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Is there a regularity: the change of arable land use pattern under the influence of human activities in the Loess Plateau of China?

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Abstract

Conventionally, the evolutions of landscape patterns show different regularities in terms of different spatial scales. Therefore, the changes of arable land use pattern under the influence of human activities in the Loess Plateau of China also follow similar rules. To examine this assumption, we selected Per Capita Arable land Area (PCAA) as an index to indicate arable land use pattern, and Human Activity Intensity (HAI) as an index to indicate the influence of human activities. We also used land use data and demographic data at a 5-year interval from 1990 to 2015 to quantify PCAA and HAI in four different spatial scales across over the Loess Plateau region. These four scales include the whole loess Plateau region, provincial (autonomous region) scale, municipal (autonomous prefecture) scale, and county (city, district) scale. The theoretical model of arable land use pattern and the HAI calculation model were used comprehensively. We performed spatial analysis on the whole PCAA and HAI with the support of GIS geographic information technology, and conducted spatial autocorrelation analysis and Pearson's correlation analysis. We performed analysis of factor driving on the PCAA and HAI for different land-use types at the county (city, district) scale. We found that the changes in arable land use pattern of the Loess Plateau were dominated by human activities at the whole region and provincial scales from 1990 to 2015. However, at the municipal and county scales, human activities account for 60% of the changes in land use pattern. Two interesting findings were found at the municipal and county scales: one is that with the changing rate of HAI increases, the changing rate of PCAA decreased substantially; the second is that with HAI decreases, PCAA increased significantly. Besides, the changes in arable land use pattern can be explained by the synergy effect of multiple factors of human activities. This study provides insight knowledge in understanding the drives under the change of arable land use pattern in the Loess Plateau and hopefully can provide guidance for the sustainable goal of the local and country scale planning from the management perspective.

Keywords Arable land use pattern · Arable land area per capita · Human activity · The Loess Plateau · Multi-scale spatial analysis

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1 Introduction

It has been proved that the spatial and temporal patterns of arable land are not only sensitive to natural environmental conditions, but also closely relevant to human activities (Halpern et al. 2015; Shi and Shi 2015). Due to the growing population and the limited arable land, changes in the pattern of arable land use can substantially affect cropland production, which in turn affects local food security (Chen et al. 2018; Hu et al. 2018). As an important indicator to measure to what extent of human influence on the natural environment, the research on the intensity of human activities has become a great endeavor to the academic community (Xu and Xu 2017; Xu et al. 2015a, b). The change of arable land pattern primarily due to two factors, including the climate change and human activities. The method to quantify the contribution of these two factors on different spatial and temporal scales is not only a scientific problem from an ecological point of view, but also involve the knowledge of surface system science perspective (Li et al. 2018, Shi and Shi 2015). The problems of arable land use pattern and human activity characteristics in the Loess Plateau region are now hotspots to the scientific community (Huang et al. 2016; Li et al. 2017a, b; Li et al. 2016; Xin et al. 2007; Xu and Xu 2017; Zhao et al. 2017, 2018; Zhu et al. 2019). Previous studies suggested that human economic activities since the industrial revolution has great feedbacks to the climate system at a global scale, and named it as "Anthropocene" to represent a new era. The indirectly human-induced climate change substantially affects grain production and has substantial impact on the pattern of arable land use, especially when the pattern of arable land use was expressed by Per Capita Arable land Area (PCAA) (Liu et al. 2018a, b; Liu et al. 2014; Shi et al. 2019; Steffen et al. 2015). In recent years, research results about the effects of climate change and human activities on the pattern of arable land use have emerged in an endless stream. Researchers have found that social economy and policy also play an active role in the change of arable land pattern (Shi and Shi 2015). However, land-use planning is a multi-scale and multi-dimensional problem (Liu et al. 2009; Newman et al. 2014; Rutten et al. 2014; Schweizer and Matlack 2014; Zhang et al. 2015). Changes in arable land patterns can be described indicators such as Human Activity Intensity (HAI) (Ge et al. 2018a, b; Li et al. 2015; Xu et al. 2015a, b; Li et al. 2017a, b). Therefore, multi-scale spatial analysis of changes in arable land use patterns under the influence of human activities is a critical technology to answer this question.

It is noted that in recent years, with the continuously increase in the intensity of human activities, the PCAA decreases inevitably, suggesting a negative correlation between the two statistically. However, everything has generality and particularity, and the geographical spatial thinking tells the spatial heterogeneity between regions and regions. The similar geographical phenomenon will suggest different scientific findings in various scales. Most scholars focus on temporal scales only but ignore the spatial scale, participant scale and land classification accuracy (Shi and Shi 2015). Therefore, the spatial scales of the Loess Plateau used in this study include the whole region scale, provincial scale, city scale and county scale of the Loess Plateau. As we all know, since the 1990s, human society developed rapidly with the progresses on information technology, especially since the developing policy of the western China was implemented in 2000, the Loess Plateau substantially suffers from intense human disturbances. Therefore, the temporal scale in this study is 25 years which ranges from 1990 to 2015. Thus, the quantitative analysis of the changes in arable land use pattern at different spatial and temporal scales was conducted (Xu and Xu 2017; Shi and Shi 2015). The characteristics, as well as the relationship between human

activities and arable land use patterns, provide a reference for understanding the changes in arable land-use patterns under the influence of human activities in the Loess Plateau. Here, we used regularities to explain this phenomenon, and this condition is also known as a spatial imbalance. We used an idealized example to describe downscaling shown in Fig. 1 which is closely relate to spatial imbalance. On the whole region scale (Fig. 1a), a phenomenon can be denoted as light gray color, but on the quarter spatial scale (Fig. 1b), the color range of the phenomenon varies from white color to gray color, and then on the sixteenth space scale (Fig. 1c), the color range of the phenomenon is from white to black. On the contrary, the reverse process is called upscaling. A recent study found that, there is a nonlinear relationship between urban population growth and sustainable development at the global scale; however, in Moldova, continuous rural–urban migration is correlated to accessibility to socio-economic resources and it is negatively correlated to environmental burden per capita (Shaker 2018).

2 Materials and methods

2.1 Research area overview

The total area of the Loess Plateau is about 640,000 km^2, covering all of Shanxi Province and Ningxia Hui Autonomous Region, most of Shaanxi, parts of Inner Mongolia Autonomous Region, Henan Province, Gansu Province, and Qinghai Province. This area involves 43 prefecture-scale cities distributed in 7 provinces and we merged the municipal districts of some cities due to research needs. For example, the six districts of Xi'an City were merged into one district (Fig. 2). The inherently fragile natural ecosystems in the region and the long-term inappropriate activities of humans led to serious soil erosion and deteriorating ecological environment. It has become an area with extremely sharp contradictions between human and earth, which has always been one of the hot topics in academic society of China and other international groups (Xu and Xu 2017).

