Spatial–Temporal Patterns of Interannual Variability in Planted Forests: NPP Time-Series Analysis on the Loess Plateau

Nigenare Amantai 1, Yuanyuan Meng 1,*, Shanshan Song 1, Zihui Li 2, Bowen Hou 2 and Zhiyao Tang 1

Abstract: Investigating how the productivity dynamics of planted forests vary over time is important for understanding the resilience of forests against disturbance and for maximizing ecological restoration and replanting efforts. In this study, the patterns of interannual variability in net primary production (NPP) were analyzed for planted forests as indicated by the inverse of the coefficient of variation (ICV) time series at a ten-year moving window on the Loess Plateau, China, from 2000 to 2021. The spatial–temporal patterns were defined based on the increase or decrease trend obtained using the ordinary least squares method between abrupt change points performed by a Mann–Kendall test in an ICV time series, as follows: only one linear trend, increase (LI), and decrease (LD); at least two trends, increase firstly and decrease lastly (ID) and decrease firstly and increase lastly (DI); and other trends. The results showed that 82.74% of the ICV on the Loess Plateau displayed LD and ID patterns, indicating an increasing variability of forest productivity in this region. Overall, 73.83% of the ICV had a lower degree of rate decrease in the last phase than during the initial increase. Thus, the variability was in an early stage of increasing degree. The ICV time series showed an LI pattern in the eastern Gansu and the southern Shanxi, indicating a decreased variability, due partly to the improved forest restoration. When the plantation age was considered, the newly planted forests (less than 19 a) exhibited a decreasing variability, indicating the proactive role of forest management and restoration in averting environmental disruptions in dry environments.

Keywords: interannual variability; planted forest; spatial–temporal patterns; NPP time series; the Loess Plateau; inverse coefficient of variation

1. Introduction

The Chinese government has carried out a number of land-management programs, establishing enormous areas of forest and grassland to solve ecological issues on the Loess Plateau [1–3]. The major changes in forest coverage on the Loess Plateau do not immediately imply that ecosystem functioning is improved by greening [4–6]. Remotely sensed planted forest monitoring and analysis are necessary for establishing spatiotemporal patterns of ecosystem functioning on the Loess Plateau. The multispectral, structural, and phenological features of multi/hyper-spectral images were utilized to extract the discrete separability characteristics of the planted forests [7,8]. Furthermore, integrating time-series change detection can help to obtain attributes of the planted forests such as location, area, change time, growth conditions, and trends [9]. Moreover, the radar vegetation index is partly complementary to the information received from passive optical sensors for avoiding the effect of cloud cover and achieving higher classification accuracies [10]. The current planted forest mapping approaches provide the fundamentals for the analysis of the spatiotemporal patterns of planted forests with accurate and detailed spatial information in restoration regions.

Due to the ecological susceptibility and sensitivity caused by high aridity, significant human activity, and long-term soil erosion in this region, it is challenging for planted forest...
forests to survive and expand [11]. Recently, major changes in vegetation cover, ecosystem structure, and functions have occurred on the Loess Plateau [12]. The role of forests is expanding to include more ecosystem functions and services, rather than just offering vegetation cover, the original goal of afforestation projects in China [13].

The interannual variability of productivity under disturbance, a key sign of ecological stability, is often ignored by long-term trend observations [14–16]. In essence, the increase in variability appears to indicate a reduction in resistance or resilience or an increase in the vulnerability of vegetation growth to environmental changes [17,18]. The impacts of land-management initiatives have been studied using vegetation index indicators such as the normalized difference vegetation index (NDVI) and Net Primary Production (NPP) [19,20]. However, many studies have focused on the vegetation dynamics in northern China, pointing out a continuous greening trend on the Loess Plateau [21]. The annual total NPP in the vegetation restoration area of the Loess Plateau calculated based on the Carnegie–Ames–Stanford approach (CASA) showed a significant upward trend over the past 30 years (1985–2016) [22], while in 2006, the annual total NPP showed a significant mutation in the Loess Plateau, from 30 to 40% of the vegetation restoration area showing an NPP loss to only about 20% of the study area showing an NPP loss. Some studies report that NPP declines with age, or peaks at middle-age and then declines in old age [23,24], while others believe that NPP increases with stand age up to old-growth forests [25–27]. However, it is still unclear how the NPP and its interannual variability of planted forests would evolve over time. It is vital to investigate the spatial–temporal patterns of interannual variability of NPP in order to understand the resilience of planted forests under land management and climate change.

