**Article:**

Li, T, Lu, Y, Fu, B et al. (3 more authors) (2017) Gauging policy-driven large-scale vegetation restoration programmes under a changing environment: Their effectiveness and socio-economic relationships. Science of the Total Environment, 607. pp. 911-919. ISSN 0048-9697

https://doi.org/10.1016/j.scitotenv.2017.07.044

# Gauging policy-driven large-scale vegetation restoration programmes under a changing environment: their effectiveness and socio-economic relationships

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## Abstract

Large-scale ecological restoration has been widely accepted globally as an effective strategy for combating environmental crises and to facilitate sustainability. Assessing the effectiveness of ecological restoration is vital for researchers, practitioners, and policy-makers. However, few practical tools are available to perform such tasks, particularly for large-scale restoration programmes in complex socio-ecological systems. By taking a "before and after" design, this paper formulates a composite index ($E_j$) based on comparing the trends of vegetation cover and vegetation productivity to assess ecological restoration effectiveness. The index reveals the dynamic and spatially heterogenic process of vegetation restoration across different time periods, which can be informative for ecological restoration management at regional scales. Effectiveness together with its relationship to socio-economic factors is explored via structural equation modeling for three time periods. The results indicate that the temporal scale is a crucial factor in representing restoration effectiveness, and that the effects of socio-economic factors can also vary with time providing insight for improving restoration effectiveness. A dual-track strategy, which promotes the development of tertiary industry in absorbing the rural labor force together with improvements in agricultural practices, is proposed as a promising strategy for enhancing restoration effectiveness. In this process, timely and long-term ecological restoration monitoring is advocated, so that the success and sustainability of such programmes is ensured, together with more informative decision making where socio-ecological interactions at differing temporal scales are key concerns.

**Key-words:** ecological restoration, effectiveness assessment, temporal scale, socio-ecological system, rural economy, structural equation modeling.

## 1. Introduction

Since the turn of the millennium, numerous restoration initiatives have been established across the globe to restrain environmental degradation and ecological destruction caused by human activities (Benayas et al., 2009). As an interventionist activity, evidence strongly indicates that ecological restoration has achieved its major goal of enhancing biodiversity and restoring ecosystem services (Clewell and Aronson, 2013). A meta-analysis of 89 restoration assessments across a wide range of ecosystem types, revealed that biodiversity and ecosystem services were on average enhanced by 44% and 25%, respectively (Benayas et al., 2009). Significant restoration achievements in some specific ecosystem types and degraded regions have also been reported (Calmon et al., 2011; Meli et al., 2014). As a result, ecological restoration activities are now widely recognized as significant contributors to global sustainability. Given the large spatial extent of restoration and conservation coverage, more than 11% of the global land surface (Andam et al., 2008), coupled with government funding, analytical tools are needed to accurately assess restoration effectiveness so that researchers and policy-makers can promote successful management interventions. Unfortunately, even well-designed research programmes are often poor at evaluating the effectiveness of large-scale ecological restorations (Martin et al., 2014). This is in part due to poorly specified metrics, limited information on spatial and temporal variability, and insufficient knowledge of human impacts. The lack of agreed scientific methods for assessing restoration effectiveness limits the incorporation of ecological restoration in land-use planning and decision making. In turn, this presents a challenge to governments and managers when restoration projects up-scale from individual sites to landscape and regional levels (Cao et al., 2009; Lamb et al., 2005).

Focusing on the temporal dimension of ecological restoration can provide detailed understanding of the effects of restoration activities (Levrel et al., 2012), and research has investigated temporal responses of different types of ecosystems to restoration initiatives. For instance, Jones and Schmitz (2009) compared ecosystem recovery and noted forest ecosystems took the longest to recover, with an average time of 40 to 50 years, whereas aquatic and terrestrial grassland ecosystems had much shorter recovery times of 20 to 25 years. Vegetation recovery in coastal marine and estuarine ecosystems has been found to take less than 5 years due to the short-lived and high-turnover nature of its biological components (Borja et al., 2010). In these cases, the focus was on the recovery of the ecosystem's structural characteristics without considering the degree to which functional ecosystem performance was regained. While a general consensus is that temporal scales of restoration strategies should not be ignored (Jones and Schmitz, 2009; McAlpine et al., 2016), few studies have established a restoration chronosequence that characterizes the dynamics and functionality of restored regions over time (Berkowitz, 2013).

In these evaluations, the process of ecological restoration is affected both by natural factors and by human activities, which provides multifaceted interactions between ecological effects and socio-economic drivers (Timilsina et al., 2014). In fact, recent research has indicated that socio-economic factors exhibit a growing influence on changes to ecological processes (Lü et al., 2015; Petursdottir et al., 2013; Zhang et al., 2013). The impacts caused by socio-economic factors were found to be dominant over climate variations, in driving large scale ecological changes nationally in China and related to the implementation of a series of large scale ecological conservation and restoration programmes (Lü et al., 2015; Zhang et al., 2013). However, detailed mechanisms concerning the role of socio-economic factors on ecological restoration effectiveness are still unclear at the regional scale. The purpose of this study is to tackle these deficiencies and to examine the effectiveness of large-scale ecological restoration over different temporal scales, as well as the possible time dependent relationships between restoration effectiveness and socio-economic factors.

