remote sensing

MDPI

Article

Quantitatively Assessing and Attributing Land Use and Land Cover Changes on China's Loess Plateau

Xiaozheng Du [1,2], Xiang Zhao [1,2,*], Shunlin Liang [3], Jiacheng Zhao [1,2], Peipei Xu [4] and Donghai Wu [5]

1 State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and Institute of Remote Sensing and Digital Earth of Chinese Academy of Sciences, Beijing 100875, China; duxzheng@mail.bnu.edu.cn (X.D.); zhaojiacheng@mail.bnu.edu.cn (J.Z.)
2 Beijing Engineering Research Center for Global Land Remote Sensing Products, Institute of Remote Sensing Science and Engineering, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
3 Department of Geographical Sciences, University of Maryland, College Park, MD 20742, USA; sliang@umd.edu
4 School of Geography and Tourism, Anhui Normal University, Wuhu 241002, China; xupei@ahnu.edu.cn
5 College of Urban and Environmental Sciences, Peking University, Beijing 100871, China; donghai.wu@pku.edu.cn
* Correspondence: zhaoxiang@bnu.edu.cn; Tel.: +86-010-5880-0152

Received: 28 November 2019; Accepted: 19 January 2020; Published: 21 January 2020

check for updates

Abstract: The global land surface cover is undergoing extensive changes in the context of global change, especially in the Loess Plateau, where ecological restoration policies have been vigorously implemented since 2000. Evaluating the impact of these policies on land cover is of great significance for regional sustainable development. Nonetheless, there are few quantitative assessment studies of the impact of ecological restoration policies on land use and land cover change (LULCC). In this study, a relative contribution conceptual model (RCCM) was used to explore the contribution of the policies to LULCC under the influence of natural background change, which was based on the Markov chain and the future land use simulation (FLUS) model. The results show that LULCC is influenced by ecological restoration policies and the natural environment, of which the policies contribute about 72.37% and natural change contribute about 27.63%. Ecological restoration policies have a profound impact on LULCC, changing the original direction of LULCC greatly. Additionally, these policies regulate the pattern of LULCC by controlling the amount of cropland as a rebalanced leverage. These findings provide useful information for facilitating sustainable ecological development in the Loess Plateau and theoretically supporting environmental decision-making.

Keywords: land use and land cover change; ecological restoration policy; Grain for Green program; FLUS model; natural effects

1. Introduction

The global land surface cover is undergoing extensive changes in the context of global change, which have profound effects on terrestrial ecosystems [1–5]. Land use and land cover change (LULCC) is a comprehensive reflection of the interaction between the natural environment and human activities [6,7]. Global warming leads to the forest boundaries moving northward [8,9], the shrinking of glaciers and icecaps [10], and the changes of vegetation in coastal beaches [11]. Simultaneously, human activities (e.g., grazing, agricultural intensification, urbanization, and afforestation) have transformed up to half of the global land surface [12,13], which significantly disturbs the surface energy and regional carbon storage balance [13,14]. Therefore, timely and quantitative assessment of LULCC is of great significance for promoting regional sustainable development and has become a hot spot in the field of geography and sustainable science [6,15].

The implementation and promotion of ecological restoration policy are one of the important drivers of LULCC [6,16]. There are many ecological restoration projects led by the government or the regions around the world, which directly change the land surface cover [17–21]. For example, the Bonn Challenge is the first global commitment for forest restoration under international cooperation [19]. America's Conservation Reserve Program (CRP) encourages farmers to discontinue their crops on the fragile farmland and instead plant permanent vegetation [17,18]. The Common Agricultural Policy (CAP) of the European Union (EU) has influenced the evolution of European agricultural landscapes by promoting the change of land use and agricultural practices [20,21]. The Grain for Green program (GFGP) implemented by the Chinese government is one of the largest ecological restoration programs in the world and aims at transforming cropland to forest and grassland [22]. These ecological restoration policies provide a variety of environmental benefits, such as increasing greening [23,24], creating wildlife habitats [19,25], and storing carbon [26], but are also controversial because of some of the adverse effects on regional ecological environment [21,27]. Therefore, it is necessary to assess the effectiveness of ecological restoration policy and balance the favorable and adverse effects timely.

A variety of studies for assessing the effect of ecological restoration policy have been reported. Comparison methods are typically used to identify the influence of policies. Wu et al. compared the vegetation activities in and outer of the Beijing–Tianjin Sand Source Control Program region and evaluated the impacts of ecological restoration program on the vegetation [28]. Melanie et al. identified the impact of zoning regulations on urban watersheds by comparing before and after the implementation of zoning [16]. Renato et al. analyzed the global forest restoration effect by meta-analysis [19,25]. Fu et al. compared the indicators of ecosystem services in different scenarios in the Altai region [29]. However, few studies quantify the effect of ecological restoration policies on the background of environmental change. Despite the numerous studies focusing on the assessment of the effectiveness of ecological restoration policies, some questions remain unclear. How do ecological restoration policies affect LULCC? To what extent do these policies influence LULCC under the background of environmental change?

To quantitatively assess the net effect of the ecological restoration policy on LULCC, it is necessary to distinguish the policy effects from the influence of natural background, and determine LULCC under natural conditions [30]. LULCC modeling is one of the common methods for simulating land use and land cover in different scenarios [31–33]. A future land use simulation (FLUS) model [33] provides a reliable and reproducible way to analyze the attribution of possible future land use dynamics. The FLUS model is an integrated model that can be used to simulate multi-type future land use scenarios by coupling human activities and natural effects [33–35]. Based on this model, the pattern of LULCC in China from 2010 to 2050 [33] and the urban growth boundary of pearl river delta in 2020–2050 [36] have been simulated. Li et al. simulated the change of global land use pattern over the next 100 years in different climate change scenarios with the FLUS model [34]. Thus, the FLUS model can effectively simulate the land use dynamics under different scenarios and further explore the possible causes and consequences of LULCC. However, given that the influence of natural background change on LULCC is perpetual and underlying, it is challenging to separate the role of supplementary ecological policies from that of potential natural background [12,37].

Against this background, our main objective was to quantitatively assess the impact of the GFGP on LULCC in the Loess Plateau of China. Thus, we developed a relative contribution conceptual model (RCCM) to separate policy effect from normal background change. In this study, the temporal and spatial variation trend of LULCC since 1990 was investigated first. Additionally, the contributions of the normal background change and the GFGP to different types of land use and land cover were evaluated. Finally, for further understanding the effect of the GFGP on LULCC, the change trajectory of the LULCC after the GFGP implementation was compared with the normal background LULCC.

The study results provide useful information for facilitating sustainable ecological development in the Loess Plateau and theoretically supporting environmental decision-making.

2. Study Area and Data

2.1. Study Area

The Loess Plateau is located in central China, including parts of Ningxia, Shaanxi, Shanxi, Henan, Gansu, Qinghai, and Inner Mongolia, with a total area of 640,000 km^2. It is an arid and semi-arid region with annual precipitation of 200–800 mm [26,30] and a mean annual temperature of 3.6–14.0 °C [38]. The lowest and highest elevations in the Loess Plateau are 94 and 4987 m, respectively (Figure 1). Grassland, cropland, and woodland constitute the most important land use and land cover types in the Loess Plateau [23]. Cropland and woodland are mainly distributed in the southeastern region of the Loess Plateau, while the main land use and land cover types in the northwestern region are grassland and cropland. The Loess Plateau has experienced dramatic LULCC, especially after 2000, when China began investing heavily in the conservation and restoration of natural ecosystems [39–42]. The GFGP is one of the largest ecological restoration programs in the world, which began in Shanxi province, and then was widely implemented in the Loess Plateau around 2000 [22]. The year 2000 was selected as a turning point to explore the impact of policies on LULCC in this study.

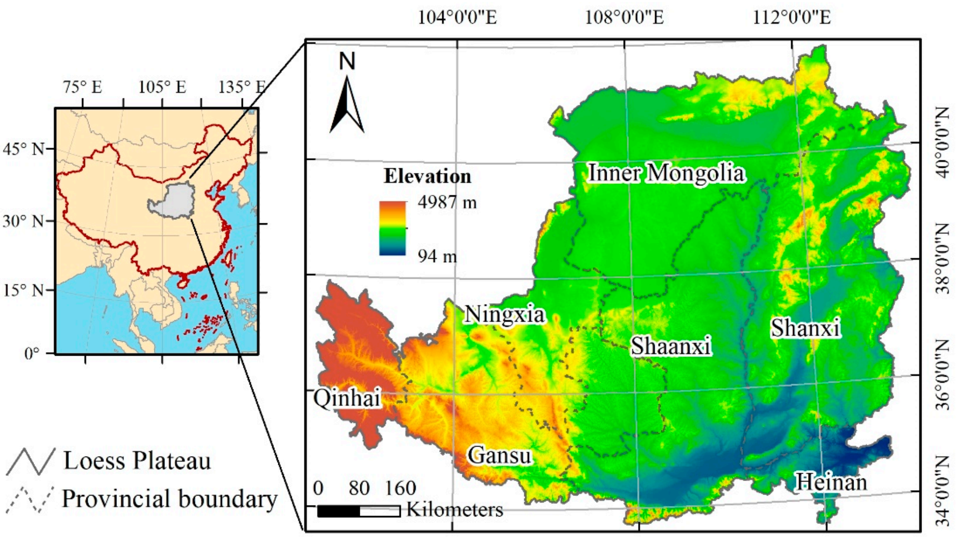

Figure 1. Geographic location of the study area.

