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Interaction of ecological and social factors affects vegetation recovery in China

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ABSTRACT

Global environmental problems have significant natural and socioeconomic consequences. However, the consequences are often evaluated independently by ecologists and social scientists. In an effort to integrate the consequences of the two types of problem during ecological restoration and thereby improve future development of environmental policy, we used regression analysis and remote sensing to calculate the relative contributions of human activities, climate change, and socioeconomic development to land use and cover change during China's huge investments in ecological restoration since the 1980s. We performed this analysis both for China as a whole, and for eight regions with distinctive ecological and social characteristics. We found that China's fast socioeconomic development and decreasing rural population were dominant factors in ecological restoration, whereas direct human intervention was a paradoxical factor that did not always lead to recovery. However, the changes in vegetation cover and the dominant causal factors differed among the regions of China as a result of differences in local conditions. Because of the complexity of ecosystem restoration, a region-specific strategy based on integrating ecological and socioeconomic factors should be developed. In particular, we urge caution when considering single, monolithic approaches (such as the afforestation that is currently the main approach) because these approaches ignore the local limits imposed by ecological factors such as climate and soils and human factors such as socioeconomic characteristics; such approaches can be dangerous if they neglect key social or natural factors.

1. Introduction

Land degradation is a global environmental problem with important political and socioeconomic ramifications (D'Odorico et al., 2013). These ramifications result from complex combinations of several factors, including natural factors such as ecological and climatic variations, and anthropogenic factors such as human activities (Sivakumar, 2007; Steltzer et al., 2009) and restoration policies that lead to changes in vegetation cover (Cao et al., 2011). As a result of this complexity, we often cannot tell whether a given policy instrument has succeeded or failed, or the reason why (Carpenter et al., 2009). Given these complexities, finding solutions that are both equitable and ecologically effective is even more challenging (Ostrom et al., 1999). Although models and a conceptual framework for social–ecological systems exist, few are explicitly designed to guide long-term interdisciplinary research (Collins et al., 2011). Typically, a call to action is accompanied by one or more illustrative case studies that provide a general rationale for why such research is needed, yet such papers rarely define a specific road map that can lead to the implementation of a quantifiable research hypothesis for studying social–ecological systems and developing management recommendations that account for both aspects of these systems. For example, it is widely accepted that environmental degradation and poverty are linked and that conservation and poverty-reduction should be tackled together. However, success with integrated strategies has been elusive (Cao et al., 2009).

In an effort to halt soil erosion, desertification, and sandstorms, which are critically important problems in many regions of China, the Chinese government has launched a series of land conservation programs and developed a series of policies to address the problem

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from both socioeconomic and ecological perspectives (Yang, 2004). Among them, the Six Key Forestry Programs (since 1978, the Three Norths Shelter Forest System Project and the Wildlife Conservation and Nature Reserves Development Program; since 2000, the Natural Forest Conservation Program, Sand Control Program, Grain for Green Project, and Forest Industrial Base Development Program) were unprecedented in world history in terms of their geographic extent, the government budget, and the magnitude of the mobilization of social factors by these programs (Dai, 2010). China has invested nearly RMB 700 billion (US$120 billion) in these programs, covering more than 97% of China's counties (State Forestry Administration, 1952–2013). In addition, 15% of the country is now included within some 2700 nature reserves (Cyranoski, 2008). Although these programs have had significant ecological and socioeconomic consequences, the consequences have generally been evaluated independently by ecologists and social scientists (Liu et al., 2008). Cross-disciplinary research to tackle the complexities of managing China's hybrid socioeconomic and ecological systems to achieve multiple goals has been rare (Cao et al., 2009), and the lack of such research poses severe challenges for effective policy development. For example, from 1952 to 2011, 32.3% of China's territory (nearly 3.1×10^6 km^2) was afforested to provide wood for the forest industry, for ecological conservation, and for water conservation, among other goals (State Forestry Administration, 1952–2013). However, this massive "greening" effort has been less effective than expected in some geographic regions (Cao et al., 2011). In addition, these studies have not integrated a sufficient number of dimensions of sustainability, and they have not adequately integrated the socioeconomic and ecological effects of the policies (i.e., that farmers and herders who can no longer farm or raise livestock must find other ways to earn a living) (Schwilch et al., 2009; Cao et al., 2010). Therefore, we lack a firm methodological basis for multidisciplinary research and a strong body of statistical data generated by multidisciplinary research that researchers can build on (Cyranoski, 2009).