In China, large-scale ecological restoration and conservation programmes, such as the 'Three Norths Shelter Forest System Project' (since 1978), the 'Natural Forest Conservation Program' (since 2000) and the 'Grain to Green Program' (GTGP, since 2000) have been established to support and promote ecosystem resilience, ecological security, and socio-economic sustainability (Lü et al., 2012), and ecological restoration policies have been established and refined. The GTGP is a large-scale programme converting steep cultivated land to forest and grassland. It was established in 1999 and was fully implemented in 2000 with 97% of China's counties involved (Liu et al., 2008). Central government offered farmers grain and financial subsidy every year based on the area of cropland on slopes that they converted (Liu et al., 2008; Miyasaka et al., 2017). The northern part of Shaanxi province in the central Loess Plateau was selected as a pilot and demonstration area for the GTGP. It provides a good case study to demonstrate a restoration effectiveness assessment toolkit in a regional scale. Here the vegetation cover has markedly increased since the late 1990s (Fan et al., 2015; Zhai et al., 2015), but also socio-economic factors such as population migration and industrial changes in this region has have an impact on restoration effectiveness.

Re-vegetation is the most intuitive and effective approach for restoration projects. It promotes ecological functions, such as increasing biodiversity, carbon sequestration and improved soil quality (Jin et al., 2014). Changes in vegetation provide simple and cost-effective indicators of effectiveness of restoration and conservation programmes (Lü et al., 2015). Using high temporal and high spatial resolution remote sensing data, it is possible to quantify the basic characteristics of vegetation / land cover change as well as changes in functional characteristics, such as biomass productivity. Fractional vegetation cover (FVC) can be derived from remote sensing data and used to provide an index for characterizing vegetation changes (Wu et al., 2014). Similarly, net primary production (NPP) provides a measure of standing biomass (Donmez et al., 2011) and is a critical indicator of ecosystem function (Watanabe and Ortega, 2014). Therefore, these two remote sensing data products were used to assess the effectiveness of regional ecological restoration in this research. Specifically, this research: (1) formulates a composite indicator approach for assessing the effectiveness of ecological restoration at a regional scale based on mentioned FVC and annual accumulated NPP; (2) quantifies the effectiveness of ecological restoration and the impacts from different socio-economic factors by using a structural equation modeling (SEM) approach; (3) highlights the significance of temporal scale effects and the practical implications of this research for ecological restoration policy and management across large spatial scales.

## 2. Materials and methods

### *2.1. Study area*

Northern Shaanxi is situated in the middle of Loess Plateau (35° 21′ - 39° 34′ N, 107° 28′ - 111° 15′) and covers an area of $8.03\times10^4$ $km^2$ (Fig.1). This region is dominated by a semi-arid and continental climate with a mean annual temperature ranging from 7 to 12 °C, and an annual precipitation ranging from 350 mm to 600 mm. The study area includes the Yulin and the Yan'an prefectures consisting of 25 counties, which acted has as a pilot and demonstration region for the GTGP since 1999 (i.e. over 15 years for the purposes of this study).

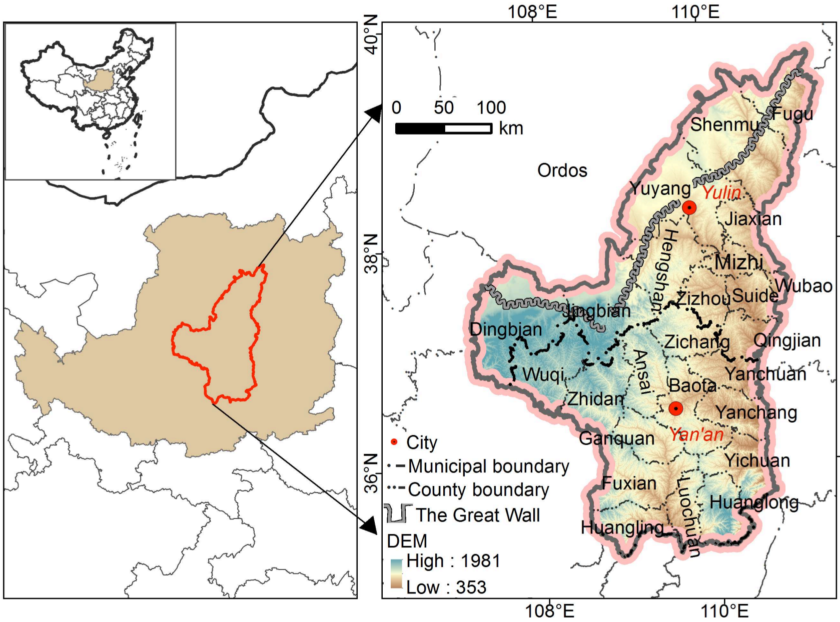


**Fig. 1** Location of the study area on the Loess Plateau of China.

*2.2. Data sources*

The FVC and NPP data products were both derived from MODIS imagery with a 250 m spatial resolution from 2000 to 2014 during a 16-day time interval. The dimidiate pixel model for FVC estimation was calculated from the Normalized Difference Vegetation Index (NDVI) to assess vegetation response (Leon et al., 2012). The NPP data was computed based on the CASA (Carnegie-Ames-Stanford) ecosystem model (van der Werf et al., 2006). Socio-economic data covering 2000-2014 at the prefectural level was taken from the Shaanxi Province Statistical Yearbooks and annual socio-economic statistical bulletin of each county. These data were used to describe the underlying socio-economic factors that may influence vegetation restoration at the county scale.

