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

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17

18 **Abstract**

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

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

40 **1. Introduction**

41 Since the turn of the millennium, numerous restoration initiatives have been established
42 across the globe to restrain environmental degradation and ecological destruction caused by
43 human activities (Benayas et al., 2009). As an interventionist activity, evidence strongly indicates
44 that ecological restoration has achieved its major goal of enhancing biodiversity and restoring
45 ecosystem services (Clewell and Aronson, 2013). A meta-analysis of 89 restoration assessments
46 across a wide range of ecosystem types, revealed that biodiversity and ecosystem services were on
47 average enhanced by 44% and 25%, respectively (Benayas et al., 2009). Significant restoration
48 achievements in some specific ecosystem types and degraded regions have also been reported
49 (Calmon et al., 2011; Meli et al., 2014). As a result, ecological restoration activities are now
50 widely recognized as significant contributors to global sustainability. Given the large spatial extent
51 of restoration and conservation coverage, more than 11% of the global land surface (Andam et al.,
52 2008), coupled with government funding, analytical tools are needed to accurately assess
53 restoration effectiveness so that researchers and policy-makers can promote successful
54 management interventions. Unfortunately, even well-designed research programmes are often
55 poor at evaluating the effectiveness of large-scale ecological restorations (Martin et al., 2014).
56 This is in part due to poorly specified metrics, limited information on spatial and temporal
57 variability, and insufficient knowledge of human impacts. The lack of agreed scientific methods
58 for assessing restoration effectiveness limits the incorporation of ecological restoration in land-use
59 planning and decision making. In turn, this presents a challenge to governments and managers
60 when restoration projects up-scale from individual sites to landscape and regional levels (Cao et
61 al., 2009; Lamb et al., 2005).

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

75 In these evaluations, the process of ecological restoration is affected both by natural factors
76 and by human activities, which provides multifaceted interactions between ecological effects and
77 socio-economic drivers (Timilsina et al., 2014). In fact, recent research has indicated that
78 socio-economic factors exhibit a growing influence on changes to ecological processes (Lü et al.,
79 2015; Petursdottir et al., 2013; Zhang et al., 2013). The impacts caused by socio-economic factors
80 were found to be dominant over climate variations, in driving large scale ecological changes
81 nationally in China and related to the implementation of a series of large scale ecological
82 conservation and restoration programmes (Lü et al., 2015; Zhang et al., 2013). However, detailed
83 mechanisms concerning the role of socio-economic factors on ecological restoration effectiveness

84 are still unclear at the regional scale. The purpose of this study is to tackle these deficiencies and
85 to examine the effectiveness of large-scale ecological restoration over different temporal scales, as
86 well as the possible time dependent relationships between restoration effectiveness and
87 socio-economic factors.

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

103 Re-vegetation is the most intuitive and effective approach for restoration projects. It
104 promotes ecological functions, such as increasing biodiversity, carbon sequestration and improved
105 soil quality (Jin et al., 2014). Changes in vegetation provide simple and cost-effective indicators of

106 effectiveness of restoration and conservation programmes (Lü et al., 2015). Using high temporal
107 and high spatial resolution remote sensing data, it is possible to quantify the basic characteristics
108 of vegetation / land cover change as well as changes in functional characteristics, such as biomass
109 productivity. Fractional vegetation cover (FVC) can be derived from remote sensing data and used
110 to provide an index for characterizing vegetation changes (Wu et al., 2014). Similarly, net primary
111 production (NPP) provides a measure of standing biomass (Donmez et al., 2011) and is a critical
112 indicator of ecosystem function (Watanabe and Ortega, 2014). Therefore, these two remote
113 sensing data products were used to assess the effectiveness of regional ecological restoration in
114 this research. Specifically, this research: (1) formulates a composite indicator approach for
115 assessing the effectiveness of ecological restoration at a regional scale based on mentioned FVC
116 and annual accumulated NPP; (2) quantifies the effectiveness of ecological restoration and the
117 impacts from different socio-economic factors by using a structural equation modeling (SEM)
118 approach; (3) highlights the significance of temporal scale effects and the practical implications of
119 this research for ecological restoration policy and management across large spatial scales.

120 **2. Materials and methods**

121 *2.1. Study area*

122 Northern Shaanxi is situated in the middle of Loess Plateau (35° 21' - 39° 34' N, 107° 28' -
123 111° 15') and covers an area of 8.03×10^4 km² (Fig.1). This region is dominated by a semi-arid and
124 continental climate with a mean annual temperature ranging from 7 to 12 °C, and an annual
125 precipitation ranging from 350 mm to 600 mm. The study area includes the Yulin and the Yan'an
126 prefectures consisting of 25 counties, which acted has as a pilot and demonstration region for the
127 GTGP since 1999 (i.e. over 15 years for the purposes of this study).

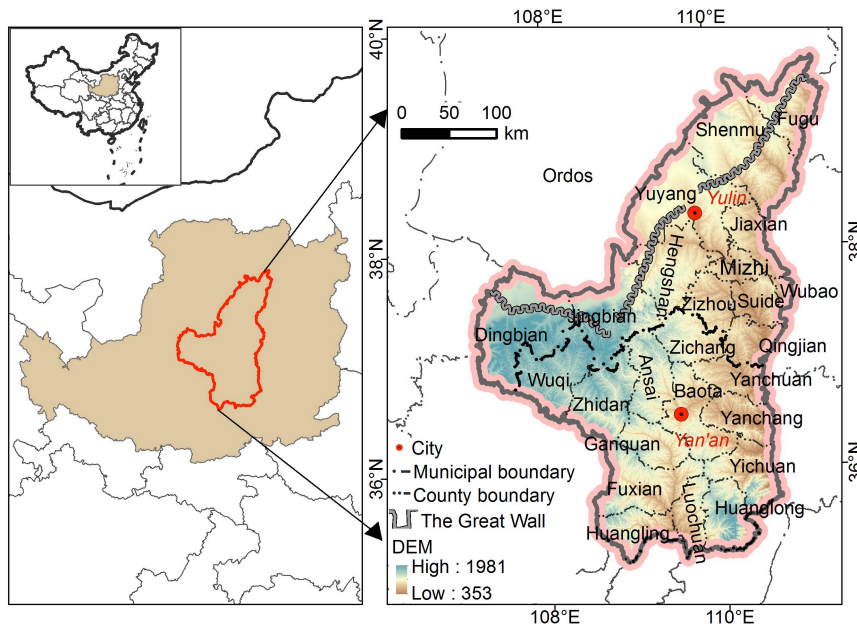


Fig. 1 Location of the study area on the Loess Plateau of China.