Since the dynamics of land use and land cover change are central to the study of how ecosystems respond to natural and anthropogenic environmental change, any ecological restoration strategy must be assessed by understanding these dynamics at a range of scales, from local to national, and from both human and ecological perspectives (Xu et al., 2010; Zhou et al., 2012). Analyzing the trends in land use and cover change at multiple scales and from both perspectives can help to reveal the linkages between the ecological and social changes promoted by these policies, and the relationships between the driving forces and the resulting changes. However, there have been few detailed and systematic assessments of policy success from this perspective despite China's huge investments in ecological restoration, the long-term effects of these programs, and the huge area covered by the programs (Cao et al., 2009). Therefore, it is necessary to begin studying the dynamics of land use change and land degradation in China from a more integrated, holistic perspective to support the development of appropriate policies that can promote more sustainable land use and that can counteract the negative ecological and social impacts of undesirable land use changes (Zhang et al., 2007).

2. Research framework and hypotheses

Changes in vegetation cover result from multiple and possibly confounded driving factors. Unsustainable human activities such as over-grazing, over-reclamation of land for agriculture, and over-cutting of natural vegetation are primary causes of desertification and rehabilitation, though they have undoubtedly been exacerbated by trends resulting from long-term changes in China's climate (Zhang et al., 2007; Wang et al., 2008). However, there is little understanding of which factors will best predict the ecosystem impacts and the associated vegetation cover change. If we know the strengths of the contributions of the different driving forces and how their dynamics affect vegetation cover, ecological restoration policy can be made more effective.

To understand how these factors have affected vegetation cover, we analyzed specific driving factors that our literature review suggested would be primary factors responsible for vegetation cover change (Li et al., 2006; Cao et al., 2009, 2011; Zhang et al., 2007; Wang et al., 2008, 2010, 2013; Dai, 2010): the rural population, grain yield, rural net income, livestock population, area of farmland, area of forest in which agriculture and grazing were forbidden, reforestation area, mean annual temperature, total annual precipitation, and infrastructure (roads, railways, and mining). We hypothesized that these factors would differ in their effects on vegetation cover, that certain key factors would explain most of the overall effect, that the key factors and magnitude of their effects would differ among the regions of a country as large as China, and that identifying these differences would provide empirical evidence to support improved policy development. We divided the driving forces into five groups of factors: social (the rural population), economic (grain yield, rural net income, livestock population, area of farmland), policy (area of forest in which agriculture and grazing were forbidden, reforestation area), infrastructure (roads, railways, and mining), and climate (mean annual temperature, total annual precipitation). To improve the precision of our analysis, we eliminated one of each pair of parameters that were strongly correlated from the regression analysis that we used to identify the key factors in each group (see Section 3 for details). We selected four models (see Section 3) that are frequently used in econometrics to reflect the impacts of China's restoration policies and of the different social and environmental drivers.

In the present study, we selected the maximum normalized-difference vegetation index (NDVI) during the growing season as an indicator of vegetation cover conditions in China, since this parameter represents a good proxy for vegetation cover that can unify the impacts of climate change and human activities on the success of ecological restoration. We then used this information to quantify the relative roles that these factors have played in ecological restoration. Based on the results of this analysis, we discuss key socioeconomic and ecological issues for China as a whole and for each of eight regions of China, and the lessons learned from China's ecological strategy. The results will provide important information to guide sustainable development in China and in other nations that are facing similar problems. Because government data is primarily consolidated at a provincial level, it is difficult to obtain reliable data for smaller areas. Therefore, even though high-resolution geographic and climatic data is available, we have not used geographically weighted regression techniques in our analysis because most of the data for the other driving factors is not available at a sub-provincial scale for each province. However, to detect potential differences among the regions, we defined eight regions (each composed of several provinces) that had similar climate and socioeconomic characteristics, and used this division instead of geographically weighted regression analysis to compare the eight regions.

