Assessing the ecological effectiveness of payment for ecosystem services to identify priority areas and vegetation restoration modes: A case study of the Sloping Land Conversion Programme in the Northern Shaanxi Loess Plateau, China

Zhenmin Ding, Shunbo Yao

Centre for resource economy and environmental management, Northwest A & F University, Yangling, Shaanxi, China

Corresponding author: *yaosunbo@163.com (Yao, S)*

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Abstract: Identifying priority areas and vegetation restoration modes is important for alleviating the conflicting demands for water between the ecosystem and humans based on the ecological effectiveness of payment for ecosystem services (PES) in arid or semi-arid areas. This study uses the treatment effect model to estimate the marginal contribution of Sloping Land Conversion Programme (SLCP) in the Northern Shaanxi Loess Plateau towards greater vegetation cover in the Northern Shaanxi Loess Plateau, including conversion of farmland to forestland (CFF) and conversion of farmland to grassland (CFG). In addition, we build a relative advantage index (RAI) to identify priority areas and vegetation restoration modes based on an assessment of the PES` ecological effectiveness. The RAI can identify priority areas and vegetation restoration modes. Furthermore, the areas with a RAI of more than 1 qualify for afforestation reach 11460 km^2, accounting for 14.101% of the Northern Shaanxi Loess Plateau, mainly distributed in the south of the Northern Shaanxi Plateau while others are more suitable for grass-planting. The government should improve PES schemes to guide farmers to choose the appropriate vegetation restoration modes in different areas from a cost-effectiveness perspective.

Keywords: Payment for ecosystem services; Sloping Land Conversion Programme; Ecological effectiveness; Treatment effects model; Vegetation restoration modes

1. Introduction

Ecosystem services are basic conditions for human survival and are essential in maintaining life and the dynamic balance of the environment (Daily, 1997). However, human activities have profound impact on the structures and functions of the ecosystem (Peng et al., 2018). The concept of payment for ecosystem services (PES) has been widely used in biodiversity conservation (Schirpke et al., 2018), soil and water conservation (Wang et al., 2019), addressing of climate change (Sheng and Qiu, 2018; Robert et al., 2017), and correction of other environmental externalities (Kroeger, 2013). Several PES initiatives have been implemented to increase ecosystem services supply around the world, such as Costa Rica's national PES project (Sánchez-Azofeifa et al., 2007), Mexico's national project for forest protection (Southgate and Wunder, 2009), and the China's Sloping Land Conversion Programme(SLCP) (Liu et al., 2008).

Ecological effectiveness of PES is crucial for the optimal management of environmental problems (Boerema et al., 2018), and has received great attentions though there are major challenges as a result of the complex nature of the contemporary PES project (Kroeger et al., 2013). Ecological effectiveness is defined as a change in the services provided by the project, when compared to a counterfactual without PES (Börner, 2017). Employing the straightforward method of comparing differences or changes of ecology or environment in space or time for assessing ecological effectiveness in geography or ecology is common (Cai et al., 2015; Lü et al., 2020). However, it is difficult to truly evaluate the performance caused by the PES separately without controlling for other factors. Thus, models such as geographical weighted regression, simultaneous equations, and the panel regression model accompanied with remote sensing technology have been used to evaluate the impact of the SLCP on the ecosystem services or vegetation at different scales (Zhang et al., 2018; Wang et al., 2019; Qian et al., 2019). Moreover, the counterfactual analysis methods, such as difference-in-differences model and propensity score matching mode, are then also used to assess more precisely the ecological effectiveness of PES when controlling other factors in the social sciences (Scullion et al., 2011; Andam et al., 2018).

China's SLCP is the largest PES project in the world. Initially, it was implemented to control soil and water loss by increasing vegetation cover since 1999 and provided farmers with incentives to change their land use types and structures to achieve ecological restoration and improvement in social welfare (Cai et al., 2015). The SLCP has included 33.86 million hm^2 farmland and invested more than CNY 500 billion in China. The project is crucial in vegetation restoration (Li et al., 2015) and water and soil conservation (Wang et al., 2019). However, the scarce rainfall and poor soil nutrient levels have led to the low survival rate of trees and resulted in the wide distribution of old and dwarf trees (Chen et al., 2014). Such conditions are also likely to increase the costs of afforestation without earning any of the expected benefits (Liang et al., 2015). Simultaneously, the unsuitable vegetation restoration model intensified evapotranspiration, and caused soil layers to dry up (Liang et al., 2018), and, in turn, caused water scarcity at the local level due to due to the mismatch of ecological restoration modes and regional conditions (Wang et al., 2011). Nevertheless, revegetation is approaching sustainable water resource limits, which causes potentially conflicting demands for water between the ecosystem and humans in China's Loess Plateau (Feng et al., 2016).

The SLCP mainly includes two vegetation restoration modes: conversion of farmland to forestland (CFF) and conversion of farmland to grassland (CFG) (Zhang et al., 2018). Additionally, it is necessary for maximising the ecological effectiveness and sustainable development of both the ecosystem and humans to identify priority areas and vegetation restoration modes. The effectiveness or suitability of vegetation planted is discussed frequently with climate and topographic factors (Fu et al., 2010; Dou et al., 2020; Hou et al., 2016), based on the statistical analysis method. Although these studies provide insights into the vegetation restoration modes, they have not formulated the definite standard of vegetation types selection. In addition, vegetation mapping is popular for identifying the vegetation styles and the sites planted based on the ecological niche theory and vegetation gradient analysis including conceptual models based on expert opinion, geographic envelopes and spaces, climate envelopes, multivariate-associated methods, and tree-based and machine learning methods (McVicar et al., 2010; Okujeni et al., 2018; Erinjery et al., 2018). These methods depend on expert opinion and specific functions and parameters and ignore human interventions and actual vegetation conditions, which may result in some decision distortions for policymaking.