2.2. Data Sources

2.2.1. Land Use and Land Cover Data

The land use and land cover data from 1990 to 2010 were provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn), with a spatial resolution of 1 km and a temporal resolution of 5 years [6,43]. These data were produced through visual interpretation of Landsat TM/ETM+ and Landsat OLI after being georeferenced and ortho-rectified [43] and included six land use and land cover types: cropland, woodland, grassland, water body, built-up land, and unused land (including sandy land, Gobi, salina, swampland, bare soil, bare rock, and others) [6,15] (Figure 2). The accuracy assessments for land use classification were addressed in previous studies [44,45], and the accuracy was greater than 90% [6,15,43]. To verify the applicability of these data, 50 random sampling points were selected for each of the six types and compared with the high spatial resolution images in Google Earth (http://www.google.com/earth) with the help of the Environment for Visualizing Images (ENVI 5.2). The overall accuracy of the verification was over 92%, which indicated that it could be used to analyze the LULCC in the Loess Plateau.

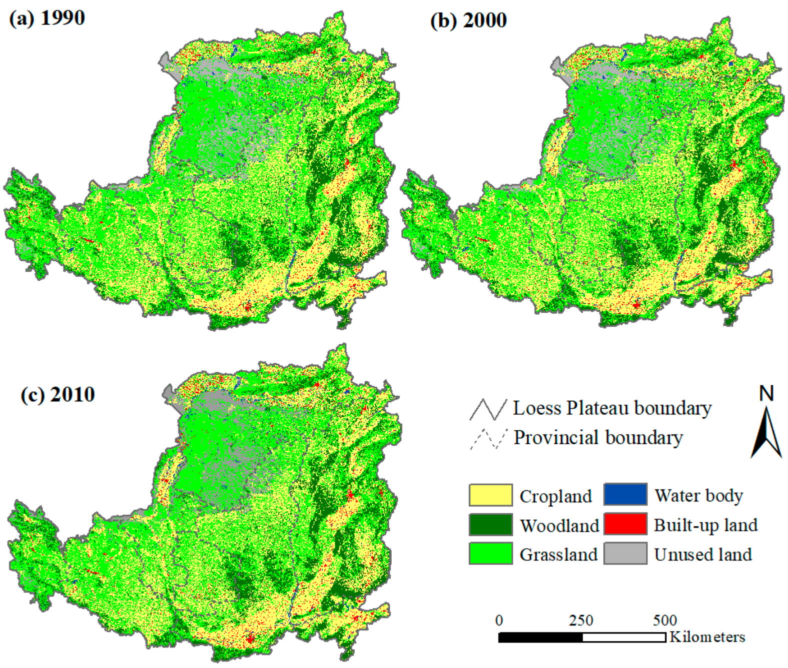

Figure 2. The spatial distribution of land use and land cover in the Loess Plateau in (**a**) 1990, (**b**) 2000, and (**c**) 2010.

2.2.2. Other Data

Other data used in this study include climate factors, topographic factors, soil characteristic factors, and locational factors. The climate raster data were derived from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn) with a spatial resolution of 1 km. The climate raster data were established based on more than 2400 meteorological daily observations in China by sorting, calculation, and spatial interpolation [46]. We extracted the mean annual precipitation and temperature data in the Loess Plateau from 1990 to 2010. The soil characteristic data were obtained from the China Soil Map-Based Harmonized World Soil Database (v1.1) provided by the Cold and Arid Regions Sciences Data Center at Lanzhou (http://westdc.westgis.ac.cn). These include soil organic carbon, percentage of clay, percentage of sand, and percentage of silt [47]. The digital elevation model (DEM) data, with a spatial resolution of 90 m, were obtained from the Geospatial Data Cloud website, Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn). The topographic factors, such as slope and aspect, were calculated based on the elevation. The geographic ancillary data, including administrative boundary, administration center, railways, highways, and rivers, were collected from the National Administration of Surveying, Mapping, and Geoinformation of China (http://ngcc.sbsm.gov.cn). These vector data were transformed to raster data with a spatial resolution of 1 km, and the distances from each pixel to the administration center, railways, highways, and rivers were calculated. To match the spatial reference of the land use and land cover data, all data were geo-registered to the same coordinate system and resampled to a spatial resolution of 1 km.

3. Methods

Following the overall research flowchart (Figure 3), we first analyzed the spatial and temporal characteristics of the LULCC since 1990. Then, a RCCM was used to separate the contribution of supplementary ecological policies in LULCC from the normal background LULCC. Besides, the demand for each land use and land cover type was calculated as an input for the FLUS model. Finally, we simulated the patterns of land use and land cover under the no-policy scenario and the policy scenario respectively. The scenario in which the LULCC is less affected by the policy is considered as the no-policy scenario, and the scenario in which the LULCC is both influenced by the normal background change and the intervention of supplementary policy is defined as the policy scenario. We compared the LULCC after the policy intervention (GFGP) with the normal background LULCC in the Loess Plateau to explore the effect of the GFGP on the trajectory of LULCC.

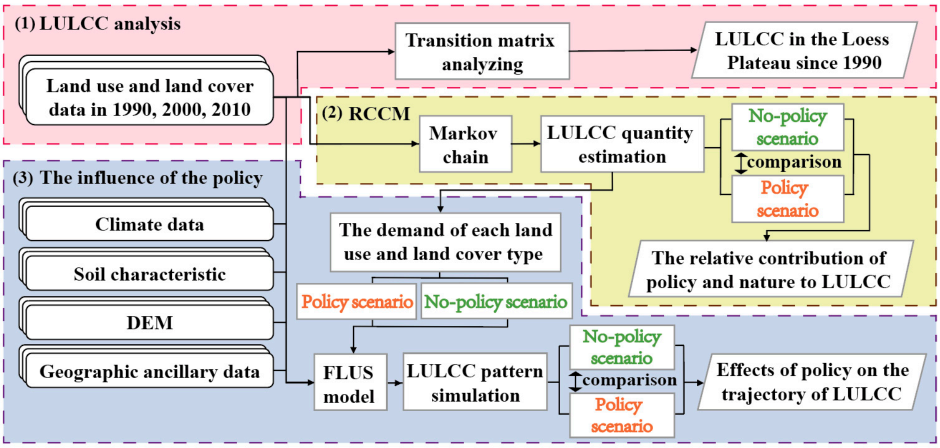

Figure 3. Flowchart of the research methods. LULCC refers to land use and land cover change. RCCM is the relative contribution conceptual model. No-policy scenario: a scenario where the LULCC is less affected by the policy intervention (GFGP). Policy scenario: a scenario where the LULCC is affected by the normal background change and the policy (GFGP).

3.1. Analyzing LULCC in the Loess Plateau Since 1990

To reveal the spatial and temporal characteristics of LULCC, a transition matrix was used to describe the scale of LULCC in two periods, from 1990 to 2000 and from 2000 to 2010. The transition matrix not only expresses the pattern and composition of land use in different periods but also reflects the direction of the transition between different types during the study period [48–50]. In this study, the LULCC transition matrix of the Loess Plateau was established for different periods, and the gains and losses were calculated based on the LULCC transition matrix. A gain in one type of land use and land cover was equivalent to the increase in this type, while a loss in one type of land use and land cover is the amount of this type that was converted to other types during the study period [49,51].

3.2. LULCC Estimation by Markov Chain

3.2.1. Description of the Markov Chain

To obtain theoretical predictions of every single land use type in the future, the Markov chain model was used to simulate the amount of future land use types. The Markov chain model is one of the common methods used to simulate the scale and trend of LULCC [52–54], which reflects the process of land use and land cover undergoing transitions from one status to another [55,56]. It can explain the transition possibilities between different types of land use and land cover and predict the possible quantity and changes of each type in the future according to the transition possibilities [49,57].

