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Landscape Patterns Affect Precipitation Differing across Sub-climatic Regions

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Received: 24 October 2018; Accepted: 14 December 2018; Published: 19 December 2018

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Abstract: Assessment of the impacts of landscape patterns on regional precipitation will help improve ecosystem management and strategies for adaption to global changes. This study aimed to identify the key landscape metrics that affect precipitation across three sub-climatic regions in Inner Mongolia, China, using 266 landscape metrics and daily precipitation data from 38 weather stations for 1995, 2000, 2005, and 2015. Pearson correlation, stepwise linear regression, and Redundancy analysis were used to identify the contributions of landscape patterns to local precipitation in each sub-climatic region. Three-year datasets were used for model development and a one-year data set was used for validation. It was found that the contribution of landscape patterns is higher than that of climatic variations in semi-arid or humid regions. The Core Area Coefficient of Variance (CACoV) of grasslands and Landscape Area (TLA) in non-irrigated croplands have a negative relationship with precipitation in arid regions. Further, the Total Core Area Index (TCAI) of grasslands has a negative correlation with precipitation, while the area proportion (C%LAND) in waters has a significant positive relationship with precipitation in semi-arid regions. Additionally, the Mean Core Area (MCA), Core Area (CA), and Core Area Standard Deviation (CASD) of grasslands and Total Core Area Index (TCAI) of waters are negatively related to precipitation in humid regions. Suitable land use configuration and composition, especially the proportion of grasslands and waters, should be considered in ecosystem management for alleviating the possible harmful effects due to climate change.

Keywords: precipitation variation; landscape metrics; attribute analysis; stepwise regression model; redundancy analysis

1. Introduction

Climate change is the core issue and has important content for global environmental change research [1]. According to the IPCC Fourth Assessment Report, the global average surface temperature has risen by 0.74 °C in the past 100 years, precipitation and water resources in the mid-latitude regions of world will decrease and middle and high latitude regions may increase in 2100 [2]. Land use/cover change (LUCC) is a significant driving force of regional and global climate change, and it may also induce other ecological, environmental, and climatic results [3]. LUCC could impact mesoscale convective development and circulation, meso and regional-scale heat and moisture fluxes, precipitation, and temperature. Many local, regional, and global-scale studies have demonstrated this assertion [4,5]. Regional climate change, especially regional precipitation is sensitive to LUCC, and the respond may not be limited to only areas where LUCC occurs [6].

A better understanding of how land use influences precipitation patterns is of great scientific and economic importance, and is currently a widespread concern [7–11]. Relations between land cover types and precipitation in Northern Europe have been examined in many studies [12]. Eastern Siberia possesses a vast region of coniferous forest known as taiga; taiga plays an important role in the hydro-circulation, leads to very dry conditions with a total annual precipitation of 200-300mm [13]. Transpiration in the tropical Amazon forests increases water supply, which promotes precipitation [14]. Forests in temperate humid regions of East Asia and Europe experience increased rainfall due to increased surface roughness and intensifying atmospheric vertical motion [15,16]. In temperate and semi-arid regions, three-North shelterbelt forests can also increase regional precipitation [17]. In addition, some simulation studies have found that the changeover from forests to farmland generally results in reduced precipitation, approximately 12.8% from 1990 to 2000 in India [18]. By the simulation model study in the Huang-Huai-Hai region, China, agricultural area expansion from natural land uses can also weaken water vapor supply, and as a result, causes precipitation reduction [19]. By only considering the changes in LUCC, the annual precipitation shows a declining trend in the next 50 years in South China, and an increasing trend until 2050 in Northern China in the model study [6]. Meanwhile, an obvious variation across study sites is also demonstrated [20].

Most past studies have focused on the effects of LUCC on precipitation, however, the effects of land use composition and configuration, as well as land sue area, shape, and edge characteristics, i.e, the effect of landscape pattern on precipitation, are still not well researched. Landscape metrics are quantitative indictors to indicate landscape patterns [21–23]. Hundreds of landscape metrics have been developed to characterize landscape patterns for various land uses at multiple scales [24,25]. A variety of redundant information exists among these metrics, and only very few indices contain unique information about ecological pattern, function, and processes of a specific landscape area. Identification of the key metrics is essential to explore the relationship between landscape pattern and ecological process, as precipitation [26,27]. Many studies have found that landscape metrics evidently affect regional temperature [28,29]. As a closed component in regional climate, we can reasonably assume that landscape patterns also influence regional precipitation.

