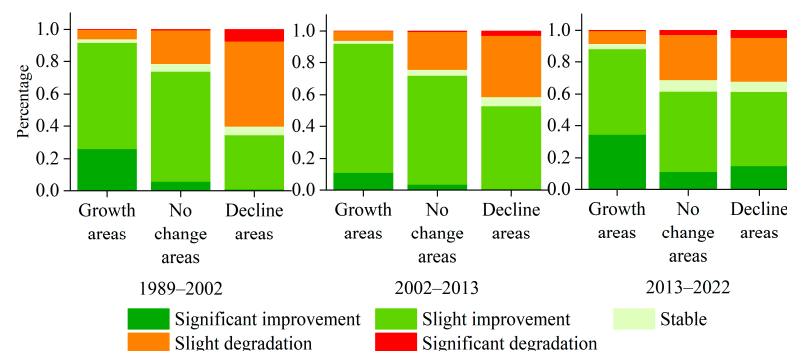


Figure 10. Proportions of mean NDVI change trends in poplar plantation areas in the Anguli Nao watershed for three periods. The definitions of growth areas, no change areas and decline areas are same to that in Figure 9.

4. Discussion

4.1. The Uncertainty of and Its Impact on Existing Land Cover Products

Forests have the highest carbon sequestration capacity among land cover types [5,61,62]. Thus, accurately mapping their distribution and evaluating changes are crucial for material cycling (e.g., water cycling, carbon cycling, and nutrition cycling) research and management. However, in the Anguli Nao watershed, a typical region of the farming-pastoral ecotone, all six existing land cover products showed poor accuracy in classifying forest areas, let alone mapping poplar plantations (Figure 5 and Table 4). The existing six products not only did not reflect the spatial distribution of forest (including poplar) but also significantly underestimated the plantation areas by at least 58.02%, assuming that extracted poplar by this study was reliable (extracted poplar area by this study: 289.20 km²; forest areas by existing products: WorldCover10—121.39 km², ESRI GLC10—22.35 km², FROM_GLC10—74.02 km², FROM_GLC30—40.53 km², GLC_FCS30—36.75 km², and GlobeLand30—52.91 km²). The poor classification performance of these products likely stems from their global-scale generalization, which prioritizes overall accuracy across diverse ecosystems by using general algorithms and large-scale training samples. However, this generalization can lead to reduced classification accuracy in specific areas, especially in regions with high land surface heterogeneity, for example, the farming-pastoral ecotone. The farming-pastoral ecotone of northern China has significant climate diversity and complex terrain. This area includes farmland, grassland, and partially desertified regions, with land use forms and vegetation types being significantly more complex than in single farming or pastoral areas [63]. It indicated that, in the farming-pastoral ecotone of northern China, evaluation of material cycling based on existing products has great uncertainty and risk.

Sun et al. conducted a comparative assessment of six widely used global and national land use/cover datasets, including MODIS-MCD12Q1, ESA CCI-LC, GlobeLand30, GLASS-GLC, CAS-CLUDs, and ChinaCover [27]. Their findings revealed that MODIS and GLASS products exhibited particularly low classification accuracy (55.3%–58.2% and 34.7%–39.4%, respectively), with widespread misclassification of croplands as natural grasslands and a failure to distinguish forests from shrublands or grasslands. Even relatively high-accuracy products like GlobeLand30 (86.6%–86.7%) and ESA CCI-LC (73.9%–74.2%) struggled to capture critical land cover changes, such as the conversion of cropland to forest under the “Grain to Green” project. These findings underscore that land cover datasets with high global accuracy may still be unreliable at regional scales, particularly in areas with complex landforms and dynamic land-use transitions [27]. Fortunately, when extracting poplar plantations in the Anguli Nao watershed, this study used more targeted samples: sample points with different growth conditions for poplar plantations in strip areas beside farmland and in large patch areas were considered. This approach can well reflect the ecological characteristics of poplar plantations in the typical farming-pastoral ecotone. The results demonstrated that using localized samples and imagery with thoughtful design and reasonable input variables for classification can fully consider the specific environmental conditions and then significantly improve classification accuracy.