128

129

130 *2.2. Data sources*

131

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.

140

2.3. Vegetation restoration effectiveness assessment and the use of SEM

141

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

143

144 area. The linear trends of these indicators were calculated by using an ordinary least-squares
 145 regression approach for each pixel in northern Shaanxi (Lü et al., 2015), where a was the slope of
 146 the resultant linear equation which was subjected to the usual t -test for significance from zero. If
 147 $a > 0$ and $p < 0.05$, there was a significant positive trend for the variable in question. By contrast,
 148 when $a < 0$ and $p < 0.05$, there was a significant negative trend for the variable in question. The
 149 change in trends for the three indicators were estimated for three different overlapping periods,
 150 namely 2000-2005, 2000-2010, and 2000-2014 (see supplementary material Fig. S1). A “before
 151 and after” design (Martin et al., 2014) was used to estimate the effectiveness of vegetation
 152 restoration. Different weights were assigned to the three variables. FVC provides a basic structural
 153 index for assessing vegetation condition and NPP is a functional indicator for vegetation
 154 production that is important for regulating ecosystem processes and functions (Watanabe and
 155 Ortega, 2014). Therefore, an equal weighting of 0.5 was allocated to FVC and NPP as measures of
 156 the structure and function in ecosystems, respectively. Additionally, a greater weight was assigned
 157 to FVC_{\max} as its explanatory power has been found to be higher than FVC_{mean} (Wu et al., 2014).

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

$$159 \quad e_j = 100\% \times \sum w_i \times (IN_{ij} - DE_{ij}) \quad (1)$$

160 where variable i could be one of FVC_{mean} , FVC_{\max} , or NPP_{annual} ; $j=1$ for 2000-2005, $j=2$ for
 161 2000-2010, $j=3$ for 2000-2014, w_i denoted the weighting factor for variable i set at 0.2, 0.3, and
 162 0.5 for FVC_{mean} , FVC_{\max} , and NPP_{annual} , respectively, IN_i denoted the percentage area in each
 163 county with a significant increasing trend on variable i and DE_i represented the percentage area of
 164 each county with significant decreasing trend on variable i . The difference between IN_i and DE_i is
 165 referred to as the net relative change on variable i .

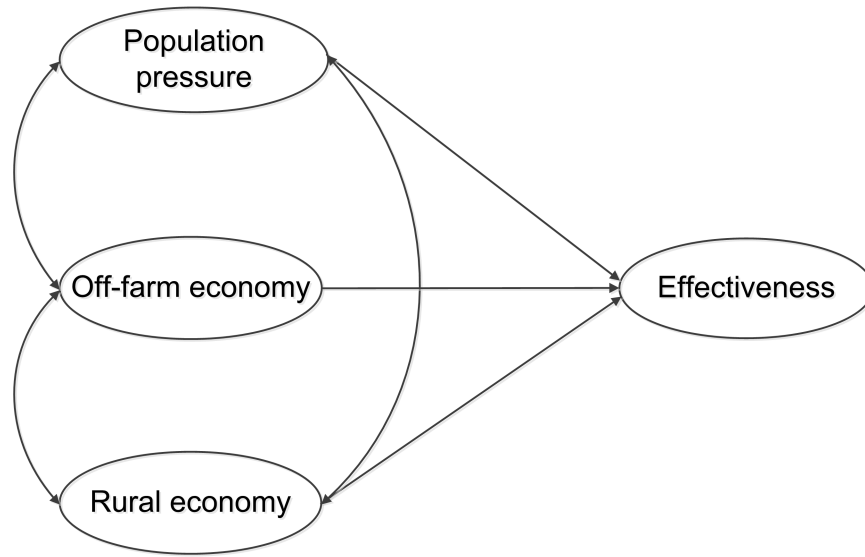
166 To determine the temporal trends in restoration effectiveness, the average of the
167 comprehensive effectiveness during the initial stage (i.e. 2000-2005, $j=1$) in the study area was set
168 as the reference value (\bar{e}). Then the relative comprehensive effectiveness index (E_j) for each
169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

$$170 \quad E_j = \frac{e_j}{\bar{e}} \quad (2)$$

$$171 \quad \bar{e} = \left[100\% \times \sum w_i \times (IN_{i1} - DE_{i1}) \right]_{avg} \quad (3)$$

172 SEM is a method for examining hypotheses about multivariate causal relationships in
173 complex systems, which can involve either observed variables, latent variables or both (Grace,
174 2006). The basic assumption of SEMs is that explanatory models may include hidden or latent
175 variables. To examine this a series of latent equations are used to generate parameters that are
176 passed to regression operations and residual correlation evaluations. This method is particularly
177 useful for identifying latent variables, as it allows a range of variables to be tested simultaneously
178 and the best fitting model selected for any possible set of measured variables (Byrne, 2016). SEMs
179 are being increasingly used to explore the interactive effects that drive mechanisms on the
180 sustainability of socio-ecological systems. For example, Standish et al. (2015) estimated climate
181 factors, restoration practice and their interactive effects on the richness of restored plant
182 assemblages by developing a SEM. Tian et al. (2014) assessed the relationships among land cover
183 change, economic development and population growth in the context of sustainably managing
184 urban ecosystems. Therefore, this method can be adapted to explore the relationships between
185 different categories of socio-economic factors and the effectiveness of vegetation restoration. The
186 contributed indicators for each socio-economic factors could be identified and screened from a
187 range of measured variables.

