Journal of Arid Environments 108 (2014) 19–28

Contents lists available at ScienceDirect

Journal of Arid Environments

journal homepage: www.elsevier.com/locate/jaridenv

A multilevel analysis of effects of land use policy on land-cover change and local land use decisions

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ARTICLE INFO

Article history:
Received 12 August 2013
Received in revised form
7 April 2014
Accepted 10 April 2014
Available online

Keywords:
Desertification
Household
Multi-scale drivers
Multilevel statistical model
Policy change

ABSTRACT

Drylands, which occupy more than 40% of the Earth's land surface, are highly susceptible to degradation. It is important to understand causes, mechanisms, and environmental consequences of dryland ecosystem degradation. Land use policies are known to play a critical role in driving land cover changes, as well as in mitigating land degradation and promoting sustainable development in drylands. We analyzed the effects of different policies on vegetation cover and the attitude of local people toward policy changes in Uxin county, Inner Mongolia, China, based on remote sensed Normalized Difference Vegetation Index (NDVI) time series and household surveys. Overall vegetation in the study area was found to recover during 1987–2007. Multilevel statistical modeling results demonstrated that NDVI, density of agricultural population, density of livestock, land use, accessibility to market, and mean annual precipitation all had significant effects on re-vegetation. Changes in land use policy, which restricted farmers and herdsmen in certain land use practices and eliminated rangeland overload, were found to be an important driver of vegetation recovery during 1997–2007. Local households in the area generally approve the policy but adjust it according to their cultural traditions or land use practices.

1. Introduction

Land degradation is one of the world's most serious environmental problems (Fernández, 2002; UNCED, 1992). It is often triggered by human activities and, combined with climate change, it reduces overall biological productivity (Reynolds and Stafford Smith, 2002; UNCCD, 1994). Drylands occupy more than 40% of the Earth's land surface and are home to more than 38% of the global human population (GLP, 2005; MEA, 2005). Dryland ecosystems sustain important ecological and environmental functions (Omuto et al., 2010) and provide food, fuel wood, and pasture for communities' livelihood (Reynolds et al., 2007). Land degradation, which is often referred to as desertification in drylands (Dregne, 2002; UNCED, 1992), has occurred in about 10–20% of drylands with over 250 million people in developing countries being directly affected by this process (UNCCD, 1994).

Adequate knowledge is required to understand and monitor mechanisms of land degradation, eliminate its negative effects on environment and human society, and develop sustainable land management strategies (Pickup, 1996; UNCCD, 1994). Such knowledge on patterns of land degradation dynamics and their drivers can be effectively obtained by a combination of time series analysis of remotely sensed data and regression statistical analysis (Fabricante et al., 2009; Millington et al., 2007). One major shortcoming of previous studies that analyzed drivers of land degradation using regression models was the focus on a single scale (Verburg et al., 2003). However, land use dynamics rarely take place at a single scale (Mather, 2006), but often occur over a wide range of temporal and spatial scales (Lambin et al., 2003). Processes at these different scales are interdependent and driving factors should be analyzed via hierarchical relationships (Sun et al., 2006). To deal with such tasks multilevel statistical models were developed in 1980s and first applied in the social sciences, psychology, and education (Singer, 1998). By organizing data in a nested hierarchical

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http://dx.doi.org/10.1016/j.jaridenv.2014.04.006
0140-1963/

structures and building multilevel statistical models one can simultaneously handle driving variables at different scales. Recently multilevel statistical modeling has been introduced in ecology and land change science (Chelgren et al., 2011).

Desertification is the product of the interplay between human actions and climatic factors (Adamo and Crews-Meyer, 2006; Kellner, 2009). Human activities at local scales tend to accumulate and have significant effects on land cover patterns and processes at regional scales. The cross-scale effects have been a focus of some recent studies. Pan and Bilsborrow (2005) and Wyman and Stein (2010) analyzed the relationship between household decision-making and land degradation and found direct links with household socio-economic status, natural resources, and other geographical factors. Climate changes and local land cover dynamics influencing household land use strategies were the focus of Zhen et al. (2009) study. Gray et al. (2008) investigated links between land use decision-making and ethnic and cultural characteristics of households. However, only a few studies included policy factors which affect land use decisions and management at the local household level. Policies often play critical roles in land use and land cover dynamics. For example, they target unsustainable land use and shape land use decisions of local stakeholders, e.g., farmers, pastoralists (Lambin and Geist, 2003; Reid et al., 2006). Understanding the response of local land owners to changes in policies is also an important problem in studying land degradation at multiple scales.

In our study, we focused on desertification processes in Uxin Banner (administrative unit equivalent to a county, hereafter referred to as Uxin) of the Inner Mongolia Autonomous Region of China. The area was subject to the Household Production Responsibility System (HPRS) introduced after the launch of economic reforms in China in 1980s. Put in effect in Uxin after 1985 the HPRS contracted both livestock and pastureland, previously owned by communes, to households. This had a profound effect on land use and the environment. As a result, most households became involved in pastoral production for the market (Jiang, 2004). The drought of 1998–2000 caused significant vegetation losses and loss of income among herdsmen, which eventually triggered vegetation recovery in this region and the shift from extensive to a more intensive husbandry in Ordos. Since 2000 a new policy prohibited grazing during April–June in pastoral areas and all year around in agricultural areas and set limits to livestock numbers per hectare (Xin et al., 2008). It became common to feed livestock in pens and keep them at high densities. Our research goals were two-fold. First, we used Landsat TM data and multilevel statistical models to analyze spatiotemporal patterns of desertification in Uxin and identify major land use policy and environmental factors that drive these patterns. Spatial patterns were analyzed as a 3-level nested hierarchy of local, landscape, and regional levels. Accordingly, 3-level statistical models were constructed to investigate these multi-scale drivers of land cover dynamics. We hypothesized that: 1) Land use policies should most strongly influence land use of households at the regional scale; 2) Precipitation is the important driver of land degradation at local to landscape scales; 3) Vegetation dynamics, which are affected by practices of individual land managers who are influenced by policy incentives, is an indicator of land degradation at the local scale. Our second goal was to understand the response of local land managers to changes in policies. Specifically, the questionnaire was designed to assess the response to the grazing prohibition policy and its effects on land use decisions. We asked land managers about their choices of land use, for example, whether they pursue the grazing prohibition system, adopt rotation grazing system, or practice cultivation in response to changes in policies. The framework of our study is shown in Fig. 1.