2.2 Data sources and pre-processing

The population data were obtained from the statistical yearbook of the several provinces (autonomous regions) and cities (autonomous prefectures) within the Loess Plateau between 1990 and 2015. In order to facilitate the expression, the provinces (autonomous regions), cities

a On the whole scale   **b** On the quarter scale   **c** On the sixteen scale
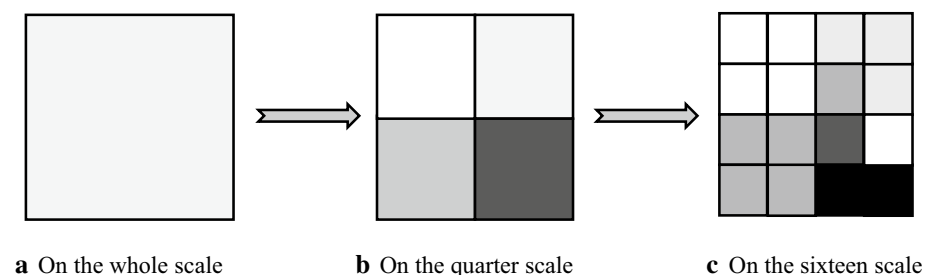
Fig. 1 The representation of a phenomenon on different scales
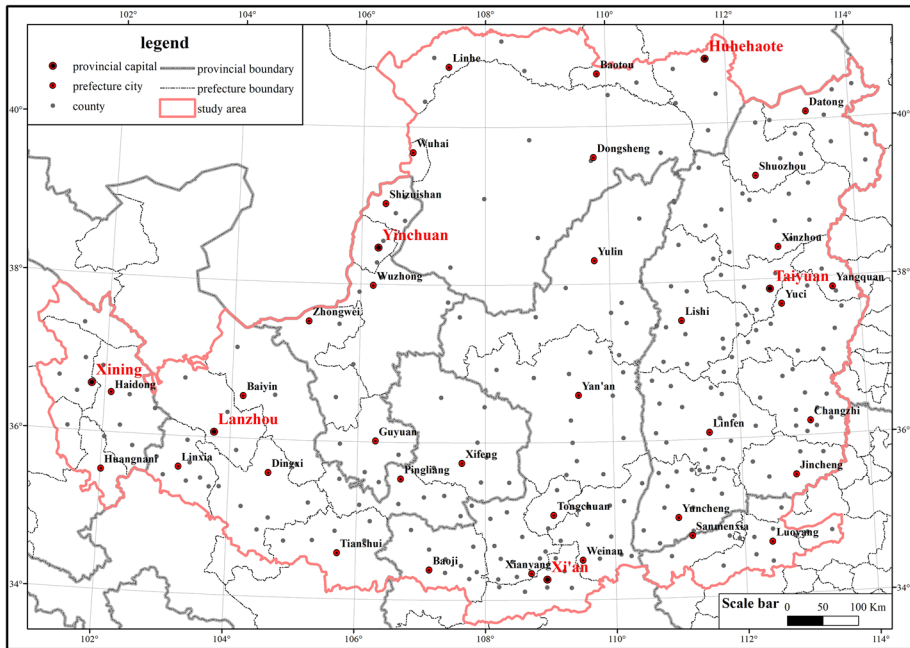
Fig. 2 The location map of study area

(autonomous prefectures), counties (cities, districts) involved in the article are all corresponding areas of the province (autonomous region) located in the Loess Plateau region.

The land use data were obtained from the Remote Sensing Monitoring Database of China's Land Use Status provided by the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn). This database covers the national land area year-to-year, supported by a number of major scientific and technological projects and important projects of the National Science and Technology Support Program and the Chinese Academy of Sciences Knowledge Innovation Project. The data set covers six time periods including the late 1980s (1990), 1995, 2000, 2005, 2010 and 2015. The raw data of land-use are mainly based on the Landsat TM/ETM remote sensing image, which is generated by visual interpretation. The major land-use classifications include 6 primary land types and 25 secondary types. These 6 primary land types include arable land, forest land, grassland, water area, construction land and unused land, respectively. The 25 secondary types include paddy field, dry land, woodland, shrub, sparse woodland, other woodland, high coverage grass, medium coverage grass, low coverage grass, river channel, lake, reservoir pit, permanent glacier snow, beach, shallows, urban land, rural settlement, other construction land, sandy land, Gobi, saline-alkali land, wetlands, bare land, bare rock texture, other unused land, respectively. The data of arable land area were post-processed by arable land data of the Loess Plateau with the regional statistics of the provincial, municipal, and county scales.

2.3 Analysis methods

(1)   Characterization of arable land use pattern

The PCAA is an important indicator used to quantify the characteristics of the transformation pattern of arable land use, which represents the ratio of the arable land area and the population for each statistical unit.

$$\text{PCAA} = \frac{\text{AA}}{\text{POP}} \tag{1}$$

where PCAA is the per capita arable land area (hm^2/person), AA denotes the arable land area (hm^2) in each statistical unit; POP is the population (person) in the corresponding statistical unit.

(2) Quantification of Human Activity Intensity (HAI)

The HAI is an indicator used to quantify the characteristics of human activities, and it represents the influence of human activities on the region. This study uses the measurement method named "Equivalent area of construction land as a percentage of total area" proposed by Xu et al. (2015a, b), emphasizing the total proportion and spatial difference of HAI on the landform. Then the weight of different land types was adjusted, combined with the land-use data in this study. Thus, HAI is calculated as follows:

$$\text{HAI} = \frac{S_{\text{CLE}}}{S} \tag{2}$$

where HAI is the HAI; S_{CLE} is the equivalent area of the construction land; S is the total land surface area of the study;

$$S_{\text{CLE}} = \sum_{i=1}^{n} (\text{SL}_i \times \text{CI}_i) \tag{3}$$

where SL_i is the area of the ith land-use/cover type; CI_i is the construction land equivalent conversion factor of the ith land use/cover type (Table 1); n is the number of land-use/cover types in the area (Xu et al. 2015a, b).