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



208

209

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

210

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

Socioeconomic factors	Indicators	Description	Literature
Population pressure	Total population	Total permanent population	
	Rural populations	Permanent population in rural areas	(Cao et al., 2014; Li et al., 2013; Lü et al., 2015; Luck et al., 2009)
	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	
	Tertiary industry	Annual value-added of tertiary industry	(Li et al., 2015; Lü et al., 2015; Michishita et al., 2012; Su et al., 2014; Wittemyer, 2011)
	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	
	Income	Per capita annual net income of rural households	(Cao et al., 2014; Cobon et al., 2009; Deng et al., 2016)
	Grain yield	Total outputs of rice, wheat, corn and other grains and beans	
	Arable land	Area of farmland	

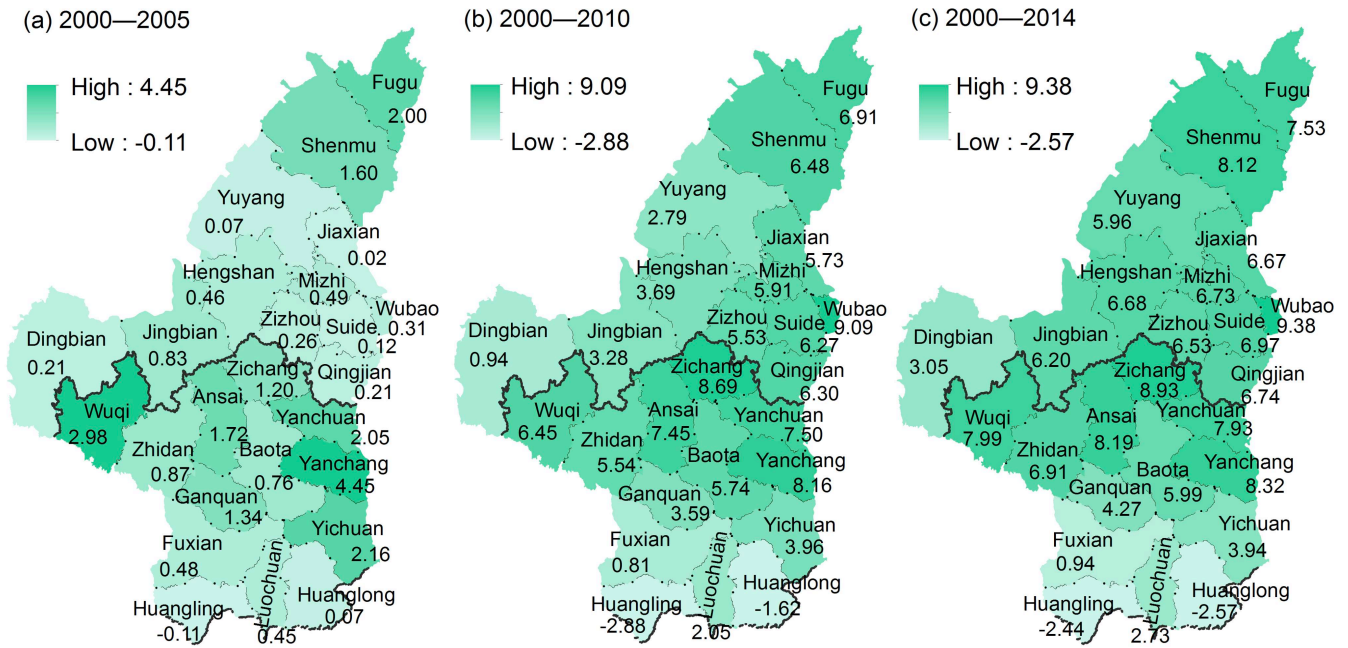
213 **3. Results**

214 *3.1. Restoration effectiveness*

215 Although vegetation cover in northern Shaanxi has largely increased in the last 15 years, the
216 degree of recovery significantly differed over the three cumulative temporal periods. In the early
217 stage of the GTGP (Fig. 3a), only 9 out of the 25 counties had effective vegetation restoration (E_j
218 > 1), with the rest showing low effectiveness ($E_j < 1$). This is because the three vegetation
219 indicators (FVC_{mean} , FVC_{max} , and NPP_{annual}) showed no significant change in most of the study
220 area, with only a scattered distribution of a few significant greening areas (Fig. S1). Over the
221 longer temporal scale (2000-2010), due to the widespread and significant increases of vegetation
222 (Fig. S1), E_j increased markedly (Fig. 3b). This trend of increasing effectiveness continued for
223 2000-2014 (Fig. 3c). Geographically, E_j seems to increase from the northern and south central
224 counties (Fugu, Wuqi, and Yanchang) to the whole study area, which is largely in line with the
225 spatial trends observed for the three vegetation indicators (Fig. S1). These results are supported by
226 previous studies which noted that the GTGP in northern Shaanxi mainly concentrated on shrub
227 and grassland bio-climate zones with large areas of re-vegetated sloping croplands (Feng et al.,
228 2013; Song et al., 2011).

229 Notable exceptions can be observed however, in the three southern counties of Fuxian,
230 Huangling and Huanglong, where large tracts of natural forest remained with an area coverage of
231 60%, which resulted in lower and lower overall relative effectiveness of vegetation restoration
232 values across all three time periods. This is because the baseline condition of vegetation cover was
233 already high in these counties and as such, they are not a priority for vegetation restoration, but are
234 for nature conservation. In these counties, the mean values of FVC_{mean} , FVC_{max} , and NPP_{annual}

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



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

240 *3.2. Relationships between socio-economic factors and vegetation restoration effectiveness*