The transition possibilities P_{ij} from the i th type to the j th type from time t to time $t+1$ is determined as Equations (1) and (2) [52,54]:

$$P_{ij} = \frac{n_{ij}}{n_i} \tag{1}$$

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1k} \\ P_{21} & P_{22} & \cdots & P_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ P_{k1} & P_{k2} & \cdots & P_{kk} \end{bmatrix} \sum_{j=1}^{k} P_{ij} = 1 \;\; 0 \leq P_{ij} \leq 1 \; (i, j = 1, 2, 3 \ldots, k) \quad (2)$$

where n_i is the total number of pixels of ith type transformed over the transition period, n_{ij} is the number of pixels transformed from ith type to jth types, and k is the number of land use and land cover types in the study area.

The status of land use and land cover at time $t+1$ (LC_{t+1}) relies only on the current status at time t (LC_t) and is independent of any time before time t [53–55]. Equation (3) describes the properties of the Markov chain model:

$$LC_{t+1} = P_{ij} \times LC_t \quad (3)$$

3.2.2. A Relative Contribution Conceptual Model (RCCM)

To quantitatively assess the response of LULCC to ecological restoration policy under the influence of natural background change, a RCCM was established to separate the role of ecological restoration policy in LULCC from that of the normal background change. Normal background change refers to the factors that make land use and land cover itself change without ecological restoration policy, which were considered as the nature factors in this study (Figure 4). It is assumed that under the influence of the natural environment, the land use and land cover changed evenly over time based on the Markov chain, that is, the LULCC of the latter period is the same as that of the previous period, which is represented by the solid green line "AC" in Figure 4a. This scenario in which the LULCC is less affected by the policy is considered as the no-policy scenario. The policy intervention is supplemented at time t_2, leading to the LULCC deviating from the changing trend under the no-policy scenario, which is shown as the solid orange line "BD." This scenario in which the LULCC is both influenced by the normal background change and the intervention of supplementary policy is defined as the policy scenario.

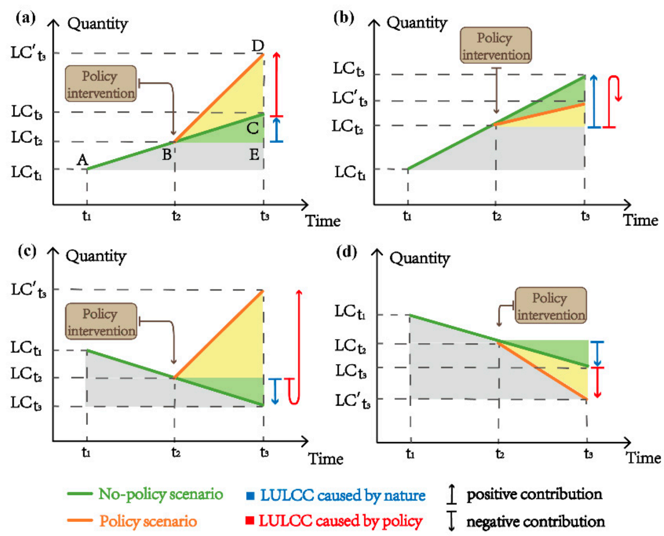

Figure 4. The conceptual diagram used to separate the policy effect on LULCC from the effect of normal background. (**a**) The positive effects of nature and the policy on LULCC. (**b**) The positive effect of nature, while the negative effects of the policy. (**c**) The positive effect of the policy, while the negative effects of nature. (**d**) The negative effects of nature and the policy. LC_t is the quantity of each land use and land cover type at time t under the no-policy scenario, LC'_{t_3} is the quantity of each land use and land cover type at time t_3 under the policy scenario. No-policy scenario: a scenario where the LULCC is less affected by the policy. Policy scenario: a scenario where the LULCC is affected by the nature and the policy.

The difference of LC_{t_3} and LC_{t_2} (i.e., DE) represents the LULCC caused by both natural background and supplementary policies. The deviation of LC_{t_3} from LC_{t_2} (i.e., CE) represents the LULCC caused by natural background change. The deviation of LC'_{t_3} from LC_{t_3} (i.e., DC) represents the LULCC caused by supplementary policies (Figure 4a).

By comparing the quantity of changing areas for each land use and land cover type of the t_2–t_3 period under the two scenarios, the contributions of natural background and supplementary policy to different types of land use and land cover were extracted. For example, the quantity of each type increased in the no-policy scenario (Figure 4a,b), which means the potential effect of the natural background on that type is positive. In this context, if the quantity of this type under the policy scenario is more than the quantity under the no-policy scenario at time t_3, this means that the contribution of the supplementary policy to that type is consistent with that of the natural background, and is a positive contribution (Figure 4a). While, if the quantity of this type under the policy scenario is less than the quantity under the no-policy scenario at time t_3, this means that the negative contribution of the supplementary policy is more than the positive contribution of the natural background. The negative contribution of the policy after offsetting the natural positive effect, still causes the quantity of this type in the policy scenario to be lower than that in the no-policy scenario (Figure 4b). The natural background has a negative effect on the type of land use and land cover shown in Figure 4c,d. Using the absolute value of change quantity of each type as the total contribution, the percentage of the relative contribution of nature and policy to each type was calculated.

3.2.3. Implementation of the RCCM

The GFGP was one of the most important ecological restoration policies and was implemented widely in the Loess Plateau after 2000 [39,40,58]. The RCCM was used in the Loess Plateau to separate the role of the GFGP in LULCC from that of the normal background change. Normal background change refers to the factors that make land use and land cover itself change without the GFGP. The LULCC before 2000 was dominated by the natural background change because the human activities involved in policies had less impact on LULCC at that time [58]. The LULCC after 2000 was jointly affected by normal background change and the GFGP [39]. Thus, we selected the year 2000 as the turning point. It is assumed that historical LULCC trends are maintained according to the Markov chain model. The LULCC in the period of 2010–2020 under the no-policy scenario can be estimated according to the initial transition probability matrix for the period of 1990–2000. The LULCC in the period of 2010–2020 under the policy scenario can be estimated according to the initial transition probability matrix for the period of 2000–2010. By comparing the changing areas of each land use and land cover type in the period of 2010–2020 under the two scenarios, the relative contributions of normal background change and the GFGP to different types of land use and land cover were extracted.

3.3. LULCC Pattern Simulation Based on the FLUS Model

3.3.1. Description of the FLUS Model

The FLUS model is an integrated model that can be used to simulate multi-type future land use scenarios by coupling human activities and natural effects [33–35]. It has been successfully applied in regional and global LULCC studies [29,33–36,59]. The model first uses the artificial neural network (ANN) algorithm to obtain the suitability probability of various types of land use and land cover, and then uses the coupling Markov chain and cell automatic (CA) model to improve the suitability of the model.

The total probability of land use and land cover type on each pixel depends on the suitability probability of the ANN, the neighborhood effect, the self-adaptive inertia coefficient, the conversion cost, and the competition among the different types. Use Equation (4) to estimate the total probability that each pixel will be occupied by a specific land use and land cover type. The suitability probability (*sp*) represents the probability-of-occurrence for the *k* land use and land cover type on a pixel. Considering the neighborhood effect (Ω) in the CA model, the neighborhood effect value of type k on a pixel at iteration time is calculated. We selected the neighborhood size of 5 × 5. The neighborhood weight value for each type is determined based on the expert knowledge and a series of model tests, which was obtained from the study of Liu et al. [33]. The self-adaptive inertia coefficient (inertia) for each type of LULCC is defined to automatically adjust the current type inheritance on each pixel based on the difference between the current allocation of each type and the final demand. The conversion cost is a brief summary of the difficulty for a pixel converting from one land use and land cover type to another, and the conversion cost value of each land use and land cover type pair was referenced by the study of Liu et al. [33]. The self-adaptive inertia coefficient and the mechanism of competition among the different types were introduced in the CA model to deal with the complexity and uncertainty in the LULCC under the influence of the natural effects and human activities [33].

$$TP_{p,k}^{t} = sp_{p,k} \times \Omega_{p,k}^{t} \times Inertia_{k}^{t} \times (1 - sc_{c \to k}) \tag{4}$$

where $TP_{p,k}^{t}$ is the total probability of p pixel to covert from the original type to the target type k at iteration time t; $sp_{p,k}$ is the suitability probability of type k occurring on p pixel. $\Omega_{p,k}^{t}$ is the neighborhood effect of type k on p pixel at iteration time t; $Inertia_{k}^{t}$ is the self-adaptive inertia coefficient of type k at iteration time t; and $sc_{c \to k}$ is the conversion cost from the original land type c to the target type k.

Before simulating the pattern of land use and land cover, it is necessary to project the demands for each land use and land cover type as inputs of the FLUS model [33]. Thus, the Markov chain model was applied to estimate the amount of each type. Then, considering the influence of human activities and natural ecological factors on LULCC, 14 biophysical and socioeconomic variables, including climate factors, topographic factors, soil characteristic factors, and locational factors, were selected as the driving factors of land use and land cover simulation to estimate the suitability probability of each type in each pixel [32,60]. The total probability of land use and land cover type were calculated by combining the suitability probability, the neighborhood effect, the self-adaptive inertia coefficient, the conversion cost, and the competition among the different types. All of the above processes can be run using GeoSOS-FLUS software (http://www.geosimulation.cn/FLUS.html).