3. Methods

To understand how the driving factors have affected land use and cover change (thus, the success of China's ecological restoration efforts), we analyzed the processes responsible for the changes of vegetation cover since 1983 in China. To do so, we used NDVI as a proxy for vegetation cover, and compared changes in NDVI with changes in the underlying forces that are driving land use and cover change. First, we superimposed the NDVI values from 1983 to 2012 on the map of China, and used linear regression to calculate the rate of change in NDVI for each pixel during the study period. We then calculated an arithmetic average of these rates for all pixels that fell within the boundaries of each region of China (our determination of the eight regions is described later in Section 3) This allowed us to examine the relationship between region-level NDVI and data on the driving factors for each region. Next, we used meteorological and socioeconomic data from China's annual statistical, forestry, agricultural, and climate yearbooks from 1983 to 2012 (Statistical Bureau of China, 1984–2013) to analyze the degree of association of several driving factors with the vegetation cover changes by means of factor analysis. The resulting province-level dataset contained information from all of mainland China from 1983 to 2012. The dataset covers 22 provinces, 5 autonomous regions, and 4 provincial-scale municipalities, but excludes data from Hong Kong, Macao, and Taiwan. We divided China into eight regions (as described later in Section 3), and used the totals of the values for all provinces in a region to represent the value for that region. For each province and for the region as a whole, we calculated the change in the value of each driving factor from 1983 to 2012.

To produce a continuous NDVI time series from 1983 to 2012, we first employed linear regression (as described later in this section) to combine the data from two NDVI products: the Advanced Very High Resolution Radiometer (AVHRR) Global Integrated Maintenance Management System (GIMMS) NDVI data (http://glcf.umd.edu/data/gimms/) from 1983 to 2006 and the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI data (http://glcf.umd.edu/data/ndvi/) from 2000 to 2012. The AVHRR GIMMS NDVI value is based on monthly maximum-value compositing of biweekly data with a spatial resolution of about 0.0727° of latitude and longitude (equivalent to a resolution of about 1 km for China as a whole). This is a simple method that minimizes the effects of atmospheric and cloud contamination on the NDVI data (Holben, 1986). To be consistent with the spatial resolution of the AVHRR GIMMS NDVI data, we first spatially aggregated the monthly 500-m-resolution MODIS NDVI data to a resolution of 0.0727° of latitude and longitude using the spatial interpolation algorithm of Zhao et al. (2005). We then performed the following steps to combine the two series: first, we regressed the monthly MODIS NDVI data on the corresponding AVHRR GIMMS NDVI data for the overlapping period from 2000 to 2006 using simple linear regression on a pixel-by-pixel basis. We used the resulting regression equation to adjust the AVHRR GIMMS NDVI time series and compute an integrated AVHRR–MODIS NDVI monthly time series from 1983 to 2011 (Zhang et al., 2008). The result was a single, integrated, continuous record from 1983 to 2012.

To measure the impact of various factors on vegetation restoration processes, we used four methods of regression analysis. Because regression techniques based on different approaches and different assumptions will produce different results, we combined (averaged) the results of these different techniques to provide a more broadly representative description of the relationship between NDVI and the factors that affect this variable. To avoid the impact of overlapping factors on the results, we employed the regression analysis module of version 19 of SPSS (http://www-01.ibm.com/software/analytics/spss/) to calculate the regression coefficients for the relationships between all pairs of driving factors. To avoid problems with covariation, we eliminated one factor from each pair of factors that were significantly correlated ($p < 0.05$); the factor in each pair that was most strongly correlated with NDVI was retained for use in the subsequent multiple-regression analysis.

We used the four following regression methods to determine the relative importance of each driving factor (the % of the total variation that it explained):

(1) SPSS: We used the standardized regression coefficients to measure the strength of the relationship between NDVI and the factors responsible for changes in NDVI. We computed a standardized regression coefficient ($\boldsymbol{\rho}$) by multiplying the estimated value of the parameter ($\boldsymbol{E}$) by the ratio of the standard deviation of the independent variable ($\boldsymbol{\sigma_x}$) to that of the dependent variable ($\boldsymbol{\sigma_y}$):

$$\boldsymbol{\rho} = \boldsymbol{E}\boldsymbol{\sigma_x}/\boldsymbol{\sigma_y}$$

