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Spatial variation and influencing factors of the effectiveness of afforestation in China's Loess Plateau

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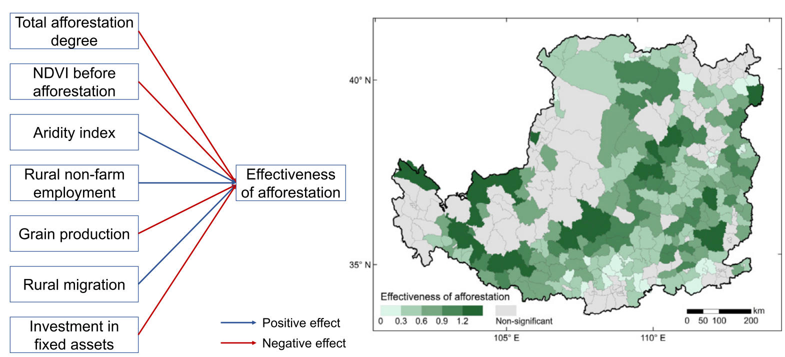
HIGHLIGHTS

- We assessed the county-level effectiveness of afforestation in the LP.
- We analyzed the spatial variation in afforestation effectiveness.
- We identified metacoupled factors that affected afforestation effectiveness.
- Our results suggest ways to improve afforestation design and implementation.

GRAPHICAL ABSTRACT



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ABSTRACT

Payment for ecosystem services (PES) has become a widely accepted strategy for combining environmental conservation or restoration with socioeconomic development. Understanding the spatial heterogeneity of the effects of PES programs and their influencing factors is necessary for the design and implementation of effective programs. However, few researchers have both distinguished the effects of PES and analyzed their spatial variation simultaneously. Here, we analyzed the spatial differences in the effectiveness of afforestation under China's Grain-to-Green Program (GTGP), a well-known PES program, in the Loess Plateau. The approach is based on remote sensing data and county-level statistical data, which reflects the basic implementation unit of the GTGP. We identified several local and non-local influencing factors: the aridity index, rural non-farm employment, and rural migration improved afforestation effectiveness, whereas the total afforestation degree (the cumulative area of afforestation divided by the total area), vegetation conditions before afforestation, grain production, and investment in fixed assets decreased its effectiveness. Based on our results, we propose several suggestions for improvement: preferring afforestation in humid counties with low vegetation cover, identifying an optimal degree of afforestation, and promoting the transformation of rural livelihoods. Our study provides a general approach to analyze the effectiveness of PES and its spatial variation, thereby providing insights into future PES programs both within China and around the world.

Abbreviations: GDP, gross domestic product; GTGP, Grain-to-Green Program; LP, Loess Plateau; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, normalized-difference vegetation index; PES, payment for ecosystem serveries.

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1. Introduction

Land use and land cover changes due to human activities have caused environmental degradation and biodiversity loss around the world (Newbold et al., 2015; Vitousek et al., 1997). To address the trade-offs between ecosystem conservation and socioeconomic development, researchers and land managers have proposed the use of payment for ecosystem services (PES), which exchange value for land management that will protect or increase the provision of ecosystem services (Salzman et al., 2018). This has become a popular paradigm in environmental governance and conservation in the past two decades (Wunder et al., 2018). PES represents an innovative economic intervention to protect biodiversity and ecosystem functions while also accounting for the needs of residents of program areas, and has been implemented at local, regional, and national scales with a focus on watershed ecosystem services, biodiversity and habitat, and the effects of forests and land-use change on carbon sequestration (Salzman et al., 2018; Wunder et al., 2018). Since billions of dollars are being invested in PES annually around the world (Salzman et al., 2018), there is considerable interest in improving analytical methods and our understanding of the outcomes of PES programs (Yang and Lu, 2018).

Assessing the performance of PES in terms of ecological effectiveness, economic efficiency, and social equality, and identifying the factors that influence this performance, can help planners to improve the design and implementation of PES and enhance the desired benefits (Lü et al., 2020). Thus, this has become a major research focus of PES studies (Salzman et al., 2018; Yang and Lu, 2018). Numerous studies have analyzed the ecological and socioeconomic changes after the implementation of PES programs and have assessed the degree to which these changes were attributable to PES, after accounting for other relevant factors (Ouyang et al., 2016; Tallis et al., 2008; Viña et al., 2016). Some studies have assessed or tried to enhance the efficiency of certain PES programs through cost–benefit analysis (Chen et al., 2010; Zheng et al., 2013).