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

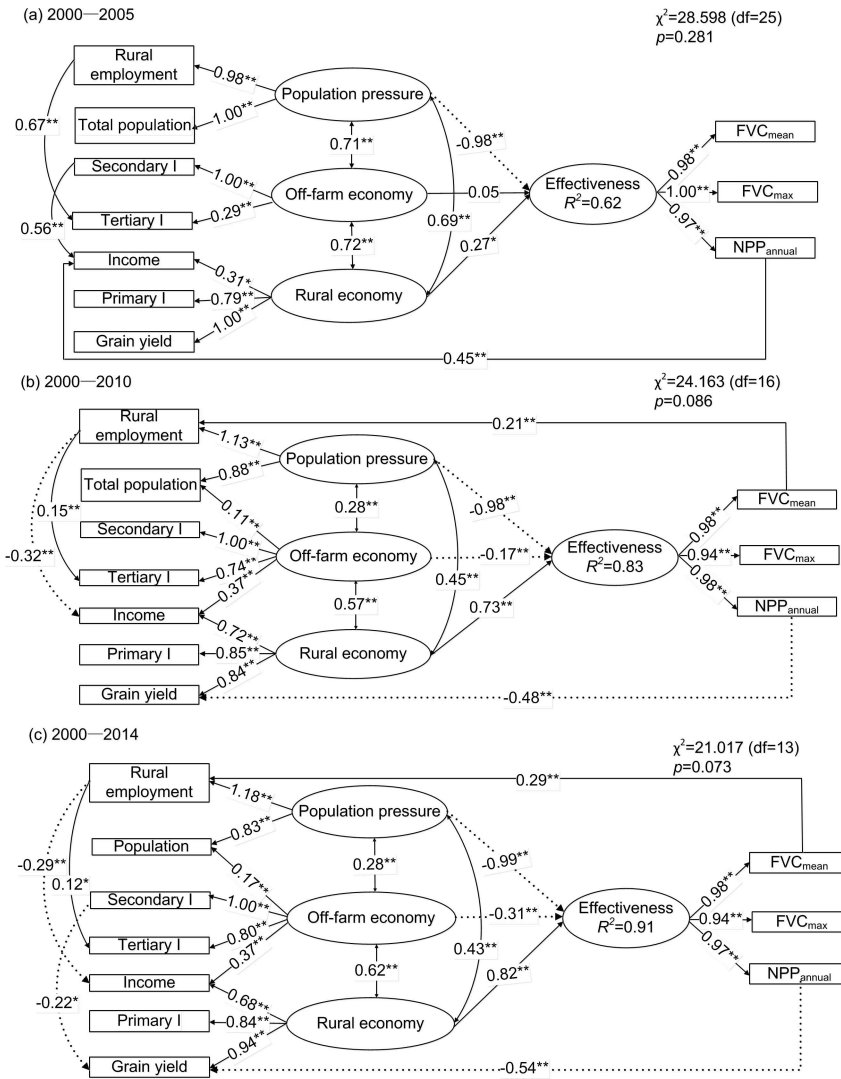
247 The strength of the relationships between socio-economic factors and restoration
 248 effectiveness varied over time. In the first five years (Fig. 4a), the strong negative impact of

249 socio-economic factors on restoration effectiveness was only reflected by population pressures.
250 The impact contributed by the off-farm economy was weak and non-significant but the rural
251 economy had a positive effect (0.27) in relation to restoration effectiveness. Over longer temporal
252 scales (Fig. 4b~c), both population pressure and the off-farm economy exhibited significantly
253 negative impacts on restoration effectiveness, whereas the rural economy was strongly positively
254 correlated with restoration effectiveness.

255 Specifically, population pressure was always the most important factor that negatively acted
256 on restoration effectiveness. However, the contribution from the total population showed a
257 decreased tendency with path coefficients of 1.00, 0.88 and 0.83, respectively, while the rural
258 employment were more important contributors over time. As for the off-farm economy, secondary
259 industry was the leading indicator across time. But the contribution from the secondary industry
260 did not change while that from the tertiary industry increased significantly over time, which
261 suggests the latter might be responsible for the increased negative impacts. Only the rural
262 economy showed a consistent positive impact on restoration effectiveness with path coefficients of
263 0.27, 0.73 and 0.82, respectively, which was reinforced over time. Despite the rural economy
264 being sensitive to all three indicators (i.e. income, primary industry and grain yield), income
265 showed less contribution at the three temporal scales.

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

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



279

280 **Fig. 4** The SEM for the relationships between socio-economic factors and the effectiveness of
 281 vegetation restoration in different time periods. Solid lines indicate a positive influence and
 282 dashed lines indicate a negative influence. Double asterisks (**) means a significant trend at $P <$
 283 0.01, and one asterisk (*) means a significant trend at $P < 0.05$. Un-marked paths indicate a
 284 non-significant relationship.

285

Table 2 Measures of fit for the SEM model.

Model fit indices	Recommended levels	Estimate values		
		2000-2005	2000-2010	2000-2014
χ^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

288 **4. Discussion**

289 *4.1. The effectiveness index provides a quantitative indicator of regional restoration performance*

290 Much of the existing research for assessing the effectiveness of vegetation restoration has
291 used NDVI to quantify vegetation temporal and/or spatial variation (Tong et al., 2017; Zhang et al.,
292 2012). Spatial pattern analysis based on landscape metrics are also widely adopted in effectiveness
293 assessment to examine spatial pattern, structure and composition of vegetation conservation or
294 restoration (Fava et al., 2016; Qi et al., 2013). However, vegetation function and the dynamics of
295 restoration effectiveness are rarely considered. The effectiveness index (E_j) we formulated
296 provides a comprehensive measure of the effect of vegetation restoration based on changes in
297 vegetation cover and NPP. Using this elegant and easily calculated index, this paper revealed the
298 temporal dependency of restoration effectiveness and its spatial heterogeneity. In northern Shaanxi,
299 three stages were characterized: 1) emergent effectiveness in the early stage of the GTGP (i.e.
300 2000-2005), 2) increasing effectiveness over a longer temporal scale (i.e. 2000-2010), and 3)
301 further changes over the entire period (i.e. 2000-2014) resulting in significant improvements
302 caused by prolonged restoration (Fig. 3a~c). Given the complexity of regional variations, local
303 knowledge is also needed to identify the reasons for differences in vegetation recovery. For
304 instance, E_j in the southern counties of northern Shaanxi (Huangling and Huanglong) was
305 critically related to persistent forest conservation in these counties, but confounded the assessment
306 of vegetation restoration. Nevertheless, the index provides an indication of effective management
307 in different stages of restoration.