(3) The rate of interannual variation

The rate of interannual variation is used to characterize the change of a certain element in year-to-year, quantitatively and is expressed as a percentage. In this study, the rate of interannual variation of PCAA and that of HAI were quantified. Firstly, using the PCAA of the current year minus the PCAA of the previous statistical year to get a value "a"; Secondly, using the value "a" divided by the PCAA of the previous statistical year to get the rate of interannual variation of PCAA.

(4) Spatial overlay analysis

This method is a spatial analysis method commonly used in GIS. It refers to overlapping and adding spatial and attribute data of two different geographical features in the same area under the same spatial coordinate system to generate multiple attribute features of spatial regions or establish spatial correspondence among geographic objects. According to the data structure, it can be divided into vector-based spatial overlay analysis and

Table 1 Construction land equivalent conversion factor of land use/cover type

Code	Name	Factor	Code	Name	Factor
11	Paddy field	0.2	51	Urban land	1
12	Dry land	0.2	52	Rural settlement	1
21	Woodland	0	53	Other construction land	1
22	Shrub	0	61	Sandy land	0
23	Sparse woodland	0	62	Gobi	0
24	Other woodland	0.167	63	Saline-alkali land	0
31	High coverage grass	0	64	Wetlands	0
32	Medium coverage grass	0.067	65	Bare land	0
33	Low coverage grass	0.133	66	Bare rock texture	0
41	River channel	0.067	67	Other unused land	0
42	Lake	0			
43	Reservoir pit	0.067			
44	Permanent glacier snow	0			
45	Beach	0			
46	Shallows	0			

grid-based spatial overlay analysis. In this study, vector-based spatial overlay analysis was used.

(5)   Correlation analysis

For the correlation analysis of spatial variables, Moran's is one of the widely used index to characterize the spatial autocorrelation of each variable, and Pearson's correlation coefficient is commonly applied to test the correlation between two variables. Then this study used the Moran's index and Pearson's correlation coefficient for correlation analysis.

Spatial autocorrelation analysis of ESDA (Exploratory Spatial Data Analysis) refers to the potential interdependence of observational data of some variables in the same distribution area, and its coefficient varies in terms of the observation scales (or analysis scale). If the value of a regionalized variable becomes more similar when the spatial scale shrinks, this variable presents a spatial positive correlation; if the value of the variable becomes more different when the spatial scale shrinks, it is called spatial negative correlation; if the value of the variable does not exhibit any spatial dependence, then this variable exhibits spatial irrelevance or spatial randomness. This study used the Moran's I index to characterize the spatial autocorrelation of HAI and PCAA and then analyzes the spatial correlation between the two.

Pearson's correlation, also known as Pearson Product-Moment Correlation, is a very common way to measure correlation. It is used when both variables are at least at interval scale and data are parametric. It is calculated by dividing the covariance of the two variables by the product of their standard deviations. In other words, it is the proportion of variation that can be explained. A high explained proportion is good, and value 1 means perfect correlation. This study used the Pearson's correlation coefficient to characterize the correlation of HAI and PCAA and then analyzed the correlation between the two.

In order to further explore the changes in arable land use patterns under the influence of human activities on the Loess Plateau, this study conducted the two methods of correlation

analysis including HAI and PCAA. There are spatial autocorrelation analysis and Pearson's correlation analysis. Spatial autocorrelation index scores differ from each other; however, positive scores indicate similar values which are spatially grouped and negative scores indicate unlike values which are spatially grouped. Pearson's correlation coefficients are commonly classified into very positive (> 0.75), medium positive (0.75 to 0.50), positive (0.50 to 0.25), neutral (0.25 to -0.25), negative (-0.25 to -0.50), medium negative (-0.50 to -0.75) or very negative (< -0.75) scale, respectively. (Shaker 2018).

(6) Geodetector's analysis

Spatial stratified heterogeneity is the spatial expression of natural and socio-economic process, which is an important approach for human to recognize nature since Aristotle. Geodetector is a new statistical method used to detect spatial stratified heterogeneity and reveal the driving factors behind it. It contains the four sub-detectors, which are factor detector, risk detector, interaction detector, ecological detector. They are used to detect spatial heterogeneity of the variable Y, and detect to what extent one factor X can explain the variable Y. There is a "q" value in measuring the spatial variations. Q-statistic in Geodetector has already been applied in many natural and social sciences studies which can be used to measure spatial stratified heterogeneity, detect explanatory factors and analyze the interactive relationship between variables (Wang and Xu 2017).

In this study, factor detector and interaction detector in the geodetector are used to analyze the factors effecting the spatial heterogeneity of the change of arable land use pattern under the influence of human activities in the Loess Plateau. Due to the request of discrete independent variables in geodetector, this study did some preparatory work for the follow-up analysis, such as classifying these ten explanatory variables. Natural breaks classification method was used and carried out in software ArcGIS 10.2.

① Factor detection

The factor detector is used to detect the influence of each factor on the spatial variations in the change of arable land use pattern. It is measured by q value. The larger the q value, the stronger the effect of factor X on the spatial variations in the change of arable land use pattern, and the weaker the opposite meaning. The q value indicates that factor X explains the spatial variations in the change of arable land use pattern of 100*q %. More detailed information could be found in Wang and Xu (2017).

② Interaction detection

Interaction detection is used to indicate the relationship between two-factor and spatial variations of the changes in arable land use pattern. Take factors X_a and X_b effect the spatial variations of the changes in arable land use pattern as follows: $q(X_a)$ and $q(X_b)$, and the driving force after interaction is $q(X_a \cap X_b)$.

If $q(X_a \cap X_b) < \text{Min}(q(X_a), q(X_b))$, it shows that the interaction of factors X_a and X_b has a *nonlinear weakening* effect on the spatial heterogeneity of the change in arable land use pattern.

If $\text{Min}(q(X_a), q(X_b)) < q(X_a \cap X_b) < \text{Max}(q(X_a), q(X_b))$, it shows that the interaction of factors X_a and X_b has a *one-factor nonlinear weakening* effect on the spatial variations of the changes in arable land use pattern.

If $q(X_a \cap X_b) > \text{Max}(q(X_a), q(X_b))$, it shows that the interaction of factors X_a and X_b has a *two-factor enhancement* effect on the spatial variations of the changes in arable land use pattern.

If $q(X_a \cap X_b) = q(X_a) + q(X_b)$, it shows that factors X_a and X_b are *independent of each other*.

If $q(X_a \cap X_b) > q(X_a) + q(X_b)$, it shows that the interaction of factors X_a and X_b has a *nonlinear enhancement* effect on the spatial variations of the changes in arable land use pattern (Wang and Xu 2017).