For the long term and on a wide scale, metrics created from satellite remote sensing data have been well established [28,29]. Prior research has often concentrated on the current state or monotonic trends of interannual variability [30,31]. However, it is necessary to capture the spatial–temporal dynamics of forest growth, especially before and after planting trees in a region with ecological restoration [32,33]. Recent studies have recommended the spatial–temporal analysis of interannual variability trends, as current TRENDY models cannot adequately represent the changing trends in the vegetation variability of an ecosystem’s productivity [34,35]. In this scenario, separating the trends in a time series to capture particular vegetation conditions or stages throughout time can help to assess changes in ecosystem functioning [36]. Analyzing spatial–temporal patterns at different time stages could reveal various variability dynamics of planted forests in more detail, which would benefit a better understanding of the patterns of historical trajectory in the successional process of planted forests. Additionally, plantation age also plays an important role in the development of ecosystem functioning [37–40]. The spatial–temporal patterns of trend variations allow for a spatial comparison among planted forests of different plantation ages.

In particular, ecosystem productivity serves as both a significant ecosystem service and a key measure of ecosystem functioning in planted forests [41]. It has been shown that NPP time series produced using Moderate Resolution Imaging Spectroradiometer (MODIS) products [42,43] are appropriate for quantifying the interannual variability of forests. This work aims to answer three novel questions: (1) What were the change laws and trends in the NPP dynamic from 2000 to 2021? (2) What are the spatial–temporal patterns of interannual variability of satellite-based NPP for the planted forests on the Loess Plateau? (3) How has the response of the interannual variability of NPP changed with varying plantation ages?

2. Materials and Methods

2.1. Study Area

The Loess Plateau spans from 34° to 40° N and 102° to 114° E in northern China, covering around 64 Mha (Figure 1). The region lies within an arid and semi-arid temperate climate zone, characterized by a mean annual precipitation of approximately 430 mm [44]. Of this, around 60% of the precipitation occurs during the summer months. The average
annual temperature is recorded at 9.02 °C, with a minimum average temperature of ~4.6 °C experienced during winter and a maximum average temperature of 20.9 °C observed in summer [44]. A total of 11.27% (7.13 Mha) of the Loess Plateau is covered with planted forests, most of which are densely distributed in the steep areas of the southeast [45]. The southeast–northwest 400 mm isohyet divides the Loess Plateau into two different zones [46]. Arid and semi-arid climatic patterns are highlighted by the continuous difference between annual potential evaporation and annual precipitation [44].

Figure 1. Geographic location and planted forest map of the Loess Plateau: (a) general location in China; (b) NPP data from the MODIS sensor on 1 January 2021 from Google Earth Engine (GEE) imagery; and the spatial distribution of (c) planted forest and (d) planting year.

2.2. Data Preparation

There are four main dataset we used in this study. The NPP product data of Modis, the planted forest data of the Loess Plateau, the soil conservation (SC) dataset and official statistic data of planted forests were also described in Table 1.

The MODIS yearly NPP package (MOD17A3) offers worldwide annual NPP from the MODIS sensor in near-real time [47]. The yearly NPP time series at a pixel resolution of 500 m was obtained from 2000 to 2021 using the Google Earth Engine (GEE) platform. The 8-day net photosynthetic products (MOD17A2H) from the given year were added up to create the NPP dataset (MOD17A3HGF V6 product) [48] (https://doi.org/10.5067/MODIS/MOD17A3HGF.006, accessed on 1 March 2023).