(2) Eviews (http://www.eviews.com): We correlated the dependent variable (NDVI) with the independent variables for the social, economic, policy, infrastructure, and climate factors. We calculated the relative contribution rate by dividing the correlation coefficient for group i (β_i) by the sum of the absolute values of the correlation coefficients:

$$\boldsymbol{\rho} = \beta_x \Big/ \sum \beta_y$$

(3) Matlab (http://www.mathworks.com/products/matlab/): We calculated the correlation between each pair of factors, and eliminated one of each pair of factors (the one with the weakest correlation with NDVI) that were not independent effects. According to this model:

$$\mathbf{X}\boldsymbol{A} = \mathbf{Y}$$

where $\mathbf{X}$ is the value of each factor that affects NDVI, $\boldsymbol{A}$ is the magnitude of the impact of each factor that affects NDVI, and $\mathbf{Y}$ is the value of NDVI. To obtain $\boldsymbol{A}$, we must multiply both sides of the equation by $\mathbf{X}^{-1}$. Thus:

$$\boldsymbol{A} = \mathbf{Y}\mathbf{X}^{-1}$$

Matlab can then be used to obtain the coefficient matrix:

$$\begin{pmatrix} x_{1,1} & \cdots & x_{1,8} \\ \vdots & \ddots & \vdots \\ x_{20,1} & \cdots & x_{20,8} \end{pmatrix} \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} = \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}$$

where x represents the value of each factor, a is a coefficient that represents the magnitude of the factor's effect on the value of NDVI, and m is the number of years in the study period. For the columns of the $\mathbf{X}$ matrix, the values are 1 = agriculture and grazing prohibited, 2 = rural population, 3 = area of farmland, 4 = rural net income, 5 = temperature, 6 = infrastructure factors (roads, railways, and mining), 7 = precipitation, and 8 = area of afforestation. For the rows of the matrix, 1 = 1983, and the values increase by intervals of 1 year to 20 = 2012. The relative contribution rate (ρ) is the value of the correlation coefficient for parameter i (a_i) divided by the sum of the absolute values of the m correlation coefficients:

$$\boldsymbol{\rho} = a_i \Big/ \sum |a_m|$$

(4) Correlation coefficient matrix (calculated using Eviews): To obtain standardized correlation coefficients, we must first standardize all of the data. Using the regression module of Eviews, we obtained standardized coefficients for each factor. The relative contribution rate (ρ) is the standardized coefficient for $\mathbf{X}$ (S_{Xi}), divided by the sum of the absolute values of the standardized coefficient for $\mathbf{Y}$ (S_Y):

$$\boldsymbol{\rho} = S_{Xi} \Big/ \sum S_Y$$

The coefficient describes the relationship between NDVI and each individual factor, excluding the effects of the other factors. First, we normalized all data by dividing each value of a parameter by the mean value of the parameter from 1983 to 2012 to remove the effects of its units of measurement. Next, we computed the absolute value of the standardized regression coefficient so that we could sum all coefficient values and calculate the proportion of this total accounted for by each individual coefficient. This proportion reflects the relative impact of each factor on NDVI. We then validated this relative impact by means of canonical correlation analysis (http://en.wikipedia.org/wiki/Canonical_correlation_analysis). The canonical correlation analysis confirmed that each of our four regression methods produced valid results; we therefore assumed that it was legitimate to calculate an overall average for the four methods. To assess the effect of a time lag before the impact of certain factors was observed, we compared the values of the independent variables (the driving factors) in one year with the value of the dependent variable (NDVI) in the same year, in the next year, and in the third year.

To determine the impact of the factors that affected NDVI on the vegetation cover of ecosystems in different regions of China, we divided China into eight regions based on the total annual precipitation (from arid to humid) and socioeconomic characteristics (from poor to developed). The eight regions are the arid poor Northwest, semi-arid developed North, semi-arid developing Loess Plateau, cold and semi-humid developing Northeast, cold and high-altitude poor Tibetan Plateau, semi-humid developing Southwest, warm and semi-humid developed Central, and warm and humid developed East.

We performed repeated-measures ANOVA to identify whether significant relationships between NDVI and other factors existed all tests were performed using version 12.0 of the SPSS software.