Inner Mongolia, China, has a semi-arid to arid continental climate with a significant proportion of forest, grassland, and desert from the West to the Northeastern [30]. Generally, there is a drying trend in the whole of Inner Mongolia, and severe droughts were revealed at multi-time scale during the past 500 years [31]. Due to the arid climate, the ecological environment of Inner Mongolia is very vulnerable, especially for animal husbandry. As one key industry, it has a strong dependence on local climate, which is mostly precipitation [4,32]. Hence, it is necessary to explore the interrelationship between landscape pattern and precipitation and how landscape pattern has an influence on regional precipitation. Few studies have compared and analyzed landscape pattern affect precipitation across different sub-climatic regions. In this study, we chose three representative sub-climatic regions, Alxa League, Xilingol League, and Hulun buir, to determine (1) if landscape patterns affect local annual precipitation in different sub-climatic regions, and (2) which landscape metrics (Appendix A) are key ones in annual precipitation in each sub-climatic region.

2. Materials

2.1. Study Area

The Inner Mongolia Autonomous Region of Northern China covers an area of 1.18 million km^2, which is the important grazing base and national ecological protection shelter. It is located between 37°–54° N and 97°–127° E with a mean elevation of about 1000 m. Inner Mongolia, with a temperate continental monsoonal climate, has a cold and long winter and a warm and short summer. The study area, including Alxa League, Xilingol League, and Hulun buir, are regions of typical transitional zones in different climatic zones (Figure 1). Alxa League (37°–42° N, 97°–106° E) is located at the Western end of Inner Mongolia, which far from the sea and surrounded by mountains and forms a typical continental climate. Arid and lack of rain, with more wind, greatly differs temperature differs between day and night. The region landform is mainly composed of the Gobi Desert, sandy lands, hilly areas, and low mountains. Xilingol League (43°–44° N, 115°–117° E) is located at the middle of Inner Mongolia. Its main climate is windy, arid, and cold. The landform of the region is the high grassland plains as the main body. Hulun buir (47°–53° N, 115°–126° E) is named after Hulun Lake and Bell Lake, and it is located in the Northeastern part of Inner Mongolia and is one of the four largest grasslands in China and is known to be one of the best grasslands in the world. It belongs to the significant continental climate where the winter is cold and long, and the summer is cool and short. On the whole, from Alxa, Xilingol to Hunlun buir, the main types of landscape are from desert to grassland to forests as well. It is an ideal area to study landscape pattern-precipitation correlation across different sub-climatic types.

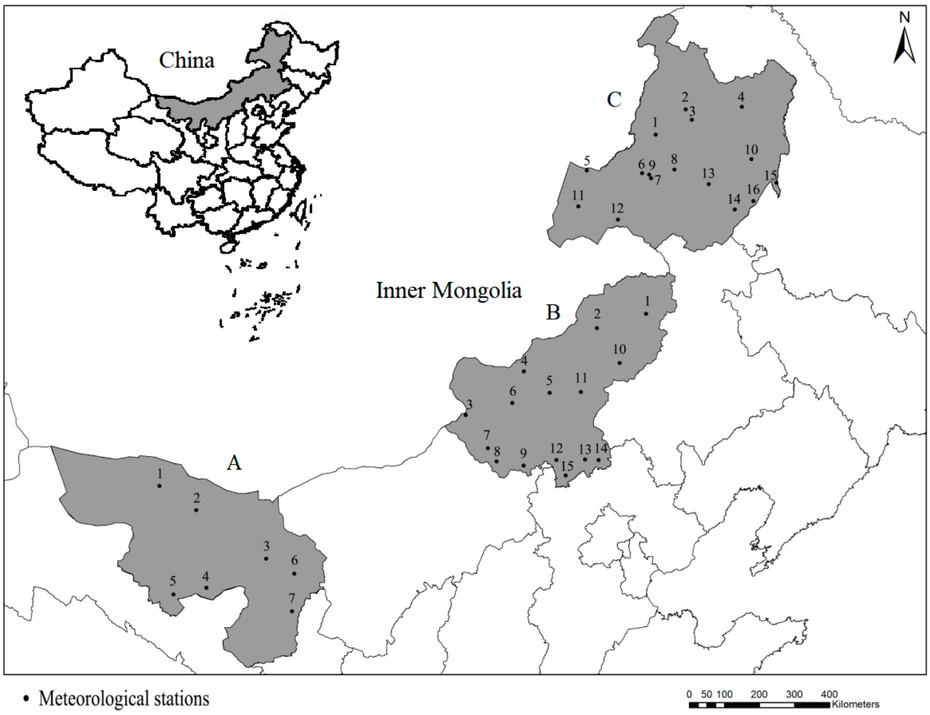


Figure 1. Location of the study areas: three sub-climatic regions A (Alxa League), B (Xilingol League), and C (Hulun buir) of Inner Mongolia in the North of China, and the numbers of meteorological stations are marked in the map.