*2.3. Vegetation restoration effectiveness assessment and the use of SEM*

The annual mean fractional vegetation cover ($FVC_{mean}$), the annual maximum fractional vegetation cover ($FVC_{max}$), and the annual accumulated net primary production ($NPP_{annual}$) were selected as three indicators for an effectiveness assessment of vegetation restoration in the study area. The linear trends of these indicators were calculated by using an ordinary least-squares regression approach for each pixel in northern Shaanxi (Lü et al., 2015), where $a$ was the slope of the resultant linear equation which was subjected to the usual $t$-test for significance from zero. If $a > 0$ and $p < 0.05$, there was a significant positive trend for the variable in question. By contrast, when $a < 0$ and $p < 0.05$, there was a significant negative trend for the variable in question. The change in trends for the three indicators were estimated for three different overlapping periods, namely 2000-2005, 2000-2010, and 2000-2014 (see supplementary material Fig. S1). A "before and after" design (Martin et al., 2014) was used to estimate the effectiveness of vegetation restoration. Different weights were assigned to the three variables. FVC provides a basic structural index for assessing vegetation condition and NPP is a functional indicator for vegetation production that is important for regulating ecosystem processes and functions (Watanabe and Ortega, 2014). Therefore, an equal weighting of 0.5 was allocated to FVC and NPP as measures of the structure and function in ecosystems, respectively. Additionally, a greater weight was assigned to $FVC_{max}$ as its explanatory power has been found to be higher than $FVC_{mean}$ (Wu et al., 2014).

The comprehensive effectiveness index ($e_j$) was first formulated for each temporal scale:

$$e_j = 100\% \times \sum w_i \times (IN_{ij} - DE_{ij}) \quad (1)$$

where variable $i$ could be one of $FVC_{mean}$, $FVC_{max}$, or $NPP_{annual}$; $j$=1 for 2000-2005, $j$=2 for 2000-2010, $j$=3 for 2000-2014, $w_i$ denoted the weighting factor for variable $i$ set at 0.2, 0.3, and 0.5 for $FVC_{mean}$, $FVC_{max}$, and $NPP_{annual}$, respectively, $IN_i$ denoted the percentage area in each county with a significant increasing trend on variable $i$ and $DE_i$ represented the percentage area of each county with significant decreasing trend on variable $i$. The difference between $IN_i$ and $DE_i$ is referred to as the net relative change on variable $i$.

To determine the temporal trends in restoration effectiveness, the average of the comprehensive effectiveness during the initial stage (i.e. 2000-2005, $j$=1) in the study area was set as the reference value ($\bar{e}$). Then the relative comprehensive effectiveness index ($E_j$) for each temporal scale could be calculated as:

$$E_j = \frac{e_j}{\bar{e}} \quad (2)$$

$$\bar{e} = \left[100\% \times \sum w_i \times (IN_{i1} - DE_{i1})\right]_{avg} \quad (3)$$

SEM is a method for examining hypotheses about multivariate causal relationships in complex systems, which can involve either observed variables, latent variables or both (Grace, 2006). The basic assumption of SEMs is that explanatory models may include hidden or latent variables. To examine this a series of latent equations are used to generate parameters that are passed to regression operations and residual correlation evaluations. This method is particularly useful for identifying latent variables, as it allows a range of variables to be tested simultaneously and the best fitting model selected for any possible set of measured variables (Byrne, 2016). SEMs are being increasingly used to explore the interactive effects that drive mechanisms on the sustainability of socio-ecological systems. For example, Standish et al. (2015) estimated climate factors, restoration practice and their interactive effects on the richness of restored plant assemblages by developing a SEM. Tian et al. (2014) assessed the relationships among land cover change, economic development and population growth in the context of sustainably managing urban ecosystems. Therefore, this method can be adapted to explore the relationships between different categories of socio-economic factors and the effectiveness of vegetation restoration. The contributed indicators for each socio-economic factors could be identified and screened from a range of measured variables.

Demographic changes, urbanization and economic productivity, affluence and rural economy are major socio-economic factors that affect large-scale vegetation restoration in many developing countries (Cao et al., 2014; Lü et al., 2015; Madu, 2009). In this paper, we hypothesized that socio-economic factors can be represented as three latent variables, i.e. population pressure, off-farm economy and rural economy, each of which have an impact on the effectiveness of vegetation restoration. The *a-priori* model of the expected relationships among variables is described in Fig. 2. We identified a number of socio-economic indicators that could affect vegetation restoration based on a literature search (Table 1). We then performed an extensive analysis depending on the *a-priori* model to to identify the most representative indicators for each of the three latent variables. Total population and rural employment were selected as indicators of population pressure. Secondary industry and tertiary industry were selected as the indicators of off-farm economy. Primary industry, income and grain yield were selected as the variables for the rural economy. The effectiveness of vegetation restoration was treated as an endogenous latent variable and measured by $FVC_{mean}$, $FVC_{max}$ and $NPP_{annual}$. Counties with $E_j$ greater than 1 during the three different overlapping time periods indicated they were relatively effective, and as a result, were selected to develop relationships between socio-economic factors and effectiveness. The feasibility of the model depends on a goodness-of-fit assessment via the chi-square statistic ($\chi^2$). Here a $p$-value greater than 0.05 indicates that the modelled relationships and the ‘real’ relationships are considered a match (Hopcraft et al., 2012). AMOS ver.22 was used for the SEM analysis (Tayyebi and Jenerette, 2016).