3 Results and analysis

Here, we quantified HAI and PCAA in different spatial scales. The characteristics of arable land use patterns under the influence of human activities are analyzed in four spatial scales, including whole region scale, provincial scale, city scale and county scale, respectively.

3.1 Whole region scale correlation analysis

At the scale of the entire Loess Plateau, while the HAI is increasing, the PCAA, which is an important indicator of the pattern of arable land use, show large variations. The two have a strong negative correlation, with a correlation coefficient value of -0.89. Obviously, with the intensification of regional human activities induced by the increase in population and urbanization in the region, the PCAA decreased inevitably (Fig. 3).

3.2 Provincial scale correlation analysis

In provincial scale (autonomous regions) within the Loess Plateau, the changes of arable land use are still obvious, but the PCAA value of each province has been reduced. Moreover, HAI values are still high in various provinces, and the negative correlation still
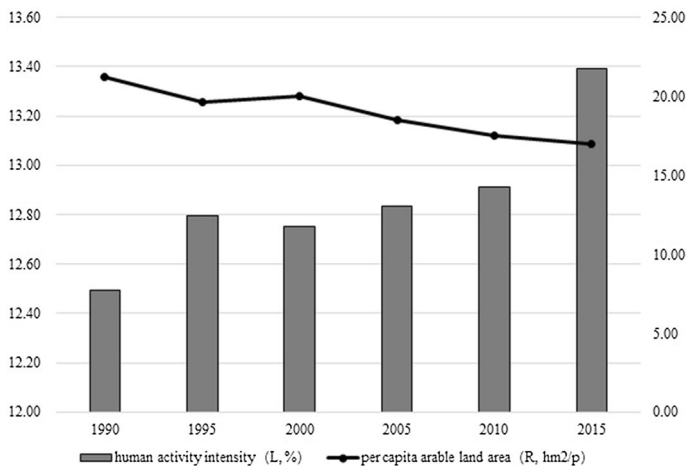
Fig. 3 The change of arable land use pattern under the influence of human activities at entire-area scale

exist between the two variables. The average correlation coefficient value is −0.73. The largest deceased in PCAA between 1990 and 2015 was in Inner Mongolia Autonomous Region, with the value decreased from 28.05 (hm^2/person) in 1990 to 20.78 (hm^2/person) in 2015 (25.93%), followed by Shanxi Province 23.31%. The smallest decreased was in Henan Province (12.66%). We sort it in decreasing order as: Inner Mongolia Autonomous Region > Shanxi Province > Qinghai Province > Shaanxi Province > Ningxia Hui Autonomous Region > Gansu Province > Henan Province. The largest increase in HAI between 1990 and 2015 was in Ningxia Hui Autonomous Region, which increased from 12.85% in 1990 to 14.73% in 2015, followed by Inner Mongolia Autonomous Region, with an increasing rate of 9.62%. The smallest increase was in Qinghai Province, with the value of 2.68%. We sort it in decreasing order as: Inner Mongolia Autonomous Region > Ningxia Hui Autonomous Region > Shanxi Province > Shaanxi Province > Gansu Province > Henan Province > Qinghai Province. The largest negative correlation is in Qinghai Province, with a correlation coefficient value of −0.92, and the smallest is Henan Province with a correlation coefficient value of −0.37.

3.3 City scale spatial overlap analysis

With the support of the ArcGIS software, we conducted the GIS spatial superposition analysis on the inter-annual variations of PCAA and HAI at the municipal scale and edited the associated attribute table. The corresponding situation of the two grades is characterized, that is, the corresponding situation of the inter-annual variations of PCAA and the HAI in each city, as shown in Fig. 4. Then, by summarizing the attribute table according to "classification" field in ArcGIS software, we classified the number of cities (autonomous prefectures) into the different categories.

According to Fig. 4 and Table 2, there is a negative correlation between the change of PCAA and the change of HAI in 26 cities (autonomous prefectures) in the Loess Plateau, whose coefficient is −0.63. As the green color shown in Fig. 3 and the values in first block and the fourth block in Table 2, which includes 60.5% of the 43 cities (autonomous prefectures) in the Loess Plateau, the intensity of human activities in these cities (autonomous prefectures) has increased, and the PCAA has decreased, that is, the 23 cities (autonomous prefectures) corresponding to the first block in Table 2. The increase in the intensity of human activity is reduced, and the reduction in per capita arable land area is reduced, that is, the 3 cities corresponding to the fourth block in Table 2, indicating that the human activities of these cities (autonomous prefectures) in the Loess Plateau region are arable, which has a larger negative impact on the pattern of land use. There is a strong positive correlation between the changes in PCAA and HAI in 15 cities (autonomous prefectures) in the Loess Plateau, and the correlation coefficient is 0.68, which is shown in red in Fig. 3 and in Block 2 and Block 3 of Table 2, representing 34.9% of the 43 cities (autonomous prefectures) in the Loess Plateau. This shows that the intensity of human activities in these cities (autonomous prefectures) has increased, with the PCAA decreased, that is, the 6 cities corresponding to the second block in Table 2. Or the increase in the HAI decreased, with the PCAA decreasing, that is, the corresponding 9 cities in Block 3 in Table 2, indicating that human activities in these cities (autonomous prefectures) in the Loess Plateau have a greater impact on the pattern of arable land use, and they are positive. Only 2 cities (Hohhot City and Lvliang City) do not show significant relationship between the change of PCAA and HAI, indicating that the per capita arable land area and human activity intensity of these two cities are basically unchanged.
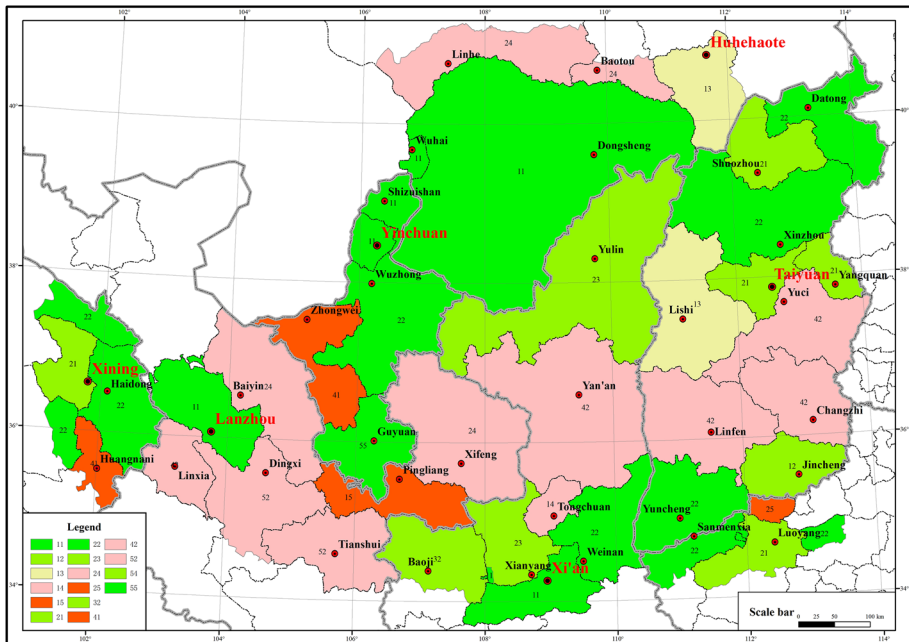
Fig. 4 Changes in arable land use pattern under the influence of human activities at city-area scale. Note: The meaning of the two digits in the legend is that the number on the ten digits indicates the changing rate of the HAI, and the number on the digit indicates the changing rate of the PCAA, and the corresponding values are as follows: the rate of change in HAI is 1: 4.1 to 51.4%; 2: 0.1 to 4.1%; 3: −0.1 to 0.1%; 4: −2.2 to −0.1%; 5: −5.9 to −2.2%; the rates of change in PCAA, 1: −3.2 to −1.3%; 2: −1.3 to −0.1%: 3: −0.1 to 0.1%: 4: 0.1 to 1%: 5: 1 to 2.8%. Green color indicates negative correlation and red indicates positive correlation