308 Improving the effectiveness of ecological restoration can positively affect water flow
309 regulation and soil conservation (Ran et al., 2013). Vegetation restoration provides opportunities

310 to achieve effective control in nutrient losses, sediment loads and non-point source pollution
311 (Palmer et al., 2014). The effectiveness index formulated in this research provides a simple but
312 efficient tool for indirectly estimating the relative contributions of vegetation restoration on
313 hydrological regulation and pollution mitigation at regional scales.

314 *4.2. Socio-economic and temporal dimensions are crucial for understanding restoration*
315 *effectiveness*

316 Large-scale restoration projects are part of a complex social-ecological system. The
317 effectiveness of restoration projects is related to both biophysical and socio-economic factors. At
318 decadal time scale, changes in geomorphology and soil are negligible but changes in climate have
319 the potential to be the most significant biophysical factor effecting ecological restoration. For
320 these reasons, we examined changes in precipitation and temperature based on 21 meteorological
321 stations within and near northern Shaanxi, from 2000 to 2014 (see supplementary material Fig.
322 S3). We found that annual precipitation increased significantly in only one of the 21 stations
323 (Suide) and the mean annual temperature decreased significantly in another (Yan'an) (Table S1).
324 However, regionally (across the entire study area) no significant change in precipitation and
325 temperature were found during this period (Fig. S4). These findings are in line with Feng et al.
326 (2013) who found no significant change in precipitation or temperature across the entire Loess
327 Plateau and component bioclimatic zones during last decade. Therefore, climate variation was not
328 considered to be a significant factor associated with regional ecological restoration in this study.

329 Dynamic restoration processes are subject to continuous change. Consequently, the findings
330 and outcomes of research into these processes will inevitably vary over time (Lake et al., 2007;
331 Levrel et al., 2012). In this research, restoration effectiveness was found to change during different

332 periods, reflecting temporal effects on the vegetation restoration process, where the spatial
333 heterogeneity of vegetation restoration also varied with time (Fig. 3). Moreover, we quantified the
334 significant relationships between socio-economic factors and the effectiveness of the
335 regional restoration—factors have been found to be locally-specific and temporally dynamic
336 (Borja et al., 2010). Previous studies have often depended on sparse information or specific
337 indicators and have been mostly grounded in untested assumptions rather than an integrated
338 analysis (Miyasaka et al., 2017). Here, we integrated a number of core socio-economic factors of
339 different categories and quantified their changing relationships with restoration effectiveness. Our
340 results support the hypothesis that socio-economic factors (i.e. population, measures of industrial
341 and agricultural economies) can have significant implications on restoration effectiveness. The
342 spatially heterogeneous impacts of some socio-economic factors have been explored and
343 addressed before (Cao et al., 2014; Jiang et al., 2017). However, we quantified the time dependent
344 characteristics of different socio-economic impacts using a SEM approach (Fig. 4), which is able
345 to factor specific information in relation to the effectiveness of regional restoration projects.
346 Subsequently, a long-term horizon of monitoring and assessment needs to be embraced that
347 includes socio-economic factors as key components for a comprehensive understanding of
348 restoration effectiveness at large regional scales.

349 *4.3. Socio-economic factors are important for improving the effectiveness of large-scale*
350 *ecological restoration*

351 Demographic factors have a significant negative correlation with vegetation change as
352 reported in much regional and national scale research (Jiang et al., 2017; Li et al., 2013; Lü et al.,
353 2015; Mganga et al., 2015). In this study, population pressure was also found to have negative

354 impacts on restoration effectiveness, consistent with other research. Empirical studies have shown
355 that improvements in economic welfare can contribute to vegetation restoration, emphasizing the
356 positive effects of rural economic improvements (Jiang et al., 2017; Lü et al., 2015; Madu, 2009)
357 and that rural income has a positive relationship with vegetation change (Cao et al., 2014).
358 However, secondary industry has been found to negatively impact on vegetation in ecologically
359 fragile regions as a result of industrial growth or urban expansion (Su et al., 2014; Wang et al.,
360 2016). In this research, such economic factors (i.e. the off-farm and rural economies) were found
361 to have the opposite influence, highlighting a complex relationship between socio-economics and
362 regional ecological restoration. Secondary industry was the major contributor for its economic
363 growth for over a decade in northern Shaanxi.

364 Changes in relationship between socio-economic factors and restoration effectiveness offer
365 insights for improving the management of large-scale ecological restoration projects. The rural
366 labor force represents a vigorous group of stakeholders that could facilitate, impede or even
367 reverse ecological restoration progress (Petursdottir et al., 2013). Promoting the migration of rural
368 labor could provide an opportunity to mitigate the negative impacts of population pressure on
369 restoration effectiveness when population growth rates plateau. Deshingkar (2012) noted that
370 many districts in Eastern India experienced a significant increase in forest cover in situations of
371 high migration. Examples of successful ecological restoration in Southeast China also
372 demonstrated the positive impacts resulting from temporary or permanent migration in the rural
373 labor force (Wang et al., 2011). The labor-intensive tertiary industry plays an irreplaceable role in
374 absorbing rural labor (Madu, 2009), which was reflected in the early stage of the GTGP, with a
375 path coefficient of 0.67 found in our research (Fig. 4a). This was because of a large amount of

376 rural labor was released at one time. However, the effects of rural labor migration or the pull from
377 tertiary industry was weakening, which might explain the continuous negative effect of population
378 (Fig. 4b~c). Fragmentation and the irregularity of vegetated landscapes were also observed with
379 the development of tertiary industry (Michishita et al., 2012; Su et al., 2014). Thus, the increased
380 negative effect of the off-farm economy suggests a constraint from the rapid development of
381 tertiary industry. Therefore, tertiary industry should be promoted as a low emission,
382 resource-saving and livelihood-supporting approach to urbanization and industrial production to
383 both realize the transfer of rural labor and facilitate ecological restoration.