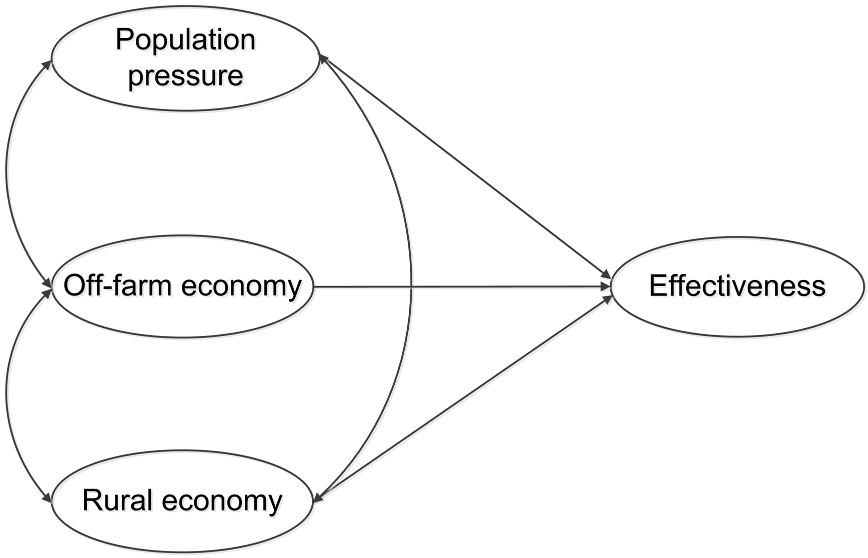


**Fig. 2** The *a-priori* model for the SEM. Ellipses show the latent conceptual variables.

**Table 1** The socio-economic indicators that may have an impact on vegetation restoration via a literature search.

| **Socioeconomic factors** | **Indicators** | **Description** | **Literature** |
|---|---|---|---|
| Population pressure | Total population | Total permanent population | (Cao et al., 2014; Li et al., 2013; Lü et al., 2015; Luck et al., 2009) |
| | Rural populations | Permanent population in rural areas | |
| | Rural employment | Rural labor forces | |
| | Educated population | Population with 12 years education and high school qualifications | |
| Off-farm economy | Secondary industry | Annual value-added of secondary industry | (Li et al., 2015; Lü et al., 2015; Michishita et al., 2012; Su et al., 2014; Wittemyer, 2011) |
| | Tertiary industry | Annual value-added of tertiary industry | |
| | Investment | Total investment in fixed assets | |
| | Fiscal revenues | Local fiscal revenues | |
| | Fiscal expenditure | Local fiscal expenditure | |
| | Deposit | Per capita annual disposable income of urban households | |
| Rural economy | Primary industry | Annual value-added of primary industry | (Cao et al., 2014; Cobon et al., 2009; Deng et al., 2016) |
| | Income | Per capita annual net income of rural households | |
| | Grain yield | Total outputs of rice, wheat, corn and other grains and beans | |
| | Arable land | Area of farmland | |

## 3. Results

### *3.1. Restoration effectiveness*

Although vegetation cover in northern Shaanxi has largely inceased in the last 15 years, the degree of recovery significantly differed over the three cumulative temporal periods. In the early stage of the GTGP (Fig. 3a), only 9 out of the 25 counties had effective vegetation restoration ($E_j$ ＞ 1), with the rest showing low effectiveness ($E_j$ < 1). This is because the three vegetation indicators ($FVC_{mean}$, $FVC_{max}$, and $NPP_{annual}$) showed no significant change in most of the study area, with only a scattered distribution of a few significant greening areas (Fig. S1). Over the longer temporal scale (2000-2010), due to the widespread and significant increases of vegetation (Fig. S1), $E_j$ increased markedly (Fig. 3b). This trend of increasing effectiveness continued for 2000-2014 (Fig. 3c). Geographically, $E_j$ seems to increase from the northern and south central counties (Fugu, Wuqi, and Yanchang) to the whole study area, which is largely in line with the spatial trends observed for the three vegetation indicators (Fig. S1). These results are supported by previous studies which noted that the GTGP in northern Shaanxi mainly concentrated on shrub and grassland bio-climate zones with large areas of re-vegetated sloping croplands (Feng et al., 2013; Song et al., 2011).

Notable exceptions can be observed however, in the three southern counties of Fuxian, Huangling and Huanglong, where large tracts of natural forest remained with an area coverage of 60%, which resulted in lower and lower overall relative effectiveness of vegetation restoration values across all three time periods. This is because the baseline condition of vegetation cover was already high in these counties and as such, they are not a priority for vegetation restoration, but are for nature conservation. In these counties, the mean values of $FVC_{mean}$, $FVC_{max}$, and $NPP_{annual}$

during 2000-2014 were the highest observed, but the coefficients of variation of these indicators were the lowest (see supplementary material Fig. S2), which directly implied effective forest conservation.