To identify and understand the influencing factors that determine the effects of PES, researchers have analyzed the program characteristics that may affect the success of a given PES scheme, such as the ecosystem services being traded, the scale, the transaction types, and the actors involved. This has been done through comparative analysis of different case studies at continental or national scales (Grima et al., 2016; Sattler et al., 2013). In addition to the characteristics of a PES program, the program's specific impacts are affected by multiple socioeconomic, political, and environmental factors (e.g., economic development, industrialization, and urbanization) that operate concurrently and that vary spatially (Bryan et al., 2018; Liu, 2014). Thus, the effects of a given PES program may vary among areas (Li et al., 2017; Wunder et al., 2018). However, there have been few studies of how these metacoupled processes, which involve human–nature interactions within and across adjacent and distant places (Liu, 2017), affect the effectiveness of PES programs.

Forests provide multiple ecosystem services (e.g., carbon sequestration, biodiversity conservation, pollination, protection of soil and water resources), and therefore play an important role in achieving the United Nations Sustainable Development Goals (FAO, 2016), and thus PES programs related to forests have received a considerable attention (Salzman et al., 2018). Many international initiatives (e.g., the Bonn Challenge) have established ambitious targets to promote forest conservation, afforestation, and forest restoration at a global scale (Bastin et al., 2019).

Forest-related PES has also become a central part of China's national environmental protection strategies (Salzman et al., 2018). After several major droughts and floods in the late 1990s, the Chinese government realized that deforestation threatened the nation's ecological security, and implemented a series of PES programs to address these environmental crises while simultaneously promoting rural development (Liu et al., 2008). These programs include the Three-North Shelter Forest Program, the Natural Forest Conservation Program, and the Grain-to-Green Program (GTGP). Among these, the GTGP is one of the largest PES programs in the world and has global implications because it increases vegetation cover, enhances carbon sequestration, and controls soil erosion, while simultaneously addressing socioeconomic challenges (Liu et al., 2008; Wu et al., 2019b). Under the GTGP, cropland on steep slopes was converted to forest and grassland, and more than 120 million farmers and 30 million households were involved by 2009 (Ouyang et al., 2016). Previous assessments found that most ecosystem services increased after implementation of the GTGP (Lu et al., 2012; Ouyang et al., 2016). The restoration effectiveness was also analyzed based on the trends for vegetation cover and productivity at regional and national scales (Li et al., 2017; Lü et al., 2020). However, as the degree of participation in the GTGP varied across China, considering only the vegetation trends by comparing vegetation cover before and after the GTGP may not reflect the actual contribution of the program. Thus, studies that distinguish the ecological effects of the GTGP and analyze their spatial variation and metacoupled influencing factors are needed.

In the present study, we focused on China's Loess Plateau (LP), a region where the GTGP has been most intensively implemented (Wu et al., 2019a). Much of this area used to experience severe soil erosion, and the transported sediments have affected downstream reaches and river deltas (Chen et al., 2015). Our objective was to analyze the differences in the effectiveness of afforestation and the influencing factors that determine the effectiveness at a county level, which represents the basic design and implementation unit of the GTGP. To do so, we first developed an approach to assess the effectiveness of afforestation based on a time series for the normalized-difference vegetation index (*NDVI*) and the degree of afforestation. We selected several factors that could affect the effectiveness of afforestation based on the metacoupling framework (Liu, 2017). We then quantified the relationships between the effectiveness of afforestation and these factors. By identifying the crucial factors that most strongly determined the effectiveness of afforestation, we provide guidance on how to improve the design, implementation, and sustainability of the GTGP, thereby providing insights for other PES programs in China and around the world.

2. Materials and methods

2.1. Study area

The LP, which is the world's largest and deepest loess deposit (Fu et al., 2017), comprises more than 300 county-level regions in seven Chinese provinces and covers 640,000 km^2 (Fig. 1). It lies within the Asian continental monsoon region, where the average annual precipitation is approximately 400 mm, increasing from the northwest to the southeast (Fu et al., 2017). Evaporation accounts for 85% of the precipitation, making this region a typical water-limited landscape (Feng et al., 2016). Inappropriate agricultural management in the past has caused severe environmental degradation, particularly in terms of vegetation loss (Fu et al., 2017; Wu et al., 2020). The plateau's fine-textured soils are highly vulnerable to erosion when they are exposed, and when this is combined with periodic high-intensity rainstorms and decreased vegetation cover, it has caused serious soil erosion in the LP, making it the largest sediment source for the Yellow River (Wang et al., 2015). This region was notorious for its environmental deterioration, high population pressure, and poverty of local farmers for a long time (Fu et al., 2017).