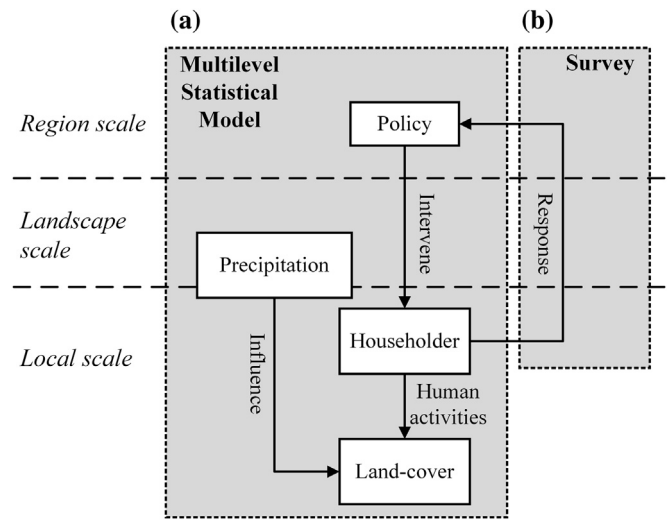

Fig. 1. The framework of the study. (a) A multilevel analysis of the impact of land use policy on land-cover change (an indicator of land degradation) is shown in the left dotted line box. Land use policy influence decision-making of household at the regional scale. Precipitation is the important driver of land-cover change at regional to landscape scales. Land-cover dynamics at the local scale are affected by land use of household influenced by policy incentives. (b) A questionnaire survey was used to study decision-making of household response to policy change.

2. Method

2.1. Study area

Uxin is located in southwestern Inner Mongolia, China (Fig. 2), covering an area of 11,645 km^2 and spanning from 37°39′N to 39°24′N in latitude and from 108°16′E to 109°40′E in longitude. Its population size was about 103,000 in 2010 with 30% consisting of Mongolian nationality. The area has a typical temperate continental climate with mean annual temperature of 6.8 °C. Annual precipitation changes from 350 mm in the southeast to 400 mm in the northwest and occurs mainly between June and September. Common soil types in Uxin are aeolian sandy soils and kastanozems. Fixed and moving sand dunes cover a major portion of its landscape. Dominant vegetation is composed of lowland grasses (e.g., *Achnatherum splendens* and *Carex duriuscula*) and shrubs (e.g., *Caragana intermedia* and *Artemisia ordosica*). Traditional land uses in Uxin have been farming and livestock husbandry, a typical combination in the agro-pastoral transitional zone of northern China (Fig. 2).

2.2. Multi-scale data

The multilevel statistical model includes dependent variables at level 1 and independent variables at the three levels. In addition we included two group (auxiliary) layers, which were used to sample lower level variables with group effects (Table 1).

2.2.1. Remote sensing data preprocessing

Three cloud-free Landsat-5 TM images were used for land cover change analysis. These images have the spatial resolution of 30 m and were acquired during growing seasons of 1987, 1997, and 2007. The three images were georeferenced using ENVI 4.7 software and 1:50,000 topographic maps as a reference. Geometric correction with the nearest neighbor resampling resulted in the root mean square error (RMSE) of less than 2 pixels. All images were

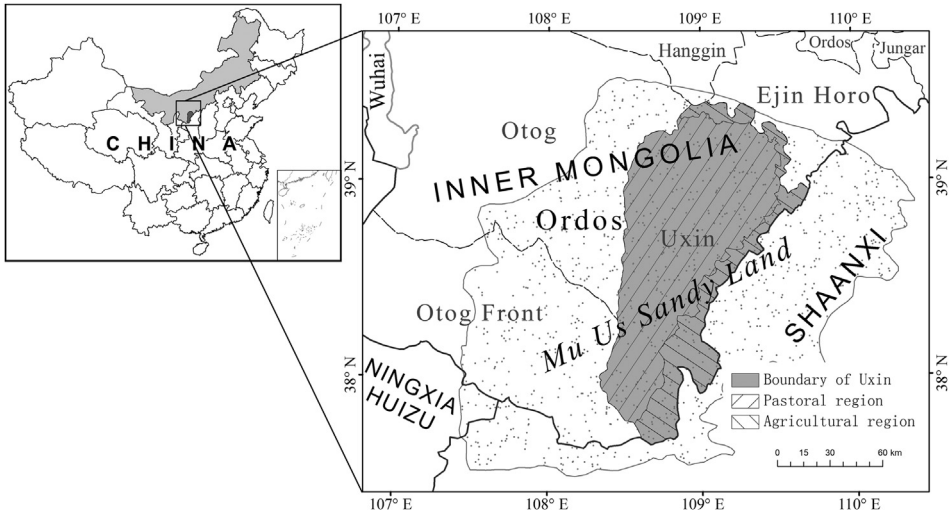

Fig. 2. Location of the study area. Uxin is located in the southwestern part of Inner Mongolia, China (gray color).

atmospherically corrected and digital numbers converted to reflectance using FLAASH for ENVI 4.7.

2.2.2. Dependent variables

Vegetation cover is used as one of the indictors for assessing desertification. According to Zhu et al. (1980) and Wang et al. (2008b), in arid and semiarid China, an area with sandy substrate is defined as fixed sandy land if it is covered by more than 40% of vegetation cover. It is defined as semi-fixed sandy land if vegetation cover is between 15 and 40%. Areas with vegetation cover below 15% are classified as moving sandy land. In mid-1980s, the Household Production Responsibility System (HPRS) introduced in this areas, contracted public rangeland to households. In order excluding the influences of pre-HPRS, therefore, we chose 1987 condition as a baseline. Desertification layers were visually interpreted and on-screen digitized from Landsat TM images. Changes in desertification were detected by intersecting polygon maps in ArcGIS 9.3. Two layers were generated – re-vegetation and desertification expansion.

Table 1
Dependent and independent variables in the multilevel statistical model.

Variables	Acquisition time of data	Description
Dependent variables		
Vegetation recovery	1987–1997 1997–2007	Categorical. 1 if desertification is reversed, 0 otherwise
Desertification expansion	1987–1997 1997–2007	Categorical. 1 if desertification is expanded, 0 otherwise
Independent variables		
Level 1 – local level		
NDVI	1987, 1997	Continuous
Agricultural population density	1987, 1997	Continuous
Livestock density	1987, 1997	Continuous
Land use	1987, 1997	Categorical. 6 land use type.
Accessibility to market	1987, 1997	Continuous. Cost distance
Mean precipitation at local level	1987–1997, 1998–2007	Continuous. Mean annual precipitation per pixel.
Level 2 – landscape level		
Landform	1987	Group layer, 10 geomorphology types
Mean precipitation at landscape level	1987–1997, 1998–2007	Continuous. Mean annual precipitation per landform.
Level 3 – region level		
Land use region	–	Group layer, 2 land use types,
Prohibition of open grazing	2000	Categorical. 1 if prohibition of open grazing is implemented, 0 otherwise

2.2.3. Independent variables

Two layers corresponding to the regional and to the landscape level were used to group independent variables above the local level. Data at the regional level were aggregated by land use regions, either pastoral or agricultural (Fig. 2). Landform map served as the group layer at the landscape level. There were 10 main geomorphology types (based on geomorphological map of Uxin, 1987): wind eroded and dry sand denudated rolling high plain; pluvial-alluvial and wind eroded valley plain; alluvial-pluvial valley plain; pluvial-alluvial and wind eroded lacustrine plain; pluvial-lacustrine and wind eroded lacustrine plain; lacustrine-pluvial and wind eroded lake-marshland plain; pluvial and wind eroded lake-marshland plain; moving sandy land; semi-fixed sandy land; fixed sandy land.