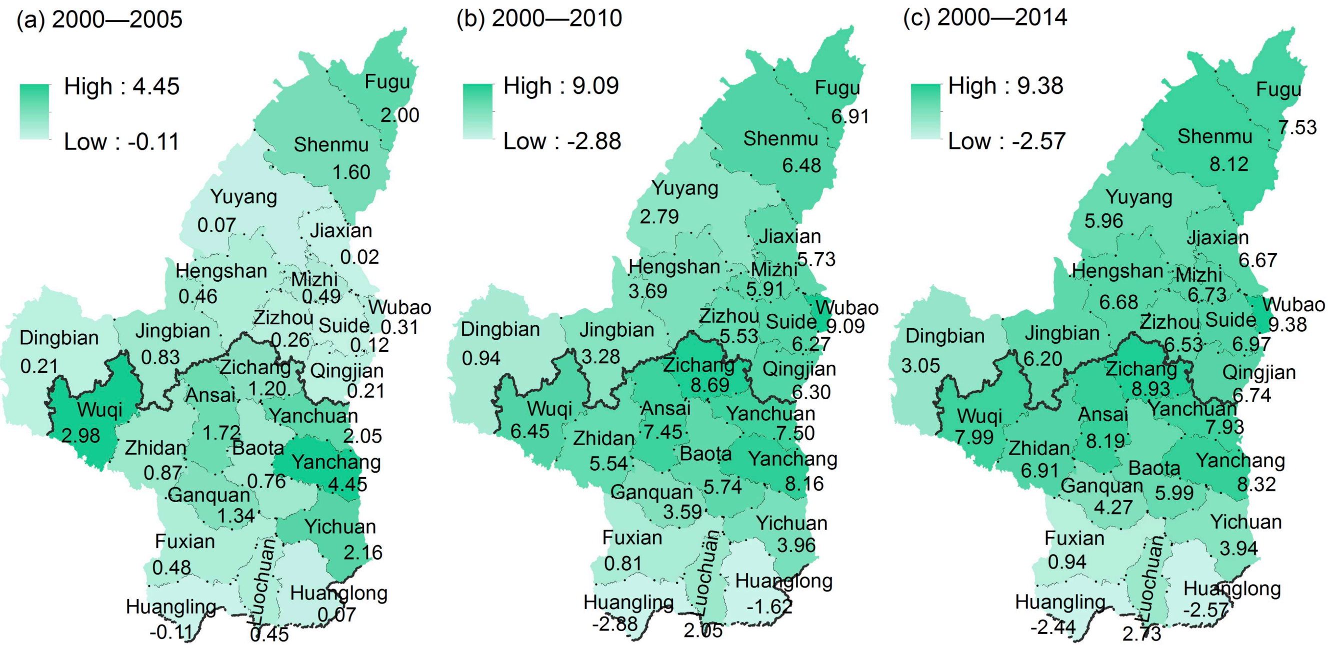


**Fig.3** The comprehensive relative effectiveness of vegetation restoration at a county scale in three different time periods.

*3.2. Relationships between socio-economic factors and vegetation restoration effectiveness*

The factors selected for describing socio-economic status in northern Shaanxi included population pressure and measures of the industrial and agricultural economies. The variance explained by the three socio-economic factors was 62%, 83% and 91%, respectively over the three temporal scales, indicating a significant influence on restoration effectiveness. The three latent variables (i.e. population pressure, off-farm economy and rural economy) were highly correlated, as hypothesized in the *a-priori* model (Fig. 2).

The strength of the relationships between socio-economic factors and restoration effectiveness varied over time. In the first five years (Fig. 4a), the strong negative impact of socio-economic factors on restoration effectiveness was only reflected by population pressures. The impact contributed by the off-farm economy was weak and non-significant but the rural economy had a positive effect (0.27) in relation to restoration effectiveness. Over longer temporal scales (Fig. 4b~c), both population pressure and the off-farm economy exhibited significantly negative impacts on restoration effectiveness, whereas the rural economy was strongly positively correlated with restoration effectiveness.

Specifically, population pressure was always the most important factor that negatively acted on restoration effectiveness. However, the contribution from the total population showed a decreased tendency with path coefficients of 1.00, 0.88 and 0.83, respectively, while the rural employment were more important contributors over time. As for the off-farm economy, secondary industry was the leading indicator across time. But the contribution from the secondary industry did not change while that from the tertiary industry increased significantly over time, which suggests the latter might be responsible for the increased negative impacts. Only the rural economy showed a consistent positive impact on restoration effectiveness with path coefficients of 0.27, 0.73 and 0.82, respectively, which was reinforced over time. Despite the rural economy being sensitive to all three indicators (i.e. income, primary industry and grain yield), income showed less contribution at the three temporal scales.