To address these issues, China's national government implemented several land management programs to restore the environment (Lu et al., 2012) and promote sustainable rural development (Daily et al., 2013). The GTGP is the largest and best known of these programs (Liu et al., 2008). It was implemented in Shaanxi and Gansu provinces as pilot regions in 1999 and then expanded to all seven provinces in the LP in 2000. Under the GTGP, more than 45 billion yuan (US\$1 = 6.10 yuan in 2014) was invested in Shanxi, Shaanxi, and Ningxia provinces, which make up the main part of the LP, by 2014. A total area of

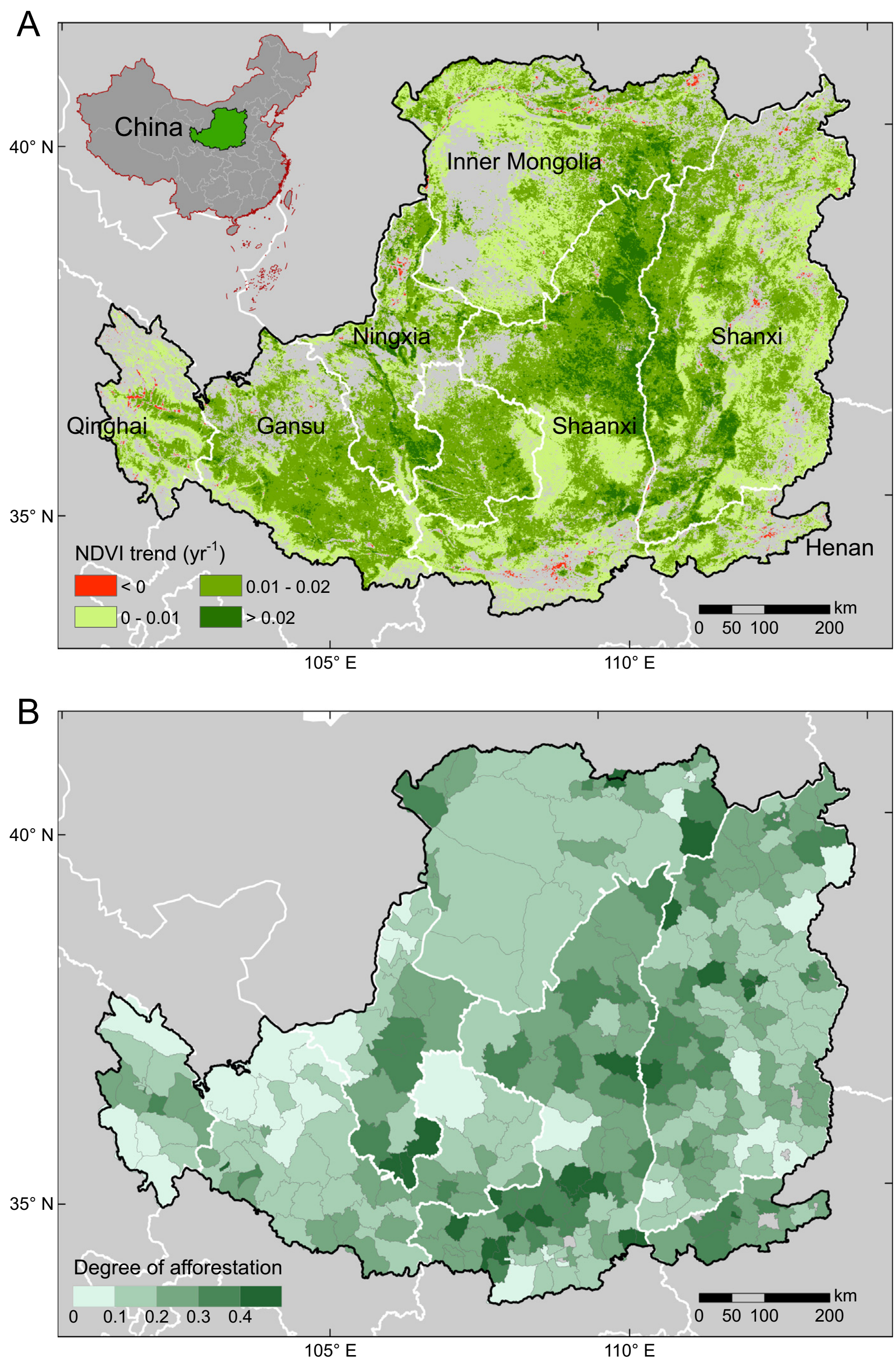

Fig. 1. Study area. A, Map of regions in which the normalized-difference vegetation index (*NDVI*) has changed significantly ($p < 0.05$) from 2000 to 2015. B, Map of the total degree of afforestation (the cumulative area of afforestation divided by the total area) in each county from 2002 to 2014.

47.93×10^3 km^2 underwent afforestation in the three provinces, of which 62.7% represented afforestation on barren land and 33.4% returned cropland to forest (Wu et al., 2019a). Previous studies found that provision of the main ecosystem services increased after the implementation of the GTGP (Lu et al., 2012; Wu et al., 2019a), and that the socioeconomic effects were mostly positive (Li et al., 2011; Liu et al., 2008).