Therefore, the goal of our paper is to identify priority areas and vegetation restoration modes based on assessing ecological effectiveness of PES. First, we used the land use transition to define the variables of PES including CFF and CFG. Second, we used treatment effect model to evaluate the ecological effectiveness of PES in the counterfactual framework. Third, we designed the relative advantage index (RAI) to identify priority areas and vegetation restoration modes based on the contribution of CFF and CFG to the vegetation. Our research could evaluate the adaptability of vegetation restoration modes in different zones more objectively based on interdisciplinary advantages. Finally, the conclusion would provide a valuable policy reference for implementing a new round of SLCP.

2. Theoretical and methods

2.1 Theoretical analysis

The main purpose of the project's implementation is to control soil and water loss by changing the land use types to improve surface vegetation on the steep slope farmland in the Loess Plateau of China(Cai et al., 2015). Therefore, slope and amount of farmland are two geomorphic factors, which determine whether the SLCP would be implemented in an area. In general, the higher the slope and the amount of the farmland are, the greater the probability of implementing the SLCP becomes. However, the SLCP includes two vegetation restoration modes of CFF and CFG (Zhang et al., 2018). For the choice of CFF or CFG, it needs to be judged by the local climate factors (Xu, 2006; Guo et al., 2007). As the most basic climate component, precipitation and temperature are the core factors affecting the vegetation (Li et al., 2015; Qu et al., 2018; Qian et al. 2019). The Loess Plateau in arid and semi-arid climate areas, where the precipitation becomes a limiting factor for vegetation growth. Furthermore, the forest and grass both depend on the local precipitation; that is, the increase in precipitation will increase the possibility of CFF and CFG being implemented. After controlling for precipitation, temperature may become a competitive factor in the selection of vegetation restoration modes. With the same precipitation, areas with higher temperature are more suitable for forests, which leads to the increase of the probability of CFF, while that of CFG decreases.

In addition to the SLCP, socioeconomic factors and natural factors impacting on the vegetation should also receive more attention (Qian et al., 2019; Zhang et al., 2018; Liang et al., 2015; Qu et al., 2018; Hou et al., 2012). Human activities are widely regarded as socioeconomic factors that directly affect vegetation growth (Li et al., 2015; Cai et al., 2015), and results in a huge threat to an ecosystem supported by vegetation (Peng et al., 2018). Amongst the natural factors, temperature, precipitation, wind speed, relative humidity, slope, and aspect may have both important impacts on the vegetation growth. As a sensitive factor for photosynthesis of vegetation, temperature will increase the photosynthetic efficiency appropriately, which is conducive to vegetation (Michaletz et al., 2014). Precipitation is also a positive factor affecting vegetation growth in the Loess Plateau (Qian et al., 2019; Liang et al., 2015). Additionally, the abundant precipitation can not only improve the survival rate but also promote the self-healing ability of vegetation. Increased wind speed in arid and semi-arid areas will accelerate the process of desertification (Zhang and Fan et al., 2018), which may have adverse effects on vegetation. The relative humidity often used to measure the degree of air dryness can promote and induce plant stomatal opening to improve photosynthetic efficiency (Zuo et al., 2011) and contribute greatly to the vegetation especially in semi-arid areas (Hou et al., 2012). With regard to topographical factors, slope impacts positively on vegetation and will prevent humans from interfering with ecosystem and destroy vegetation, and it is conducive to maintaining the original habitat for vegetation (forest) (Qu et al., 2018). Moreover, the aspect would affect the amount of solar radiation and evaporation intensity (Moore et al., 1993). Although the south receives more solar than others at the same latitude, which is more beneficial to the vegetation to some extent, the increase of the radiation would aggravate the evaporation intensity and also cause adverse effects on vegetation when the receiving solar radiation exceeds the appropriate value. Therefore, considering both effects, we put the quadratic term of the aspect into the regression model.

Finally, the relative advantage index (RAI), the rate of contribution of CFF and CFG to the vegetation, was designed as the criterion for identifying priority areas and vegetation restoration modes by measuring the ecological effectiveness of PES, as shown in Figure 1.

[Figure 1 near here]

2.2 Treatment effect model

The SLCP is generally chosen to be implemented in the poor environmental quality in the

Northern Shaanxi Loess Plateau. The program may underestimate the ecological effectiveness of PES using the ordinary least squares model with sample self-selection problems. Therefore, the treatment effect model is used to evaluate the ecological effectivenessof SLCP for overcoming the endogenous problems caused by sample self-selection (Maddala, 1983). The specific form of the model is as follows:

$$vege_i = \beta x_i + \gamma pes_i + \varepsilon_i \tag{1}$$

where $vege_i$ is the surface vegetation status, x_i is the control variables including nature and socioeconomic factors, γ is the ecological effect of PES, ε_i is the residual error, β is the model estimation parameter, and pes_i is the treatment variable indicating whether the SLCP have been implemented or not.