Our previous study produced the distribution and planting year data of the planted forests on the Loess Plateau (available at https://code.earthengine.google.com/?asset=users/mengyy225/landcovermapofLoessPlateau, accessed on 1 April 2023) [45]. These served as the foundation for an examination of the spatial–temporal patterns of the interannual variability of NPP. The distribution and planting year were rescaled to 500 m (in Figure 1c,d) using the majority algorithm via ArcGIS 10.5, in order to maintain the consistency of spatial resolution between the planted forest dataset and NPP dataset.

The soil conservation (SC) dataset in China was established from 1992 to 2019 at a 300 m resolution based on the Revised Universal Soil Loss Equation (RUSLE) model [49]. The dataset agrees with previous measurements ($R^2 > 0.5$ in all the basins) and other regional simulations. This dataset is available at https://doi.org/10.11888/Terre.tpdc.272668, accessed on 5 June 2023.
The official statistical data pertaining to the planted forests used in this study were sourced from the statistical yearbooks of the seven provinces (Henan, Gansu, Inner Mongolia, Ningxia, Shanxi, Shaanxi, and Qinghai) within the study area, as well as from the inventory data of China’s forest resources available on the website of the Forestry Knowledge Service System (http://lygc.lknet.ac.cn/, accessed on 5 June 2023). The statistical yearbooks can be accessed on the website of the National Bureau of Statistics of China (http://www.stats.gov.cn/, accessed on 5 June 2023).

Table 1. Summary of the datasets used in the analysis.

<table>
<thead>
<tr>
<th>Data</th>
<th>Source</th>
<th>Bands</th>
<th>Temporal Resolution</th>
<th>Spatial Resolution</th>
<th>Available Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPP</td>
<td>MOD17A3 [45]</td>
<td>Net primary productivity</td>
<td>Yearly</td>
<td>500 m</td>
<td>2000–2021</td>
</tr>
<tr>
<td>Planted forest</td>
<td></td>
<td>Soil conservation (SC)</td>
<td>Yearly</td>
<td>30 m</td>
<td>1986–2021</td>
</tr>
<tr>
<td>Soil conservation (SC) dataset</td>
<td></td>
<td></td>
<td>Average</td>
<td>300 m</td>
<td>2000–2020</td>
</tr>
</tbody>
</table>

2.3. Constructing Variability Time Series

The inverse coefficient of variation (ICV) was used to evaluate the interannual variability of NPP, with an increase in ICV indicating a decrease in interannual variability, and vice versa. To eliminate stochastic and deterministic trends, a second-order difference and the augmented Dickey–Fuller (ADF) [50] test were used to detrend NPP time series before calculating ICV [16].

In the arid and semi-arid regions, planted forests continue to grow despite ongoing climatic perturbations, and these effects will linger for a few years. Thus, the ICV dynamics over time, applying a ten-year moving window, were examined in the NPP time series from 2000 to 2021 to capture the change patterns in ecosystem variability. The ICV values of NPP over a given ten-year period were calculated and allocated to the last year of each window. This method produced a set of 13 ICV values. The interannual variability time series was constructed on the GEE platform.

\[
ICV = \left( \frac{\sigma}{\mu} \right)^{-1}
\]

where \(\mu\) represents the mean and \(\sigma\) represents the standard deviation of the original long-term time series of the NPP within the ten-year window, which were computed pixel by pixel.