Our final models indicated that the off-farm economy was positively influenced by total population and income (Fig. 4b~c), an influence which had not been revealed in the first five years (Fig. 4a). In the early stage of the GTGP (Fig. 4a), vegetation restoration had a positive impact on rural income with a path coefficient of 0.45, because increases in farm income were mainly dependent on governmental subsidies (Liu et al., 2008). Also, a negative impact of $NPP_{annual}$

increases on grain production reflected the influences that the grain cultivation on steep farmland (slopes ≥ 25°) being replaced by re-vegetation under the GTGP. Our results also revealed that rural employment benefits from the restoration programmes, which has been similarly identified in related empirical research (Aronson et al., 2010). These relationships were retained, as well as relationships among socio-economic factors, because their relevance and interactions are widespread across a range of linked socio-economic activities. The $\chi^2$ and other fit indices suggested that the SEM was reliable and suitable (Table 2).

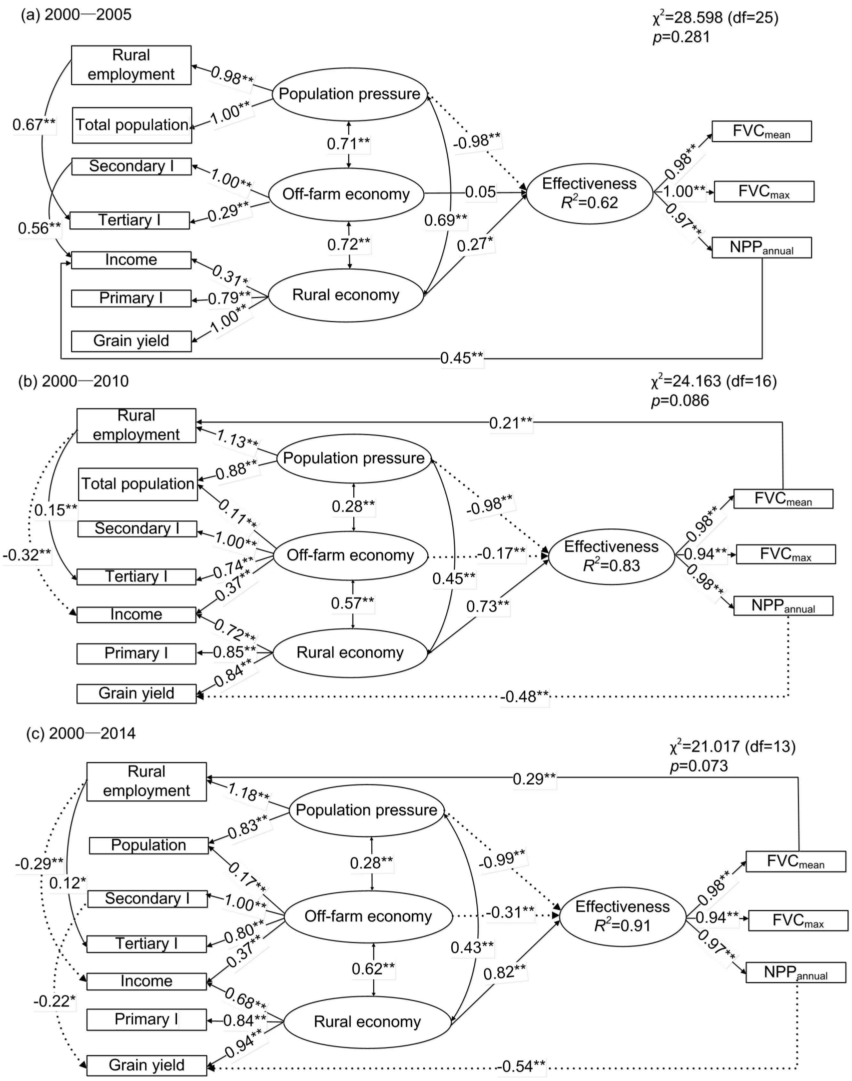


**Fig. 4** The SEM for the relationships between socio-economic factors and the effectiveness of vegetation restoration in different time periods. Solid lines indicate a positive influence and dashed lines indicate a negative influence. Double asterisks (**) means a significant trend at $P < 0.01$, and one asterisk (*) means a significant trend at $P < 0.05$. Un-marked paths indicate a non-significant relationship.

**Table 2** Measures of fit for the SEM model.

| Model fit indices | Recommended levels | Estimate values | | |
|---|---|---|---|---|
| | | 2000-2005 | 2000-2010 | 2000-2014 |
| $\chi^2$/df | <5.000 | 1.144 | 1.51 | 1.617 |
| RMSEA | <0.050 | 0.057 | 0.051 | 0.048 |
| GFI | >0.900 | 0.901 | 0.977 | 0.983 |
| CFI | >0.900 | 0.995 | 0.996 | 0.997 |
| NFI | >0.900 | 0.963 | 0.990 | 0.992 |

## 4. Discussion

*4.1. The effectiveness index provides a quantitative indicator of regional restoration performance*