2.2. Data Sources

2.2.1. Landscape Classification data

The well-classified landscape dataset of three study areas in 1995, 2005, 2010, and 2015 were provided by Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). A total of nine land use/cover categories include Forest, Shrub, Grass, Non-irrigated cropland, Irrigated cropland, Water, Bare lands, Buildings, and Desert at 30m resolution. We defined the landscape categories as forestland-1, shrubland-2, grassland-3, non-irrigated cropland-4, irrigated cropland-5, water-6, bareland-7, buildings-8, and desert-9 of three regions in 1995, 2005, and 2015 (Figure 2).

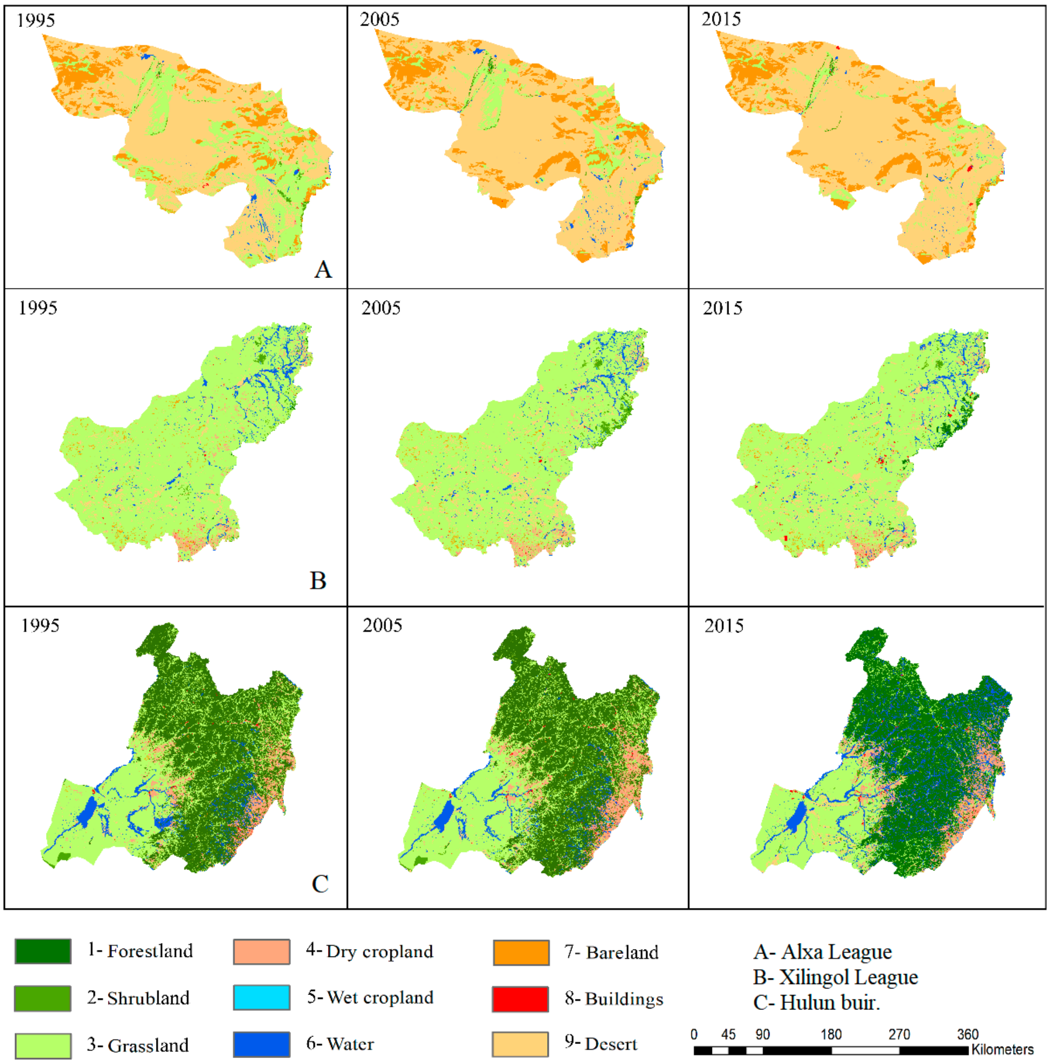


Figure 2. The land use/cover categories of three sub-climatic regions (from left to right) in 1995, 2005, and 2015. A—Alxa League, B—Xilingol League, and C—Hulun buir.

2.2.2. Precipitation Data

This study selected precipitation observation daily data from 38 meteorological stations in three regions from 1966 to 2015. The data was provided by the Meteorological Administration of China and passed preliminary quality control (Ren et al. 2000).