2.2. Data sources

The data used in our analysis include *NDVI* data, climate data, GTGP statistics, and socioeconomic data. We obtained the *NDVI* data from the Moderate Resolution Imaging Spectroradiometer (MODIS) dataset, which was obtained from the National Aeronautics and Space Administration Earth Observing System (http://modis.gsfc.nasa.gov). The spatial resolution was 1 km × 1 km, and the time interval was 16 days. We determined the annual *NDVI* from 2000 to 2015 in each pixel by the maximum-value-composite method to reduce the effects of cloud and haze contamination (Holben, 1986), and summarized these values at a county level. Annual temperature and precipitation data from 2003 to 2015 were obtained from the National Meteorological Administration of China (http://data.cma.cn) and were interpolated to cover the entire LP based on data from 172 stations within and near the LP, then were summarized at a county level. The annual afforestation areas from 2002 to 2014 in each county were collected from the Chinese Forest

Statistical Yearbook (www.forestry.gov.cn). The cumulative afforestation degree of each county in a given year was derived as the ratio of cumulative afforestation area to the total county land area. We obtained the following socioeconomic statistics for each county from 2003 to 2015: per capita gross domestic product (GDP); per capita net income of rural households; number of rural laborers; number of rural employees employed in farming, forestry, animal husbandry, and fisheries; output of grain crops; livestock number; consumption of chemical fertilizer; and total investment in fixed assets (e.g., infrastructure). The data were obtained from the Statistical Yearbook of each province and prefecture, which was accessed from the Loess Plateau Data Center website (http://loess.geodata.cn). We obtained population data for each county in 2010 from the 6th national census (www.stats.gov.cn).

2.3. Assessment of the effectiveness of afforestation

We chose *NDVI* as the indicator of the ecological effect of afforestation, as vegetation conditions can influence the environment both directly and indirectly through their effect on the carbon cycle (Feng et al., 2013), as well as affecting the regional hydrology (Li et al., 2018) and soil erosion (Fu et al., 2011). We chose the regression coefficient between *NDVI* and the cumulative afforestation degree to represent the effectiveness of afforestation in each county, because it can be interpreted as the change in *NDVI* per unit change in the cumulative afforestation degree. Because vegetation conditions are mainly affected by climate and revegetation activities (Lu et al., 2015), the effect of afforestation was calculated as follows:

$$NDVI_{i,t} = \alpha + \beta_{1i} CFD_{i,t-1} + \beta_{2i} Pre_{i,t} + \beta_{3i} Tem_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $NDVI_{i,t}$ refers to the annual *NDVI* of county i in year t ($t = 2003$, 2004, …, 2015); α refers to the intercept of the dependent variable; β_{1i} refers to the effectiveness of afforestation in county i; $CFD_{i,t-1}$ refers to the cumulative afforestation degree of county i in year $t-1$; $Pre_{i,t}$ and $Tem_{i,t}$ refer to the annual precipitation and temperature, respectively, of county i in year t; and $\varepsilon_{i,t}$ refers to the residuals.

Only the counties with a statistically significant ($p < 0.05$) regression coefficient β_{1i} were selected for further analysis. To account for autocorrelation, which involves similarity of a time series over successive time intervals and can lead to underestimation of the stand error and incorrect determination of statistical significance, we used the Durbin–Watson test to detect the presence of autocorrelation in the residuals from the regression analysis of each county and excluded the counties with significant autocorrelation. A total of 214 counties with significant β_{1i} and no autocorrelation remained.

2.4. Selection of metacoupled factors that affected the effectiveness of afforestation

After estimating the effectiveness of afforestation at a county level, we wanted to identify which factors had the strongest effect. To do so, we first selected several potential influencing factors (listed in Table 1) based on previous studies and the metacoupling framework. We then performed correlation analysis (Pearson's r) and multiple linear regression to identify significant relationships between these factors and the effectiveness of afforestation. Previous studies found that economic development, urbanization, the rural economy, and demographic changes were the main factors that influenced large-scale vegetation restoration (Bryan et al., 2018; Cao et al., 2014; Li et al., 2017). The metacoupling framework has been widely used to study many important issues such as the impacts of trade on the UN Sustainable Development Goals (Liu et al., 2018; Xu et al., 2020), socioeconomic effects of PES programs, and global marine fisheries (Carlson et al., 2020). It can uncover hidden systemic connections that may not be found while focusing only on a particular system (Liu, 2017). Based on this framework, the influencing factors can be divided into local and non-local factors.

The local factors refer to factors within the local study area (here, a county), and include socioeconomic factors such as the local economy of the county, income of rural households, rural population density, rural non-farm employment, grain production, livestock numbers, and environmental factors such as the aridity index. We used the average value of these factors from 2003 to 2015 for each county in our analysis. The *NDVI* value before afforestation and the total afforestation degree during the whole study period were also analyzed. The non-local factors include agricultural technology, investment in fixed assets, and rural migration. Due to limitations on data availability at a county level, it was difficult to distinguish whether the destination of rural migration was within or outside the source county, and whether the sources of investment and agricultural technology came from within or outside the county. Thus, we treated these variables as non-local factors. Table 1 summarizes the indicators for each factor. The variance inflation factor of each independent variable was less than 5.5, which means that the level of multicollinearity was acceptable.