Much of the existing research for assessing the effectiveness of vegetation restoration has used NDVI to quantify vegetation temporal and/or spatial variation (Tong et al., 2017; Zhang et al., 2012). Spatial pattern analysis based on landscape metrics are also widely adopted in effectiveness assessment to examine spatial pattern, structure and composition of vegetation conservation or restoration (Fava et al., 2016; Qi et al., 2013). However, vegetation function and the dynamics of restoration effectiveness are rarely considered. The effectiveness index ($E_j$) we formulated provides a comprehensive measure of the effect of vegetation restoration based on changes in vegetation cover and NPP. Using this elegant and easily calculated index, this paper revealed the temporal dependency of restoration effectiveness and its spatial heterogeneity. In northern Shaanxi, three stages were characterized: 1) emergent effectiveness in the early stage of the GTGP (i.e. 2000-2005), 2) increasing effectiveness over a longer temporal scale (i.e. 2000-2010), and 3) further changes over the entire period (i.e. 2000-2014) resulting in significant improvements caused by prolonged restoration (Fig. 3a~c). Given the complexity of regional variations, local knowledge is also needed to identify the reasons for differences in vegetation recovery. For instance, $E_j$ in the southern counties of northern Shaanxi (Huangling and Huanglong) was critically related to persistent forest conservation in these counties, but confounded the assessment of vegetation restoration. Nevertheless, the index provides an indication of effective management in different stages of restoration.

Improving the effectiveness of ecological restoration can positively affect water flow regulation and soil conservation (Ran et al., 2013). Vegetation restoration provides opportunities to achieve effective control in nutrient losses, sediment loads and non-point source pollution (Palmer et al., 2014). The effectiveness index formulated in this research provides a simple but efficient tool for indirectly estimating the relative contributions of vegetation restoration on hydrological regulation and pollution mitigation at regional scales.

### *4.2. Socio-economic and temporal dimensions are crucial for understanding restoration effectiveness*

Large-scale restoration projects are part of a complex social-ecological system. The effectiveness of restoration projects is related to both biophysical and socio-economic factors. At decadal time scale, changes in geomorphology and soil are negligible but changes in climate have the potential to be the most significant biophysical factor effecting ecological restoration. For these reasons, we examined changes in precipitation and temperature based on 21 meteorological stations within and near northern Shaanxi, from 2000 to 2014 (see supplementary material Fig. S3). We found that annual precipitation increased significantly in only one of the 21 stations (Suide) and the mean annual temperature decreased significantly in another (Yan'an) (Table S1). However, regionally (across the entire study area) no significant change in precipitation and temperature were found during this period (Fig. S4). These findings are in line with Feng et al. (2013) who found no significant change in precipitation or temperature across the entire Loess Plateau and component bioclimatic zones during last decade. Therefore, climate variation was not considered to be a significant factor associated with regional ecological restoration in this study.

Dynamic restoration processes are subject to continuous change. Consequently, the findings and outcomes of research into these processes will inevitably vary over time (Lake et al., 2007; Levrel et al., 2012). In this research, restoration effectiveness was found to change during different periods, reflecting temporal effects on the vegetation restoration process, where the spatial heterogeneity of vegetation restoration also varied with time (Fig. 3). Moreover, we quantified the significant relationships between socio-economic factors and the effectiveness of the regional restoration—factors have been found to be locally-specific and temporally dynamic (Borja et al., 2010). Previous studies have often depended on sparse information or specific indicators and have been mostly grounded in untested assumptions rather than an integrated analysis (Miyasaka et al., 2017). Here, we integrated a number of core socio-economic factors of different categories and quantified their changing relationships with restoration effectiveness. Our results support the hypothesis that socio-economic factors (i.e. population, measures of industrial and agricultural economies) can have significant implications on restoration effectiveness. The spatially heterogeneous impacts of some socio-economic factors have been explored and addressed before (Cao et al., 2014; Jiang et al., 2017). However, we quantified the time dependent characteristics of different socio-economic impacts using a SEM approach (Fig. 4), which is able to factor specific information in relation to the effectiveness of regional restoration projects. Subsequently, a long-term horizon of monitoring and assessment needs to be embraced that includes socio-economic factors as key components for a comprehensive understanding of restoration effectiveness at large regional scales.

*4.3. Socio-economic factors are important for improving the effectiveness of large-scale ecological restoration*

Demographic factors have a significant negative correlation with vegetation change as reported in much regional and national scale research (Jiang et al., 2017; Li et al., 2013; Lü et al., 2015; Mganga et al., 2015). In this study, population pressure was also found to have negative impacts on restoration effectiveness, consistent with other research. Empirical studies have shown that improvements in economic welfare can contribute to vegetation restoration, emphasizing the positive effects of rural economic improvements (Jiang et al., 2017; Lü et al., 2015; Madu, 2009) and that rural income has a positive relationship with vegetation change (Cao et al., 2014). However, secondary industry has been found to negatively impact on vegetation in ecologically fragile regions as a result of industrial growth or urban expansion (Su et al., 2014; Wang et al., 2016). In this research, such economic factors (i.e. the off-farm and rural economies) were found to have the opposite influence, highlighting a complex relationship between socio-economics and regional ecological restoration. Secondary industry was the major contributor for its economic growth for over a decade in northern Shaanxi.