4. Results

At a national scale, our results showed significant effects for six of the eight parameters that were retained after eliminating parameters that were significantly correlated with other parameters (Table 1). For the effect of parameter values on NDVI in the current year, an increasing area of forest in which agriculture and grazing were prohibited had the highest contribution (it accounted for 27.3% of the total change in NDVI), followed by decreasing rural population (23.7%), decreasing area of farmland (18.4%), increasing rural net income (9.2%), increasing temperature (5.8%), and infrastructure factors (roads, railways, and mining; 5.5%). The precipitation (2.6%) and afforestation area (2.4%) were not statistically significant factors.

Ecological restoration must often be conducted for a long time to achieve a satisfactory result. Therefore, there was a time lag before the impact of certain factors became evident (Table 2). For example, the strongest impact of the forest area in which agriculture and grazing were forbidden on vegetation cover occurred in the second year (32.1% of the total effect). The contribution of increasing temperature also reached its maximum effect in the second year (11.9%). However, the impacts of rural net income and infrastructure factors (roads, railways, and mining) were not completely evident until the third year, when they contributed 19.8% and 19.6% of the total effect, respectively.

It is evident that the process of land use and cover change in China is complicated and that given China's huge size, these changes and their regional variation will have an impact at local to global scales. For example, the impact of the rural population on vegetation cover in Northwest China was positive, whereas it was negative in all other regions (Fig. 1). Similarly, the effect of farmland was positive in Northwest China, but negative in the other regions. Afforestation and infrastructure factors (roads, railways, and mining) had negative impacts in Southwest China, but positive impacts in the other regions (Fig. 1). In Northwest region, precipitation had the strongest positive effect on NDVI, and temperature had the strongest negative effect. This is like caused by the region's arid climate, which causes severe water stress for vegetation in years with low precipitation and high temperature. In the Loess region, precipitation was a strong positive factor, because the region is semi-arid. However, the rural population had a strong negative influence on NDVI because this is a major agricultural region, and the impact of agriculture increases as the rural population increases. In the North region, rural population had the same negative effect, for the same reason, but temperature had the strongest positive impact because the region's cold temperatures limit vegetation growth.

5. Discussion

NDVI is a key vegetation cover index because it is tightly linked with successful ecological restoration (Li et al., 2006; Zhang et al., 2007; Wang et al., 2010, 2013; Cao et al., 2011). Our results (Tables 1 and 2) demonstrate that degradation of the vegetation cover is caused by both natural and socioeconomic factors, which agrees with previous research (Olukoye and Kinyamario, 2009; Schwilch et al., 2009). To combat environmental degradation, China has implemented a range of policies to decrease human impacts on ecosystems, such as forbidding agriculture and grazing in forested areas to allow aboveground and belowground biomass to recover (Zheng et al., 2006; Sivakumar, 2007; Wang et al., 2008). This approach has been more successful for increasing vegetation cover

Table 1
Regression results for the relationship between various driving factors and NDVI for China as a whole from 1983 to 2012 using four regression methods based on data from the same year (i.e., no time lag). Contributions (%) represent the proportion of the total change in vegetation cover (represented by NDVI) accounted for by a given driving factor.

	R^2	Contribution based on data from the current year (%)				
		SPSS	Eviews	Matrix	MATLAB	Average
Rural population	−0.638**	14.91	15.34	31.22	33.34	23.70
Rural income	0.667**	3.388	16.04	8.49	9.03	9.24
Farmland area	−0.803**	41.968	19.31	5.89	6.25	18.35
Forest area in which agriculture and grazing were forbidden	0.643**	20.032	15.46	35.70	38.07	27.32
Reforestation area	−0.038	5.477	0.914	1.51	1.62	2.38
Precipitation	−0.160	3.461	3.85	1.58	1.66	2.64
Temperature	0.475**	3.655	11.42	4.00	4.26	5.83
Infrastructure (roads, railways, and mining)	0.735**	7.111	1.63	7.53	5.77	5.51

Notes: R^2 is the regression goodness of fit based on the mean % for each driving factor from the four models. Parameters with significant contributions to the regression for a given time lag were identified by repeated-measures ANOVA.
** $P < 0.01$.