It is assumed that the treatment variables are determined by the following treatment equation:

$$pes_i = I(z_i^T \delta + u_i) \tag{2}$$

where δ is the parameter of the model, u_i indicates the residual error, and I(*) represents an indicative function. Further, z_i refers to the exogenous variables including x_i and other additional instruments unrelated to ε_i. The probability of SLCP is affected by the amount of sloping farmland, and we put the proportion of farmland area, slope, and their interaction into the selection model. Furthermore, the temperature and precipitation were also added into the model for calculating the probability of CFF and CFG. Moreover, we assume that the residuals (u_i, ε_i) obey a two-dimensional normal distribution:

$$\begin{pmatrix} \mu_i \\ \varepsilon_i \end{pmatrix} : N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \rho\sigma_u \\ \rho\sigma_u & 1 \end{pmatrix}\right] \tag{3}$$

Hence, the conditional expectation of the participants is as follows:

$$\begin{aligned} E(vege_i \mid pes_i = 1, x_i, z_i) &= x_i\beta + \gamma + E(\varepsilon_i \mid pes_i = 1, x_i, z_i) \\ &= x_i\beta + \gamma + E(\varepsilon_i \mid z_i\delta + u_i > 0, x_i, z_i) \\ &= x_i\beta + \gamma + E(\varepsilon_i \mid u_i > -z_i\delta, x_i, z_i) \\ &= x_i\beta + \gamma + \rho\sigma_\varepsilon\lambda(-z_i\delta) \end{aligned} \tag{4}$$

where $\lambda(*)$ is the hazard function, namely $\lambda(c) = \dfrac{\phi(c)}{1-\phi(c)}$.

Similarly, the conditional expectation of the non-participants is as follows:

$$\begin{aligned} E(vege_i \mid pes_i = 0, x_i, z_i) &= x_i\beta + \gamma + E(\varepsilon_i \mid pes_i = 0, x_i, z_i) \\ &= x_i\beta + \gamma + E(\varepsilon_i \mid z_i\delta + u_i \le 0, x_i, z_i) \\ &= x_i\beta + \gamma + E(\varepsilon_i \mid u_i \le -z_i\delta, x_i, z_i) \\ &= x_i\beta + \gamma - \rho\sigma_\varepsilon\lambda(-z_i\delta) \end{aligned} \tag{5}$$

The differences in the conditional expectations between participants and non-participants can be obtained by subtracting equation (4) from equation (5) as follows:

$$E(ndvi_i \mid pes_i = 1, x_i, z_i) - E(ndvi_i \mid pes_i = 0, x_i, z_i) = \gamma + \rho\sigma_\varepsilon[\lambda(-z_i\delta) + \lambda(z_i\delta)] \tag{6}$$

Clearly, if we directly observe the difference of the *vege$_i$* of the treatment and the control groups, it would result in biased estimates owing to omitting $\rho\sigma_\varepsilon[\lambda(-z_i\delta) + \lambda(z_i\delta)]$ at the condition of $\rho \neq 0$. To integrate the two groups in a regression equation, we define the individual hazard function as follows:

$$\lambda_i = \begin{cases} \lambda(-z_i^T\delta) & if\ pes_i = 1 \\ -\lambda(z_i^T\delta) & if\ pes_i = 0 \end{cases} \tag{7}$$

Thus, equations (4) and (5) can be merged into one:

$$E(vege_i \mid x_i, z_i) = x_i\beta + \gamma pes_i + \rho\sigma_\varepsilon\lambda_i \tag{8}$$

The first step is to estimate equation $P(pes_i = 1 \mid z_i) = \Phi(z_i^T\delta)$ using the Probit model to derive the estimates δ and λ_i. The second step is to use ordinary least squares model to estimate equation (8) for an unbiased estimate of γ.

2.3 Relative advantage index

The effects of CFF or CFG may present a few differences owing to the locational conditions in different regions. Thus, we designed a relative advantage index for comparing the spatial ecological effectiveness of both CFF and CFG as shown in equation (9):

$$RAI_i = (p_{i,f} \times \gamma_f) / (p_{i,g} \times \gamma_g) \quad (9)$$

where RAI_i is the ratio of the contributions of CFF and CFG to the NDVI for observing, which one is more effective in different spaces; $p_{i,f}$ and $p_{i,g}$ are the occurrence probabilities of CFF and CFG, respectively, calculated using the Probit model in the treatment equation (2); and γ_f and γ_g are the marginal contributions of CFF and CFG, respectively. When RAI_i is greater than or equal to 1, region *i* is prior for afforestation; otherwise, grass-planting is deserved.

3. Study area and data

3.1 Study area

The Northern Shaanxi Loess Plateau is in the centre of the Loess Plateau in China, including Yan'an and Yulin city of Shaanxi province (Figure 2., 107°28'–111°15'E and 35°21'–39°35'N). The Northern Shaanxi Loess Plateau belongs to a typical hilly area of the Loess Plateau dotted with many crisscrossing gullies and valleys of various sizes. The Northern Shaanxi Loess Plateau has become a typical PES zone for vegetation restoration since 1999. By the end of 2018, the North Shaanxi Loess Plateau had completed the afforestation mission covering 1.29 million hm^2, with a cumulative investment of CNY 17.821 billion. Additionally, the forest coverage rate had reached about 41.91% with an increase of 13.03%. In 2017, the silt produced by Yellow River has decreased from 2.58 to 0.31 million t/a, with a drop of 88% only in Yan'an City.

[Figure 2 near here]

3.2 Variable design and data source

(1) **Vegetation**. The NDVI data were captured using the $500m \times 500m$ monthly composite products of the Geospatial Data Cloud in China (http://www.gscloud.cn/) for 2000 and 2015. The

maximum monthly NDVI values were retained as the NDVI values of that year by the maximum composite method (MVC) using ArcGIS.