Changes in relationship between socio-economic factors and restoration effectiveness offer insights for improving the management of large-scale ecological restoration projects. The rural labor force represents a vigorous group of stakeholders that could facilitate, impede or even reverse ecological restoration progress (Petursdottir et al., 2013). Promoting the migration of rural labor could provide an opportunity to mitigate the negative impacts of population pressure on restoration effectiveness when population growth rates plateau. Deshingkar (2012) noted that many districts in Eastern India experienced a significant increase in forest cover in situations of high migration. Examples of successful ecological restoration in Southeast China also demonstrated the positive impacts resulting from temporary or permanent migration in the rural labor force (Wang et al., 2011). The labor-intensive tertiary industry plays an irreplaceable role in absorbing rural labor (Madu, 2009), which was reflected in the early stage of the GTGP, with a path coefficient of 0.67 found in our research (Fig. 4a). This was because of a large amount of rural labor was released at one time. However, the effects of rural labor migration or the pull from tertiary industry was weakening, which might explain the continuous negative effect of population (Fig. 4b~c). Fragmentation and the irregularity of vegetated landscapes were also observed with the development of tertiary industry (Michishita et al., 2012; Su et al., 2014). Thus, the increased negative effect of the off-farm economy suggests a constraint from the rapid development of tertiary industry. Therefore, tertiary industry should be promoted as a low emission, resource-saving and livelihood-supporting approach to urbanization and industrial production to both realize the transfer of rural labor and facilitate ecological restoration.

A sustainable restoration project should also involve the rural economy and take full consideration of objectives and values of the rural community (Lamouroux et al., 2015). Recent research has suggested that the direct economic benefit may not be the dominant driver for improving ecological restoration. A survey in Iceland suggested that aesthetic values over economic interests were the main reasons for stakeholders practicing restoration projects (Petursdottir et al., 2013). Deng et al. (2016) also noted that ecological benefits play a more active role than economic benefits in promoting farmers to conserve the restoration achievements in the GTGP. Our results indicated that rural income had a minimal impact on the rural economy, at the three temporal scales. In contrast, improvements in agricultural practice have been found to alleviate the burden on environment and natural resources (Deshingkar, 2012; Sjogersten et al., 2013). For example, case studies in India indicated that improvements of farm productivity reduced the area farmed and pressure on forests (Deshingkar, 2012). Our results clearly highlighted the contribution to restoration effectiveness from agricultural productivity (including grain yield and primary industry). Therefore, another promising strategy for enhancing restoration effectiveness is to fundamentally improve rural livelihoods. Together the migration of the rural labor force and improvements in farming practice have the ability to promote the rural economy by diversifying income streams, subsequently improve the effectiveness of restoration in the long run.

### *4.4. Spatially-explicit quantification of the relationships between restoration effectiveness and socio-economics*

Our research explored the relationships between socio-economic factors and ecological restoration effectiveness, and identified the major socio-economic drivers that facilitate restoration programmes. However, our study also revealed that the relationships between different indicators of three socio-economic factors (i.e. population pressure, off-farm economy and rural economy) and their inter-correlations varied over time (Fig. 4). This suggests that multiple interactions exist in socio-economic systems, interactions that were not the main focus of this study. Nonetheless, we believe that these changing relationships could be potentially responsible for altering the effects of socio-economic factors on the restoration effectiveness.

Clarifying these specific relationships, requires for a more sophisticated quantitative approach, such as adapting the SEM to account for spatial structure in the data with a more specified objective of detecting local or regional effects on the relationships between the socio-economy and ecological restoration effectiveness. This requires the investigation of the effects of spatial autocorrelation in the component linear regressions of the SEM (Lamb et al., 2014), and/or the effects of spatial heterogeneity in the relationships of the same component regressions. For the latter, the adaptation of the SEM to a geographically weighted methodology (Gollini et al., 2015; Lu et al., 2014) as explored by Comber et al (2017) is a subject for future research. Adapting SEMs to account for spatial effects will potentially provide spatially-explicit decision support for improving regional effectiveness of ecological restoration through regulating the socio-economic context and key drivers accurately. This could be a priority for the next steps in ecological restoration research.

## 5. Conclusions

This paper proposes a simple and rapid quantitative method for assessing the effectiveness of large-scale vegetation restoration based on changes in vegetation cover and net primary production under a "before and after" analytical framework. A composite index ($E_j$) at different temporal scales revealed the continuous improvement of vegetation restoration at a regional scale. By using a structural equation modeling approach, this paper indicated that population pressure and economic development, dominated by secondary industry, could negatively impact the improvement of restoration effectiveness. Whereas, improvements in the rural economy could positively contribute to improving restoration effectiveness. The influence of socio-economic factors varied over time, which offers dual perspectives for enhancing restoration effectiveness. First, tertiary industry could potentially relieve population pressure caused by the rural labor force and facilitate ecological restoration. Second, promoting a rural economy and introducing comprehensive policies is advocated, particularly focusing on improvements in agricultural practices. Our research highlighted quantitatively the time-dependent characteristics of the effectiveness of regional ecological restoration and its relations with socio-economic factors. Therefore, the dynamic nature of socio-economic context should always be considered in the planning, monitoring, and adaptive management of large-scale ecological restoration programmes for developing and promoting effective and flexible restoration interventions.

## Authors' Contributions

Y.L. and B.F. designed the research; T.L. analyzed the data and wrote the paper; A.C., P.H. and L.W. contributed critical ideas in improving the manuscript.

## Acknowledgments

This research was supported by the National Key Research and Development Program of China (No. 2016YFC0501601) and the China-UK bilateral collaborative research on critical zone science (National Natural Science Foundation of China NO. 41571130083 and the Natural Environment Research Council Newton Fund NE/N007433/1).

## Appendix A. Supplementary data

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