4.2. The Significance of Poplar Plantations

Poplar have been widely planted in the farming-pastoral ecotone of northern China to realize the primary objectives of controlling wind erosion, preventing desertification, and then improving the ecological environment. From 1989 to 2002, vegetation cover in the Anguli Nao watershed significantly improved, with a total improved area of 150.53 km². Newly planted poplar accounted for 43.81 km², making up 29.1% of this area. Moreover, the NDVI increase in the newly planted poplar areas was significantly higher than that in the other improved areas, rising from 0.212 to 0.335 (increase of 0.123) compared to

an increase from 0.194 to 0.254 (0.060) in other areas. This highlights poplar's crucial role in ecosystem restoration. Time series NDVI analysis showed that newly planted poplar areas had an improvement rate of around 90%, indicating long-term ecological benefits beyond initial planting. In addition, poplar plantations also contribute significantly to carbon sequestration. Studies suggest poplar biomass and carbon storage increase with tree age [64]. During the period from 1989 to 2002, 167.3 km² of new poplar plantations was added. To provide a preliminary estimate of their carbon sequestration potential, we applied a generalized coefficient from the literature, which suggests that each hectare of poplar plantations can absorb and store approximately 10–20 tons of carbon dioxide per year [65]. It is important to note that this estimate carries inherent uncertainty, as the actual carbon sequestration rate can vary substantially, resulting from local factors such as tree age structure, planting density, site quality, and management practices, for which detailed field data are not available. Bearing this limitation in mind, this coefficient implies that the newly added poplar plantations during this period could have sequestered approximately 167,300 to 334,600 tons of carbon dioxide annually. In the periods of 2002–2013 and 2013–2022, although there were some fluctuations in the total area of poplar plantations, their overall area remained large (more than 250 km²), continuing to play an important role in carbon sequestration. During the period from 2002 to 2013, due to the degradation of some poplar plantations, the carbon sequestration capacity in some areas decreased. However, during the period from 2013 to 2022, the total area of poplar plantations increased, indicating ongoing restoration and renewal. Despite some fluctuations in poplar plantations in these two periods, their overall carbon absorption capacity remains significant.

4.3. Degradation of Poplar Plantations

As mentioned before, poplar plantation area exhibited both new plantation and degradation for a period. From 2002 to 2013, large-scale degradation of poplar plantations occurred in the Anguli Nao watershed. During this period, 83.4 km² of poplar plantations disappeared, and among the remaining poplar plantations, 24.4% exhibited signs of degradation. By 2022, this degradation ratio had increased to 31.1%. Most of the poplars in the Anguli Nao watershed were planted in the 1970s. In northern regions, poplars older than 30 years enter an over-mature stage, where their growth vigor decreases and their resistance to pests and diseases weakens, leading to widespread degradation [66]. Additionally, the impact of human activities and changes in climatic conditions could be other reasons for the degradation of poplars [29]. Since the 1990s, the region has shifted from pastoralism to agriculture, and the increased water usage for farming has caused a sharp decline in the groundwater table. In addition, the annual precipitation in this region has been below average for many years, resulting in insufficient soil moisture, which adversely affects the growth and survival of poplars. The large fluctuations in precipitation in northern regions, coupled with prolonged droughts, exacerbate the water deficit problem for poplars, making it difficult for them to maintain healthy growth [67]. Some scholars even argue that, due to water scarcity, the farming-pastoral ecotone of northern China, being an arid and semi-arid region, is inherently unsuitable for large-scale afforestation, especially for planting water-intensive species like poplar, which exacerbates water scarcity and leads to poor ecological restoration outcomes [68,69]. Beyond the absolute water scarcity, another critical aspect determining the sustainability of poplar plantations is their water use efficiency (WUE). Defined as the ratio of gross ecosystem production (GEP) to evapotranspiration (ET), WUE characterizes the ability of trees to balance carbon gain and water consumption under conditions of limited soil moisture [70]. Previous studies have shown that, in arid environments, poplar plantations often exhibit relatively low WUE: increases in soil moisture lead to a disproportionate rise in ET compared to photosynthesis,

resulting in substantial “waste” of water [71]. Tree-ring analyses in Inner Mongolia further revealed that drought stress (low soil water availability) offsets CO₂-driven gains in WUE, thereby constraining growth [72].