Normalized Difference Vegetation Index (NDVI) is a proxy measure of vegetation cover, which is one of the important factors influencing household land use decisions (Ebanyat et al., 2010). The NDVI is the ratio of the difference between the near-infrared (NIR) band and the red band of Landsat imagery (RED) to the sum of NIR and RED (Eq. (1)).

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED})/(\mathrm{NIR} + \mathrm{RED}) \quad (1)$$

In arid and semi-arid regions precipitation is known as the primary limiting factor of terrestrial ecosystem production (Nemani et al., 2003), so spatial and temporal variation in precipitation is expected to predict natural land cover dynamics. Therefore, we chose it as the primary natural driver of land cover change and obtained precipitation data from the China Meteorological Data Sharing Service System (NMIC). Precipitation grids (30 × 30 m spatial resolution) were derived for 1987–2007 by spatial interpolation of data for 50 weather stations in and around Uxin using ordinary kriging (spherical model) in ArcGIS 9.3. To account for precipitation variability at the local and the landscape level separately, we constructed two kinds of precipitation grids. The local level precipitation was calculated as the 10 year average precipitation at the original 30 m resolution for two time periods – 1987–1997 and 1998–2007. Landscape level grids for the same time periods were derived by aggregating precipitation values by landforms using Zonal Statistics tool in ArcGIS 9.3.

Agricultural population data and livestock data were acquired from statistical yearbooks of Uxin. Densities were computed by dividing population or livestock totals by the area of each county area (6 counties in total). These density maps were used as independent variables at the local level.

Land use reflects human activities on land and their decisions about how to exploit natural resources (Lambin and Geist, 2006). Land use was classified into 6 categories: Forest and Shrub, Cultivated Land, Rangeland, Moving Sand Land, Town, and Water Body. These land uses were visually interpreted and on-screen digitized in ArcGIS 9.3. Classification accuracy was assessed using 177 reference locations verified in the field in 2008 and 2009. Overall accuracies for the two years used in analyses were 89% and 86%. Land use is used as an independent variable at the local level.

We used distance to roads and towns as the measure of accessibility to the market and the factor influencing household land use decision-making (Gorton et al., 2008; Pan and Bilsborrow, 2005). The combined distance to roads and towns was calculated as the cost distance in Spatial Analyst of ArcGIS 9.3. Road maps were acquired from the Map of Uxin (2001) and Atlas of Inner Mongolia (2007). Town locations were acquired from remote sensing images. Accessibility to the market is the local level independent variable.

Lastly, open grazing prohibition policies, which have effect on land use management decisions, were used as a categorical variable in the regional level model.

2.2.4. Data pre-processing

All vector layers were converted into rasters with the resolution of 30 m. Continuous independent variables were standardized to a mean of 0 and one standard deviation. We used REG procedure of SAS statistical software to check for multi-collinearity. The highest variance inflation factor (VIF) was 1.796 (below the warning level of 10) (Kleinbaum et al., 2007). Multilevel statistical models were constructed for all pixels using GLIMMIX procedure (Singer, 1998; Wang et al., 2008a) of SAS. All models were estimated using the RSPL (Restricted/Residual Pseudo Likelihood) method. Wald Z test was used to determine the significance of coefficients. The relative operating characteristic (ROC) value, which varies between 0.5 (random) and 1 (discrimination), was used to check the goodness of fit of models.

2.3. Multilevel statistical modeling

Multilevel statistical modeling is a methodology designed for dealing with hierarchically structured data, which are both nested and clustered (Goldstein, 2003). Variables at the level of individuals (lower level) can be explained partly by variation at the individual level and partly by variation at the group level (higher level). The simplest example is performance of students who are members of their classes that are in turn members of schools. The performance of students is analyzed by simultaneously considering variation within each class and variation between schools.

The description of multilevel statistical modeling is based on Snijders and Bosker (1999) and Wang et al. (2008a). The modeling process starts with an empty or intercept-only model. We chose a logistic regression model as a link function between levels, which is defined as follows:

$$\mathrm{Log}\left(p_{ij}\big/1-p_{ij}\right) = \beta_{0j} + \varepsilon_{ij} \tag{2}$$

$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{3}$$

where i denotes indexes at level 1; j denotes indexes at level 2; p_{ij} is the probability of occurrence of an event at level 1; β_{0j} is the intercept of j_{th} group (higher level); ε_{ij} is i_{th} random variation associated with j_{th} group; γ_{00} is the overall intercept for both levels; u_{0j} is the group dependent deviation. Using this empty model, the variance of the dependent variable can be decomposed into within-group variance (level 1) and between-group variance (level 2).

Variables at higher levels are added to the empty model to construct a multilevel statistical model (Singer, 1998; Wang et al., 2008a). The following model (Eqs. (4) and (5)) is called a mixed model since it includes level 1 and level 2 explanatory variables. Eqs (4) and (5) can be rewritten into a combined, or composition, model (Eq. (6)):

$$\mathrm{Log}\left(p_{ij}\big/1-p_{ij}\right) = \beta_{0j} + \sum_{p=1}^{P}\alpha_p x_{pij} + \sum_{q=1}^{Q}\beta_{qj} z_{qij} + \varepsilon_{ij} \tag{4}$$

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \sum_{m=1}^{M}\gamma_{0m} w_{mj} + u_{0j} \\ \beta_{1j} &= \gamma_{10} + \sum_{m=1}^{M}\gamma_{1m} w_{mj} + u_{1j} \\ \ldots \quad & \ldots \\ \beta_{Qj} &= \gamma_{Q0} + \sum_{m=1}^{M}\gamma_{Qm} w_{mj} + u_{Qj} \end{aligned} \tag{5}$$

Combined model:

$$\begin{aligned} \mathrm{Log}\left(p_{ij}\big/1-p_{ij}\right) = {} & \gamma_{00} + \sum_{m=1}^{M}\gamma_{0m} w_{mj} + \sum_{p=1}^{P}\alpha_p x_{pij} \\ & + \sum_{q=1}^{Q}\gamma_{q0} z_{qij} + \sum_{q=1}^{Q}\sum_{m=1}^{M}\gamma_{qm} w_{mj} z_{qij} \\ & + \left(u_{0j} + \sum_{q=1}^{Q} z_{qij} u_{qj} + \varepsilon_{ij}\right) \end{aligned} \tag{6}$$

where x_{pij} are level 1 P explanatory variables with fixed effects (or fixed slope) and z_{qij} are level 1 Q explanatory variables with random effects (or random slope); α_p are fixed slopes of level 1 explanatory variables; β_{0j} is the random intercept at level 1; β_{Qj} are random slopes at level 1 that correspond to response variables explained by level 2 explanatory variables w_{mj}; w_{mj} are level 2 M explanatory variables. In our study we further extended this model to a 3 levels model.