The precipitation data (annual precipitation of 1995,2005, 2010, and 2015) in Inner Mongolia used in this study was acquired from Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn) at 1000m resolution.

3. Methodology

3.1. Climate Attribution Analysis

Research shows that regional climate variation (temperature and precipitation) may be influenced by both natural climatic fluctuations, as well as landscape pattern change caused by human activities [3,4,33]. In order to quantitatively assess the effects of landscape pattern on precipitation, it needs to discern the contributions of natural climatic variation to precipitation. Therefore, we take a simple approach to extract information directly from observations. First, we reference the method mentioned by Fan et al. [4] in their study on natural climatic variation attribution analysis.

The method proposed takes into consideration the reality that variation of local landscape pattern is closely associated with local climate change instead of neglecting the interaction between landscape pattern change and natural global climatic change, and it avoided extensive modelling experiments [34]. Landscape pattern may have contributed to the climate variation in addition to natural climate fluctuation. Using precipitation as a response variable, the actual precipitation can be expressed as:

$$P = \overline{P} + P'_C + P'_L SR = C_t/C_o = e^{-kIt}, \quad (1)$$

$$P'_C = (P_n - P_{n-1})/38, \quad (2)$$

For equation (1), P represents the actual annual precipitation in every year of 1995, 2005, 2010, and 2015, $\overline{P}$ is the average annual precipitation during 1965–2015, and P'_C is the variation in precipitation caused by climate natural fluctuation across two years (subscript "C" represents climate variation). P'_L is the variation in precipitation caused by landscape pattern (subscript "L" represents landscape pattern). In Equation (2), P_n represents the total annual precipitation of all meteorological stations in three regions on 1995, 2005, 2010, and 2015, and P_{n-1} represents that of the last year, respectively. Thirty-eight in Equation (2) indicates the account of weather stations. The relative contribution from natural climatic and landscape pattern can be estimated and measured by the following contribution ratios, as defined using standard deviations (denoted by σ):

$$r_C = \sigma_{P'_C}/\sigma_P SR = C_t/C_o = e^{-kIt}, \quad (3)$$

$$r_L = \sigma_{P'_L}/\sigma_P SR = C_t/C_o = e^{-kIt}, \quad (4)$$

where r_C and r_L represent the contribution ratios of climate variation and landscape pattern, respectively. The utilization of standardized data further assures that the above inference and calculation is appropriate.

3.2. Landscape Pattern Metrics

The complexity and diversity of spatial-temporal scale changes in landscape patterns and processes are reflected in the response of landscape pattern metrics [35]. According to previous researches [36,37], land use/cover has a significant effect on temperature and precipitation in the 4 km buffer zone of the weather station (a circle with 4-km radius). Therefore, this paper takes the 4 km buffer to analyze the extent and to calculate the landscape metrics of the 4 km-radius circle surrounding each meteorological station in three regions, in four years total. The landscape and class metrics of each buffer are calculated in Patch Analyst module of ArcGIS 10.4 software. There are 26 metrics at class level for nine types of land use/cover, and 32 indices at landscape level for the entire landscape, a total of 266 landscape metrics in each circle are calculated. In order to avoid redundant information among landscape metrics, try to find out key metrics that can reflect the characteristics of landscape, and what is closely associated with precipitation; stepwise linear regression was used by considering multi-collinearity (see below for details).

3.3. The Development and Validation of Predict Models

In order to select the optimal landscape metrics, the stepwise regression model was applied to regress the precipitation (spatial interpolation precipitation data) and landscape metrics in three regions to obtain the optimal regression model, and the metrics remaining in the model are the optima metrics. The formula of the stepwise regression is Equation (5):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k, \quad (5)$$

where Y is explanatory variables; β_0 is regression constant; β_1 is the partial regression coefficient of the independent variable X_1; β_2 is the partial regression coefficient of the independent variable X_2;

β_k is the partial regression coefficient of the independent variable X_k; and k is the number of independent variables. Compare the regression models in three regions and select the largest R^2 and lowest collinearity (VIF) as the optimal model.

The dataset of 1995, 2005, and 2015 were used for model development and those of 2010 were used for validation. In this study, in order to test the accurate of the proposed regression models, and to confirm whether the selected key landscape metrics are essential to the models, we used the dataset of landscape pattern and annual precipitation in 2010 to validate the proposed stepwise regression models. This indicates high accuracy that will be regarded as the best models in predicting precipitation, and hence, the landscape variables in the best models were regarded as key landscape components affecting local weather.