Except for the 214 counties with significant afforestation effectiveness, a total of 105 counties showed non-significant afforestation

Table 1
Variables used in the analysis, and the county-level mean and standard deviation (SD).

	Description	Mean	SD
Dependent variable			
Effectiveness of afforestation	Regression coefficient for the relationship between the normalized-difference vegetation index (*NDVI*) and the cumulative afforestation degree	0.739	0.470
Independent variables			
Total afforestation degree	The ratio of the cumulative afforestation area from 2002 to 2014 to the total area of each county	0.253	0.129
NDVI before afforestation	Average annual *NDVI* from 2000 to 2002	0.649	0.144
Aridity index	Average value of the ratio of the annual precipitation to the potential evapotranspiration from 2003 to 2015	0.562	0.133
Local economy	Average per capita gross domestic product (GDP) from 2003 to 2015 ($\times 10^4$ yuan)	2.588	2.596
Income of rural households	Average annual per capita net income of rural households from 2003 to 2015 ($\times 10^3$ yuan)	5.186	2.141
Rural population density	The ratio of the average rural population from 2003 to 2015 to the total area of each county ($\times 10^3$ individuals/km^2)	0.175	0.138
Rural non-farm employment	Average value of the ratio of the number of rural non-farm work laborers to the total number of rural laborers in the county from 2003 to 2015	0.378	0.122
Grain production	The ratio of average grain production from 2003 to 2015 to the total area of each county (tonnes/km^2)	89.895	81.830
Livestock number	The ratio of average livestock numbers from 2003 to 2015 to the total area of each county (sheep units/km^2)	74.033	75.407
Rural migration	(Population of agricultural registered permanent residents −rural population)/population of agricultural registered permanent residents in 2010	0.256	0.141
Investment in fixed assets	Average total investment in fixed assets from 2003 to 2015 ($\times 10^9$ yuan)	5.977	5.592
Agricultural technology	The ratio of average consumption of chemical fertilizer from 2003 to 2015 to the total area of each county (tonnes/km^2)	13.998	19.553

effectiveness. To discuss why the afforestation was not successful in these counties, we used the Kruskal–Wallis test to analyze the differences in the influencing factors between counties with significant afforestation effectiveness and counties with non-significant afforestation effectiveness. The Kruskal-Wallis test is a widely used non-parametric method for testing whether there are statistically significant differences between groups of an independent variable on a continuous dependent variable (Kruskal and Wallis, 1952).

3. Results

3.1. The effectiveness of afforestation on the LP

The average annual MODIS *NDVI* on the LP increased significantly ($p < 0.001$), from 0.538 in 2000 to 0.655 in 2015, with a slope of 0.010 yr^{-1}. Most areas experienced significant greening, with only a few pixels in urban areas that showed decreasing annual *NDVI* (Fig. 1A). From 2002 to 2014, 12.8×10^6 ha was afforested, accounting for 20% of the plateau's total area (Fig. 1B).

Although the *NDVI* increased with afforestation, the effectiveness of afforestation differed among the counties (Fig. 2). We found that the effectiveness of afforestation, which was calculated as the regression coefficient for the relationship between *NDVI* and the cumulative afforestation degree, was significant in 214 of 319 afforestation counties. The average effectiveness of afforestation in these counties was 0.739, which means that if all of a county is afforested, the *NDVI* would increase by 0.739.

3.2. Metacoupled factors that affected the effectiveness of afforestation

Several metacoupled factors, including both local and non-local socioeconomic and environmental factors, affected the effectiveness of afforestation (Table 2). These factors explained a total of 57.8% of the variance.

Among the significant factors, the total afforestation degree and *NDVI* before afforestation were both significantly negatively related to the effectiveness of afforestation ($p < 0.001$), which means that the effect of afforestation was lower in counties with a higher afforestation degree and higher *NDVI* before afforestation. The aridity index was significantly positively related to the effectiveness of afforestation ($p < 0.05$), indicating that the effectiveness of afforestation was higher in more humid counties. Of the local socioeconomic factors, rural non-farm employment had a marginally significant positive impact on the effect of afforestation ($p < 0.10$), whereas grain production had a significant negative impact ($p < 0.05$), which suggests that the effect of afforestation was higher in counties where rural households had higher non-farm employment and relied less on grain production. In terms of non-local factors, rural migration had a marginally significant positive effect on the effectiveness of afforestation ($p < 0.10$), whereas investment in fixed asserts had a marginally significant negative impact ($p < 0.10$), meaning that counties with higher rural migration and less investment in fixed assets tended to have higher afforestation effectiveness.