Note that poplar plantation is a time-consuming and costly undertaking. Determining the suitable places for stable poplar survival is very important. However, the mechanisms for poplar degradation and the mapping of suitable places for poplar growth currently still need further research.

4.4. Future Perspectives and Uncertainty Analysis

Although the Landsat-based random forest (RF) framework developed in this study successfully captured the long-term spatiotemporal dynamics of poplar plantations at 30 m resolution, emerging remote sensing technologies offer new possibilities for higher-precision monitoring. Sentinel-2 imagery, with its 10~20 m spatial resolution and 5-day revisit cycle, has demonstrated high effectiveness in distinguishing poplar plantations from surrounding vegetation. Hamrouni et al. (2022) developed a poplar index based on Sentinel-2 data, utilizing red-edge and shortwave infrared bands to achieve classification accuracy exceeding 92% [73]. The integration of such high-resolution, multispectral data could further optimize plantation mapping, particularly in ecotones with high heterogeneity, such as the farming–pastoral transition zone.

In addition, it should be noted that this study relied solely on NDVI to characterize growth degradation. While NDVI is a reliable indicator of overall vegetation vigor, future studies could combine other indices (e.g., EVI to reduce canopy background noise or NDWI to assess water stress) with high-resolution validation in order to better disentangle the effects of transient stress and permanent structural degradation.

Furthermore, unmanned aerial vehicles (UAVs) equipped with high-resolution RGB, multispectral, or even hyperspectral sensors can provide centimeter-scale data. This unprecedented level of detail is highly suitable for validating satellite-derived classifications, detecting degradation signals, and investigating the intrinsic mechanisms of poplar decline at the individual tree level. UAVs with multispectral cameras have already been employed to estimate single-tree height and biomass in poplar plantations [74], enabling refined assessment of plantation structure and growth conditions.

Therefore, future work should focus on integrating the temporal depth of Landsat with the spatial detail of Sentinel-2 and the ground-level precision of UAVs. Such a multi-platform framework will not only improve the accuracy of poplar plantation mapping but also enhance the understanding of the ecophysiological drivers behind plantation degradation, ultimately supporting more sustainable forest management practices in farming–pastoral ecotones.

5. Conclusions

This study developed an RF classification framework that integrates phenological spectral features and texture features to extract poplar plantation in a typical region of the farming–pastoral ecotone of northern China from 1989 to 2022. The spatiotemporal changes in poplar plantations in terms of planted area and growth status were then analyzed based on the extracted maps. The framework achieved highly accurate poplar plantation extraction (PA > 90% and Kappa coefficient > 0.80) and outperformed six global land-cover products, which failed to capture the forest distribution in the study area, effectively addressing the methodological gap with monitoring plantations within ecological transition zones. The results revealed a typical “expansion–degradation–recovery” cycle: plantation area expanded rapidly between 1989 and 2002; declined substantially from 2002 to 2013

due to aging stands, groundwater overuse, and aridity; and showed partial recovery by 2022, though the degradation trend continued to intensify.

In summary, this study established an approach to extract poplar plantations, analyzed the uncertainty of existing land use/cover products, and revealed the spatiotemporal changes in poplar plantations in a typical region of the farming-pastoral ecotone of northern China. It provides an instructive reference for similar research.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/f16101502/s1>, Figure S1: Spatial distribution of randomly selected pixels. (a) 2022, (b) 2013, (c) 2002, (d) 1989; Figure S2: Spatial distribution of training and validation samples across environmental gradients: (a) soil moisture (cm^3/cm^3); (b) elevation (m a.s.l.); Figure S3: Examples of obvious misclassification of poplar plantations by six existing products; Table S1: Key parameters of six existing global high-resolution land cover products; Table S2: Confusion matrix for different schemes of this study and six existing products in different years.

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