3.3.2. Validation of the FLUS Model

To verify whether the FLUS model can accurately reflect the spatial distribution of land use and land cover types under the influence of the natural environment and the GFGP, we designed two verification experiments in the Loess Plateau. The first experiment was to verify the validity of the FLUS model simulating the LULCC under the no-policy scenario. Based on the land use and land cover data of 1990 and the actual amount of each type of demand for 2000, the spatial distribution of land use and land cover in 2000 was simulated using the FLUS model. Compared with the actual land use and land cover status in 2000, the feasibility of the FLUS model simulating the land use and land cover status under a no-policy scenario was evaluated. The second experiment was to verify the validity of the FLUS model simulation of the LULCC under the policy scenario. Based on the land use and land cover data of 2005 and the actual amount of each type of demand for 2010, the spatial distribution of land use and land cover in 2010 was simulated, and compared with the actual status in 2010 to evaluate the feasibility of the FLUS model under the policy scenario was evaluated.

Under the two scenarios, the kappa coefficient and overall accuracy were both calculated for verification. Under the no-policy scenario, the RMSE of the suitability probability of land use and land cover in 1990 obtained from ANN was 0.24. The kappa coefficient of the actual and simulated status in 2000 was 0.93, and the overall accuracy was 95.14%. Under the policy scenario, the RMSE of the suitability probability of land use and land cover in 2000 obtained from ANN was 0.22. The kappa coefficient of the actual and simulated status in 2010 was 0.96, and the overall accuracy was 97.13%. Additionally, we randomly selected 1000 points for verification of the results in 2000 and 2010 within the Loess Plateau. The comparison reported 952 consistent points in 2000 and 969 consistent points in

2010. Therefore, the simulation results are consistent with the actual situation, and the FLUS model is effective for simulating LULCC in both no-policy and policy scenarios.

4. Results

4.1. The Temporal and Spatial Variation Trend of LULCC Since 1990

Considering that the GFGP was widely implemented since 2000 in the Loess Plateau and had an important impact on the land cover [39], we discussed LULCC in the Loess Plateau in the period of 1990–2000 and 2000–2010.

The LULCC processes and patterns are presented with the transition matrix (Tables 1 and 2). The spatial characteristics of LULCC are presented in Figure 5. From 1990 to 2000, the total area of LULCC was 13,330 km^2 in the Loess Plateau. There were three main LULCC processes: decreased grassland, cropland expansion, and grassland expansion. Grassland degradation and expansion coexisted during 1990–2000 because the grassland was widely distributed in the Loess Plateau and was mixed with other types. A total of 3777 km^2 of cropland was converted from grassland and further caused the expansion of cropland accompanied by the decrease in grassland. In addition, grassland expansion occurred because of the land transformations from unused land; grassland expansion most obviously occurred in the northern part of Shaanxi province.

Table 1. Transition matrix of LULCC in the Loess Plateau between 1990 and 2000 (Unit: km^2).

	Cropland	Woodland	Grassland	Water Body	Built-Up Land	Unused Land	Losses
Cropland	211,003	225	1159	183	865	314	2746
Woodland	220	94,427	816	17	34	52	1139
Grassland	3777	602	264,463	220	145	1403	6147
Water body	419	17	125	8686	8	81	650
Built-up land	2	2	1	0	14,807	0	5
Unused land	434	122	1968	100	19	41,564	2643
Gains	4852	968	4069	520	1071	1850	

Table 2. Transition matrix of LULCC in the Loess Plateau between 2000 and 2010 (Unit: km^2).

	Cropland	Woodland	Grassland	Water Body	Built-Up Land	Unused Land	Losses
Cropland	209,440	1640	2617	479	1339	340	6415
Woodland	97	94,810	280	36	130	42	585
Grassland	1159	1563	263,754	235	371	1450	4778
Water body	313	31	164	8414	33	251	792
Built-up land	17	14	40	11	15,789	7	89
Unused land	212	100	932	138	71	41,961	1453
Gains	1798	3348	4033	899	1944	2090	

From 2000 to 2010, the total area of LULCC was 14,112 km^2 in the Loess Plateau. There were four main LULCC processes: decreased cropland, decreased grassland, grassland expansion, and forest expansion. Cropland was reduced by 6415 km^2, and it was mainly converted into grassland (2617 km^2), woodland (1640 km^2), and built-up land (1339 km^2), which corresponded to the GFGP and the progress of urbanization. The conversion of cropland into built-up land was mainly distributed around cities. Compared with the period from 1990 to 2000, the amount and area of built-up sprawl both increased. Grassland degradation and grassland expansion continued to coexist in this period. Grassland degradation was accompanied by afforestation and reforestation, which were concentrated in the eastern part of Gansu and in the border areas of Shaanxi and Inner Mongolia. These areas were barren hills and wastelands, with an average elevation of approximately 1700 m, and they were covered with sparse grassland before 2000. The GFGP was implemented and forest planting was encouraged by the government starting 2000; these efforts transformed some grassland to woodland and expanded the area of woodland. In this period, 2617 km^2 of cropland was changed into grassland. At the same time, 1640 km^2 of woodland was transformed from cropland, and 1563 km^2 was transformed from grassland.

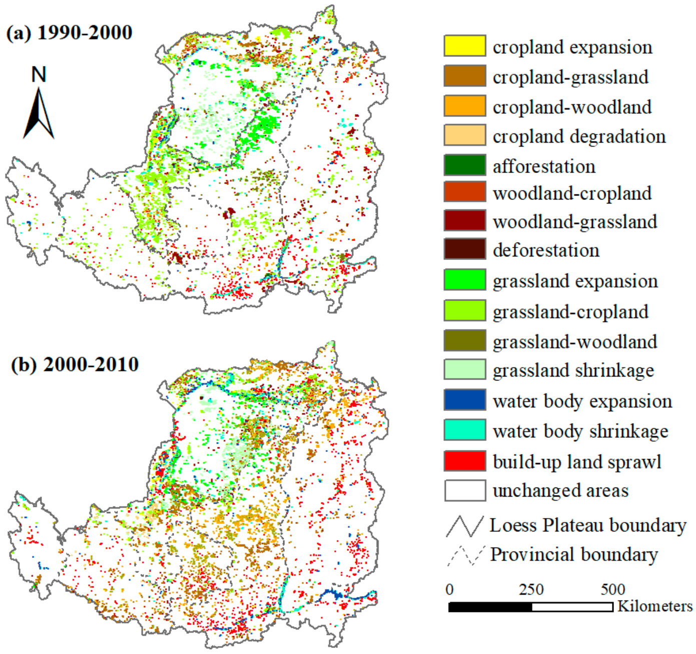

Figure 5. The spatial distribution of LULCC in two periods: (**a**) from 1990 to 2000, (**b**) from 2000 to 2010.

Comparing the temporal and spatial characters of LULCC in the periods of 1990 to 2000 and 2000 to 2010, the original LULCC trend changed with the implementation of GFGP. The results showed that cropland originally increased in the previous decade (1990–2000), and cropland expansion transformed into cropland contraction after some ecological management practices. The shrinkage in woodland was transformed into increased woodland, and built-up land sprawled more rapidly than before, which was related to the acceleration of urbanization and the GFGP in the decade after 2000.

4.2. The Contribution of Nature and Policy to LULCC

To quantitatively assess the impact of the GFGP implemented since 2000 on the status of land use and land cover in 2020, we used the RCCM to calculate the relative contribution of nature and the GFGP to them. The theoretical status of the land cover of 2020 under the no-policy and policy scenarios was based on the land cover data in 1990 and 2000 and the land cover data in 2000 and 2010, respectively. By 2020, the potential covers of various land use and land cover types under the no-policy and policy scenarios are shown in Table 3. Under the no-policy scenario, the potential coverage of grassland cropland and woodland in 2020 was 264,438 km^2, 219,859 km^2, and 95,045 km^2, respectively. With the effect of the GFGP, the potential coverage of grassland cropland and woodland in 2020 was 267,028 km^2, 206,767 km^2, and 100,868 km^2. Compared with normal background conditions, grassland increased by 2590 km^2. Cropland shrank by 13,092 km^2, woodland expanded by 5823 km^2. In summary, there were differences in the status of land use and land cover under the two scenarios in 2020. The most prominent changes included the visible reduction of cropland, the expansion of woodland and grassland, and the sprawl of built-up land.

Table 3. The areas of each type of land cover in 2020 under two scenarios (Unit: km^2).