4. Discussion

Understanding the spatial heterogeneity of the effect of PES programs and its influencing factors is necessary for the design and implementation of effective PES programs (Li et al., 2017). Using the regression coefficient between the *NDVI* time series and the cumulative afforestation degree, we developed an approach to assess the county-level effectiveness of afforestation and quantify the relationship between this effectiveness and multiple metacoupled factors. We found that the total afforestation degree, *NDVI* before afforestation, aridity index, and grain production significantly affected afforestation effectiveness, and that rural non-farm employment, rural migration, and investment in fixed assets had a marginally significant effect on the effectiveness of afforestation. Previous studies of the relationship between PES programs and social or ecological changes that analyzed

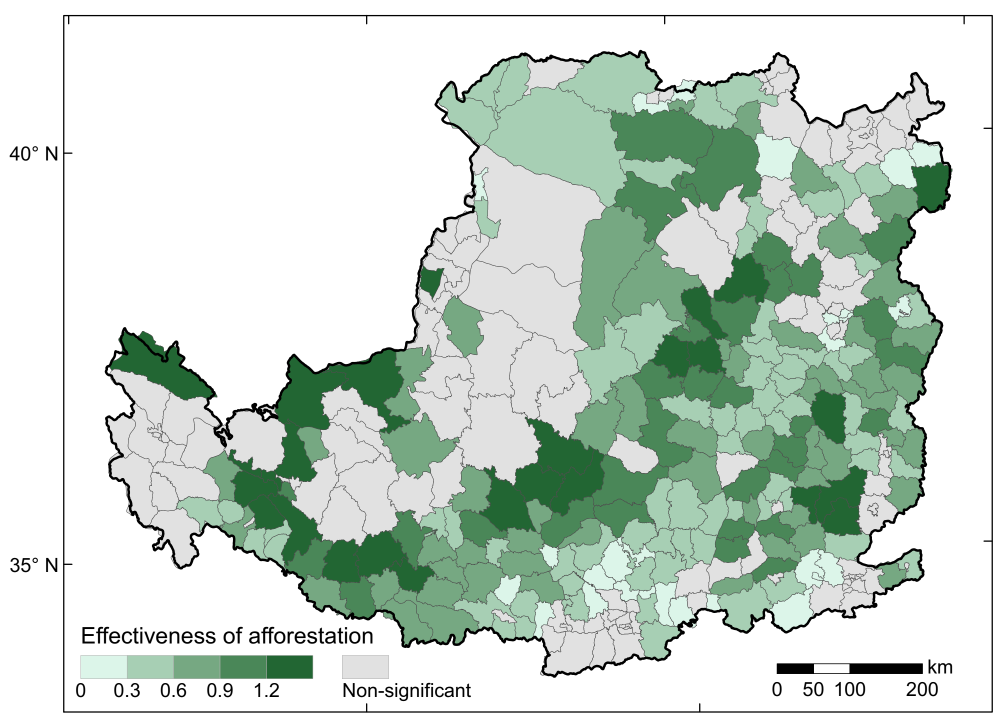

Fig. 2. The effectiveness of afforestation in different counties in the Loess Plateau.

Table 2
Relationships between the effectiveness of afforestation and the metacoupled factors.

	Standardized regression coefficient
Total afforestation degree	−0.670***
NDVI before afforestation	−0.487***
Aridity index	0.237*
Local economy	−0.078
Income of rural households	−0.066
Rural population density	0.127
Rural non-farm employment	0.099†
Grain production	−0.223*
Livestock number	0.015
Rural migration	0.102†
Investment in fixed assets	−0.132†
Agricultural technology	0.003
R^2	0.578

*** $p < 0.001$.
* $p < 0.05$.
† $p < 0.10$.

the effect of these programs focused on a single spatial extent (Ouyang et al., 2016; Viña et al., 2016). Thus, they were able to identify the contribution of the PES programs but could not define spatial differences in their effects. In contrast, other studies that used trends of vegetation cover and productivity in different areas to represent PES effectiveness (Li et al., 2017; Lü et al., 2020) were able to analyze the spatial differences in PES effectiveness, but could not identify the actual contribution of the PES program. In the present study, we were able to perform both analyses by combining remote sensing data (*NDVI*) with county-level statistical data over a long time period. Compared with the first type of studies (Ouyang et al., 2016; Wu et al., 2019a), our study not only shows that afforestation contributed to the increase in NDVI, but also indicates that effectiveness of afforestation varied across space and was even non-significant in some counties. Compared with the second type of studies (Li et al., 2017; Lü et al., 2020), our study also shows that socioeconomic and environmental factors were important for improving the effectiveness of afforestation, but the indicator used in our study is more rational and reflects the contribution of afforestation. This simple but efficient approach can be modified and applied in future studies of the spatial variation of the impact of PES programs on multiple ecosystem services, such as carbon sequestration, soil conservation, and water retention.