3.4. Redundancy Analysis (RDA)

RDA was applied to separate the multiple correlations among the landscape metrics and their relations with the annual precipitation. RDA is a direct gradient analysis method, and from the perspective of statistics, it assesses the relationship between one or a group of variables and another group of multivariate data [38,39]. This method permits the determination of the relative importance of landscape metrics with respect to the spatial variability of the dependent variables. We used the landscape pattern metrics as explanatory variables in a forward selection in RDA and used the annual precipitation data loading as the dependent matrix. In the RDA figure, the longer vector arrow indicates more important landscape metrics; the cosine of the vector represents the relation between the landscape metrics and precipitation. The same direction indicates positive correlation, however, opposing directions show negative correlations [38–40]. RDA was performed through the application of Canoco software for Windows 4.5 [39,40].

4. Results

4.1. Annual Precipitation Variation

Studies have shown that the temperature has increased significantly and precipitation has decreased in most areas of Inner Mongolia in the past 50 years, which shows a strong dry tendency [39]. Figure 3 shows the annual precipitation recorded at meteorological stations in the three regions in 1995, 2005, and 2015. For Alxa League, both the maximum and minimum annual precipitation recordes show a trend of initail decrease and then increase after a point. For Xilingol League, the maximum and minimum of annual precipitation of weather stations have the same trend with Alxa League. Annual precipitation changes in Hulun buir are different with both of them. For the maximum value, it keeps an increasing trend, the minimum annual precipitation has the same trend as Alxa and Xilingol.

We calculated the mean annual precipitation for the 50 years period, from 1966 to 2015, for the three regions (Figure 4), and they differently demonstrate each other, which are also largely different to the 50-year average annual precipitation. For the meteorological stations in Alxa League (Figure 4a), the annual precipitation of all meteorological stations of 1995 and 2015 fluctuated around the 50-year average value, except for 2005. For the 1,2,3,7 meteorological stations, the annual precipitation in 1995 was the largest, and in 2005, it was the least, and the land surfaces of these stations were converted from grasslands to buildings. As for stations 4 and 5, while the annual precipitation was the largest in 2015 and smallest in 1995, the land surface remained unchanged as desert. For meteorological station 6, the precipitation in 2005 was much higher than that in 2015, and during that time, the underlying surface of the station was transformed from shrubland to grassland. We can infer that grasslands and buildings have some effects on annual precipitation; this connection is explored in Section 4.3. For the meteorological stations in Xilingol League (Figure 4b), the annual precipitation amounts were recorded between 1995 and 2015 and also fluctuated around the 50-year average value. The underlying land surfaces at these meteorological stations also varied and included desert, grassland, and buildings. The landscape type near some stations was transformed from buildings to grasslands, and the annual precipitation had a decreasing trend when this occurred; this trend was also found when land was converted from grasslands to built-up land around stations. Therefore, only considering the influence of landscape types on annual precipitation is not enough, landscape pattern may also exert an effect on precipitation. The annual precipitation in Hulun Buir is more regular over the 50-year period and has a moist trend (Figure 4c). For the three regions, the annual precipitation variation in different years is smaller, but there was a dry trend in 2005, which may be related to the climate in the larger context.