	Cropland	Woodland	Grassland	Water Body	Built-Up Land	Unused Land
Policy scenario	206,767	100,868	267,028	9404	19,553	44,660
No-policy scenario	219,859	95,045	264,438	8968	18,029	41,941

The RCCM was used to demonstrate the contribution of the normal background change and the GFGP to each type of land use and land cover (Figure 6). We calculated the percentage of the relative contribution of nature (normal background change) and policy (GFGP) to each type by the sum of the absolute values of the amount of changes of each type as the total contribution. The GFGP had a negative impact on cropland, reversing the expansion of cropland under natural conditions. The implementation of GFGP shrank the area of the originally expanded cropland, contributing about 81.02% with a negative role. The positive contribution of nature to cropland was approximately 18.98% (Figure 6a). The GFGP had a positive effect on woodland, which was far greater than the contribution from nature. The GFGP contributed approximately 94.63% to the change of woodland area with positive effect, and the nature contributed approximately 5.37% with negative effect (Figure 6b). Although the policy cannot completely reverse the degradation of grassland, its positive effect on grassland alleviated the seriousness of the situation. About 61.25% of the changes in grassland area were from the contribution of nature, which played a negative role. About 38.75% were from the policy contribution, which played a positive role (Figure 6c). Overall, the GFGP contributed about 72.37% to LULCC, and normal background changes contributed about 27.63% to LULCC.

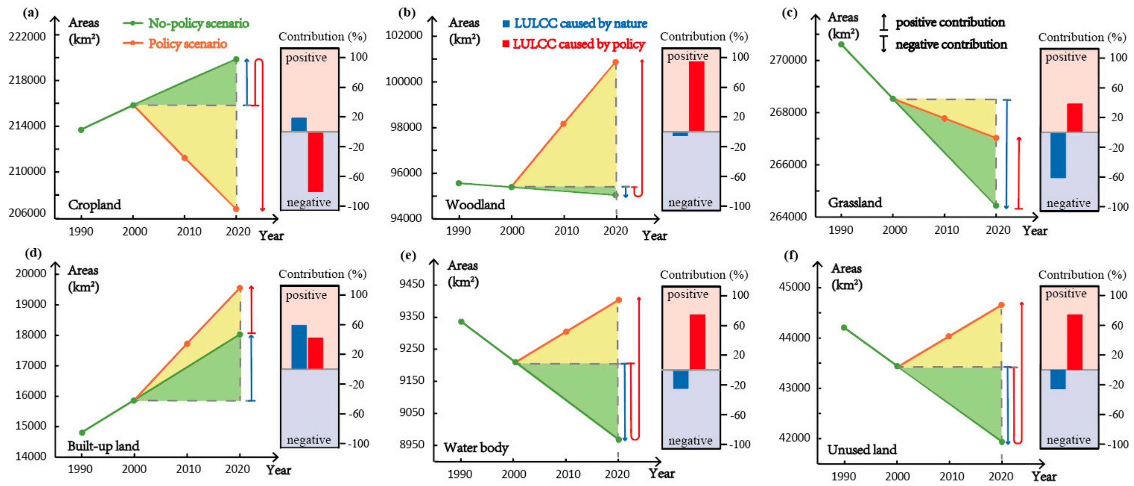

Figure 6. Trends of each type of land use and land cover under the no-policy and policy scenarios from 1990 to 2020, and the percentage of the relative contribution of nature and policy to the quantitative changes of each type. (**a**–**f**) Represent changes in the area of cropland, woodland, grassland, built-up land, water body, and unused land, respectively.

4.3. The Difference in LULCC from 2000 to 2020 in Two Scenarios

Considering the interaction of various types of land use and land cover, we compared the net gains and losses of various types from 2000 to 2020 under the two scenarios, so as to better understand the causes for the various area changes and further explore the role of the GFGP in LULCC. Prior to this, two verification experiments were designed to verify whether the FLUS model can accurately reflect the spatial distribution of land use and land cover types before and after the implementation of GFGP. The results showed the FLUS model was effective for simulating LULCC in both no-policy and policy scenarios. The theoretical contributions of every type received from other types under the two scenarios are displayed in Figure 7. Under the no-policy scenario, cropland experienced an expansion trend during 2000–2020 because of the positive contribution of woodland, grassland, water body, and unused land, with grassland contributing the most (Figure 7a). In addition, built-up land had a negative effect on cropland. However, under the policy scenario, the area of cropland was decreased because of the negative contribution of every other type. Cropland was most often converted to woodland, followed by built-up land and grassland, with a total negative contribution of over 93.4% (Figure 7b).

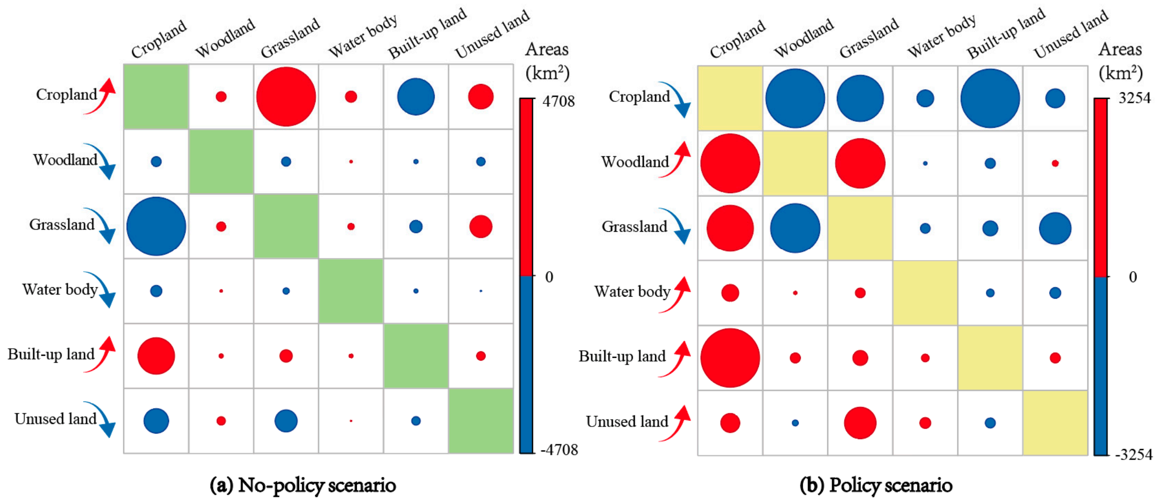

Figure 7. The contribution of every type theoretically received from other types from 2000 to 2020. (**a**) No-policy scenario, (**b**) policy scenario. Red indicates a positive contribution from other types, and blue indicates a negative contribution from other types. The upward red arrow indicates the increased trends of this type, and the downward blue arrow indicates the decreased trends of this type from 2000 to 2020.

Woodland under the no-policy scenario had a decreasing trend, and woodland became occupied by other land use and land cover types, especially cropland and grassland (Figure 7a). There was a dramatic increase in the area of woodland under the policy scenario (Figure 7b), with cropland and grassland contributing 59.4 and 41.8%, respectively, which indicated that ecological management practices such as afforestation, reforestation, and returning cropland to forest positively affected woodland expansion. In addition, urbanization was not conducive to the expansion of woodland, with the negative contribution of built-up land to woodland.

There was a decreasing trend in the area of grassland under the no-policy scenario, but the GFGP intervened in the otherwise heavily degraded grasslands. The decrease in grassland in the no-policy scenario was attributed to the occupation of grassland by cropland and built-up land (Figure 7a). The policy effect reversed the negative contribution of cropland to grassland, with a large amount of cropland transforming into grassland, but other land use and land cover types still had negative effects on grassland (Figure 7b). A large area of grassland transformed into woodland, and this conversion was related to government incentives for afforestation and other ecological management practices since 2000.

Comparing the contributions of each land use and land cover type from other types under the two scenarios, we found that cropland is critical as a rebalanced leverage for regulating all kinds of land use and land cover types. By controlling the amount of cropland, the GFGP regulates the pattern of land use and further promotes the sustainable development of human-terrestrial relations.

5. Discussion

In this study, a RCCM was used to separate the relative contribution of supplementary ecological restoration policy to LULCC from the normal background LULCC and was applied in the Loess Plateau. Considering that the impact of the normal background change on LULCC is perpetual and underlying, the RCCM suggests that the LULCC after policy implementation is affected by the normal background changes and the supplementary policy. One of the keys to applying the RCCM is to determine when to implement ecological restoration policies. The GFGP is the dominant policy of regional ecological restoration, which was implemented widely in the Loess Plateau around 2000 [22]. Thus, the year 2000 was selected as a turning point to explore the impact of the GFGP on LULCC. In addition, validation experiments on land use and land cover simulations under the policy and no-policy scenarios showed that the FLUS model with Markov model performs well in simulating LULCC in both scenarios and can be used to assess the policy's contribution to LULCC. The RCCM is not subject to regional and policy constraints, and is also suitable for other policies such as urbanization in other regions.