(2) **Natural and socioeconomic factors**. The site data of precipitation, air temperature, relative humidity, and wind speed were provided by the National Meteorological Information Centre of China (http://data.cma.cn/) and then interpolated into grid layers using the Kriging method. Then the slope and aspect were also calculated based on the DEM data. However, aspect, calculated by DEM data, is not scalar and is the azimuth of the projection of the slope on the horizontal plane and. If being put into the regression or correlation model, it would lose actual physical meaning (Ding et al., 2019). Thus, we converted it as the angle between its own azimuth and the South's (The azimuth is 180 in the South) in every grid based on Ding (2019). Furthermore, the human activity intensity of land surface (HAILS) computed using land use data might become an alternative variable for socioeconomic factors due to the unavailability of that in grids (Xu et al., 2015). Land use data and DEM data with a spatial resolution of $30m \times 30m$ were both extracted from the Resources and Environment Data Cloud Platform of the CHINESE ACADEMY OF SCIENCES (http://www.resdc.cn).

(3) **SLCP variable design**. SLCP was measured by area ratio of the CFF or CFG according to Zhang et al. (2018). We also measured CFF and CFG similarly. But the CFF or CFG measured by area ratio was continuous data, and we converted them into categorical ones to obtain the land transition probability for matching the treatment effect model. The conversion rules were that when the areas of farmland to be converted to forestland from 2000 to 2015 were greater than 0 in the grid, 1 was assigned to the variable of *CFF* variable, if not, 0 was assigned, and the *CFG* variable was also measured similarly. Additionally, if the *CFF* or *CFG* variables were equal to 1 in the grid,

it indicated that SLCP had occurred, and we assigned 1 to the *SLCP* variable.

All variables were calculated by their average in the $1000m \times 1000m$ fishing net established according to the boundary file in ArcGIS. The descriptive statistics were presented in the Table 1.

[Table 1 near here]

4. Results

4.1 Assessing the ecological effectivenessof PES

The treatment effect model might reduce sample self-selection bias resulting from the ordinary least squares model. As a reference, ordinary least squares model was applied for setting equations in the models (1) and (2). The treatment effect model was then applied for measuring ecological effectivenessof PES in the model (3) to (5), as shown in Table 2.

[Table 2 near here]

First, we should test the rationality of the model setting. In the main equation, temperature and precipitation have significant and positive effects on NDVI. In addition, the wind increasing will decrease the NDVI in the Northern Shaanxi Loess Plateau. Furthermore, the aspect has a significant inverted U-shaped effect on the NDVI, which indicates the aspect in the east or west is more conducive to vegetation growth than that in the south or north overall. As for the slope, it brings about a significantly positive contribution to the NDVI because of the lower possibility of vegetation destruction from humans when slope rises. The intensity index of human activities impacts on the NDVI significantly and negatively when human activities occupy more ecological space with intensive production and life. Additionally, the NDVI of a lagged period can significantly promote that of the current period, that is, the richer the current vegetation cover is, the higher its contribution to future vegetation growth. In the treatment equation, the proportion of farmland land area, slope, and their interaction promotes the probability of the SLCP including CFF and CFG, as shown in model (3). In addition, the precipitation will both increase the probability of CFF and CFG both in models (4) and (5), while temperature will increase the probability of CFF in model (4) and decrease that of CFF in model (5). The coefficient symbols of these variables are consistent with theoretical expectations.

However, coefficient of the relative humidity is unreasonable in model (1). Relative humidity likely acts on the NDVI in nonlinear form, and the *humidity*152 variable, quadratic term of *humidity*15, was added into model (2). After introducing the *humidity*152 variable into the model (2), the effect of relative humidity on NDVI appears to increase first and then decrease. Maybe the marginal contribution of relative humidity to vegetation in low relative humidity areas is less than that in high relative humidity areas as seen Figure 3. Therefore, we used the average value of relative humidity (56.35%) as the sample segmentation point and drew scatter plots and linear fitting between the relative humidity and NDVI, respectively (Figure 3a and 3b). When relative humidity is less than 56.35%, the marginal contribution of relative humidity to vegetation is 0.0155 ($P < 0.01$), while exceeding 56.35%, it reaches 0.0542 ($P < 0.01$), being 3.497 times the former one[1]. The influence of relative humidity on NDVI presents a flat bottom U-shaped style, but only with the right part (Figure 3c), and its marginal contribution will increase when relative humidity rises.

[Figure 3 near here]

Second, we assess the ecological effectiveness of PES. In the ordinary least squares model, the SLCP has a positive effect on the NDVI, and the marginal contribution is 0.0246 in model (2), indicating that implementing PES has a certain ecological effectiveness from the perspective of land

[1] The marginal contributions are calculated by simple linear regression.

use change. However, as SLCP is generally implemented in areas with a poor environmental quality, the problem of sample self-selection may lead to underestimating the real ecological effectiveness of PES. Thus, treatment effect model was established in model (3). The p value of ρ and λ is less than 1%, and we can prove the conjecture of sample selection deviation by using ordinary least squares model. The marginal contribution of the SLCP is 0.0425 in the treatment effect model, namely 72.764% higher than that estimated by the ordinary least squares model. Moreover, the ecological effectiveness of CFF and CFG is estimated using the treatment effect model, such as in models (4)-(5), respectively. In general, CFF and CFG both positively affect the NDVI, and the marginal contribution of CFF is 1.8717 times that of CFG.

4.2 Identifying priority areas and vegetation restoration modes based on the RAI

Although the marginal contribution of CFF is greater than that of CFG, it's not suitable to implement CFF instead of CFG in the whole Northern Shaanxi Loess Plateau without considering the ecological effectivenessof spatial heterogeneity. Hence, we used the RAI to determine the vegetation restoration mode in different regions, as shown in Figure 4.