The use of metacoupled factors to explain the differences in the effectiveness of afforestation at a county level revealed some processes that would not have been apparent when focusing only on specific influencing factors within a given county. We found that afforestation effectiveness decreased as the afforestation degree and *NDVI* value before afforestation increased. This is because the growth and distribution of vegetation on the LP are affected by geological conditions (Zhao et al., 2015) and by soil chemical and physical characteristics (Cao et al., 2007), especially in the hilly portions. Less suitable lands for afforestation remained in counties with a high cumulative afforestation degree and good vegetation conditions before afforestation, resulting in a low effectiveness of afforestation. Climate also affects the growth of vegetation (Cao et al., 2007). There is not enough available water to maintain normal tree growth rates in some arid areas; as a result, some planted trees are only about 20% of their normal height and are colloquially referred to as “little old man trees” (McVicar et al., 2007). This explains why the effectiveness of afforestation was higher in more humid counties. We also found that the effectiveness of afforestation increased with increasing rural non-farm employment and decreasing grain production. This is because the pressure on the land to provide livelihoods would decrease as more laborers worked outside of agriculture and as the reliance on grain production decreased (Bryan et al., 2018), and this would enhance the restoration effectiveness. However, the decrease of grain production in one region may cause spillover effects in other regions and put more pressure on the land in these regions (Liu, 2014). The marginally significant positive impact of the non-local factor “rural migration” on afforestation effectiveness is consistent with previous studies in Inner Mongolia and southeast China (Li et al., 2016; Wang et al., 2011), and can be explained by the reduction of pressure on the land. The negative effect of investment in fixed assets on afforestation effectiveness may be because the investment promoted infrastructure construction, industrial development, and urban expansion, which have been found to negatively affect vegetation in ecologically fragile regions (Chen et al., 2003; Su et al., 2014). These metacoupled factors can also partly explain why the afforestation was not successful in some counties. We found that the climate was drier and socioeconomic factors (e.g., local economy and investment in fixed assets) were higher in the counties with non-significant afforestation effectiveness (Fig. 3). The constraint of climate and influence of socioeconomic development, combined with the lower total afforestation degree in these counties, may lead to the non-significant afforestation effectiveness. The quantitative influences of each factor still need further research.

Our analysis suggests that the design, implementation, and effectiveness of the GTGP could be improved based on the improved understanding of the relationships between afforestation effectiveness and the metacoupled factors. First, the selection of counties for afforestation should consider both the climate conditions and vegetation conditions before choosing afforestation, since afforestation was more effective in humid counties with less vegetation cover. Alternatives such as grassland restoration may be more appropriate in areas that are too dry for trees. Second, the effectiveness of afforestation per unit degree decreases with increasing total afforestation degree, determining the optimal degree of afforestation will require additional research that aims to balance the ecological efficiency and total ecological effect and balance environmental protection and socioeconomic development (Chen et al., 2015). Third, the effectiveness of afforestation could be improved by addressing some metacoupled processes during the implementation period. For example, the local governments and policy makers should create more non-farm jobs (Cao et al., 2011) and provide skills training to help rural laborers qualify for new jobs (Yang et al., 2018). This could facilitate the transfer of surplus rural labor to urban industries that require more skilled workers and promote a structural adjustment of production, thereby releasing pressure on the land to provide a livelihood. Barriers to rural labor migration should be overcome by offering equal job opportunities and information services of employment for migrant rural workers in urban areas (Yang et al., 2018; Yin et al., 2014). However, the rural-to-urban migration may cause other associated problems like environmental issues and disparities in medical care and education (Gong et al., 2012), which need more systematic and comprehensive solutions. In addition, the role of development policies in forest conservation, the impacts of conservation policy, and their interactions need further research (Börner et al., 2020).

Our study has several limitations. First, due to limitations on data availability, we used the ratio of cumulative afforestation area to total area to represent the afforestation degree. However, the details of afforestation, such as differences in the tree species planted and in vegetation management, are not reflected in this approach, even though they will have strong impacts on effectiveness. Second, the *NDVI* reflects not only the conditions of the trees, but also other vegetation types such as grassland and shrubland. However, only the afforestation area data are available. A similar problem results from the difficulty of excluding areas restored under non-GTGP programs from areas that were only restored under the GTGP. Our method should be revised to account for these differences. Third, some small-scale factors such as microtopography (Zhao et al., 2015) and soil characteristics (Cao et al., 2007) will also affect the afforestation effectiveness, but cannot be analyzed at a county scale. For example, afforestation will have different effectiveness in flat and hilly terrain and in land with different severities of degradation. These problems may influence the accuracy of our estimates. More research will be needed at a smaller scale using observational data collected at that scale.