Comparing the differences of LULCC in the Loess Plateau between the period of 1990–2000 and the period of 2000–2010, it can be seen that the trajectories of LULCC were different in these two periods. Grassland was the main land cover type, distributed in the Loess Plateau, followed by cropland and woodland. Our statistical results indicated that these three types accounted for more than 85% of the total area, which was consistent with other studies [7,61]. In addition, the trajectory of LULCC in the decade before and after 2000 was different. Cropland area expanded broadly before 2000 and decreased apparently after 2000, and the GFGP was considered one of the dominant reasons for the reduction in cropland [15,61]. Additionally, a large amount of capital, experts, and technologies has been attracted to the central and western regions driven by national development strategies since 2000 [15]. Consequently, urban areas in the central and western regions expanded more rapidly than they did before 2000, which was consistent with our findings.

The results implied that the ecological restoration policy in China has had a great impact on LULCC. During the past three decades, besides the GFGP, other five national key ecological restoration projects have been launched across China to protect the environment and restore the degraded ecosystems [22,62], including the Three North Shelterbelt System Construction, Yangtze River and Zhujiang River Shelter Forest Projects, Natural Forest Protection Program, Beijing–Tianjin Sand Source Control Project, and Returning Grazing Land to Grassland Project, which have a considerable impact on surface cover [63], especially for cropland, woodland, and grassland. Forest cover increased significantly to approximately 1.6% of China's territory between 2000 and 2010 because of the effectiveness of the Natural Forest Protection Program [12]. Most of the increased forest areas were concentrated in the project zones, which was mainly due to a series of management practices within the framework of these ecological restoration projects, such as afforestation, reforestation, forest enclosure and tending, transforming cropland to forests, and reducing the timber harvest [62,64]. Additionally, forest cover increased more on steep slopes than in flat terrain, reflecting the intention to mitigate soil erosion in mountainous environments [64,65].

Apart from the forests, the function of grassland ecosystems was improved under the implementation of large-scale restoration projects, such as the GFGP and Returning Grazing Land to Grassland Project [63,66,67]. Since the implementation of these projects, grazing exclusion [68] and fencing in grasslands [69] were the effective ways to rehabilitate vegetation and sequestrate carbon in degraded grasslands. The area of Inner Mongolia grassland had a net increase of 77,993 km^2 during 2001–2009 [70]. Compared with the period of 2000 to 2007, the mean normalized difference vegetation index (NDVI) increased by 14.16% in the period from 2009 to 2016 in grassland of the Loess Plateau [37]. Through a meta-analysis, the amount of carbon stored in aboveground biomass increased by 84.7% under grazing exclusion measures [68]. These vegetation restoration projects based on forest and grass were also one of the main reasons for the decline in cropland [15,30,61]. On average, the occupancy of cropland for restoration projects accounted for 34.54% of the cropland decrease since 2000 [15]. Given that the precipitation was limited and its large inter-annual variability was not conducive to cereal cropping in arid and semi-arid regions, farmers were more willing to shift from vulnerable grain cultivation to more resilient grazing [64].

Although the relative contributions of normal background and the GFGP to LULCC were quantitatively evaluated, there are still some limitations in this study. The authenticity of the original data is the key to establishing the model. The spatial resolution of the original land use and land cover datasets is 1 km, implying that there may be various types mixed in a single pixel [15]. LULCC is affected by both natural environment and human activities. The method of this study combining the FLUS model with the Markov chain can effectively assess the effect of normal background and the GFGP on LULCC to a certain extent. However, the assumption that the GFGP was the only dominated policy after 2000 was insufficient. Some intermediate variables generated by the GFGP, such as runoff changes, may affect LULCC near rivers, which were not considered in this study. Besides that, the assumption of the RCCM was simplified, which may introduce some uncertainties. Despite these limitations, it is meaningful to use effective methods to separate the effect of human activities from normal background changes. If we know some new policies that will be implemented in the future and consider them in the model, the result of the predictions will be more accurate, which is important for assessing the effectiveness of policy implementation.

6. Conclusions

The purpose of this study is to quantitatively assess the relative contribution of the GFGP to LULCC in the Loess Plateau under the normal background change. Thus, a RCCM was used to separate policy effect from potential nature, and the status of LULCC under no-policy and policy scenarios was simulated by the FLUS model and Markov chain. Our results demonstrated that the original trend of LULCC was changed with the implementation of GFGP since 2000. Cropland expansion transformed into cropland shrinkage, woodland shrinkage turned to woodland expansion. From the result of quantitatively assessing and attributing LULCC in the Loess Plateau, the GFGP since 2000 reversed the expansion of cropland under natural conditions, and its negative contribution to cropland change was accounting to approximately 81.02%. The GFGP contributed approximately 94.63% to the change of woodland area with positive effect, while the normal background contributed approximately 5.37% with a negative effect. As for the contribution of grassland change, about 61.25% of contributions were from nature with a negative role, and about 38.75% of contributions came from the GFGP with a positive role. Overall, the GFGP contributed about 72.37% to LULCC and normal background changes contributed about 27.63% to LULCC.

Comparing the contributions of each type of land use and land cover from other types under the two scenarios, we found that cropland is critical as a leverage for the regulation of all kinds of land use and land cover types. Our findings implied that ecological restoration policies had a great impact on various types of land use and land cover, especially for cropland. Ecological restoration policies regulate the land use pattern by controlling the amount of cropland and promote regional sustainable development. The study results provide useful information for facilitating sustainable ecological development in the Loess Plateau and theoretically supporting environmental decision-making.

Author Contributions: Conceptualization, X.D. and X.Z.; methodology, X.D.; formal analysis, X.D., X.Z., and S.L.; writing—original draft preparation, X.D.; Writing—review & editing, X.D., X.Z., S.L., J.Z., P.X. and D.W. Funding acquisition, X.Z. and S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the National Key Research and Development Program of China (Nos. 2016YFA0600103 and 2016YFB0501404).

Acknowledgments: We thank Yifeng Peng, Haoyu Wang, and Qian Zhou for helpful comments that improved this manuscript. We would like to thank the organizations that shared their datasets and software for use in this study. We greatly appreciate the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) for providing the land use and land cover data, climate raster data. We also appreciate the Cold and Arid Regions Sciences Data Center for the soil database, the National Administration of Surveying, Mapping, and Geoinformation of China for the geographic ancillary data, and the Computer Network Information Center, Chinese Academy of Sciences for the digital elevation model data respectively. We appreciate for the data support from "National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn)\T1\textquotedblright.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Gardner, A.S.; Moholdt, G.; Wouters, B.; Wolken, G.J.; Burgess, D.O.; Sharp, M.J.; Cogley, J.G.; Braun, C.; Labine, C. Sharply increased mass loss from glaciers and ice caps in the Canadian Arctic Archipelago. *Nature* **2011**, *473*, 357–360. [CrossRef]
2. Khanna, J.; Medvigy, D.; Fueglistaler, S.; Walko, R. Regional dry-season climate changes due to three decades of Amazonian deforestation. *Nat. Clim. Chang.* **2017**, *7*, 200–204. [CrossRef]