2.4. Analyzing the Spatial–Temporal Patterns of Interannual Variability of NPP

The patterns in ICV time series were determined in order to understand the dynamics of interannual variability of the NPP. A sequential Mann–Kendall (MK) [51] test was used to identify the abrupt changes when the trend was not monotone and to determine the year in which the trend began. Additionally, this approach did not need the series to follow a particular distribution and was unsensitive to outliers [52,53]. There are two sets in this test: the forward-moving series, UF, and the backward-moving series, UB. The points where the UF and UB statistics overlap show the years in which the breakpoint emerges [54]. The MK test’s significance was evaluated at a confidence level of 0.05. Five ICV change patterns were established based on possible trends found with the ordinary least squares (OLS) method between abrupt changes in the ICV time series. An increasing or decreasing trend
is indicated by a positive or negative slope (K), with its value representing the rate of a trend. For the five ICV change patterns, the LI pattern is defined as an increasing linear trend; the LD pattern is defined as a decreasing linear trend; the ID pattern is defined as initially displaying an increasing trend, followed by any change trend or not, and ending with a decreasing trend; the DI pattern is defined as initially displaying a decreasing trend, followed by any change trend or not, and ending with an increasing trend; and when there is no trend, or the change trends are not regular when compared to another pattern, this is defined as an other pattern (Table 2). Additionally, the slope (K) was calculated as shown in Equation (2):

\[
K = \frac{\sum [(x - \bar{x})(y - \bar{y})]}{\sum (x - \bar{x})^2}
\]  

(2)

where \(x\) represents the time, with a value of 1 for the first year, 2 for the second year, and so on, \(y\) represents ICV, and \(\bar{x}\) and \(\bar{y}\) represent the mean values of \(x\) and \(y\), respectively.

Table 2. The spatial–temporal patterns of interannual variability identified by the OLS method, taking into account the abrupt changes.

<table>
<thead>
<tr>
<th>Change Patterns</th>
<th>Description</th>
<th>Graphs</th>
</tr>
</thead>
<tbody>
<tr>
<td>LI</td>
<td>One linear trend, increase</td>
<td><img src="image1" alt="Graph1" /></td>
</tr>
<tr>
<td>LD</td>
<td>One linear trend, decrease</td>
<td><img src="image2" alt="Graph2" /></td>
</tr>
<tr>
<td>ID</td>
<td>At least two trends, increase in the first trend and decrease in the last trend</td>
<td><img src="image3" alt="Graph3" /></td>
</tr>
<tr>
<td>DI</td>
<td>At least two trends, decrease in the first trend and increase in the last trend</td>
<td><img src="image4" alt="Graph4" /></td>
</tr>
<tr>
<td>Others</td>
<td>There is no trend, or the change trends are not regular</td>
<td><img src="image5" alt="Graph5" /></td>
</tr>
</tbody>
</table>

Note: The black line denotes the ICV time series, the blue and pink lines denote the UF and UB statistics, respectively, and the red and green lines denote the increasing and decreasing trends, respectively.

Finally, the slope of each trend phase of all change patterns was extracted using Python 3.7 to reflect the change rate of the variability of NPP. In addition, the ICV change patterns and slopes in the last trend phase for planted forests of different ages were analyzed to explore the response of the interannual variability of planted forest NPP patterns to plantation age on the Loess Plateau.
3. Results

3.1. Dynamic Characteristics of NPP before and after Planting

The NPP values in planted forests showed a significant increase, both in terms of total amount and mean value (Figure 2). Since 2009, the contribution of planted forests to the NPP of the entire Loess Plateau had surpassed that of natural forests, emerging as the primary driver of the NPP increase in the region (Figure 2c). The total amount of NPP in natural forests and its percentage relative to the total area have remained relatively stable (Figure 2c). However, the change per unit area in natural forests exhibited a significant increase, surpassing that of planted forests (Figure 2d).

The change trends of NPP values in the entire Loess Plateau, for planted forests and different provinces, are depicted in Figure 2e. The NPP values of the entire Loess Plateau and the planted forest both showed significant increase trends, with increasing rates of 68.45 and 92.88 gC/m²/year⁻¹, respectively. The increase rates of NPP varied across provinces. Among them, the NPP in Shaanxi Province increased the fastest, with a rising rate of 91.95 gC/m²/year⁻¹, followed by Gansu (81.08 gC/m²/year⁻¹), Shanxi (72.87 gC/m²/year⁻¹), Henan (53.23 gC/m²/year⁻¹), Ningxia (51.52 gC/m²/year⁻¹), Inner Mongolia (35.49 gC/m²/year⁻¹), and Qinghai (33.49 gC/m²/year⁻¹).