Table 2 Summarizing the changes in arable land use pattern under the influence of human activities at city-area scale

HAI \ PACC	1	2	3	4	5
1	① 7	1	0	② 1	0
2	5	10	1	4	1
3	0	1	0	0	0
4	③ 2	5	0	④ 0	0
5	0	2	0	1	2

In general, at the municipal scale, there is a large internal spatial imbalance in the characteristics of arable land use patterns under the influence of human activities. About 60% of the cities (autonomous prefectures) are characterized by an increase in the intensity of human activities, resulting in a decrease in PCAA. Nearly 40% of counties (cities, districts) showed the opposite pattern.

3.4 County scale spatial overlap analysis

This analysis method is the same as the method in analyzing the characteristics of the city. With the support of ArcGIS software, the result layer can be obtained. The same method can be used to obtain the inter-annual variations of PCAA and the inter-annual variations of HAI in the Loess Plateau. In order to visualize the correspondence of each other, we made the map (Fig. 5). By summarizing the attribute table according to "classification" field in ArcGIS software, we get the number of counties (cities, districts) at the different classification.

Through the observation shown in Fig. 5, counting of its attribute table, and the analysis of Table 3, it can be concluded that there is a certain negative correlation between the change of PCAA and the change of HAI in 167 counties (cities, districts). The correlation coefficient is − 0.34, which is shown in green in Fig. 4, and in Table 3 as the block 1 and block 4, accounting for 57.2% of the total 292 counties (cities, districts). While the intensity of human activities in these counties (cities, districts) increased significantly, the PCAA decreased greatly that is, the 151 counties (cities, districts) corresponding to block 1 in Table 3. While the intensity of human activities decreases, the PCAA decreases slowly, that is, the 16 counties (cities, districts) corresponding to the block 4 in Table 3, indicating that human activities have a great impact on the arable
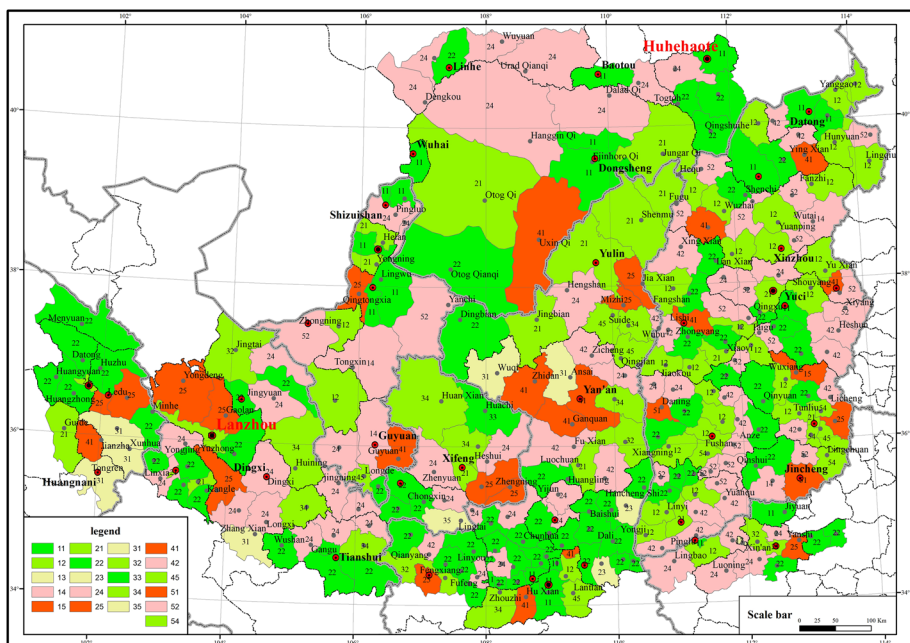
Fig. 5 The change of arable land use pattern under the influence of human activities at county-area scale. Note: The meaning of the two digits in the legend is that the number on the ten digits indicates the rate of change of the intensity of human activity, and the number on the digit indicates the rate of change of the per capita arable area, and the corresponding values are as follows: the rates of change in HAI, 1: 6.6 to 60.3%; 2: 0.1 to 6.6%; 3: − 0.1 to 0.1%; 4: − 6.9 to − 0.1%; 5: − 23.1 to − 6.9%; the rates of change in PCAA, 1: − 8.5 to − 3.2%; 2: − 3.2 to − 0.1%; 3: − 0.1 to 0.1%; 4: 0.1 to 4.8%; 5: 4.8 to 11.5%. Green indicates negative correlation and red indicates positive correlation

Table 3 Summarizing the change of arable land use pattern under the influence of human activities at county-area scale