Intra-class correlation coefficient (ICC), which ranges from 0 to1, is important to multilevel statistical models. Calculated from the empty or intercept-only model, the ICC is used to estimate the proportion of variance among group (higher) levels. Lower values of ICC mean lower degree of similarity of measurements within a group. If the value of ICC is 0 than no hierarchical structure between variables exists, and traditional estimation procedures are applicable, e.g., Ordinary least squares (Goldstein, 2003). Eqs. (7) and (8) show the calculation of the ICC for the 3 levels model. ICC_u is the intra-class correlation coefficient of level 1 dependent variable within the same group of level 2 and level 3. ICC_w is the intra-class correlation coefficient of level 1 dependent variable within the same group of level 3.

$$\mathrm{ICC}_u = \left(\sigma_u^2 + \sigma_b^2\right)\Big/\left(\sigma_w^2 + \sigma_b^2 + \sigma_u^2\right) \tag{7}$$

$$\mathrm{ICC}_w = \left(\sigma_u^2\right)\Big/\left(\sigma_w^2 + \sigma_b^2 + \sigma_u^2\right) \tag{8}$$

where $(\sigma_w^2 + \sigma_b^2 + \sigma_u^2)$ is the total variance of the multilevel model; σ_w^2 is within-group variation or variance at level 1 (individual level),

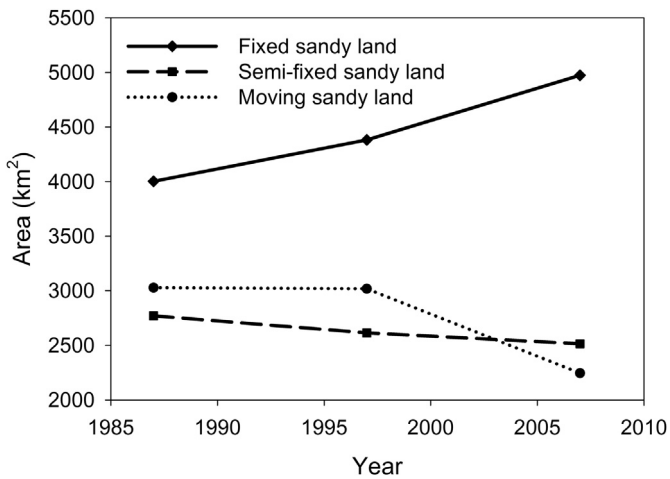

Fig. 3. Temporal changes of areas occupied by fixed sandy land, semi-fixed sandy land, and moving sands between 1987 and 2007.

which is equal to $\pi^2/3$ in a logistic regression model; σ_b^2 and σ_u^2 are level 2 and level 3 between-group variations or variances at the group level (higher level). ICC is the ratio of between-group variation and total variance.

2.4. Survey data

The survey was conducted in July 2010 by interviewing households about their land use practices and household characteristics using a structured questionnaire. It was designed to understand how grazing prohibition policies affect household land use strategies and how they respond to this policy, which may help explaining their land use decisions. Households to be interviewed were selected randomly along the road passing through 20 villages and spanning 4 counties. To guarantee the accuracy of responses to more than a decade-long policy, we selectively interviewed middle-aged householders if possible. A total of 119 households were interviewed including 80 herdsman households and 39 farmer households. The age of interviewees ranged from 28 to 83 with the average 54.

3. Results

3.1. Spatial and temporal changes of desertification

Desertification exhibited a consistently reversal trend between 1987 and 2007 (Fig. 3). During this time period fixed sandy land has substantially increased by 24.27% (from 4002.69 to 4974.19 km^2), semi-fixed sandy land decreased by 9.21% (from 2769.85 to 2514.64 km^2), and moving sandy land decreased by just 0.31% (from 3027.69 km^2 to 3018.29 km^2). During the period from 1997 to 2007, moving sandy land has significantly decreased by 25.60% and occupied only 2245.51 km^2 in 2007. About 745.46 km^2 of moving sandy land was converted to the semi-fixed sandy land and 183.83 km^2 to the fixed sandy land.

Some areas experienced re-vegetation, yet other areas were desertified in Uxin between 1987 and 1997 (Fig. 4a). Vegetation was ubiquitously recovering in the study area during the period from 1997 to 2007. In contrast, desertification expansion occurred mainly in the middle and northeastern parts of Uxin, primarily in lowlands, which, due to better vegetation and water conditions, had more human activities (Fig. 4a). Vegetation recovery was the dominant process in Uxin during 1997–2007, while desertification expansion was a minor process scattered throughout the study area (Fig. 4b).

3.2. Effects of multilevel driving factors on desertification changes

3.2.1. Multilevel drivers of vegetation recovery

Models 1, 2 and 3 are 3-level vegetation recovery models with random effects and fixed effects for time periods 1987–1997, 1997–2007 and 1987–2007, respectively. Models 1 and 2 do not have independent variables at the regional level, but the model structure of 3 levels is preserved in both models in order to incorporate regional level variables in the model 3.

Intra-class correlation coefficients (ICCs) of model 1 show that 11.2% of the variance can be attributed to the landscape

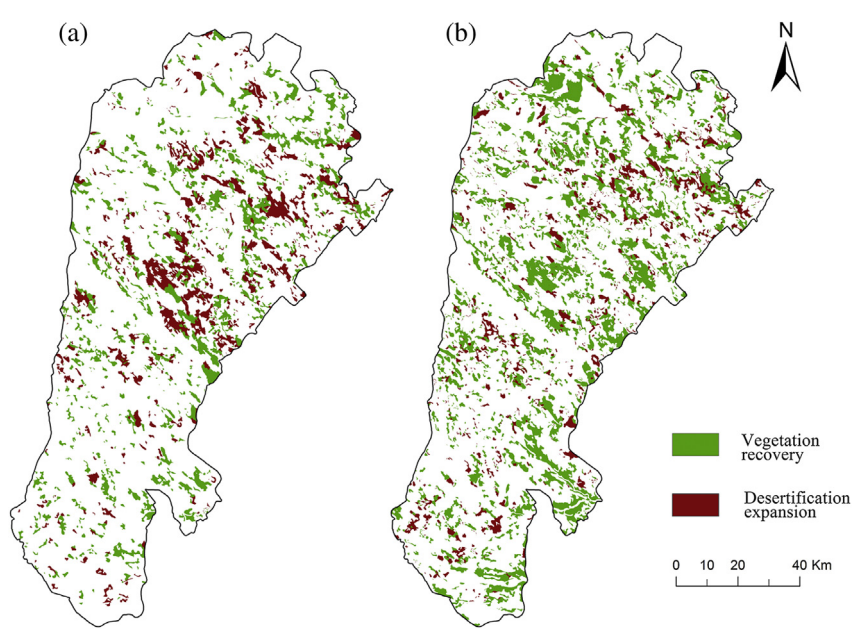

Fig. 4. The map of vegetation recovery and desertification expansion occurred during two time periods in Uxin: (a) 1987–1997; (b) 1997–2007.

level (2) and 0.2% to the regional level (3), indicating less spatial clustering at the regional level (Table 2). ICCs of model 2 are 28.8% at the landscape and 16.8% at the regional level. The spatial clustering of model 2 is greater than that of model 1. ICCs of model 3 show that 34.6% of the variance can be attributed to the landscape level (2) and 25.7% to the regional level (3), indicating substantial spatial clustering at the landscape and regional level.