Table 2
Regression results for the relationship between various driving factors and NDVI from 1983 to 2012 with three time lags for China as a whole, based on the average results produced using the four regression methods shown in Table 1. Regressions were performed for the value of the driving force in the current year (the same year as the NDVI value), the next year, and the third year. Contributions (%) represent the proportion of the total change in vegetation cover (represented by NDVI) accounted for by a given driving factor.

	Current year		Second year		Third year	
	R^2	Contribution (%)	R^2	Contribution (%)	R^2	Contribution (%)
Rural population	−0.638**	23.70	−0.638**	9.56	−0.619**	7.10
Rural income	0.667**	9.24	0.634**	11.06	0.628**	19.75
Farmland area	−0.803**	18.35	−0.774**	10.75	−0.774**	12.82
Forest area in which agriculture and grazing were forbidden	0.643**	27.32	0.644**	32.12	0.680**	22.44
Reforestation area	−0.038	2.38	−0.154	3.07	−0.186	2.13
Precipitation	−0.160	2.64	−0.253	10.60	−0.426	8.36
Temperature	0.475**	5.83	0.415*	11.86	0.325	7.78
Infrastructure (roads, railways, and mining)	0.735**	5.51	0.759**	10.98	0.752**	19.63

Notes: R^2 is the regression goodness of fit based on the mean % for each driving factor from the four models. Parameters with significant contributions to the regression for a given time lag were identified by repeated-measures ANOVA.
* $P < 0.05$.
** $P < 0.01$.

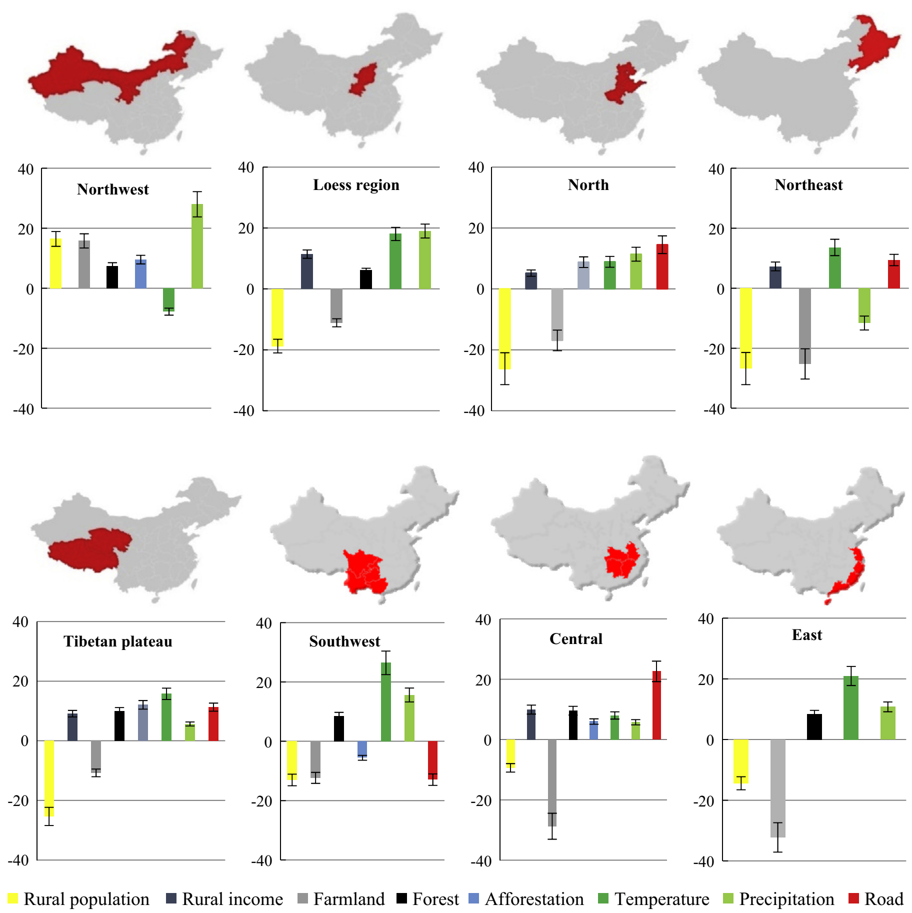

Fig. 1. Average contribution of each driving factor to the total change in NDVI at a regional scale based on the average of the four regression methods shown in Table 1 using data from the current year (the same year as the parameter value; thus, no time lag). "Forest" represents the area of forest in which agriculture and grazing were forbidden, and "Road" represents road, railway, and mining infrastructure. For each of the eight regions, regression analysis was conducted using the four methods to identify which of the eight factors shown in Table 1 contributed significantly ($p < 0.05$) to NDVI change for that region. Different factors were significant for different regions.