The rate of change and increment in NPP before and after the establishment of planted forests did not vary significantly. Nonetheless, in the context of the Loess Plateau region, both plantations and natural forests played pivotal roles in driving NPP increases across the entire region (Figure 3). The notable increases in NPP changes after plantation were concentrated primarily in Shanxi Province and Shaanxi Province. Natural forests also experienced significant NPP growth, particularly in Shaanxi Province, as well as in Ningxia (Figure 3). Planted forests have often been established in proximity to natural forests, leading to higher rates, amounts, and total NPP in the natural forest areas compared to other regions of the Loess Plateau.
3.2. Spatial–Temporal Patterns of Interannual Variability of NPP

Characteristics of the five change patterns in the ICV change of NPP time series are depicted in Figure 4. The ID pattern (46.07%) made up the majority of the planted forest, followed by the LD pattern (36.67%) (Figure 4a). The decreasing trend in the last phase of all these change patterns accounted for 82.74% of the planted forests, which indicated the overall increasing variability of NPP for the planted forests. From the Mu Us Desert in the northwest of the steppe and forest zone in the southeast of the Loess Plateau, the ID pattern was scattered in the ecotone between arid and semi-arid environments (Figure 4b). Only 9.43% of the planted forest, mainly concentrated in eastern Gansu and southern Shanxi, were covered by the LI pattern, revealing a decreasing variability of NPP (Figure 4a).

Figure 4. Characteristics of the five change patterns in the ICV change of NPP time series: (a) number and percentage, and (b) spatial distribution.
3.3. Change Rate of Planted Forest Variability

The slopes in the first phase of all ICV change patterns in the NPP time series were predominantly greater than 0 (Figure 5a), whereas the slopes in the last phase were predominantly less than 0 for the planted forests (Figure 5b). The changes from the first to the last phase occurred mainly at slopes between 0 and 0.05, −0.05 and 0, and −0.05 and −0.1 (Figure 5c), with 39.6% of the ICV patterns in NPP occurring invariably between −0.05 and 0, 34.23% (17.41% from 0 to 0.05, 9.29% from 0.05 to 0.1, and 7.53% from >0.1) and all change patterns changed to a slope of −0.05–0. This means that 73.83% of the ICV had a lower degree of decreasing rate in the last phase compared to the initial increase. Only 5.11% of the negative rate, which went from 0 to 0.05 to −0.05 to −0.1, exceeded the positive rate. In all change phases of five change patterns, ICV changed at an average slope of −0.0019 in the LD pattern and 0.006 in the LI pattern. The annual average slope for the ID pattern was 0.019 (Figure 5d).

3.4. Response of Variability Patterns of NPP to Plantation Age

The percentage of each ICV pattern for the planted forests of different ages did not manifest a distinction. The ID and LD patterns made up the majority and second largest proportions of the planted forest in the ICV time series (Figure 6a). The slopes in the last phase were primarily between 0 and −0.05 under different stand ages of planted forests (Figure 6b), indicating a relatively slow rate of increasing variability of NPP. Increasing slopes occurred almost exclusively for the planted forests below 19 a, which displayed decreasing variability (Figure 6b).

Figure 5. Change rate of planted forest variability: (a) slope of the first phase in all change patterns, (b) slope of the last phase in all change patterns, (c) chord diagram of slope from the first phase to last phase, and (d) raincloud and average of slope of all change phases in five change patterns.