The relationship between NDVI and re-vegetation is negative in model 1. Conversely, the proportion of vegetation recovery increases with increasing NDVI in models 2 and 3. Agricultural population density has negative effects on vegetation recovery in model 1 and positive effects on vegetation recovery in models 2 and 3. Livestock density has negative effects on vegetation recovery in models 1 and 3. The increase in livestock density leads to the increase in desertification. However, in model 2 the relationship between livestock density and vegetation recovery is positive. According to the results, forest and shrub, cultivated land, and rangeland correlated positively with vegetation recovery in all 3 models. Sandy lands and town variables were also positively related to vegetation recovery in models 2 and 3. Vegetation recovery was less possible if accessibility to market, i.e. proximity to roads and towns, was high according to all 3 models (Table 2). Mean annual precipitation is an important factor that boosts vegetation recovery both at the landscape and local levels. To understand policy effects on vegetation recovery during the periods of 1987–1997 and 1997–2007 we included the prohibition of open grazing variable at level 3. Unsurprisingly, this had a positive effect on vegetation recovery and the increase of vegetation cover. We also found that at the landscape level there were significant interactive effects of mean precipitation, with NDVI and with livestock density. Precipitation-NDVI interactive effect on vegetation recovery was positive in all models. Mean precipitation and livestock density interaction was negatively correlated with vegetation recovery in model 1, but positively in models 2 and 3 (Table 2).

Table 2
Multilevel statistical models of vegetation recovery.

	Model 1 1987–1997	Model 2 1997–2007	Model 3 1987–2007
Intercept	−19.972	−17.578	−3.709*
Level 1			
NDVI	−0.047*	0.117*	0.116
Density of agricultural population	−0.154*	0.190*	0.901*
Density of livestock	−0.142*	0.219*	−0.058*
Forest and shrub	0.996*	0.665*	0.975*
Cultivated land	0.758*	0.500*	2.070*
Rangeland	1.648*	1.571*	2.259*
Sandy land	−1.793*	1.699*	1.619*
Town	1.189	0.264*	0.428*
Water body	0.000	0.000	0.000
Accessibility to market	−0.403*	−0.275*	−0.129*
Mean precipitation at local level	0.503*	0.216*	0.062*
Level 2			
Mean precipitation at landscape level	0.114*	−0.075	0.378*
Level 3			
Prohibition of open grazing			0.474*
Mean precipitation at landscape level × NDVI	0.041*	0.116*	0.022*
Mean precipitation at landscape level × density of livestock	−0.176*	0.118*	0.214*
Variance components			
ICC at landscape level	11.2%	28.8%	34.6%
ICC at region level	0.2%	16.8%	25.7%
ROC	0.885	0.892	0.841

*$p < 0.05$.

Table 3
Multi-level models for desertification expansion.

	Model 1 1987–1997	Model 2 1997–2007	Model 3 1987–2007
Intercept	4.703*	−5.601*	−1.808*
Level 1			
NDVI	0.834*	6.529	−0.078*
Density of agricultural population	0.035*	−0.069*	0.181
Density of livestock	−1.650	0.098*	0.109*
Forest and shrub	0.344	−0.676*	−0.938*
Cultivated land	0.118*	−0.563*	−1.542*
Rangeland	2.866*	2.440*	1.383*
Sandy land	5.243*	4.254*	1.622*
Town	−0.102*	−0.179*	−0.669*
Water body	0.000	0.000	0.000
Accessibility to market	−0.001*	0.001*	−0.161*
Mean precipitation at local level	−0.002*	−0.004	−0.065*
Level 2			
Mean precipitation at landscape level	−0.015*	−0.011*	−0.378*
Level 3			
Prohibition of open grazing			−0.042*
Mean precipitation at landscape level × NDVI	−0.003*	−0.020*	−0.296*
Mean precipitation at landscape level × density of livestock	0.001*	0.000	−0.174*
Variance components			
ICC at landscape level	21.1%	10.6%	4.6%
ICC at region level	3.0%	1.3%	0.5%
ROC	0.858	0.843	0.834

*$p < 0.05$.

3.2.2. Multilevel drivers of desertification expansion

Desertification expansion was analyzed by constructing regressions models similarly to those described for vegetation recovery (Table 3).

Regional level ICCs of model 1, 2, and 3 are less than or equal to 3.0% indicating lower spatial clustering effects at this level. ICCs of 3 desertification expansion models explain 21.1%, 10.6%, and 4.6% variance at the landscape level, respectively (Table 3).

Regression coefficients of mean annual precipitation are negative at the landscape and the local levels for all models, although correlations are weak. NDVI correlates positively with desertification expansion in model 1, but negatively in model 3. Agricultural population density has positive effects on desertification expansion in model 1, negative effects in model 2, and no effects in model 3. Increasing livestock density increases desertification expansion in models 2 and 3. Different land uses have different effects on desertification expansion. Forest and shrub, cultivated land, and town variables have negative effects on desertification expansion in all models except model 1, where cultivated land has the opposite effect. Sandy land and rangeland both have positive effects on desertification expansion in all models. Accessibility to market has negative, but very small (in models 1 and 3), effect on desertification expansion. Mean precipitation at the landscape level has interactive effects with NDVI and livestock densities. Increasing precipitation slows down desertification expansion according to all models. Used in model 3 for the period 1987–2007, the policy variable also exhibits a restrictive effect on desertification expansion.

3.3. Response of herdsmen and farmers to policy change

Most of the interviewed farmers believed that environmental conditions have improved (97.4%). For 12.5% of herdsmen no environmental change has occurred, while those managing better quality pastures (16.3%) felt a decline in environmental quality

believed to be caused by decrease in precipitation. The majority of herdsmen (71.3%) gave the highest priority to environmental improvement (Table 4).

Most farmers (97.4%) approve the grazing prohibition policy while 30% of herdsmen disapprove it believing they can manage pastures better using their own grazing practices. About 33% of herdsmen stated that the grazing prohibition policy had no effect on their family income and 26.3% believed their family income decreased considerably because of the grazing prohibition policy. Among the farmers only 7.7% believed their income dropped significantly and 33.3% felt their income decreased slightly. The increase in income was acknowledged by 23.8% of herdsmen and 25.7% of farmers.

To comply with the grazing prohibition policy 67.3% of herdsmen and 39.6% of farmers had to reduce their livestock. About 19.6% of herdsmen increased cultivation of forage, including corn and alfalfa, to support more livestock. While few herdsmen prefer dry-lot feeding and increase in livestock off-take rates, 37.7% of farmers chose dry-lot feeding to meet the policy rules. An increase in livestock off-take rates was practiced by 18.9% of farmers.

Quite expectedly, 49.5% of herdsmen disapproved the grazing prohibition policy and would like to continue traditional grazing if the policy stopped. They stated the policy does not consider differences in pasture quality whereas their own practices allow them to better adjust to pasture dynamics. One herdsman's response was that if the pasture quality deteriorates, livestock numbers and closed grazing practices can be decided by him more efficiently rather than imposed by the policy. 12.9% of herdsmen approved the policy by stating that it helps improving their pastures. 21.5% of herdsmen believed that their former grazing systems and grazing prohibition systems could be successfully practiced in their rangelands. Almost half of the farmers (44.7%) were willing to invest more labor hours to intensify crop production and maintain the grazing prohibition policy. Farmers considered that there are many labors in their families, 29.8% respondents of farmer adopted off-farm jobs if the end of the policy. 17.0% of farmers adopted other grazing practices.