3. Grimm, N.B.; Faeth, S.H.; Golubiewski, N.E.; Redman, C.L.; Wu, J.; Bai, X.; Briggs, J.M. Global Change and the Ecology of Cities. *Science* **2008**, *319*, 756–760. [CrossRef] [PubMed]
4. Chen, C.; Park, T.; Wang, X.; Piao, S.; Xu, B.; Chaturvedi, R.K.; Fuchs, R.; Brovkin, V.; Ciais, P.; Fensholt, R.; et al. China and India lead in greening of the world through land-use management. *Nat. Sustain.* **2019**, *2*, 122–129. [CrossRef] [PubMed]
5. Zhu, Z.; Piao, S.; Myneni, R.B.; Huang, M.; Zeng, Z.; Canadell, J.G.; Ciais, P.; Sitch, S.; Friedlingstein, P.; Arneth, A.; et al. Greening of the Earth and its drivers. *Nat. Clim. Chang.* **2016**, *6*, 791–795. [CrossRef]
6. Liu, J.; Zhang, Z.; Xu, X.; Kuang, W.; Zhou, W.; Zhang, S.; Li, R.; Yan, C.; Yu, D.; Wu, S.; et al. Spatial patterns and driving forces of land use change in China during the early 21st century. *J. Geogr. Sci.* **2010**, *20*, 483–494. [CrossRef]
7. Zhao, H.; He, H.; Wang, J.; Bai, C.; Zhang, C. Vegetation Restoration and Its Environmental Effects on the Loess Plateau. *Sustainability* **2018**, *10*, 4676. [CrossRef]
8. Wang, H.; Ni, J.; Prentice, I.C. Sensitivity of potential natural vegetation in China to projected changes in temperature, precipitation and atmospheric CO_2. *Reg. Environ. Chang.* **2011**, *11*, 715–727. [CrossRef]
9. Ni, J. Impacts of climate change on Chinese ecosystems: Key vulnerable regions and potential thresholds. *Reg. Environ. Chang.* **2011**, *11*, 49–64. [CrossRef]
10. Raper, S.C.; Braithwaite, R.J. Low sea level rise projections from mountain glaciers and icecaps under global warming. *Nature* **2006**, *439*, 311–313. [CrossRef]
11. Kirwan, M.L.; Guntenspergen, G.R.; D'Alpaos, A.; Morris, J.T.; Mudd, S.M.; Temmerman, S. Limits on the adaptability of coastal marshes to rising sea level. *Geophys. Res. Lett.* **2010**, 37. [CrossRef]
12. Viña, A.; McConnell, W.J.; Yang, H.; Xu, Z.; Liu, J. Effects of conservation policy on China's forest recovery. *Sci. Adv.* **2016**, *2*, e1500965. [CrossRef] [PubMed]
13. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global Consequences of Land Use. *Science* **2005**, *309*, 570–574. [CrossRef] [PubMed]
14. Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland, T.R.; et al. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* **2013**, *342*, 850–853. [CrossRef]
15. Liu, J.; Kuang, W.; Zhang, Z.; Xu, X.; Qin, Y.; Ning, J.; Zhou, W.; Zhang, S.; Li, R.; Yan, C.; et al. Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. *J. Geogr. Sci.* **2014**, *24*, 195–210. [CrossRef]
16. Brown, M.G.; Quinn, J.E. Zoning does not improve the availability of ecosystem services in urban watersheds. A case study from Upstate South Carolina, USA. *Ecosyst. Serv.* **2018**, *34*, 254–265. [CrossRef]
17. Johnson, K.A.; Dalzell, B.J.; Donahue, M.; Gourevitch, J.; Johnson, D.L.; Karlovits, G.S.; Keeler, B.; Smith, J.T. Conservation Reserve Program (CRP) lands provide ecosystem service benefits that exceed land rental payment costs. *Ecosyst. Serv.* **2016**, *18*, 175–185. [CrossRef]
18. Jobe, A.; Kalra, A.; Ibendahl, E. Conservation Reserve Program effects on floodplain land cover management. *J. Environ. Manag.* **2018**, *214*, 305–314. [CrossRef]
19. Crouzeilles, R.; Curran, M.; Ferreira, M.S.; Lindenmayer, D.B.; Grelle, C.E.; Rey Benayas, J.M. A global meta-analysis on the ecological drivers of forest restoration success. *Nat. Commun.* **2016**, *7*, 11666. [CrossRef]
20. Lefebvre, M.; Espinosa, M.; Gomez y Paloma, S.; Paracchini, M.L.; Piorr, A.; Zasada, I. Agricultural landscapes as multi-scale public good and the role of the Common Agricultural Policy. *J. Environ. Plan. Manag.* **2015**, *58*, 2088–2112. [CrossRef]
21. Erjavec, E.; Lovec, M. Research of European Union's Common Agricultural Policy: Disciplinary boundaries and beyond. *Eur. Rev. Agric. Econ.* **2017**, *44*, 732–754. [CrossRef]
22. Liu, J.; Li, S.; Ouyang, Z.; Tam, C.; Chen, X. Ecological and socioeconomic effects of China's policies for ecosystem services. *Proc. Natl. Acad. Sci. USA* **2008**, *105*, 9477. [CrossRef] [PubMed]
23. Li, G.; Sun, S.; Han, J.; Yan, J.; Liu, W.; Wei, Y.; Lu, N.; Sun, Y. Impacts of Chinese Grain for Green program and climate change on vegetation in the Loess Plateau during 1982–2015. *Sci. Total Environ.* **2019**, *660*, 177–187. [CrossRef] [PubMed]
24. Piao, S.; Yin, G.; Tan, J.; Cheng, L.; Huang, M.; Li, Y.; Liu, R.; Mao, J.; Myneni, R.B.; Peng, S.; et al. Detection and attribution of vegetation greening trend in China over the last 30 years. *Glob. Chang. Biol.* **2015**, *21*, 1601–1609. [CrossRef] [PubMed]

25. Crouzeilles, R.; Ferreira, M.S.; Chazdon, R.L.; Lindenmayer, D.B.; Sansevero, J.B.B.; Monteiro, L.; Iribarrem, A.; Latawiec, A.E.; Strassburg, B.B.N. Ecological restoration success is higher for natural regeneration than for active restoration in tropical forests. *Sci. Adv.* **2017**, *3*, e1701345. [CrossRef]
26. Feng, X.; Fu, B.; Lu, N.; Zeng, Y.; Wu, B. How ecological restoration alters ecosystem services: An analysis of carbon sequestration in China's Loess Plateau. *Sci. Rep.* **2013**, *3*, 2846. [CrossRef]
27. Feng, X.; Fu, B.; Piao, S.; Wang, S.; Ciais, P.; Zeng, Z.; Lü, Y.; Zeng, Y.; Li, Y.; Jiang, X.; et al. Revegetation in China's Loess Plateau is approaching sustainable water resource limits. *Nat. Clim. Chang.* **2016**, *6*, 1019–1022. [CrossRef]
28. Wu, Z.; Wu, J.; Liu, J.; He, B.; Lei, T.; Wang, Q. Increasing terrestrial vegetation activity of ecological restoration program in the Beijing–Tianjin Sand Source Region of China. *Ecol. Eng.* **2013**, *52*, 37–50. [CrossRef]
29. Fu, Q.; Hou, Y.; Wang, B.; Bi, X.; Li, B.; Zhang, X. Scenario analysis of ecosystem service changes and interactions in a mountain-oasis-desert system: A case study in Altay Prefecture, China. *Sci. Rep.* **2018**, *8*, 12939. [CrossRef]
30. Li, J.; Peng, S.; Li, Z. Detecting and attributing vegetation changes on China's Loess Plateau. *Agric. For. Meteorol.* **2017**, *247*, 260–270. [CrossRef]
31. He, C.; Li, J.; Zhang, X.; Liu, Z.; Zhang, D. Will rapid urban expansion in the drylands of northern China continue: A scenario analysis based on the Land Use Scenario Dynamics-urban model and the Shared Socioeconomic Pathways. *J. Clean. Prod.* **2017**, *165*, 57–69. [CrossRef]
32. Liu, Z.; Verburg, P.H.; Wu, J.; He, C. Understanding Land System Change Through Scenario-Based Simulations: A Case Study from the Drylands in Northern China. *Environ. Manag.* **2017**, *59*, 440–454. [CrossRef]
33. Liu, X.; Liang, X.; Li, X.; Xu, X.; Ou, J.; Chen, Y.; Li, S.; Wang, S.; Pei, F. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landsc. Urban Plan.* **2017**, *168*, 94–116. [CrossRef]
34. Li, X.; Chen, G.; Liu, X.; Liang, X.; Wang, S.; Chen, Y.; Pei, F.; Xu, X. A New Global Land-Use and Land-Cover Change Product at a 1-km Resolution for 2010 to 2100 Based on Human—Environment Interactions. *Ann. Am. Assoc. Geogr.* **2017**, *107*, 1040–1059. [CrossRef]
35. Liu, X.; Wang, S.; Wu, P.; Feng, K.; Hubacek, K.; Li, X.; Sun, L. Impacts of Urban Expansion on Terrestrial Carbon Storage in China. *Environ. Sci. Technol.* **2019**, *53*, 6834–6844. [CrossRef] [PubMed]
36. Liang, X.; Liu, X.; Li, X.; Chen, Y.; Tian, H.; Yao, Y. Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landsc. Urban Plan.* **2018**, *177*, 47–63. [CrossRef]
37. Zheng, K.; Wei, J.; Pei, J.; Cheng, H.; Zhang, X.; Huang, F.; Li, F.; Ye, J. Impacts of climate change and human activities on grassland vegetation variation in the Chinese Loess Plateau. *Sci. Total Environ.* **2019**, *660*, 236–244. [CrossRef] [PubMed]
38. Li, Z.; Zheng, F.; Liu, W.; Flanagan, D.C. Spatial distribution and temporal trends of extreme temperature and precipitation events on the Loess Plateau of China during 1961–2007. *Quat. Int.* **2010**, *226*, 92–100. [CrossRef]
39. Ouyang, Z.; Zheng, H.; Xiao, Y.; Polasky, S.; Liu, J.; Xu, W.; Wang, Q.; Zhang, L.; Xiao, Y.; Rao, E.; et al. Improvements in ecosystem services from investments in natural capital. *Science* **2016**, *352*, 1455. [CrossRef]
40. Fu, B.; Wang, S.; Liu, Y.; Liu, J.; Liang, W.; Miao, C. Hydrogeomorphic Ecosystem Responses to Natural and Anthropogenic Changes in the Loess Plateau of China. *Annu. Rev. Earth Planet. Sci.* **2017**, *45*, 223–243. [CrossRef]
41. Lü, Y.; Fu, B.; Feng, X.; Zeng, Y.; Liu, Y.; Chang, R.; Sun, G.; Wu, B. A Policy-Driven Large Scale Ecological Restoration: Quantifying Ecosystem Services Changes in the Loess Plateau of China. *PLoS ONE* **2012**, *7*, e31782. [CrossRef] [PubMed]
42. Liu, L.; Tang, H.; Caccetta, P.; Lehmann, E.A.; Hu, Y.; Wu, X. Mapping afforestation and deforestation from 1974 to 2012 using Landsat time-series stacks in Yulin District, a key region of the Three-North Shelter region, China. *Environ. Monit. Assess.* **2013**, *185*, 9949–9965. [CrossRef] [PubMed]
43. Liu, J.; Liu, M.; Tian, H.; Zhuang, D.; Zhang, Z.; Zhang, W.; Tang, X.; Deng, X. Spatial and temporal patterns of China's cropland during 1990–2000: An analysis based on Landsat TM data. *Remote Sens. Environ.* **2005**, *98*, 442–456. [CrossRef]
44. Kuang, W.; Liu, J.; Dong, J.; Chi, W.; Zhang, C. The rapid and massive urban and industrial land expansions in China between 1990 and 2010: A CLUD-based analysis of their trajectories, patterns, and drivers. *Landsc. Urban Plan.* **2016**, *145*, 21–33. [CrossRef]