Figure 6. Response of Variability Patterns of NPP to Plantation Age

The percentage of each ICV pattern for the planted forests of different ages did not manifest a distinction. The ID and LD patterns made up the majority and second largest proportions of the planted forest in the ICV time series (Figure 6a). The slopes in the last phase were primarily between 0 and −0.05 under different stand ages of planted forests (Figure 6b), indicating a relatively slow rate of increasing variability of NPP. Increasing slopes occurred almost exclusively for the planted forests below 19 a, which displayed decreasing variability (Figure 6b).
4. Discussion

4.1. Effects of NPP Variability in Planted Forests

Vegetation variability significantly impacts ecosystem security and services, as well as the terrestrial carbon cycle [55–57]. This study examined the spatial–temporal patterns of the interannual variability of productivity for planted forests and explored the response of the interannual variability of NPP to plantation ages on the Loess Plateau. By highlighting the location of decreasing and increasing patterns in ICV time series of productivity for the planted forests, this mapping can reveal dynamics of ecosystem functioning after planting trees on the Loess Plateau.

The NPP in planted forests showed a significant increase, and the contribution of planted forests to the NPP of the entire Loess Plateau has emerged as the primary driver in the region since 2009 (Figure 3). This finding is linked to the increase in NPP caused by new planting [3]. Significant increases in NPP were observed in Shaanxi and Gansu Provinces, owing to the ecological project of afforestation [58]. The areas where NPP decreased were mainly distributed in the northwestern region of the Loess Plateau (Mu Us Desert) [59].

It was found that the productivity of the majority of the planted forests became less stable (Figure 2a). It was accepted that as afforestation progressed under natural growth, the interannual variability would initially increase and then decrease or sustain as a result of the fact that the growth rate of trees changed from rapidly growing at younger stages to growing very slowly at older stages [60,61]. Indeed, most of the newly planted trees on the Loess Plateau are so young that they are in the period of rapid development, thus causing an increasing trend of variability. Even at the stand age, in more than 20a, the variability has not yet decreased or become stable and is still essentially changing at a rate of less than 0 in ICV patterns with growing stand age. Under persistent stress on the Loess Plateau, the variability of planted forest productivity still exhibits an increasing trend overall. Thankfully, 73.83% of the variability of planted forests showed an increasing rate in the last phase that was lower than the initial growing rate, indicating that the variability is in an early stage of increasing degree.

Arid and semi-arid ecosystems have been hypothesized to have a significant impact on the dynamics of global carbon sinks, despite the low proportions of planted forests in arid zones [62–64]. Therefore, it can be assumed that the observed increasing variability of planted forest productivity would have a significant influence on ecosystem functions [35]. Spatially, the ecotone between arid and semi-arid regions was where the ID pattern was normally found (Figure 2b). The ID pattern denoted at least two regular tendencies, with increasing stability at first but increasing variability later. Recent decreasing trends and frequent changes

Figure 6. Percentage of each pattern (a) and slopes in the last phase (b) for different stand ages of planted forests.
revealed the susceptibility of the planted forests. The vegetation in arid and semi-arid regions was more vulnerable to disruptions from the environment, similar to the findings of earlier research [65]. In contrast, the LI pattern of the ICV time series of NPP for the planted forests in areas such as eastern Gansu and southern Shanxi showed good signs of forest restoration. This decreased variability was distributed across most newly planted forests (less than 19 a in Figure 6b), indicating a proactive role for forest management and restoration in preventing environmental disturbances in dry environments. By preserving regions with decreasing variability as an acceptable reference and regions with increasing variability as essential conservation objects, this planted forests variability-based strategy might make regional forest restoration evaluations more affordable.

4.2. Insight Analysis, Limitations, and Directions of Future Studies

Based on the official statistical data of forest coverage rate, woodland area data, planted forest area, and the afforestation area of the year in different provinces in the study area, it was found that both the forest coverage rate and woodland area in the study area had an obvious upward trend. The forest coverage rate of Shaanxi Province and the forest area of Inner Mongolia increased the fastest (Figure A2). However, there was a gap between the remote-sensing-based planted forest data and the official statistical data, which may be due to the following reasons. The statistical data available were based on the sown area, whereas our data focused on the survival area after a few years [45]. It is important to note that the survival rate in semi-arid areas was naturally low [11, 66]. Additionally, the statistical data were reported at the provincial level, but our research area specifically covered the Loess Plateau, and not all provinces within this region were fully represented (Figure 1). Therefore, it was possible that the statistical data may not have provided a complete picture of our specific research area. Lastly, the department’s statistical documents cannot provide fully recorded information, since they depend heavily on the accessibility, remoteness, and ownership of forests [67].