4. Discussions

4.1. Multi-scale drivers of vegetation recovery

Two time periods of vegetation recovery found in our study are most likely explained by the implementation of environmentally concerned policies and, partly, by environmental factors. The first period is characterized by slow vegetation recovery during 1987 and 1997 when re-vegetation both ceased and expanded in some areas in Uxin. During the second period (1997–2007) re-vegetation was the dominant process. In this decade moving sandy land reduced significantly and re-vegetated areas expanded fast. Our analyses suggested that both climate and human factors contributed to this vegetation recovery.

Precipitation is an important factor of vegetation productivity and its recovery from degradation. The multilevel statistical analysis confirmed the hypothesis that precipitation is the key driver of vegetation recovery at landscape and local levels during both time periods (vegetation recovery model 1 for 1987–1997 and vegetation recovery model 3 for 1987–2007). Vegetation recovery is highly positively correlated with the increase in mean annual precipitation. However, such correlation was not detected by the multilevel model during 1997 and 2007 (model 2 of vegetation recovery) (Table 2). We used wavelet analysis (Morlet wavelet as a mother function) to identify periodic variation of annual precipitation (Fig. 5). Using a 10-year scale we can see increases in annual precipitation during 1987–1993 and 2000–2004, whereas during 1994–1999 and 2005–2007 periods the area received little precipitation. Because a significant proportion of the time period between 1997 and 2007 was characterized by precipitation scarcity, we believe this explains the lack of precipitation – vegetation recovery correlations considering that a notable portion of the area experienced vegetation recovery. Other factors are likely responsible for processes of vegetation recovery during this time period.

NDVI dynamics can indicate land use strategies. Our data show that NDVI was negatively correlated with vegetation recovery during 1987–1997 and positively correlated during 1997–2007. Prohibition of open grazing policy restricted livestock numbers and

Table 4
Perceptions of survey respondents about grazing prohibition policy changes.

Question	Responses	% of total responses		
		Herdsmen	Farmers	Total
What environmental change is occurring?	Improvement	71.3	97.4	79.8
	No change	12.5	2.6	9.2
	Degradation	16.3	0.0	10.9
Do you cooperate with the grazing prohibition policy?	Yes	70.1	97.4	96.7
	No	30.0	2.6	3.4
How does the grazing prohibition policy affect your family income?	Greatly increase	11.3	2.6	8.4
	Moderately increase	12.5	23.1	16.0
	No change	33.8	33.3	33.6
	Moderately decrease	16.3	33.3	21.8
	Considerably reduce	26.3	7.7	20.2
What are your options for coping with the grazing prohibition policy? (more than one answer permitted)	Planting forage	19.6	3.8	14.4
	Dry-lot feeding	7.5	37.7	17.5
	Limit livestock	67.3	39.6	58.1
	Increasing livestock off-take rates	5.6	18.9	10.0
What land use decisions would you adopt if the policy was to stop? (more than one answer permitted)	Use the grazing prohibition system	12.9	44.7	23.6
	Adopt another grazing system	49.5	17.0	38.6
	Select their former grazing systems or grazing prohibition systems	21.5	8.5	17.1
	Take an off-farm job	9.7	29.8	16.4
	Tourism (i.e. hobby farm)	6.5	0.0	4.3

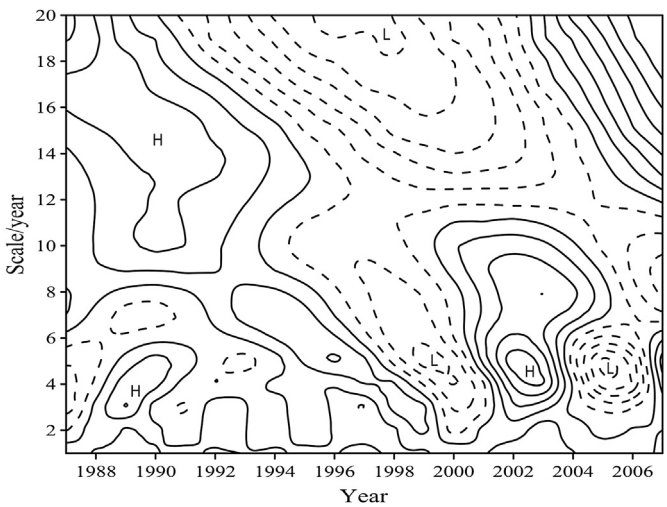

Fig. 5. Contour map of wavelet coefficients of annual precipitation from 1987 to 2007. Solid lines are positive values of wavelet coefficients; dash lines are negative values of wavelet coefficients; "H" is high value centers of wavelet coefficients; "L" is low value centers of wavelet coefficients; this map displays precipitation fluctuations in the time series.

grazing time thereby helping in grassland vegetation recovery. It is especially important during the early stages of plant development.

Population of the area increased by 6537 people from 1987 to 2007 (see Fig. 6). Agricultural population density had negative effects on vegetation recovery and enhanced desertification expansion during the period of 1987–1997. During 1997–2007, however, higher population density corresponded to expansive re-vegetation. Policies and other factors may significantly influence human activities and affect desertification processes, although our analyses suggest desertification processes did not follow population growth in a linear fashion.

Big livestock numbers are the major reason for rangeland degradation because high livestock density imposes high pressure on vegetation. The increase in livestock during 1987–1997 produced sufficient desertification expansion. On the contrary, we found that during 1997–2007 the relationship reversed suggesting the coexistence of high livestock numbers and proliferating vegetation recovery (see Fig. 6). We explain this by the effects of policy implementation which allowed re-distribution of stocking pressures through the restriction of open grazing, encouragement of

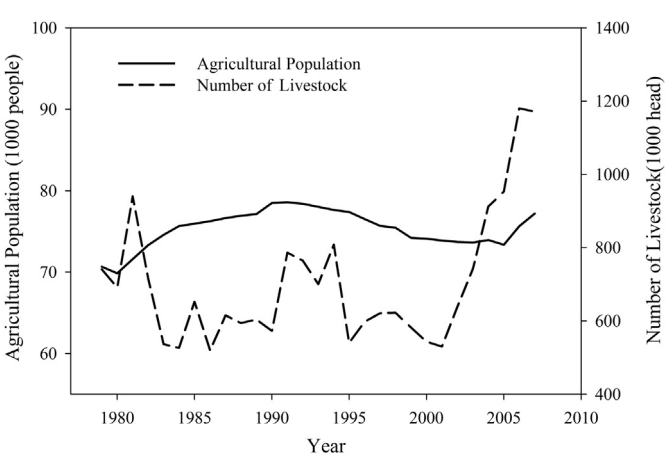

Fig. 6. Change in agricultural population and number of livestock of Uxin from 1979 to 2007. (Data source: Year book of Uxin).

fenced grazing or rotational grazing, and ultimately improved vegetation cover. Another reason is the re-consideration of wealth concept among livestock owners who turned from traditional agro-pastoral practices to a more market-oriented values in the Mu Us sandy land (Jiang, 2004). In recent years, pastoralists seek economic profits by selling sheep around the middle of vegetation growing season and reducing the grazing pressure. These practices certainly help in grassland vegetation recovery (Jiang, 2004).