384 A sustainable restoration project should also involve the rural economy and take full
385 consideration of objectives and values of the rural community (Lamouroux et al., 2015). Recent
386 research has suggested that the direct economic benefit may not be the dominant driver for
387 improving ecological restoration. A survey in Iceland suggested that aesthetic values over
388 economic interests were the main reasons for stakeholders practicing restoration projects
389 (Petursdottir et al., 2013). Deng et al. (2016) also noted that ecological benefits play a more active
390 role than economic benefits in promoting farmers to conserve the restoration achievements in the
391 GTGP. Our results indicated that rural income had a minimal impact on the rural economy, at the
392 three temporal scales. In contrast, improvements in agricultural practice have been found to
393 alleviate the burden on environment and natural resources (Deshingkar, 2012; Sjogersten et al.,
394 2013). For example, case studies in India indicated that improvements of farm productivity
395 reduced the area farmed and pressure on forests (Deshingkar, 2012). Our results clearly highlighted
396 the contribution to restoration effectiveness from agricultural productivity (including grain yield
397 and primary industry). Therefore, another promising strategy for enhancing restoration

398 effectiveness is to fundamentally improve rural livelihoods. Together the migration of the rural
399 labor force and improvements in farming practice have the ability to promote the rural economy
400 by diversifying income streams, subsequently improve the effectiveness of restoration in the long
401 run.

402 *4.4. Spatially-explicit quantification of the relationships between restoration effectiveness and* 403 *socio-economics*

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

412 Clarifying these specific relationships, requires for a more sophisticated quantitative
413 approach, such as adapting the SEM to account for spatial structure in the data with a more
414 specified objective of detecting local or regional effects on the relationships between the
415 socio-economy and ecological restoration effectiveness. This requires the investigation of the
416 effects of spatial autocorrelation in the component linear regressions of the SEM (Lamb et al.,
417 2014), and/or the effects of spatial heterogeneity in the relationships of the same component
418 regressions. For the latter, the adaptation of the SEM to a geographically weighted methodology
419 (Gollini et al., 2015; Lu et al., 2014) as explored by Comber et al (2017) is a subject for future

420 research. Adapting SEMs to account for spatial effects will potentially provide spatially-explicit
421 decision support for improving regional effectiveness of ecological restoration through regulating
422 the socio-economic context and key drivers accurately. This could be a priority for the next steps
423 in ecological restoration research.

424 **5. Conclusions**

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

442 **Authors' Contributions**

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

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450 **Appendix A. Supplementary data**

451

452 **References**

- 453 Andam, K.S., Ferraro, P.J., Pfaff, A., Sanchez-Azofeifa, G.A., Robalino, J.A., 2008. Measuring the
454 effectiveness of protected area networks in reducing deforestation. *Proc. Natl. Acad. Sci. U.S.A.*
455 105, 16089-16094.
- 456 Aronson, J., et al., 2010. Are Socioeconomic Benefits of Restoration Adequately Quantified? A
457 Meta-analysis of Recent Papers (2000-2008) in Restoration Ecology and 12 Other Scientific
458 Journals. *Restor. Ecol.* 18, 143-154.
- 459 Benayas, J.M.R., Newton, A.C., Diaz, A., Bullock, J.M., 2009. Enhancement of Biodiversity and
460 Ecosystem Services by Ecological Restoration: A Meta-Analysis. *Science* 325, 1121-1124.
- 461 Berkowitz, J.F., 2013. Development of restoration trajectory metrics in reforested bottomland
462 hardwood forests applying a rapid assessment approach. *Ecol. Indic.* 34, 600-606.
- 463 Borja, A., Dauer, D.M., Elliott, M., Simenstad, C.A., 2010. Medium- and Long-term Recovery of
464 Estuarine and Coastal Ecosystems: Patterns, Rates and Restoration Effectiveness. *Estuar. Coast.*
465 33, 1249-1260.
- 466 Byrne, B.M., 2016. Structural equation modeling with AMOS: Basic concepts, applications, and
467 programming. Routledge.
- 468 Calmon, M., et al., 2011. Emerging Threats and Opportunities for Large-Scale Ecological Restoration
469 in the Atlantic Forest of Brazil. *Restor. Ecol.* 19, 154-158.
- 470 Cao, S., Chen, L., Yu, X., 2009. Impact of China's Grain for Green Project on the landscape of
471 vulnerable arid and semi-arid agricultural regions: a case study in northern Shaanxi Province. *J.*
472 *Appl. Ecol.* 46, 536-543.
- 473 Cao, S., Ma, H., Yuan, W., Wang, X., 2014. Interaction of ecological and social factors affects

474 vegetation recovery in China. *Biol. Conserv.* 180, 270-277.

475 Clewell, A.F., Aronson, J., 2013. *Ecological Restoration: Principles, Values, and Structure of an*
476 *Emerging Profession.* Island Press, Washington, DC.

477 Cobon, D.H., et al., 2009. The climate change risk management matrix for the grazing industry of
478 northern Australia. *Rangeland J.* 31, 31-49.

479 Comber, A., Li, T., Lü, Y., Fu, B., Harris, P., 2017. Geographically Weighted Structural Equation
480 Models: spatial variation in the drivers of environmental restoration effectiveness. In *Societal*
481 *Geo-Innovation, 20th AGILE Conference Proceedings, [Online].*
482 [https://agile-online.org/images/conference_2017/Proceedings2017/shortpapers/94_ShortPaper_in_](https://agile-online.org/images/conference_2017/Proceedings2017/shortpapers/94_ShortPaper_in_PDF.pdf)
483 PDF.pdf.

484 Deng, J., et al., 2016. Analysis of the ecological conservation behavior of farmers in payment for
485 ecosystem service programs in eco-environmentally fragile areas using social psychology models.
486 *Sci. Total Environ.* 550, 382-390.