HAI \ PACC	1	2	3	4	5
1	① 21	33	1	② 12	1
2	23	74	2	36	13
3	2	0	1	3	1
4	③ 14	18	0	④ 0	9
5	2	19	0	7	0

land use pattern. Among them, 95 counties (cities, districts) have strong negative correlations (correlation coefficient is -0.67). According to the data of the inspection, in addition to one county (Huachi County) in which the HAI and PCAA are basically unchanged, the remaining 94 counties (cities, districts) have the same result: the HAI is continuously increasing, resulting in a continuous decrease in the PCAA. This result shows that human activities in these counties (cities, districts) have a great and negative impact on the pattern of arable land use. While human activities are strengthening, the PCAA decreased sharply. The reason for this phenomenon is obvious. In the process of urbanization, the population flows from the countryside to the city. In addition, the natural growth factors of the population and the pursuit of high-quality material and cultural life lead to the continuous expansion of urban land use, which makes the suburbs arable. There is a positive correlation between the changes of PCAA and HAI in 115 counties (cities, districts) in the Loess Plateau (correlation coefficient is 0.4), which is represented by red in Fig. 4, and in Table 3 Blocks 2 and 3, representing 39.4% of the 292 counties (cities, districts) in the whole region. While the intensity of human activities in these (municipal and district) increases largely, the PCAA decreases by a small amount, that is, the 62 counties (cities, districts) corresponding to block 2 in Table 3. Or with the small increase in the HAI, the PCAA decreased greatly, that is, the 53 counties (cities, districts) corresponding to block 3 in Table 3, indicating that the human activities of these counties (cities, districts) have a great impact on the arable land use pattern, but they are positive. At present, the academic community recognizes that climate change and human activities will have an impact on the pattern of arable land use. It is concluded that the changes in the pattern of arable land use in these counties (cities, districts) may be greatly affected by climate change, which will be further explored in future research. Among them, only three counties (cities, districts) have strong positive correlations (correlation coefficient is 0.99), they are Wuxiang County, Jincheng City, and Daning County. According to the data of the inspection results, the intensity of human activities in Wuxiang County increased significantly, but the PCAA decreased less, while the HAI in Jincheng City and Daning County increased slowly, but the PCAA decreased greatly. The relationship between the changes in HAI and PCAA in only 10 counties (cities, districts) is not obvious, that is, whether the HAI in the county (city, district) is increased or decreased, the PCAA changes independently.

In general, at the county scale, there are still large internal spatial heterogeneity in the characteristics of arable land use patterns under the influence of human activities. About 60% of counties (cities, districts) are in line with the increase in the intensity of

human activities, resulting in a decrease in PCAA. Nearly 40% of counties (cities, districts) show the opposite patterns.

3.5 Correlation analysis of different spatial scales

Firstly, spatial autocorrelation analysis is carried out for the rate of change of HAI and PCAA on the three spatial scales of provincial, municipal and county scales. The results are shown in Table 4.

It can be seen from Table 4 that on the same spatial scale, the Moran's *I* index expectation ($E(I)$) of the rate of change of HAI and PCAA is the same, and except for the negative value on the provincial scale, the others are positive. Besides, all of the actual Moran's *I* indexes are larger than the corresponding expectation values ($E(I)$), indicating that they have a spatial negative correlation on the provincial scale, and a spatial positive correlation at the city and county scales, that is, the change of HAI and PCAA between provinces (autonomous regions). Larger, the difference in the HAI and the PCAA between cities (autonomous prefectures) and counties (cities, districts) is small. A significant test was performed on the above results, and for the rate of change of HAI and the rate of change of PCAA at county scale, the corresponding p-values of them were less than 1%, indicating that the 99% significance scale test was passed, but the rates of them at provincial scale and city scale did not pass the significance scale of ordinary 95% confidence scale. This indicated that at the two scales, although the rate of change of HAI and the rate of change of PCAA have spatial correlations, they are non-significant. That is, at county scale, for the rate of change of HAI and the rate of change of PCAA, the significance was most significant on the provincial scale and city scale. All the above-mentioned made clear that downscaling study can contribute to reveal the spatial features of the rate of change of HAI and the rate of change of PCAA.

Secondly, on the county scale, this study selected 10 factors with weight not zero as dynamics explanatory variables from the 25 factors of land use/cover-type construction land equivalent conversion and conducted Moran's *I*-test. The test results (Table 5) disclosed various scales of spatial nonstationary for both the response and 10 explanatory variables and 7 out of 10 variables had less than a 1% chance of occurring randomly, and also these 7 variables had highly significant characteristics, because their *P*-values were less than 0.01. The remaining 3 variables (HAI on medium coverage grass, HAI on low coverage grass, HAI on river channel) and the response variable (PCAA) had significant characteristics, whose *P*-values were less than 0.1, although these values are relatively large. Specifically, for the 10 dynamics variables of HAI on different type of land use, Global Moran's *I* index scores ranged from 0.03 to 0.21 and z-scores from 1.75 to 9.72. The

Table 4 Moran's I analysis for HAI and PACC at different scales

	HAI			PACC		
	Provincial scale	City scale	County scale	Provincial scale	City scale	County scale
Moran's *I*	−0.1495	0.0559	0.0135	−0.2365	0.0596	0.0478
$E(I)$	−0.1667	−0.0222	−0.0034	−0.1667	−0.0222	−0.0034
z Score	0.0659	0.7980	0.7456	−0.2971	0.7917	2.2791
P value	0.9475	0.4249	0.4559	0.7664	0.4286	0.0227

Table 5 Global spatial autocorrelations for all study variables using Global Moran's *I*-test; Pearson product-moment correlation coefficients (two-tailed) between Loess Plateau's PACC and all independent measures of HAI ($n = 292$)

	Global Moran's *I*	*z*-score	*P*-value	Pearson's *r*	*P*-value
PCAA	0.048	2.279	0.023		
HAI on paddy field	0.086	5.600	<0.001	**0.410**	**0.016**
HAI on dry land	0.108	4.932	<0.001	**0.434**	**<0.001**
HAI on other woodland	0.201	9.342	<0.001	−0.175	**<0.001**
HAI on medium coverage grass	0.038	1.898	0.058	**0.212**	**0.006**
HAI on low coverage grass	0.030	1.749	0.080	**0.105**	**0.032**
HAI on river channel	0.045	2.418	0.016	0.070	0.057
HAI on reservoir pit	0.176	8.433	<0.001	−0.069	**<0.001**
HAI on urban land	0.124	5.778	<0.001	−0.629	**<0.001**
HAI on rural settlement	0.120	5.440	<0.001	−0.060	**<0.001**
HAI on other construction land	0.208	9.720	<0.001	−0.610	**<0.001**

A Pearson's correlation coefficient in bold depicts a statistically significant relationship above the 95% confidence level

dependent variable, PCAA, recorded a Global Moran's *I* score of 0.048 and *z*-score = 2.279 at an optional distance threshold (90 km). The greater the *z*-score deviates from zero, the more systematically dispersed (negative) or clustered (positive) the variable under investigation becomes. All these indicated that they had obvious clustering characteristics, because *z*-scores were more than 1.65, which is the lowest critical value with significant characteristics. It can be inferred from this that adjacent human activities within 90 km of each other have similar arable land pattern change. This distance is approximately equal to the average distance between urban districts in Loess Plateau, which is about 92 km. A positive aspect of this nonstationarity (spatial autocorrelation) is that it can provide statistically significant meaning to geographical patterns of arable land use. The ESDA confirmed the necessity for a spatial autoregressive technique to support findings from the nonspatial analysis (Shaker 2018).