Land use is an important human induced factor of desertification. Forest and shrub lands, cultivated lands, and rangelands all had positive effects on vegetation recovery. Cultivated lands there are located mostly in river valleys of the east and southeast parts of Uxin with better hydrologic conditions. As a result, they are spatially correlated with areas of vegetation recovery. There are two ways sandy land class is related to desertification processes. On one hand, mobilized sandy dunes enlarge the sandy area. On the other, sand dunes are rarely used by people, who instead invest in desertification control and vegetation recovery activities in such areas. For example, the Three-North Forest Shelterbelt Program (TNFSP) has been implemented since 1978 to increase biomass and stabilize sandy dunes. Despite these efforts, the survival rate of planted trees and shrubs was generally low, which resulted in increased biomass in east Ordos (Li et al., 1999; Wang et al., 2010). Parts of Uxin have been seeded from an airplane in 1980s and 1990s which may have caused the vegetation expansion and sandy dune stabilization (Runnström, 2000). Finally, town land use class has positive effects on vegetation recovery since many mobile sandy dunes were converted into this land use resulting in the overall reduction of desertified lands.

4.2. "Top down" management and "bottom up" adoption

Land use policy has a strong influence on vegetation recovery because it restricts certain land use practices and influences decision-making of farmers and herdsmen. It has the overall goal of vegetation cover improvement and combating the expansion of desert in this region. According to the survey, land use decisions of farmers and herdsmen were based on their cultural traditions or existing land use practice, but were restricted by the imposed land use policy. The policy was imposed by the government, so it is a "top down" mechanism in land use management. Household level land use decisions and management are "bottom up" mechanisms. "Top-down" mechanism uses the policy to constrain the "bottom" level, so households are obliged to comply strictly with these policy regulations and adjust their local land use decisions accordingly.

We find that the policy has achieved most of its goals. This is reflected in the steady rise of GDP and average household income during 1987–2007 (Fig. 7). The same opinion is shared among the interviewees who expressed their views on both the environmental change and their income, which did not decline sharply. It can therefore be considered a win–win scenario when ecological restoration goals are achieved and economic development is continued. Dai (2010) asserted that this transition to the new resource use system fosters closer linkage between crop and livestock production and help farmers and herdsmen to adapt to the grassland fencing policy. Our household survey revealed similar opinions from interviewees. Farming and pastoral land use decision-making has somewhat different responses to policy impacts. In pastoral areas pastures are the property of herdsman households who practice mainly traditional livestock herding while crop cultivation is a supplementary land use with the aim to provide forage for livestock. The grazing prohibition policy restricts the number of livestock and grazing time. Herdsmen respond by decreasing the number of livestock or increasing the production of corn used as forage. The policy has different regulations in

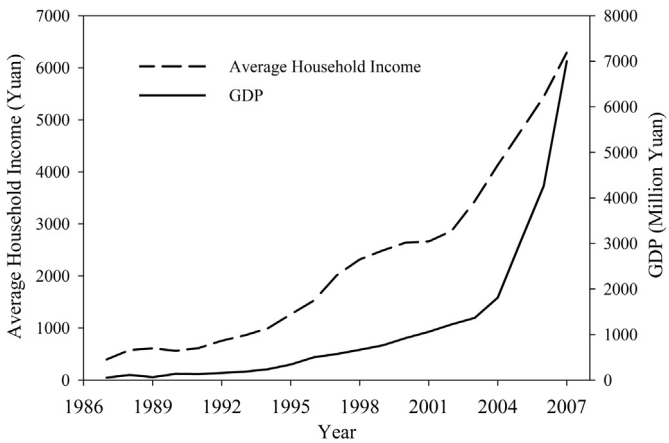

Fig. 7. Changes of GDP and average household income during 1987–2007. Solid line represents the GDP of Uxin; dash line represents the average household income. (Data source: Year book of Uxin).

agricultural areas, where livestock grazing on the grassland is banned and violators are punished. Consequently the cost of feeding of livestock kept in pens increases. Farmers, therefore, prefer to invest more labor and time into commercial crop production, and tend to reduce the number of sheep they breed. Although some localized resistance to the policy among herdsmen and farmers exists, the overall reduction of grazing intensity on grassland has significant ameliorating effect.

5. Conclusions

Our findings can be summarized as follows:

1) Desertification in our study area has reversed between 1987 and 2007. The process was first slow and then accelerated significantly after 1997.
2) Multilevel statistical modeling suggested both climate and human factors contributed to this vegetation recovery at different scales. Variables that explain this process best are NDVI, density of agricultural population, density of livestock, land use, accessibility to market, and mean annual precipitation.
3) Changes in land use policy, which restricted farmers and herdsmen in certain land use practices and overloading the rangeland, were found to be an important driver of vegetation recovery during 1997–2007. Local households in the area support the policy but adjust it according to their cultural traditions or land use practices.

Acknowledgments

We thank two anonymous reviewers for invaluable suggestions useful for improving the earlier version of our paper. This study was supported by funds from the National Basic Research Program of China (973 Program) (2012CB722201), National Natural Science Foundation of China (31060320 and 30970504), National Science and Technology Support Program (2011BAC07B01), National Department Public Benefit Research Foundation of Ministry of Environmental Protection (201109025-3).