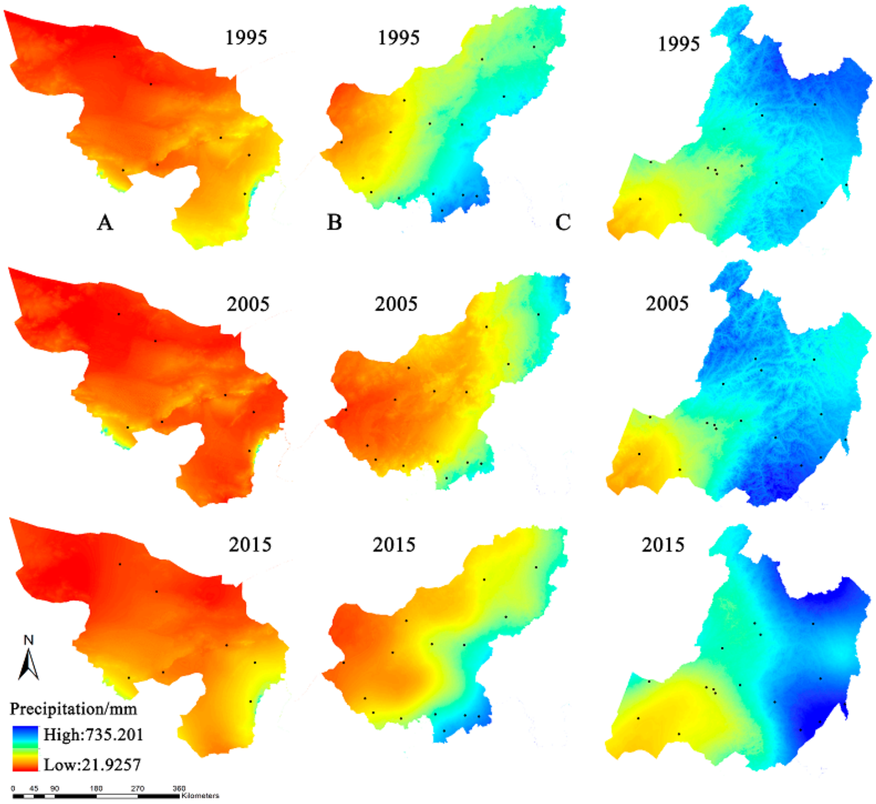


Figure 3. Annual precipitation (mm) in three sub-climatic regions (from left to right) in 1995, 2005, 2015. A—Alxa League, B—Xilingol League, and C—Hulun buir.

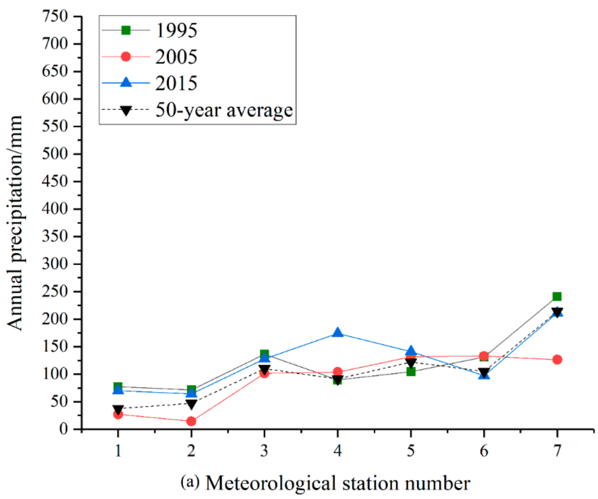


Figure 4. *Cont.*

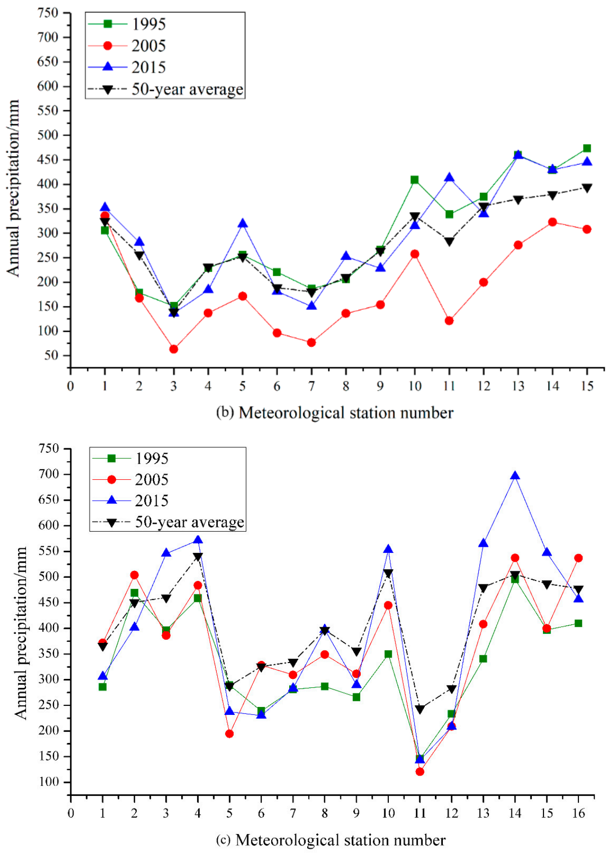
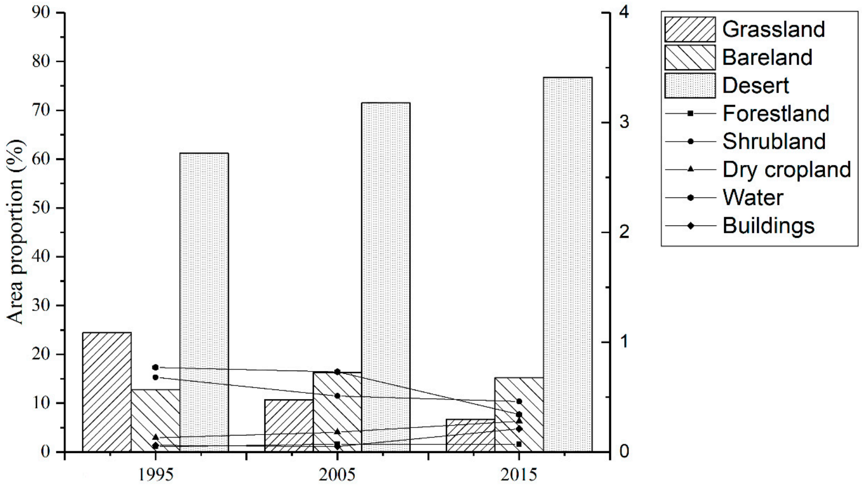