487 Deshingkar, P., 2012. Environmental risk, resilience and migration: implications for natural resource
488 management and agriculture. *Environ. Res. Lett.* 7, 015603.

489 Donmez, C., Berberoglu, S., Curran, P.J., 2011. Modelling the current and future spatial distribution of
490 NPP in a Mediterranean watershed. *Int. J. Appl. Earth. Obs.* 13, 336-345.

491 Fan, X., Ma, Z., Yang, Q., Han, Y., Mahmood, R., 2015. Land use/land cover changes and regional
492 climate over the Loess Plateau during 2001-2009. Part II: interrelationship from observations.
493 *Climatic Change* 129, 441-455.

494 Fava, F., Pulighe, G., Monteiro, A.T., 2016. Mapping Changes in Land Cover Composition and Pattern
495 for Comparing Mediterranean Rangeland Restoration Alternatives. *Land Degrad. Dev.* 27,

496 671-681.

497 Feng, X., Fu, B., Lu, N., Zeng, Y., Wu, B., 2013. How ecological restoration alters ecosystem services:
498 an analysis of carbon sequestration in China's Loess Plateau. *Sci. Rep.* 3, 2846.

499 Gollini, I., Lu, B., Charlton, M., Brunson, C., Harris, P., 2015. GWmodel: An R Package for
500 Exploring Spatial Heterogeneity Using Geographically Weighted Models. *J. Stat. Softw.* 63, 1-50.

501 Grace, J.B., 2006. Structural equation modeling and natural systems. Cambridge University Press.

502 Hopcraft, J.G.C., Anderson, T.M., Pérez - Vila, S., Mayemba, E., Olf, H., 2012. Body size and the
503 division of niche space: food and predation differentially shape the distribution of Serengeti
504 grazers. *J. Anim. Ecol.* 81, 201-213.

505 Jiang, M., Tian, S., Zheng, Z., Zhan, Q., He, Y., 2017. Human Activity Influences on Vegetation Cover
506 Changes in Beijing, China, from 2000 to 2015. *Remote Sens.* 9, 271.

507 Jin, Z., et al., 2014. Natural vegetation restoration is more beneficial to soil surface organic and
508 inorganic carbon sequestration than tree plantation on the Loess Plateau of China. *Sci. Total
509 Environ.* 485, 615-623.

510 Jones, H.P., Schmitz, O.J., 2009. Rapid Recovery of Damaged Ecosystems. *PLoS ONE* 4,e5653.

511 Lake, P.S., Bond, N., Reich, P., 2007. Linking ecological theory with stream restoration. *Freshwater
512 Biol.* 52, 597-615.

513 Lamb, D., Erskine, P.D., Parrotta, J.A., 2005. Restoration of degraded tropical forest landscapes.
514 *Science* 310, 1628-1632.

515 Lamb, E.G., Mengersen, K.L., Stewart, K.J., Attanayake, U., Siciliano, S.D., 2014. Spatially explicit
516 structural equation modeling. *Ecology* 95, 2434-2442.

517 Lamouroux, N., Gore, J.A., Lepori, F., Statzner, B., 2015. The ecological restoration of large rivers

518 needs science-based, predictive tools meeting public expectations: an overview of the Rhone
519 project. *Freshwater Biol.* 60, 1069-1084.

520 Leon, J.R.R., van Leeuwen, W.J.D., Casady, G.M., 2012. Using MODIS-NDVI for the Modeling of
521 Post-Wildfire Vegetation Response as a Function of Environmental Conditions and Pre-Fire
522 Restoration Treatments. *Remote Sens.* 4, 598-621.

523 Levrel, H., Pioch, S., Spieler, R., 2012. Compensatory mitigation in marine ecosystems: Which
524 indicators for assessing the "no net loss" goal of ecosystem services and ecological functions?
525 *Marine Policy* 36, 1202-1210.

526 Li, C., Kuang, Y., Huang, N., Zhang, C., 2013. The Long-Term Relationship between Population
527 Growth and Vegetation Cover: An Empirical Analysis Based on the Panel Data of 21 Cities in
528 Guangdong Province, China. *Int. J. Env. Res. Pub. He.* 10, 660-677.

529 Li, G., Chen, S., Yan, Y., Yu, C., 2015. Effects of Urbanization on Vegetation Degradation in the
530 Yangtze River Delta of China: Assessment Based on SPOT-VGT NDVI. *J. Urban. Plan. Dev.* 141,
531 05014026.

532 Liu, J., Li, S., Ouyang, Z., Tam, C., Chen, X., 2008. Ecological and socioeconomic effects of China's
533 policies for ecosystem services. *Proc. Natl. Acad. Sci. U.S.A.* 105, 9477-9482.

534 Lu, B., Harris, P., Charlton, M., Brunson, C., 2014. The GWmodel R package: further topics for
535 exploring spatial heterogeneity using geographically weighted models. *Geo-spatial Information*
536 *Science* 17, 85-101.

537 Lü, Y., et al., 2012. A Policy-Driven Large Scale Ecological Restoration: Quantifying Ecosystem
538 Services Changes in the Loess Plateau of China. *PLoS ONE* 7, e31782.

539 Lü, Y.H., et al., 2015. Recent ecological transitions in China: greening, browning, and influential

540 factors. *Sci. Rep.* 5, 8732.

541 Luck, G.W., Smallbone, L.T., O'Brien, R., 2009. Socio-Economics and Vegetation Change in Urban
542 Ecosystems: Patterns in Space and Time. *Ecosystems* 12, 604-620.

543 Madu, I.A., 2009. The impacts of anthropogenic factors on the environment in Nigeria. *J. Environ.*
544 *Manage.* 90, 1422-1426.

545 Martin, A., Gross-Camp, N., Kebede, B., McGuire, S., 2014. Measuring effectiveness, efficiency and
546 equity in an experimental Payments for Ecosystem Services trial. *Global Environ. Chang* 28,
547 216-226.

548 McAlpine, C., et al., 2016. Integrating plant- and animal-based perspectives for more effective
549 restoration of biodiversity. *Front. Ecol. Environ.* 14, 37-45.