References

Adamo, S.B., Crews-Meyer, K.A., 2006. Aridity and desertification: exploring environmental hazards in Jáchal, Argentina. Appl. Geogr. 26, 61–85.
Chelgren, N.D., Adams, M.J., Bailey, L.L., Bury, R.B., 2011. Using multilevel spatial models to understand salamander site occupancy patterns after wildfire. Ecology 92, 408–421.
Dai, Z., 2010. Intensive agropastoralism: dryland degradation, the Grain-to-Green Program and islands of sustainability in the Mu Us Sandy Land of China. Agric. Ecosyst. Environ. 138, 249–256.
Dregne, H.E., 2002. Land degradation in the drylands. Arid Land Res. Manag. 16, 99–132.
Ebanyat, P., de Ridder, N., de Jager, A., Delve, R.J., Bekunda, M.A., Giller, K.E., 2010. Drivers of land use change and household determinants of sustainability in smallholder farming systems of Eastern Uganda. Popul. Environ. 31, 474–506.
Fabricante, I., Oesterheld, M., Paruelo, J.M., 2009. Annual and seasonal variation of NDVI explained by current and previous precipitation across Northern Patagonia. J. Arid Environ. 73, 745–753.
Fernández, R.J., 2002. Do humans create deserts? Trends Ecol. Evol. 17, 6–7.
GLP, 2005. Science Plan and Implementation Strategy. IGBP Secretariat, Stockholm.
Goldstein, H., 2003. Multilevel Statistical Models, third ed. E. Arnold, London.
Gorton, M., Douarin, E., Davidova, S., Latruffe, L., 2008. Attitudes to agricultural policy and farming futures in the context of the 2003 CAP reform: a comparison of farmers in selected established and new Member States. J. Rural Stud. 24, 322–336.
Gray, C.L., Bilsborrow, R.E., Bremner, J.L., Lu, F., 2008. Indigenous land use in the Ecuadorian Amazon: a cross-cultural and multilevel analysis. Hum. Ecol. 36, 97–109.
Jiang, H., 2004. Cooperation, land use, and the environment in Uxin Ju: the changing landscape of a Mongolian-Chinese Borderland in China. Ann. Assoc. Am. Geogr. 94, 117–139.
Kellner, K., 2009. Integrating approaches to monitor, map and address land degradation and desertification. Afr. J. Range Forage Sci. 26, iii–iv.
Kleinbaum, D.G., Kupper, L.L., Nizam, A., Muller, K.E., 2007. Applied Regression Analysis and Other Multivariable Methods, fourth ed. Thomson Brooks/Cole, Australia.
Lambin, E.F., Geist, H.J., 2003. Regional differences in tropical deforestation. Environment 45, 22–36.
Lambin, E.F., Geist, H.J., 2006. Land-use and Land-cover Change: Local Processes and Global Impacts. Springer Berlin Heidelberg, New York.
Lambin, E.F., Geist, H.J., Lepers, E., 2003. Dynamics of land-use and land-cover changes in tropical regions. Annu. Rev. Environ. Resour. 28, 205–241.
Li, C., Koskela, J., Luukkanen, O., 1999. Protective forest systems in China: current status, problems and perspectives. Ambio 28, 341–345.
Mather, A.S., 2006. Driving forces. In: Geist, H.J. (Ed.), Our Earth's Changing Land: an Encyclopedia of Land-use and Land-cover Change. Greenwood Press, Westport, London, pp. 179–185.
MEA, 2005. In: Assessment, M.E. (Ed.), Ecosystems and Human Well-being: Desertification Synthesis. WorldResources Institute, Washington, DC.
Millington, J.D.A., Perry, G.L.W., Romero-Calcerrada, R., 2007. Regression techniques for examining land use/cover change: a case study of a Mediterranean landscape. Ecosystems 10, 562–578.
Nemani, R., Keeling, C., Hashimoto, H., Jolly, W., Piper, S., Tucker, C., Myneni, R., Running, S., 2003. Climate-driven increases in global terrestrial net primary production from 1982 to 1999. Science 300, 1560.
Omuto, C.T., Vargas, R.R., Alim, M.S., Paron, P., 2010. Mixed-effects modelling of time series NDVI-rainfall relationship for detecting human-induced loss of vegetation cover in drylands. J. Arid Environ. 74, 1552–1563.
Pan, W.K.Y., Bilsborrow, R.E., 2005. The use of a multilevel statistical model to analyze factors influencing land use: a study of the Ecuadorian Amazon. Glob. Planet. Change 47, 232–252.
Pickup, G., 1996. Estimating the effects of land degradation and rainfall variation on productivity in rangelands: an approach using remote sensing and models of grazing and herbage dynamics. J. Appl. Ecol. 33, 819–832.
Reid, R.S., Tomich, T.P., Xu, J., Geist, H., Mather, A., DeFries, R.S., Liu, J., Alves, D., Agbola, B., Lambin, E.F., Chabbra, A., Veldkamp, T., Kok, K., Noordwijk, M.v., Thomas, D., Palm, C., Verburg, P.H., 2006. Linking land-change science and policy: current lessons and future integration. In: Lambin, E.F., Geist, H.J. (Eds.), Land-use and Land-cover Change: Local Processes and Global Impacts. Springer Berlin Heidelberg, New York, pp. 157–171.
Reynolds, J.F., Smith, D.M.S., Lambin, E.F., Turner, B.L., Mortimore, M., Batterbury, S.P.J., Downing, T.E., Dowlatabadi, H., Fernández, R.J., Herrick, J.E., Huber-Sannwald, E., Jiang, H., Leemans, R., Lynam, T., Maestre, F.T., Ayarza, M., Walker, B., 2007. Global desertification: building a science for dryland development. Science 316, 847–851.
Reynolds, J.F., Stafford Smith, M., 2002. Global desertification: do humans create deserts? In: Stanford-Smith, M., Reynolds, J.F. (Eds.), Do Humans Create Deserts? Dahlem University Press, Berlin, pp. 1–22.
Runnström,, M.C., 2000. Is Northern China winning the battle against desertification? Satellite remote sensing as a tool to study biomass trends on the Ordos Plateau in semiarid China. Ambio 29, 468–476.
Singer, J.D., 1998. Using SAS PROC mixed to fit multilevel models, hierarchical models, and individual growth models. J. Educ. Behav. Stat. 23, 323–355.
Snijders, T.A.B., Bosker, R.J., 1999. Multilevel Analysis: an Introduction to Basic and Advanced Multilevel Modelling. Sage, New York, NY.
Sun, D., Richard, D., Li, B., 2006. Agricultural causes of desertification risk in Minqin, China. J. Environ. Manag. 79, 348–356.
UNCCD, 1994. Elaboration of an International Convention to Combat Desertification in Countries Experiencing Serious Drought and/or Desertification, Particularly in Africa. United Nations Convention to Combat Desertification, United Nations, New York.

UNCED, 1992. Managing fragile ecosystems: combating desertification and drought, agenda 21. In: United Nations Conference on Environment and Development. United Nations, New York.
Verburg, P.H., de Groot, W.T., Veldkamp, A.J., 2003. Methodology for multi-scale land use change modeling: concepts and challenges. In: Dolman, A.J., Verhagen, A. (Eds.), Global Environmental Change and Land Use. Kluver Academic Publishers, Dordrecht, Netherlands, pp. 17–51.
Wang, J., Xie, H., Jiang, B., 2008a. Multilevel Models: Methods and Application. Higher Education Press, Beijing, China.
Wang, X., Chen, F., Hasi, E., Li, J., 2008b. Desertification in China: an assessment. Earth-Sci. Rev. 88, 188–206.
Wang, X.M., Zhang, C.X., Hasi, E., Dong, Z.B., 2010. Has the Three Norths Forest Shelterbelt Program solved the desertification and dust storm problems in arid and semiarid China? J. Arid Environ. 74, 13–22.
Wyman, M.S., Stein, T.V., 2010. Modeling social and land-use/land-cover change data to assess drivers of smallholder deforestation in Belize. Appl. Geogr. 30, 329–342.
Xin, Z., Xu, J., Zheng, W., 2008. Spatiotemporal variations of vegetation cover on the Chinese Loess Plateau (1981-2006): impacts of climate changes and human activities. Sci. China Ser. D Earth Sci. 51, 67–78.
Zhu, Z., Wu, Z., Liu, S., Di, X., 1980. An introduction to Chinese Desert. Science Press, Beijing, China.
Zhen, L., Ochirbat, B., Lv, Y., Wei, Y.J., Liu, X.L., Chen, J.Q., Yao, Z.J., Li, F., 2009. Comparing patterns of ecosystem service consumption and perceptions of range management between ethnic herders in Inner Mongolia and Mongolia. Environ. Res. Lett. 5, 1–11.