than other approaches such as afforestation (Table 1), and the improvement in vegetation cover may help to alleviate soil erosion and improve carbon sequestration in China (Zhou et al., 2012). However, the practice of excluding grazing and agriculture may need to be combined with afforestation and other measures if the land in a given area has become sufficiently degraded that it has crossed an ecological threshold, and the land cannot subsequently recover naturally without artificial restoration measures (Sasaki et al., 2008; Gao et al., 2011). In addition, preventing local residents from farming or raising livestock means that some other form of livelihood must be provided to ensure that these residents have a way to earn a living (Cao et al., 2010).

However, ecological restoration policies are also shaped by regional needs related to the management of agriculture and natural resources. Our results demonstrate that an increased area in which grazing and agriculture were forbidden and decreases in the rural population caused by urbanization were the primary factors that contributed to the increase in NDVI in China, except in the extremely arid Northwest region (Figs. 1 and 2, top) because the irrigation of oases for agriculture and the area of forest were the primary factors responsible for the increasing vegetation cover. The most important factors differed among the regions (Figs. 1 and 2). The rural population had a positive impact on vegetation cover in Northwest China is negatively illustrate the overloading population in the fragile arid and semiarid region because most of this large region's population is concentrated in oasis areas, which are the only areas where there is sufficient water to allow cultivation and animal husbandry; thus, most of the region's land is less affected by human activities than in other areas. Afforestation and infrastructure factors (roads, railways, and mining) had negative impacts in Southwest China because its rugged landscape (with many steep slopes) is more easily damaged by human activities, and afforestation seems to have been based on species that were not suitable for this region (Fig. 1). Therefore, more attention should be paid to different factors in each region, since the most important underlying social and institutional issues differ among the regions, and these differences are at the heart of the region's natural resource management and ecological conservation problems. Neglecting these key issues can slow both socioeconomic development and ecosystem recovery (Guan et al., 2011). Our results (i.e., the combination of statistically significant social and natural driving forces) suggest that sustainable development in ecologically fragile areas is only likely to succeed if social, economic, legal, and technical measures are combined to address a region's unique combination of these types of problems, and that only this combined approach can minimize the risk of future land degradation.

Fig. 2. An example of the vegetation cover in afforestation plots in Dunhuang City of the Northwest region (top), where precipitation averages 35.7 mm yr^{-1} and the annual temperature averages 9.3 °C; in the Loess region (middle), where precipitation averages 395 mm yr^{-1} and the annual temperature averages 7.8 °C; and in Changting County of the East region (bottom), where precipitation averages 1730 mm yr^{-1} and the annual temperature averages 18.3 °C.

The environment in many regions of the world has been affected by rapid changes in the vegetation cover, plant community composition, hydrologic conditions, and soil properties, with different primary causal mechanisms in different regions. This has resulted in an overall loss of ecosystem services that poses serious threats both to the ecosystem and to a sustainable livelihood for residents of the affected regions (Zhang et al., 2007; D'Odorico et al., 2013). The mechanisms responsible for land use and cover change will differ among regions due to differences in the natural environment (e.g., climate) and in socioeconomic factors (e.g., restoration programs, dominant local industries), and the complexity of the relationships among these factors makes it difficult to accurately identify the key mechanisms (Xu et al., 2010). For example, the afforestation approach that has consumed huge government investments seems to have had no significant impact on NDVI change in the Loess region (Figs. 1 and 2, middle) or in the Northeast and East regions, and has had a negative impact in the Southwest region (Fig. 2, bottom). This is probably because the strategy has not been tailored to local environmental conditions, leading to the use of inappropriate species and an overemphasis on tree and shrub planting, thereby compromising the ability to achieve the goals of this restoration policy (Wang et al., 2007). This result has also been documented based on monitoring data from areas where afforestation has been practiced (Cao et al., 2011; Wang et al., 2013; Qu et al., 2013).