550 Meli, P., Benayas, J.M.R., Balvanera, P., Ramos, M.M., 2014. Restoration Enhances Wetland
551 Biodiversity and Ecosystem Service Supply, but Results Are Context-Dependent: A Meta-Analysis.
552 *PLoS ONE* 9, e93507.

553 Mganga, K.Z., Musimba, N.K.R., Nyariki, D.M., 2015. Combining Sustainable Land Management
554 Technologies to Combat Land Degradation and Improve Rural Livelihoods in Semi-arid Lands in
555 Kenya. *Environ. Manage.* 56, 1538-1548.

556 Michishita, R., Jiang, Z.B., Xu, B., 2012. Monitoring two decades of urbanization in the Poyang Lake
557 area, China through spectral unmixing. *Remote Sens. Environ.* 117, 3-18.

558 Miyasaka, T., Le, Q., Okuro, T., Zhao, X.Y., Takeuchi, K., 2017. Agent-based modeling of complex
559 social-ecological feedback loops to assess multi-dimensional trade-offs in dryland ecosystem
560 services. *Landscape Ecol.* 32, 707-727.

561 Palmer, M.A., Filoso, S., Fanelli, R.M., 2014. From ecosystems to ecosystem services: Stream

562 restoration as ecological engineering. *Ecol. Eng.* 65, 62-70.

563 Petursdottir, T., Arnalds, O., Baker, S., Montanarella, L., Aradottir, A.L., 2013. A Social-Ecological
564 System Approach to Analyze Stakeholders' Interactions within a Large-Scale Rangeland
565 Restoration Program. *Ecol. Soc.* 18, 29.

566 Qi, X., Wang, K., Zhang, C., 2013. Effectiveness of ecological restoration projects in a karst region of
567 southwest China assessed using vegetation succession mapping. *Ecol. Eng.* 54, 245-253.

568 Ran, L., Lu, X., Xu, J., 2013. Effects of Vegetation Restoration on Soil Conservation and Sediment
569 Loads in China: A Critical Review. *Crit. Rev. Env. Sci. Tec.* 43, 1384-1415.

570 Sjoergersten, S., et al., 2013. Responses to climate change and farming policies by rural communities in
571 northern China: A report on field observation and farmers' perception in dryland north Shaanxi
572 and Ningxia. *Land Use Policy* 32, 125-133.

573 Song, F., Kang, M., Duan, J. Driving forces for and changes in land use/cover in northern shaanxi after
574 implementation of grain-for-green protect. *Journal of Beijing Normal University (Natural Science)*
575 2011; 47: 634-639+661 (In Chinese).

576 Standish, R.J., et al., 2015. Long-term data suggest jarrah-forest establishment at restored mine sites is
577 resistant to climate variability. *J. Ecol.* 103, 78-89.

578 Su, S., Wang, Y., Luo, F., Mai, G., Pu, J., 2014. Peri-urban vegetated landscape pattern changes in
579 relation to socioeconomic development. *Ecol. Indic.* 46, 477-486.

580 Tayyebi, A., Jenerette, G.D., 2016. Increases in the climate change adaption effectiveness and
581 availability of vegetation across a coastal to desert climate gradient in metropolitan Los Angeles,
582 CA, USA. *Sci. Total Environ.* 548, 60-71.

583 Tian, L., Chen, J., Yu, S., 2014. Coupled dynamics of urban landscape pattern and socioeconomic

584 drivers in Shenzhen, China. *Landscape Ecol.* 29, 715-727.

585 Timilsina, N., Escobedo, F.J., Staudhammer, C.L., Brandeis, T., 2014. Analyzing the causal factors of
586 carbon stores in a subtropical urban forest. *Ecol. Complex.* 20, 23-32.

587 Tong, X.W., et al., 2017. Quantifying the effectiveness of ecological restoration projects on long-term
588 vegetation dynamics in the karst regions of Southwest China. *Int. J. Appl. Earth. Obs.* 54,
589 105-113.

590 van der Werf, G.R., et al., 2006. Interannual variability in global biomass burning emissions from 1997
591 to 2004. *Atmos. Chem. Phys.* 6, 3423-3441.

592 Wang, C., Yang, Y., Zhang, Y., 2011. Economic Development, Rural livelihoods, and Ecological
593 Restoration: Evidence from China. *Ambio* 40, 78-87.

594 Wang, J., Gao, Y., Wang, S., 2016. Land Use/Cover Change Impacts on Water Table Change over 25
595 Years in a Desert-Oasis Transition Zone of the Heihe River Basin, China. *Water* 8, 11.

596 Watanabe, M.D.B., Ortega, E., 2014. Dynamic emergy accounting of water and carbon ecosystem
597 services: A model to simulate the impacts of land-use change. *Ecol. Model.* 271, 113-131.

598 Wittemyer, G., 2011. Effects of Economic Downturns on Mortality of Wild African Elephants. *Conserv.*
599 *Biol.* 25, 1002-1009.

600 Wu, D., et al., 2014. Evaluation of Spatiotemporal Variations of Global Fractional Vegetation Cover
601 Based on GIMMS NDVI Data from 1982 to 2011. *Remote Sens.* 6, 4217-4239.

602 Zhai, J., Liu, R., Liu, J., Huang, L., Qin, Y., 2015. Human-Induced Landcover Changes Drive a
603 Diminution of Land Surface Albedo in the Loess Plateau (China). *Remote Sens.* 7, 2926-2941.

604 Zhang, B., Wu, P., Zhao, X., Wang, Y., Gao, X., 2013. Changes in vegetation condition in areas with
605 different gradients (1980-2010) on the Loess Plateau, China. *Environ. Earth Sci.* 68, 2427-2438.

606 Zhang, G., Dong, J., Xiao, X., Hu, Z., Sheldon, S., 2012. Effectiveness of ecological restoration
607 projects in Horqin Sandy Land, China based on SPOT-VGT NDVI data. *Ecol. Eng.* 38, 20-29.