Thirdly, on the county scale, this study still selected the above-mentioned 10 factors with weight not zero as dynamics explanatory variables. Statistically significant bivariate associations between- PCAA as the response variable- and 10 dynamics explanatory variables were found using Pearson's Product-Moment Correlation test (*r*) ($P < 0.05$, Table 5). There is no predictor entered into the categories of either "very positive" or "very negative". Only two predictors grouped into the "medium negative" category, with HAI on urban land ($r = -0.63$, $P < 0.001$) and HAI on other construction land ($r = -0.61$, $P < 0.001$) both being HAI on construction lands variables and negatively associated to PCAA. Only two predictors grouped into the "positive" category, with HAI on dry land ($r = 0.434$, $P < 0.001$) and HAI on paddy land ($r = 0.41$, $P = 0.008 < 0.01$) both being HAI on arable lands variables and positively associated to PCAA. The remaining six explanatory metrics fell into the "neutral" category.

From the correlation coefficient analysis, it can be construed that the changes in arable land pattern changes are highly contingent on both HAI on urban land and HAI on other construction land in Loess Plateau. From 1990 to 2015, the area of urban land increased 2078 km², whose rate of increase was 89.5%, and the area of other construction land

increased 3213 km^2, whose rate of increase was 315%. And the change of arable land use pattern is the result of many factors' comprehensive effects. So, it is necessary to make an analysis of factor driving.

3.6 Analysis of driving factors

Geographical detectors are used to identify factors affecting the spatial heterogeneity of PCAA, including the above-mentioned ten explanatory variables.

(1) Factor detection

The factor detector method was used to identify the influence of each factor on spatial heterogeneity of PCAA, and the q value of each impact factor is presented in Table 6. The explanatory powers of each factor to the spatial heterogeneity of arable land use pattern change are listed in a descending order: HAI on urban land (0.083), HAI on other construction land (0.057), HAI on dry land (0.05), HAI on rural settlement (0.047), HAI on paddy field (0.041), HAI on medium coverage grass (0.038), HAI on low coverage grass (0.025), HAI on other woodland (0.022), HAI on reservoir pit (0.031), HAI on river channel (0.016).

These results reveal that HAI on paddy field, HAI on dry land, HAI on urban land, HAI on rural settlement and HAI on other construction land have a strong influence on the spatial heterogeneity of arable land use pattern change (greater than 0.04 of q-value average). Moreover, HAI on paddy field, HAI on other woodland, HAI on medium coverage grass, HAI on low coverage grass, HAI on river channel and HAI on reservoir pit have less influence on the spatial heterogeneity of arable land use pattern changes among all the factors used in this study. What's more, HAI on urban land has the strongest influence on spatial heterogeneity of arable land use pattern change. The main reasons are: first, with the rapid development of urbanization, more urban lands are needed, which intensifies human activities and some outskirt arable lands are occupied; second, more and more people crowd into big cities, which results in a sharply increase of populations in cities and intensifying of human activities. Certainly, the increasing of city population and the spatial distribution imbalance of population accelerate to decline the PCAA of the cities sharply as well. All these have changed the arable land use pattern.

(2) Interaction detection

Table 6 Intensity of action of each factor (geographic detector's p statistic and q value)

	F11	F12	F24	F32	F33	F41	F43	F51	F52	F53
q statistic	0.041	0.050	0.022	0.038	0.025	0.016	0.031	0.083	0.047	0.057
P value	0.053	0.022	0.193	0.064	0.156	0.367	0.103	0.000	0.070	0.065

The items indicate the human activities intensity on the different type of land use. F11: HAI on paddy field; F12: HAI on dry land; F24: HAI on other woodland; F32: HAI on medium coverage grass; F33: HAI on low coverage grass; F41: HAI on river channel; F43: HAI on reservoir pit; F51: HAI on urban land; F52: HAI on rural settlement; F53: HAI on other construction land

By identifying each factor with the interaction detector, the influence of the interaction between two factors on the spatial heterogeneity of arable land use pattern is presented in Fig. 6.

Generally, the effects of two-factor interaction are greater than the respective effects of the corresponding two factors. In Fig. 6, the numbers in light color are the majority types, which takes about 38 numbers. The numbers in dark color are the minority types, which only has 7 numbers. The numbers in red color on diagonal are q-values. It is obvious that the nonlinear enhancement is dominant on the spatial heterogeneity of arable land use pattern. Specifically, it is worth mentioning that the interaction between HAI on urban land (F51) and HAI on other construction land (F53) has a nonlinear enhancement effect on the spatial heterogeneity of the changes in arable land use pattern, which indicates that there is a superimposed effect [q-value $= 0.199 > (0.083 + 0.057)$, i.e., ($q$-value of F51 $+$ q-value of F53)] on human activities on these two construction lands for arable land use pattern change. From the perspective of HAI on paddy field (F11), the separate interaction between HAI on paddy field (F11) and HAI on urban land (F51) has a two-factor enhancement effect, which indicates that there is an imposed effect [q-value $= 0.090 > $ Max(0.041, 0.083), i.e., (q-value of F11, q-value of F51)] on human activities on the paddy lands and the urban land for arable land use pattern change. In all, it is proved that the changes in arable land use pattern are comprehensive effects involving many factors.
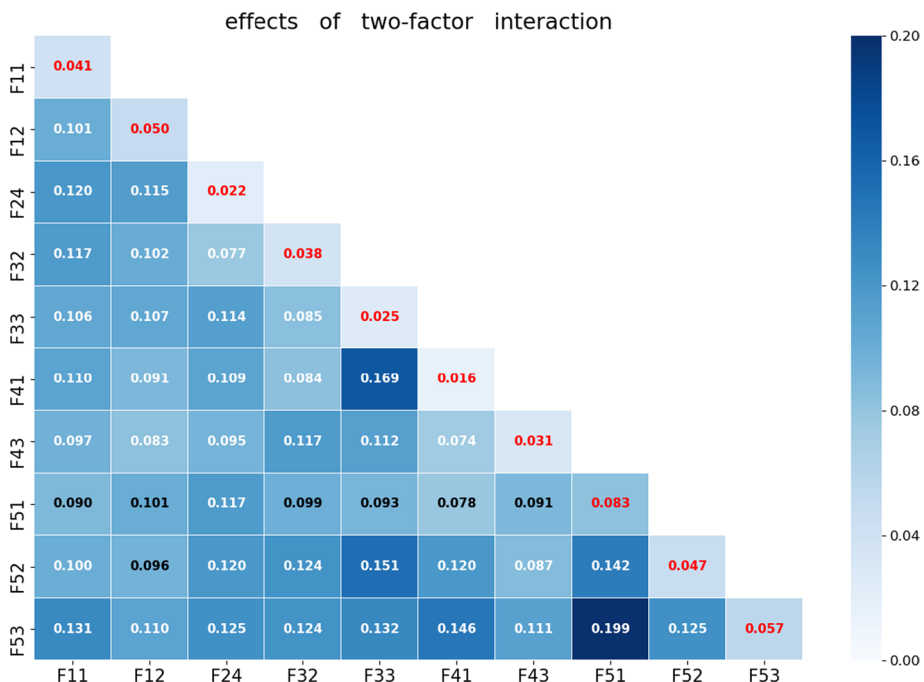