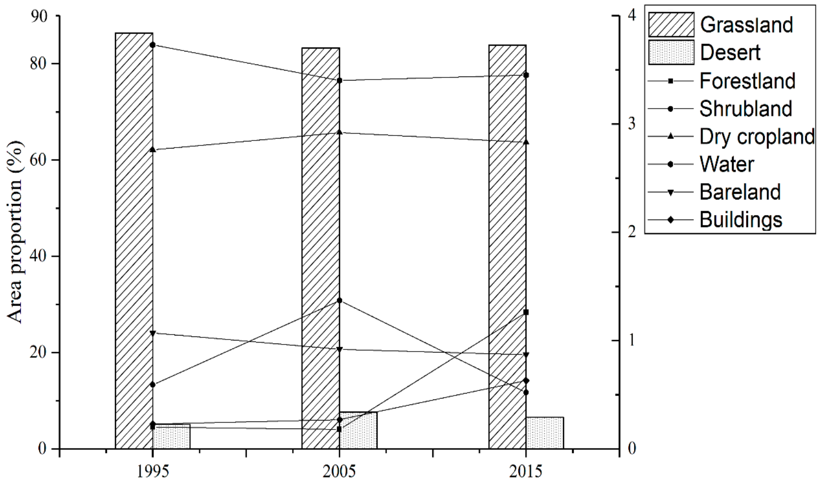
Figure 4. The annual precipitation of each weather station in (**a**) Alxa League, (**b**) Xilingol League, and (**c**) Hulun buir in 1995, 2005, 2015, and 50-year average annual precipitation.

4.2. Land Use/Cover Changes

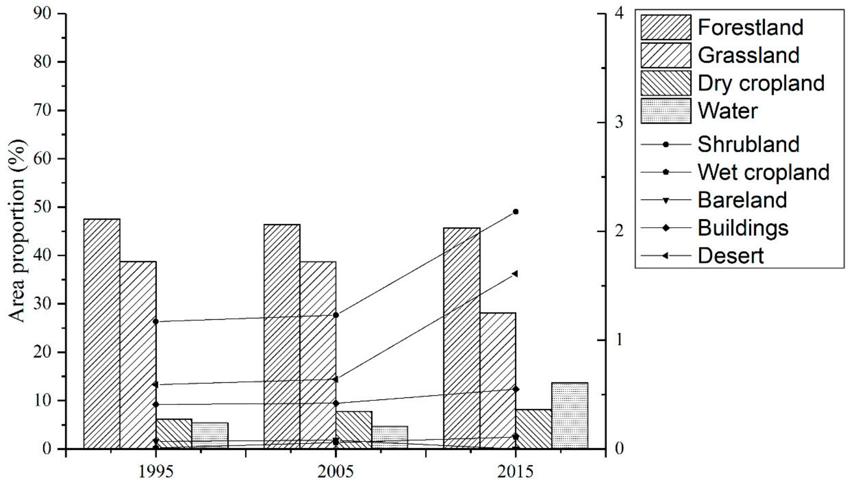
Over the past few decades, the implementation of ecological projects, such as the reclamation of large areas of natural forests and grasslands, reduction of overgrazing, and the conversion of farmland to forests via natural forest projects, has resulted in dramatic changes in Inner Mongolia landscapes [40]. It was found that the dominant landscape type varied between the three study areas: (1) Grassland, bareland, and desert are the major types in Alxa League: Up to 98% of the total area (Figure 5a). During the period of the study, the proportion of desert area increased from 61.15% to 71.53%, the proportion of grassland area reduced from 24.4% to 6.72%, and there was no obvious change in the proportion of barelands with only a variation of 3%. (2) In Xilingol League, grassland is the only dominant landscape type, covering more than 80% of the area (Figure 5b). Grassland area decreased from 86.36% to 83.26% during the 1995-2005 period, and then increased by 6.4% between 2005 and 2015. The variation in the proportion of desert area trended inverse to the proportion of grassland. This may be related to the policies of "governance sand and desert" and "the Grain for Green Project (GFGP)" that were proposed in 2000 in the Xilingol League. (3) In Hulun Buir, forestland, grassland, non-irrigated cropland, and water are the main landscape types, which account for 97% of the total area (Figure 5c). For forestland, the proportion first increased and then decreased during the study period, but the proportion of reduction was not obvious. Grassland area proportion decreased from 38.75% to 28.09%, and the cropland continued to expand from 6.16% to 8.14%, owing to human activities. At the same time, the water area increased from 5.36% to 13.62%. It also suggests that the increasing area of water contributes to precipitation, which may affect the precipitation reliant agriculture of the area (Figures 3 and 4c).