[Figure 4 near here]

The RAI decreases from the south to north in the Northern Shaanxi Loess Plateau. The suitable areas for afforestation with RAI greater than 1 reach 11460 km^2, accounting for 14.101% of the study area. Furthermore, it is mainly distributed in mostly in the south of the Northern Shaanxi Loess Plateau, especially in Huanglong, Huangling, Fu, and Yichuan counties. These regions are dotted with mountains and hills with rich precipitation and heat, so the relatively higher probability of CFF results in the contribution of CFF to the vegetation clearly higher than that of CFG. In addition, the suitable areas for grass planting are 69812 km^2 when RAI is less than 1, comprising

85.899% of the study area, mostly distributed in the north and northwest of the Northern Shaanxi Loess Plateau maybe owing to the limitation of rainfall and heat, terrain, and other reasons.

Although a 450 mm precipitation line can help determine vegetation restoration modes in arid and semi-arid areas (Xu, 2006; Guo et al., 2007), the standard is relatively rough and might fail in decision-making in a complex geographical environment without considering other factors. For instance, it is difficult to identify the appropriate vegetation restoration modes in the forest-grass transition area Feng (2017) by the 450 mm precipitation line (Figure 4c). Moreover, priority areas for afforestation (with precipitation less than 450 mm) still exist in the east of the Northern Shaanxi Loess Plateau (Figure 4b). Therefore, although precipitation is an important limiting factor for the regional vegetation types or selection of ecological restoration modes, it is not appropriate to rely on this factor alone to identify priority areas and vegetation restoration modes.

5. Discussions

Our analysis illustrates how substantial improvements can be made by identify priority areas and vegetation restoration modes. We provide a theoretical basis and technical standards to select the vegetation restoration mode. Our methodology can guide future studies in measuring the impact of land ecological policies and programs on various environmental and social outcomes. Conventional measurement of ecological effectiveness in geography or ecology focuses on describing the temporal and spatial changes of the ecological environment quality after implementing the PES policy or project (Zhang et al., 2016; Dou et al., 2020; Hou et al., 2016). However, the causality test is still based on empirical judgment rather than reliable statistical inference, and it is difficult to determine whether these changes are caused by PES. Identifying priority areas and vegetation restoration modes based on ecological effectiveness assessment of PES will improve the survival rate of vegetation and bridge the gap between vegetation restoration and water consumption of economic development to some extent. However, the incentive scheme designed in this paper simply compares the ecological effectiveness difference of two vegetation restoration modes in different spaces from the perspective of land use transition without considering the cost-effectiveness of PES. Considering utility maximization, funds must be allocated to areas with the highest ecological efficiency or the lowest investment cost. In the PES project, the financial subsidies for the CFF is much higher than CFG, which leads farmers to choose afforestation while ignoring natural suitability. Cost-effectiveness, which is critical in evaluating the sustainability of PES projects, has attracted the attention of many scholars, especially in the subjects' (or spaces') selection (Wünschera et al., 2012). The subjects' (or spaces') selection of PES is mainly affected by the level of ecosystem services, the cost of providing ecosystem services, and the risk of ecosystem degradation when there is no ecological compensation (Wünschera et al., 2012).

The new round of SLCP emphasises farmers' participating in the PES projects voluntarily without limiting their choice of vegetation types. Thus, it crucial for the government to design an effective incentive scheme of PES to lead farmers to choose suitable vegetation restoration patterns based on the ecological effectiveness of environmental policy instruments. At present, input-cost methods are applied for the reforestation projects to calculate the subsidy standard, which results in an afforestation subsidy much higher than that of planting-grass. Hence, many farmers choose afforestation instead of planting-grass for the high subsidies despite the limitations of the natural environment for forests growth and even survival. Unsuitable vegetation restoration modes eventually bring about small and old trees, which have low forest survival rate and poor contribution to overall vegetation, and aggravate the water scarcity in the Northern Shaanxi Loess Plateau.

Performance payment is the most direct and efficient means to guide farmers to participate in ecological restoration projects as it encourages suppliers of environmental services to choose the best means to fulfil a desired level of environmental services (Zabel et al., 2009). Afforestation would result in a low survival rate and improve the ecological environment little in the poor natural conditions. If farmers are compensated according to the performance payment of PES, they will choose a reasonable vegetation restoration mode to avoid losses considering future benefits and risks. However, the randomness of environmental service production would make personal investment risky owing to the production of environmental services being the result of the interaction of human activities and many other environmental factors. We must consider how to reduce the risks and interferences preventing suboptimal incentives for service providers in the production process of environmental services when using performance payment (Zabel et al., 2009).

6. Conclusions

In the counterfactual framework, the SLCP affects the NDVI positively, and the average marginal contribution of CFF is better than that of CFG. The RAI can identify priority areas and vegetation restoration modes. Furthermore, the priority zones for afforestation with RAI greater than 1 reach 11460 km^2, accounting for 14.101% of the Northern Shaanxi Loess Plateau. These regions are not only in the south of the Northern Shaanxi Loess Plateau, such as Huangling, Huanglong, Fu, and Yichuan counties, but also distributed sporadically in the eastern Northern Shaanxi Loess Plateau although its rainfall is less than 450 mm, while others are more suitable for grass-planting. It might be improper to identify priority areas and vegetation restoration modes by the precipitation alone for precise decision-making despite its important limitation for the vegetation restoration.

Reference

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. Proc. Natl. Acad. Sci. U. S. A. 105, 16089–16094. https://doi.org/10.1073/pnas.0800437105.

Boerema, A., Van Passel, S., Meire, P., 2018. Cost-effectiveness analysis of ecosystem management with ecosystem services: from theory to practice. Ecol. Econ. 152, 207–218. https://doi.org/10.1016/j.ecolecon.2018.06.005.