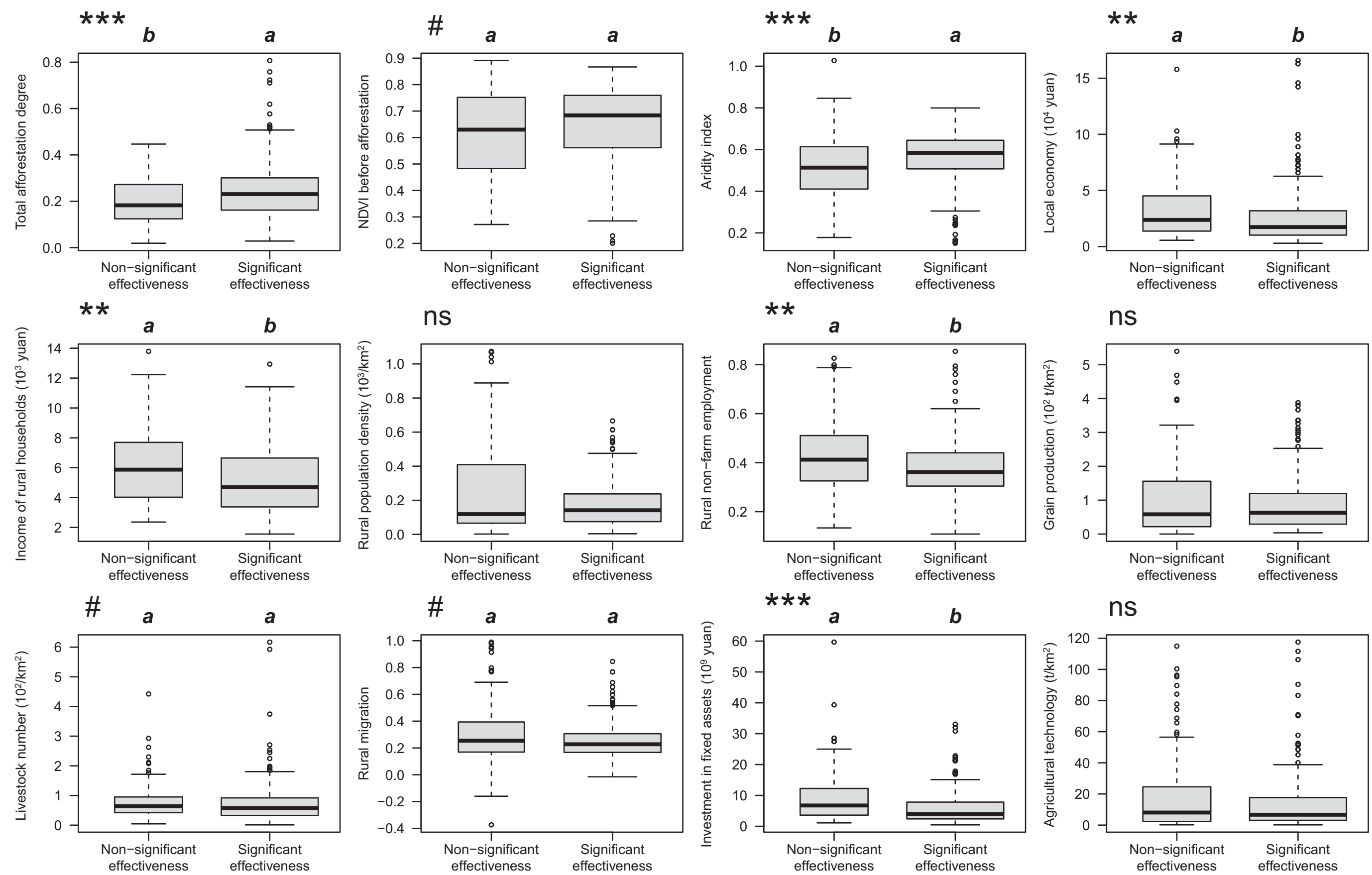

Fig. 3. Comparisons of the metacoupled influencing factors between counties with significant afforestation effectiveness and counties with non-significant effectiveness. Boxplots with different letters at the top differ significantly: ns, non-significant; #, $p < 0.10$; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$.

In conclusion, our new approach let us assess the effectiveness of afforestation at a county level based on a time series of data for *NDVI* and the cumulative afforestation degree, and let us reveal its spatial variation on the LP. In addition, we identified several metacoupled factors that were responsible for this variation. Our findings revealed several suggestions for improving the design, implementation, and effectiveness of the GTGP. Because the approach should be easily generalized, it can be used to analyze the effectiveness of PES and its spatial variation in other PES programs both within China and around the world.

CRediT authorship contribution statement

Xutong Wu: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Shuai Wang:** Conceptualization, Writing – review & editing. **Bojie Fu:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **Jianguo Liu:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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