No doubt, the climate change mechanisms that are responsible for vegetation cover change will also differ among the regions. For example, climate warming will increase evaporation, thereby increasing water stress and decreasing vegetation growth and development in the arid Northwest region (Fig. 1). In contrast, increased precipitation may decrease the spring temperature and slow vegetation development in cold and semi-humid Northeast China (Guo et al., 2007). This difference shows that policies should differ among China's regions because the local biophysical and socioeconomic factors differ, and these differences can exert large influences on regional socioeconomic and ecosystem responses (Collins et al., 2011). This finding represents a key principle for any restoration program: that the restoration efforts must be carefully tailored to the local social and environmental conditions (Cao et al., 2011). Therefore, managers will reach different conclusions about the optimal solutions for different regions (Sivakumar, 2007). Unfortunately, China's current land conservation programs are initiated and financed primarily by the central government and are based on relatively monolithic national policies (Guan et al., 2011). Local land managers, especially at the township and village levels, are not adequately empowered to modify these national programs to account for local conditions (Yang, 2004).

Table 2 shows that policy, investment, and human factors may take some time to become effective. For example, vegetation needs time to absorb rainfall and increase its growth, and soil nutrients need time to accumulate to levels at which they can stimulate growth. This suggests that policy-makers and land managers must be patient if they want to observe the effects of environmental conservation. Because physical and ecological time lags lead to delayed responses, ecological restoration programs should not change when the program managers change; instead, the programs must be evaluated over a period of several years to determine whether they have become effective. Because of the complexity of ecological restoration (Ma et al., 2013) and the time lag between the implementation of certain changes and the ecosystem's response (Table 2), local land managers are likely to be more important than the central government has acknowledged because they are more likely to identify problems with a national policy and suggest appropriate steps to solve the problem. Therefore, one important improvement to China's current approach will be to give local managers more freedom to adapt centrally mandated environmental conservation programs to account for local conditions; in short, the success of the program is more important than how that success is achieved. Concerns about global warming, the degradation of fragile ecosystems, and the risks of environmental or socioeconomic collapse have led to increased interest in adopting more flexible solutions to environmental issues (Harris, 2012). However, the impact of climate change is a particular concern because it poses challenges that will be difficult to solve given human behavior (the tendency to resist uncomfortable changes) and environmental policy (institutional resistance to change), as well as the difficulty of predicting details of the effects of climate change.

Although humans are clearly part of nature, we are qualitatively different from other parts of nature: our actions have more rapid and disruptive consequences than those of most natural phenomena. Therefore, we must be careful to avoid the adoption of extreme approaches to change natural ecosystems because our changes may occur more rapidly than it is possible for ecosystems to adapt, and the resulting problems may not be evident for some time. Economists, ecologists, and other professionals must work closely with policymakers to develop a multidisciplinary road map for intervention strategies that account for the complexity of ecological restoration: solutions must be ecologically sensible, but must also shift human actors toward more environment-friendly behavior by means of regulatory devices as well as incentives (e.g., providing alternative ways of earning a livelihood when damaging livelihoods are prohibited), thereby permitting environmental conservation to succeed on both an ecological and a human scale.

Although the approach developed in the present study is a promising way to examine the simultaneous effects of human and natural factors, our approach will require much improvement in the future. First, performing analyses at a provincial scale ignores the very high variation that exists within China's large provinces. More fine-grained data with better spatial resolution will be necessary to allow local managers to adapt their approaches to account for unique local constraints. Second, it is likely that we did not identify all potentially significant driving factors responsible for changes in vegetation cover, particularly since each region may have certain unique constraints that have not been adequately studied by researchers. For example, we included only one "social" factor in our analysis, and the effects of constraints imposed by large-scale infrastructure such as the Three Gorges Dam Reservoir (the largest such project in the world) will differ from those imposed by rapid urbanization of a city. Finally, as our results show enough variation among regions that it may be necessary to repeat an analysis similar to the one described in this paper for each area to support practical local-scale management.

Disclosure statement

The authors declare no conflict of interest. The opinions expressed here are those of the authors and do not necessarily reflect the position of the government of China or of any other organization.

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