Börner, J., Baylis, K., Corbera, E., Ezzine-de-Blas, D., Honey-Rosés, J., Persson, U. M., Wunder, S. (2017). The Effectiveness of Payments for Environmental Services. World Dev. 96, 359–374. https://doi.org/10.1016/j.worlddev.2017.03.020.

Cai, H., Yang, X., Xu, X. (2015). Human-induced grassland degradation/restoration in the central Tibetan Plateau: The effects of ecological protection and restoration projects. Ecol. Eng. 83, 112–119. https://doi.org/10.1016/j.ecoleng.2015.06.031.

Chen, J., L, Y., Zuo, L. (2014). The hydraulic acclimation of old and dwarf Populus simonii trees growing on sandy soil in northern Shaanxi Province, China. Acta Ecol. Sin. 34, 4193-4200. http://www.ecologica.cn/stxb/ch/html/2014/15/stxb201212121794.htm. (in Chinese)

Daily, G.C. (1997). Nature’s services societal dependence on natural ecosystem. Island Press, Washington DC.

Ding, Z.M., Yao, S.B. (2019). Model and measurement of payment for ecosystem services at small scale. Resour. Sci. 41, 2182-2192. https://doi.org/10.18402/resci.2019.12.03. (in Chinese)

Qian, C., Shao, L., Hou, X., Zhang, B., Chen, W., Xia, X. (2019). Detection and attribution of vegetation greening trend across distinct local landscapes under China’s Grain to Green Program: A case study in Shaanxi Province. Catena 183, 104182. https://doi.org/10.1016/j.catena.2019.104182.

Dou, Y., Yang, Y., An, S., Zhu, Z. (2020). Effects of different vegetation restoration measures on soil aggregate stability and erodibility on the Loess Plateau, China. Catena 185, 104294. https://doi.org/10.1016/j.catena.2019.104294.

Feng, X., Li, J., Cheng, W., Fu, B., Wang, Y., Lü, Y., Shao, M. (2017). Evaluation of AMSR-E retrieval by detecting soil moisture decrease following massive dryland re-vegetation in the Loess Plateau, China. Remote Sens. Environ. https://doi.org/10.1016/j.rse.2017.05.012.

Feng, X., Fu, B., Piao, S., Wang, S., Ciais, P., Zeng, Z., Lü, Y., Zeng, Y., Li, Y., Jiang, X., Wu, B. (2016). Revegetation in China’s Loess Plateau is approaching sustainable water resource limits. Nat. Clim. Chang. 6, 1019–1022. https://doi.org/10.1038/nclimate3092.

Fu, X., Shao, M., Wei, X., Horton, R. (2010). Soil organic carbon and total nitrogen as affected by vegetation types in Northern Loess Plateau of China. Geoderma 155, 31–35. https://doi.org/10.1016/j.ecocom.2011.07.003.

Guo, G.M., Xie, G.D., Zhen, L. (2007). The Relationship between NDVI Change and Precipitation in Guyuan City. Resour. Sci. 29, 178-182. http://159.226.115.21/zykx/en/y2007/v29/i2/178. (in Chinese)

Hou, G.L., Liu, D.Y., Zhang, Z.X., et al. (2012). Response of NDVI to climate change in different climatic regions of Songnen Plain. Chinese Journal of Agrometeorology, 33, 119-123. https://doi:10.3969/j.issn.1000-6362.2012.02.019.

Hou, J., Wang, H., Fu, B., Zhu, L., Wang, Y., Li, Z. (2016). Effects of plant diversity on soil erosion for different vegetation patterns. Catena 147, 632–637. https://doi.org/10.1016/j.catena.2016.08.019.

Peng, J., Liu, Z., Liu, Y., Wu, J., Han, Y. (2012). Trend analysis of vegetation dynamics in Qinghai-Tibet Plateau using Hurst Exponent. Ecol. Indic. 14, 28–39. https://doi.org/10.1016/j.ecolind.2011.08.011.

Erinjery, J. J., Singh, M., Kent, R. (2018). Mapping and assessment of vegetation types in the tropical rainforests of the Western Ghats using multispectral Sentinel-2 and SAR Sentinel-1 satellite imagery. Remote Sens. Environ.

216, 345–354. https://doi.org/10.1016/j.rse.2018.07.006.

Schirpke, U., Marino, D., Marucci, A., Palmieri, M. (2018). Positive effects of payments for ecosystem services on biodiversity and socio-economic development: Examples from Natura 2000 sites in Italy. Ecosyst. Serv. 34, 96-105. https://doi.org/10.1016/j.ecoser.2018.10.006.

Scullion, J., Thomas, C. W., Vogt, K. A., Pérez-Maqueo, O., Logsdon, M. G. (2011). Evaluating the environmental impact of payments for ecosystem services in Coatepec (Mexico) using remote sensing and on-site interviews. Environ. Conserv. 38, 426–434. https://doi.org/10.1017/S037689291100052X.

Li, S., Yang, S., Liu, X., Liu, Y., Shi, M. (2015). NDVI-based analysis on the influence of climate change and human activities on vegetation restoration in the Shaanxi-Gansu-Ningxia region, central China. Remote Sens. 7, 11163–11182. https://doi.org/10.3390/rs70911163.

Liang, W., Bai, D., Wang, F., Fu, B., Yan, J., Wang, S., Yang, Y., Long, D., Feng, M. (2015). Quantifying the impacts of climate change and ecological restoration on streamflow changes based on a Budyko hydrological model in China's Loess Plateau. Water Resour. Res. 51, 6500–6519. https://doi.org/10.1002/2014WR016589.

Liang, H., Xue, Y., Li, Z., Wang, S., Wu, X., Gao, G. (2018). Forest Ecology and Management Soil moisture decline following the plantation of Robinia pseudoacacia forests: Evidence from the Loess Plateau. For. Ecol. Manage. 412, 62–69. https://doi.org/10.1016/j.foreco.2018.01.041.