45. Kuang, W.; Liu, J.; Zhang, Z.; Lu, D.; Xiang, B. Spatiotemporal dynamics of impervious surface areas across China during the early 21st century. *Chin. Sci. Bull.* **2013**, *58*, 1691–1701. [CrossRef]
46. Hutchinson, M.F. Interpolation of Rainfall Data with Thin Plate Smoothing Splines—Part I: Two Dimensional Smoothing of Data with Short Range Correlation. *J. Geogr. Inf. Decis. Anal.* **1998**, *2*, 153–167.
47. Fischer, G.; Nachtergaele, F.; Prieler, S.; Velthuizen, H.T.V.; Verelst, L.; Wiberg, D. *Global Agro-ecological Zones Assessment for Agriculture(GAEZ 2008)*, 1st ed.; IIASA: Laxenburg, Austria; FAO: Rome, Italy, 2008.
48. Yao, W.; Ma, D.; Li, P.; Zhao, G. LUCC of a Watershed on the Northern Chinese Loess Plateau during 1978–2011. Proceedings of 2018 Fifth International Workshop on Earth Observation and Remote Sensing Applications (EORSA), Xi'an, China, 18–20 June 2018; pp. 1–5.
49. Hu, Y.; Zhen, L.; Zhuang, D. Assessment of Land-Use and Land-Cover Change in Guangxi, China. *Sci. Rep.* **2019**, *9*, 2189. [CrossRef]
50. Li, Q.; Sun, Y.; Yuan, W.; Lyu, S.; Wan, F. Streamflow responses to climate change and LUCC in a semi-arid watershed of Chinese Loess Plateau. *J. Arid Land* **2017**, *9*, 609–621. [CrossRef]
51. Mao, D.; Wang, Z.; Wu, B.; Zeng, Y.; Luo, L.; Zhang, B. Land degradation and restoration in the arid and semiarid zones of China: Quantified evidence and implications from satellites. *Land Degrad. Dev.* **2018**, *29*, 3841–3851. [CrossRef]
52. Halmy, M.W.A.; Gessler, P.E.; Hicke, J.A.; Salem, B.B. Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Appl. Geogr.* **2015**, *63*, 101–112. [CrossRef]
53. Yang, X.; Zheng, X.; Chen, R. A land use change model: Integrating landscape pattern indexes and Markov-CA. *Ecol. Model.* **2014**, *283*, 1–7. [CrossRef]
54. Guan, D.; Li, H.; Inohae, T.; Su, W.; Nagaie, T.; Hokao, K. Modeling urban land use change by the integration of cellular automaton and Markov model. *Ecol. Model.* **2011**, *222*, 3761–3772. [CrossRef]
55. Yang, W.; Long, D.; Bai, P. Impacts of future land cover and climate changes on runoff in the mostly afforested river basin in North China. *J. Hydrol.* **2019**, *570*, 201–219. [CrossRef]
56. Memarian, H.; Kumar Balasundram, S.; Bin Talib, J.; Teh Boon Sung, C.; Mohd Sood, A.; Abbaspour, K. Validation of CA-Markov for Simulation of Land Use and Cover Change in the Langat Basin, Malaysia. *J. Geogr. Inf. Syst.* **2012**, *4*, 542–554. [CrossRef]
57. Al-sharif, A.A.A.; Pradhan, B. Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS. *Arab. J. Geosci.* **2013**, *7*, 4291–4301. [CrossRef]
58. Zhang, Y.; Peng, C.; Li, W.; Tian, L.; Zhu, Q.; Chen, H.; Fang, X.; Zhang, G.; Liu, G.; Mu, X.; et al. Multiple afforestation programs accelerate the greenness in the 'Three North' region of China from 1982 to 2013. *Ecol. Indic.* **2016**, *61*, 404–412. [CrossRef]
59. Dong, N.; You, L.; Cai, W.; Li, G.; Lin, H. Land use projections in China under global socioeconomic and emission scenarios: Utilizing a scenario-based land-use change assessment framework. *Glob. Environ. Chang.* **2018**, *50*, 164–177. [CrossRef]
60. Huang, Q.; He, C.; Liu, Z.; Shi, P. Modeling the impacts of drying trend scenarios on land systems in northern China using an integrated SD and CA model. *Sci. China Earth Sci.* **2014**, *57*, 839–854. [CrossRef]
61. Li, J.; Li, Z.; Lü, Z. Analysis of spatiotemporal variations in land use on the Loess Plateau of China during 1986–2010. *Environ. Earth Sci.* **2016**, *75*, 997. [CrossRef]
62. Lu, F.; Hu, H.; Sun, W.; Zhu, J.; Liu, G.; Zhou, W.; Zhang, Q.; Shi, P.; Liu, X.; Wu, X.; et al. Effects of national ecological restoration projects on carbon sequestration in China from 2001 to 2010. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 4039. [CrossRef]
63. Bryan, B.A.; Gao, L.; Ye, Y.; Sun, X.; Connor, J.D.; Crossman, N.D.; Stafford-Smith, M.; Wu, J.; He, C.; Yu, D.; et al. China's response to a national land-system sustainability emergency. *Nature* **2018**, *559*, 193–204. [CrossRef] [PubMed]
64. Yin, H.; Pflugmacher, D.; Li, A.; Li, Z.; Hostert, P. Land use and land cover change in Inner Mongolia—Understanding the effects of China's re-vegetation programs. *Remote Sens. Environ.* **2018**, *204*, 918–930. [CrossRef]
65. Duan, L.; Huang, M.; Zhang, L. Differences in hydrological responses for different vegetation types on a steep slope on the Loess Plateau, China. *J. Hydrol.* **2016**, *537*, 356–366. [CrossRef]
66. Gang, C.; Gao, X.; Peng, S.; Chen, M.; Guo, L.; Jin, J. Satellite Observations of the Recovery of Forests and Grasslands in Western China. *J. Geophys. Res. Biogeosci.* **2019**, *124*, 1905–1922. [CrossRef]

67. Huang, L.; Xiao, T.; Zhao, Z.; Sun, C.; Liu, J.; Shao, Q.; Fan, J.; Wang, J. Effects of grassland restoration programs on ecosystems in arid and semiarid China. *J. Environ. Manag.* **2013**, *117*, 268–275. [CrossRef]
68. Xiong, D.; Shi, P.; Zhang, X.; Zou, C.B. Effects of grazing exclusion on carbon sequestration and plant diversity in grasslands of China—A meta-analysis. *Ecol. Eng.* **2016**, *94*, 647–655. [CrossRef]
69. Liu, J.; Bian, Z.; Zhang, K.; Ahmad, B.; Khan, A. Effects of different fencing regimes on community structure of degraded desert grasslands on Mu Us desert, China. *Ecol. Evol.* **2019**, *9*, 3367–3377. [CrossRef]
70. Mu, S.; Zhou, S.; Chen, Y.; Li, J.; Ju, W.; Odeh, I.O.A. Assessing the impact of restoration-induced land conversion and management alternatives on net primary productivity in Inner Mongolian grassland, China. *Glob. Planet. Chang.* **2013**, *108*, 29–41. [CrossRef]

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).