There was a weak positive correlation between the change rate of planted forest NPP and slope, and the change rate of soil conservation ($p < 0.01$) (Figure A3). Steeper slopes often led to increased water runoff and soil erosion [68]. As a result, the planted forest NPP may have experienced a higher change rate due to the redistribution of water and nutrients. Grassland and shrubland with high ground cover were found to be effective in controlling surface runoff and soil erosion. In contrast, forestlands with poor ground cover were more susceptible to surface runoff and associated soil erosion [68]. If the planted forests on the Loess Plateau primarily consisted of forestlands with inadequate ground cover, it could explain the weak positive correlation between the change rate of NPP, slope, and soil conservation. Factors such as tree species selection, planting density, and maintenance activities could also have affected the ground cover, NPP, and soil conservation outcomes. It is important to note that these explanations are speculative and require further investigation and analysis to establish their validity.

The variability in productivity for planted forests in different temporal phases would have significant impacts on the dynamics of ecosystem functions. It should be emphasized that this study has a few significant components that call for more consideration. First, the spatial–temporal patterns of interannual variability of NPP were examined only through the consistency attribute of variability over a 21-year period. Consideration must be given to patch-based dynamics and multi-dimension metrics of time-series analysis in order to assess the other ecosystem functions [31]. Second, although this study focused on the spatial–temporal patterns of the interannual variability of productivity, it is unknown what causes these patterns to shift. Therefore, further research integrating climatic and human variables (i.e., climate, land use, and CO$_2$ fertilization) is required to fully understand the mechanisms underlying the variability of productivity for planted forests [28, 69].
5. Conclusions

This study concentrated on uncovering spatial–temporal patterns in the interannual variability of productivity for planted forests and exploring the response of the variability patterns to stand ages. The interannual variability of planted forest productivity on the Loess Plateau appears to be increasing, as 82.74% of the ICV time series showed LD and ID patterns. Additionally, 73.83% of the variability of planted forests had an increasing rate degree in the last phase that was lower than the initial increasing rate degree, indicating that the variability is in an early stage of a generally increasing degree. The forest restoration was better in the eastern Gansu and southern Shanxi provinces, where the variability in planted forests showed a decreasing pattern (LI pattern in ICV time series). This decreasing variability was mainly dispersed among regions where trees had just recently been established (less than 19 a), demonstrating the important role of forest management and restoration in minimizing environmental disruptions in arid environments. This ecosystem functional variability-based approach may reduce the cost of regional forest restoration evaluations by maintaining regions with increasing variability as necessary for conservation, and regions with decreasing variability as acceptable references.

Author Contributions: Conceptualization, Y.M. and Z.T.; Methodology, N.A., Y.M. and B.H.; Resources, Y.M.; Data curation, Z.L. and B.H.; Writing—original draft, N.A. and Y.M.; Writing—review & editing, N.A., Y.M., S.S. and Z.T.; Visualization, N.A., Z.L. and Y.M.; Funding acquisition, Z.T. All authors have read and agreed to the published version of the manuscript.

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

Appendix A

Figure A1. Stand age histogram of planted forests.
Figure A2. The official statistics of forest coverage rate (a), woodland area (b), planted forest area (c), and afforestation area of the year (d) in different provinces. Additionally, remote-sensing-based data of the planted forest area (e), and afforestation area of the year (f) in different provinces.

Figure A3. Correlation coefficients between change rate of planted forest NPP and slope (a), and change rate of soil conservation (b).


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