Liu, J., Li, S., Ouyang, Z., Tam, C., Chen, X. (2008). Ecological and socioeconomic effects of China's policies for ecosystem services. Proc. Natl. Acad. Sci. U. S. A. 105, 9477–9482. https://doi.org/10.1073/pnas.0706436105.

Lü, Y., Li, T., Whitham, C., Feng, X., Fu, B., Zeng, Y., Wu, B., Hu, J. (2020). Scale and landscape features matter for understanding the performance of large payments for ecosystem services. Landsc. Urban Plan. 197, 103764. https://doi.org/10.1016/j.landurbplan.2020.103764.

Maddala, G.S. (1983). Limited-Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

McVicar, T. R., Van Niel, T. G., Li, L. T., Wen, Z. M., Yang, Q. K., Li, R., Jiao, F. (2010). Parsimoniously modelling perennial vegetation suitability and identifying priority areas to support China's re-vegetation program in the Loess Plateau: Matching model complexity to data availability. For. Ecol. Manage. 259, 1277–1290. https://doi.org/10.1016/j.foreco.2009.05.002.

Michaletz, S. T., Cheng, D., Kerkhoff, A. J., Enquist, B. J. (2014). Convergence of terrestrial plant production across global climate gradients. Nature 512, 39-43. https://doi.org/10.1038/nature13470.

Moore, I.D., Gessler, P.E., Nielsen, G.A., et al. (1993). Soil attribute prediction using Terrain analysis. Soil Sci. Soc. Am. J. 57, 443–452. https://doi.org/10.2136/sssaj1993.03615995005700020026x.

Kroeger, T. (2013). Forest Policy and Economics The quest for the "optimal" payment for environmental services program: Ambition meets reality, with useful lessons. For. Policy Econ. 37, 65–74. https://doi.org/10.1016/j.forpol.2012.06.007.

Peng, B.F., Zheng, Y., Liu Y. (2018). Coupling ecosystem services and regional ecological security pattern. Sci. Geogr. Sin. 38, 361-367. https://doi.org/10.13249/j.cnki.sgs.2018.03.005. (in Chinese)

Qu, S., Wang, L., Lin, A., Zhu, H., Yuan, M. (2018). What drives the vegetation restoration in Yangtze River basin, China: Climate change or anthropogenic factors? Ecol. Indic. 90, 438–450. https://doi.org/10.1016/j.ecolind.2018.03.029.

Robert, H., Rebecca, S., François, M., Hanna, B. S., Dirk, S., Robert, F. (2017). Interaction effects of targeted agri-environmental payments on non-marketed goods and services under climate change in a mountain region. Land use policy 66, 49–60. https://doi.org/10.1016/j.landusepol.2017.04.029.

Sánchez-Azofeifa, G. A., Pfaff, A., Robalino, J. A., Boomhower, J. P. (2007). Costa Rica's payment for environmental services program: Intention, implementation, and impact. Conserv. Biol. 21, 1165–1173.

https://doi.org/10.1111/j.1523-1739.2007.00751.x.
Sheng, J., Qiu, H. (2018). Governmentality within REDD+: Optimizing incentives and efforts to reduce emissions from deforestation and degradation. Land use policy 76, 611-622. https://doi.org/10.1016/j.landusepol.2018.02.041.
Southgate, D., Wunder, S. (2009). Paying for watershed services in Latin America: A review of current initiatives. J. Sustain. For. 28, 497–524. https://doi.org/10.1080/10549810902794493.
Wang, Y., Yao, S. (2019). Effects of restoration practices on controlling soil and water losses in the Wei River Catchment, China: An estimation based on longitudinal field observations. For. Policy Econ. 100, 120-128. https://doi.org/10.1016/j.forpol.2018.12.001.
Wang, S., Fu, B. J., He, C. S., Sun, G., Gao, G. Y. (2011). A comparative analysis of forest cover and catchment water yield relationships in northern China. For. Ecol. Manage. 262, 1189–1198. https://doi.org/10.1016/j.foreco.2011.06.013. https://doi.org/10.11821/dlxb201507004.
Wünscher, T., Engel, S. (2012). International payments for biodiversity services: Review and evaluation of conservation targeting approaches. Biol. Conserv. 152, 222–230. https://doi.org/10.1016/j.biocon.2012.04.003.
Xu, Y., Sun, X., Tang, Q. (2015). Human activity intensity of land surface: Concept, method and application in China. Acta Geogr. Sin. 70, 1068–1079. https://doi.org/10.11821/dlxb201507004.
Xu, J.X. (2006). Coupling Relationship between Precipitation and Vegetation and the Implications in Erosion on the Loess Plateau, China. Acta Geogr. Sin. 61, 57-65. https://doi.org/10.11821/xb200601006. (in Chinese)
Zabel, A., Roe, B. (2009). Optimal design of pro-conservation incentives. Ecological Economics, 69(1):126-134.
Zuo, Y.M., Chen, Q.B., Deng, Q.Q., Tang, J., Luo, H.W., Wu, T.K., Yang, C.F. (2011). Effects of soil moisture, light and air humidity on stomatal conductance of cassava. CJE 30 (04), 689-693. https://doi.org/10.13292/j .1000 - 4890.2011.0097. (in Chinese)
Zhang, D., Jia, Q., Xu, X., Yao, S., Chen, H., Hou, X. (2018). Contribution of ecological policies to vegetation restoration: A case study from Wuqi County in Shaanxi Province, China. Land use policy 73, 400–411. https://doi.org/10.1016/j.landusepol.2018.02.020.
Zhang, H., Fan, J., Cao, W., Harris, W., Li, Y., Chi, W., Wang, S. (2018). Response of wind erosion dynamics to climate change and human activity in Inner Mongolia, China during 1990 to 2015. Sci. Total Environ. 639, 1038–1050. https://doi.org/10.1016/j.scitotenv.2018.05.082.