Fig. 6 Effects of two-factor interaction on spatial differentiation of arable land use pattern

4 Discussion

4.1 Selection of the method in quantifying the influence of human activities

For the study on the changes in arable land use pattern under the influence of human activities, it is very important to quantify the influence of human activities. HAI is presented as a conception and is used as a quantitative index in representing the influence of human activities. At present, there are five commonly used quantification indexes of HAI from the perspective of land transformation and landscape change, which are Human Activity Intensity of Land Surface (HAILS), Human Activity Index (HAI), Degree of hemeroby (M), Human Activity Intensity Index (HAII), Landscape Development Intensity (LDI), respectively. These indexes have their own advantages and shortcomings for different problems (Liu et al. 2018a, b).

In this study, the land use data are derived from remote sensing interpretation. In terms of methods in quantifying the intensity of human activities, we created a fine-tuned table including the weights of land use from existing research results as a reference. Due to the reference, the weight setting would directly affect the results and the measurement of the intensity of human activities. Researchers of different professional backgrounds to explore from their respective perspectives may have different results. Thus, further quantitative research on the intensity of human activities is still needed to have better estimates of the weight values.

4.2 Representing the arable land use pattern

Analyzing the changes in spatial and temporal patterns of arable land use is helpful to provide important insights for regional food security problem and ecological environment monitoring. Some research analyzed the changes in the spatial–temporal patterns of global arable land area and land use intensification during 2000–2010 by using eight statistical indicators, i.e., arable land area, changed area, standard deviation of changed area, percentage change of area, arable land area per capita, multiple cropping index, change and percentage change of multiple cropping index at three statistical scales, i.e., continent, country and $1° \times 1°$ grid (Hu et al. 2018; Chen et al. 2018). The methods of these researches are acceptable, but due to their relatively large scales, and they are not suitable for smaller scale studies. Now, further study about how to effectively represent the arable land use pattern and comprehensively analyze the results of representing is still needed.

In this study, only one indicator, PCAA, is used to represent the arable land use pattern. Although it is relatively simple, the relevant data are easy to get when downscaling due to its simple computational process. Of course, the changes in arable land use pattern involves natural factors, locational factors, and socio-economic factors. Previous researchers found that the role of socioeconomic factors in promoting the arable land transition has been strengthened during the process of urbanization, and there were obvious differences in the driving mechanism for arable land transition in different stages (Ge et al. 2018a, b). This study conducted the comprehensive analysis of the arable land use pattern with the HAI only on different types of land.

4.3 Limitations

All phenomena have their characters with the changes in spatial and temporal scales. This study mainly aimed to the 4 spatial scales including the whole regional scale, provincial scale, city scale, county scale, but town scale and grid scale are not included. However, it is vital for the study to do some analysis on town scale and grid scale, and more valuable information may be acquired from them. Meanwhile, due to the limitation of data source, this study lacks the investigation on the different temporal scales.

China's administrative divisions are adjusted every year, including administrative region and administrative level, which brings major difficulties to the study with the problem in temporal scales. In order to reduce this effect, this study unified the use of administrative division data in 2015. Although this is inconsistent with the actual region, it will not affect the overall results of this study, and time series analysis on the grid scale will be tried in future studies.

In short, there are still some problems in the multi-scale research on the changes in arable land use pattern under the influence of human activities, which are worthy of further exploration. Future investigation not only the above-mentioned problems, but also research methods, current status-quo, change process, and influence mechanism.

5 Conclusion

The changes in arable land use pattern are substantially influenced by human activities. To well determine a regularity on the change in arable land use pattern under the influence of human activities, especially at the different spatial scale, the quantitative research is needed. This study quantified the regularity of arable land use under the influence of human activities in Loess Plateau of China in several ways by analyzing at multi-spatial scales and multi-perspectives. Firstly, the pattern of arable land use in the Loess Plateau has different characteristics at different spatial–temporal scales. On the whole and provincial scales, the Per Capita Arable land Area (PCAA) decreased significantly. On the city scale and county scale, the changing rates of PCAA in most cities and counties also show increasing trend. However, there are some cities and the county have shown decreasing trend in PCAA. Secondly, the intensity of human activities in the Loess Plateau has different variations at different spatial–temporal scales. It has an increasing trend at both whole region scale and the provincial scale. At the municipal and county scales, the overall inter-annual rate of change of human activity intensity in most cities and counties is also increasing. However, there are some cities and counties showing that the inter-annual variations of human activity intensity are weakened. Thirdly, on the whole and provincial scales, the changes in arable land use pattern in the Loess Plateau are dominant due to human activities, but on the city scale and county scale, the spatial heterogeneity is large, which exists in about 60% of the cities (autonomous prefectures) and county (city, district) showed a dominant influence. Lastly, the changes in arable land use pattern are the synergy effects of many factors. Among these factors, HAI on urban land and HAI on other construction land play the most important role and they can make a superimposed effect on the change of arable land use pattern.

Compliance with Ethical Standards

Conflict of interest The authors declare no conflict of interest.

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