Table

Table 1 Variables and descriptive statistics

Variables	Explanation	Unite	Mean	Std. Dev	Min	Max
*ndvi*00	Annual average NDVI		0.483	0.186	0.062	0.998
*ndvi*15	Annual average NDVI		0.656	0.178	0.078	0.999
*temp*00	Annual average air temperature	℃	9.744	0.895	7.578	12.075
*temp*15	Annual average air temperature	℃	9.978	1.018	7.982	13.179
*rain*00	Annual average precipitation	mm	349.361	98.225	119.593	691.230
*rain*15	Annual average precipitation	mm	363.377	95.483	190.562	576.083
*humidity*15	Annual average relative humidity	%	56.336	2.783	48.465	62.138
*wind*15	Annual average wind	m/s	2.131	0.323	1.400	3.100
aspect	Average angle between its own azimuth and the South`s		-90.121	4.393	-180	-7.167
slop	Average slop	°	11.860	5.532	0	45.881

Variables	Explanation	Unite	Mean	Std. Dev	Min	Max
*fl*00	Rate of farmland aeras in 2000		0.354	0.249	0	1
hails	HAILS		0.124	0.079	0	1
slcp	SLCP		0.741	0.438	0	1
cff	CFF		0.227	0.419	0	1
cfg	CFG		0.698	0.459	0	1

Note: *aspect*= E (-abs (180- azimuth in the grid))

Table 2 Ecological effectiveness measurement of *PES*

	Model（1）		Model（2）		Model（3）		Model（4）		Model（5）	
*ndvi*15	Coef.	Std. Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
slcp	0.0221***	0.0007	0.0246***	0.0007	0.0425***	0.0011				
cff							0.0992***	0.0014		
cfg									0.0530***	0.0012
*temp*15	0.0085***	0.0006	0.0132***	0.0006	0.0145***	0.0007	0.0036***	0.0007	0.0184***	0.0007
*rain*15	0.0009***	0.0000	0.0008***	0.0000	0.0008***	0.0000	0.0009***	0.0000	0.0008***	0.0000
*wind*15	-0.0108***	0.0013	-0.0189***	0.0014	-0.0216***	0.0014	-0.0196***	0.0014	-0.0226***	0.0014
*humidity*15	-0.0215***	0.0002	-0.0962***	0.0051	-0.1202***	0.0056	-0.1099***	0.0056	-0.1200***	0.0056
*humidity*152			0.0007***	0.0000	0.0009***	0.0000	0.0008***	0.0000	0.0009***	0.0000
aspect	-0.0088***	0.0016	-0.0092***	0.0016	-0.0100***	0.0008	-0.0114***	0.0008	-0.0100***	0.0008
*aspcet*2	$-4.92E^{-5}$***	$8.62E^{-6}$	$-5.11E^{-5}$***	$8.66E^{-6}$	$-5.55E^{-5}$***	$4.15E^{-6}$	$-6.29E^{-5}$***	$4.50E^{-6}$	$-5.53E^{-5}$***	$4.14E^{-6}$
slop	0.0032***	0.0001	0.0034***	0.0001	0.0029***	0.0001	0.0029***	0.0001	0.0023***	0.0001
*ndvi*00	0.5882***	0.0031	0.5796***	0.0032	0.5912***	0.0031	0.5789***	0.0030	0.5943***	0.0030
hails	-0.0643***	0.0038	-0.0614***	0.0038	-0.0873***	0.0037	-0.0689***	0.0036	-0.0998***	0.0037
_cons	0.7524***	0.0715	2.8384***	0.1585	3.4736***	0.1616	3.2135***	0.1619	3.4299***	0.1591
*fl*00					6.3438***	0.0453	1.3152***	0.0221	4.4376***	0.0303
slop					0.1911***	0.0017	0.0522***	0.0012	0.1593***	0.0015
*fl*00**slop*					0.5309***	0.0059	0.0776***	0.0036	0.3063***	0.0043
*temp*00							0.2341***	0.0081	-0.5002***	0.0104
*rain*00							0.0006***	0.0001	0.0008***	0.0001
_cons					-3.0477***	0.0254	-4.4037***	0.0666	2.0215***	0.0823
/athrho					-0.2314***	0.0112	-0.7555***	0.0127	-0.3381***	0.0110
/lnsigma					-2.6122***	0.0025	-2.5124***	0.0039	-2.6035***	0.0027
rho					-0.2274	0.0106	-0.6384	0.0075	-0.3258	0.0099
sigma					0.0734	0.0002	0.0811	0.0003	0.0740	0.0002
lambda					-0.0167	0.0008	-0.0518	0.0008	-0.0241	0.0008

Figure

Figure 1 Theoretical framework

Figure 2 Location of study site, which is colored according to the elevation (m).

Figure 3 Scatter plots and linear fitting between relative humidity and the NDVI; (a) Scatter plots and linear fitting between relative humidity and the NDVI when the relative humidity is less than its average; (b) plots and linear fitting between relative humidity and the NDVI when the relative humidity is more than or equal to its average;(c) Scatter plots and quadratic fitting between relative humidity and the NDVI.

Figure 4 The spatial distribution of vegetation restoration modes based on the RAI; (a) Northern Shaanxi Loess Plateau ; (b) The east of Northern Shaanxi Loess Plateau;(c)Forest-grass transition areas.