(a)



(b)



(c)

Figure 5. Area proportion of nine landscape types in (**a**) Alxa League, (**b**) Xilingol League, and (**c**) Hulun buir. Due to the area proportion of dominated landscape type in three regions are much higher than others, and in order to clearly indicate the changes of other landscape types area, the columns indicate the variation in the dominant landscape type area at the left side and the solid lines indicates the other landscape type area changes at the right side.

4.3. Attribution Analysis

4.3.1. The Attribution Ratio of Climate and Landscape Pattern on Precipitation

We use the standardized data (the mean subtracted and the result divided by eliminating impacts from deviation) according to Formula (1)–(4), to obtain the values of r_C and r_L in Table 1. The focus of this analysis was on climatic changes and landscape patterns, using the above formulas to eliminate impacts from latitude, elevation, and other localized factors. The r_C value for the Alxa League is greater than that of the Xilingol League and Hulun Buir, implying that there is a greater spatial variation in the Western arid zones than in the middle and Northeast humid zones. The dominant landscape pattern in the Alxa League is desert, it is grassland in the Xilingol League, and forestland, grassland, and water in Hulun Buir; this suggests that the fragile ecological environment in the West is vulnerable to natural climatic variations. Forestland and grassland can maintain a more stable state and resist climate changes to some extent. For the three regions, the contribution of climate variation was greater in 1995 than in 2015, which in turn was greater than that in 2005. This can partially explain why the annual precipitation in 2005 in the three areas was less than that in 1995 and 2015. Since the influence of climate variation on precipitation is less than that of landscape pattern (see Table 1), the value of r_L is high in 2005 across the three regions.

Owing to the complex nature of precipitation, many factors other than the two considered herein may contribute to precipitation variation [4]. Nonetheless, the difference in r_L among the regions suggests that landscape patterns may have stronger impacts in the Western arid area than in the relatively wet areas in the Middle and the Northeast (Table 1). One possible reason is that landscape pattern changes in less vegetated arid desert regions can modify evapotranspiration and associated latent heat partitions more than those in the densely vegetated forestlands and grasslands. r_L values were higher in the Alxa League and Xilingol League in 2005 than in the other years, and our filed survey also confirmed that the landscape pattern changed dramatically around 2005 (Figure 5). This suggests that landscape pattern change had a greater impact on precipitation in these two regions. In the Hulun Buir region, the impact of landscape pattern change on local precipitation is gradually decreasing.

Table 1. The contribution ratio of climate variation and landscape pattern to annual precipitation in the three sub-climatic regions.

	Alxa League			**Xilingol League**			**Hulun buir**		
	1995	2005	2015	1995	2005	2015	1995	2005	2015
r_C	0.34	0.13	0.28	0.18	0.07	0.14	0.20	0.05	0.09
r_L	0.21	0.64	0.43	0.24	0.42	0.25	0.49	0.28	0.25

4.3.2. The Influence of Landscape Pattern on Precipitation

The regression equations for the effects of landscape metrics on annual precipitation in the three regions were proposed by comparing R^2 and collinearity (VIF) (Table 2). We defined the landscape categories as forestland-1, shrubland-2, grassland-3, non-irrigated cropland-4, irrigated cropland-5, water-6, bareland-7, built-up area-8, and desert-9. In the three areas, the p value of the regression model was less than 0.05; this means that the regression model was reliable. According to the largest R^2 and lowest VIF values, three optimal models were selected. The key landscape metrics identified in the Alxa League region are CACoV in glasslands and TLA in non-irrigated croplands; in the Xilingol League region, the key metrics are TCAI in grasslands and C%LAND in waters; and in the Hulun Buir region, they are MCA, CA, and CASD in grasslands and TCAI in waters.

Table 2. The equations for stepwise regression with annual precipitation, based on the landscape metrics of the three sub-climatic regions.

Study Areas	Equation	R^2	Adjusted R^2
Alxa League	Y=160.322-0.646CACOV-3	0.359	0.325
	Y=-1821591.191-0.632CACOV-3+362.535TLA-4	0.603	0.559
Xilingol League	Y=1882.397-17.296*TCAI-3	0.451	0.438
	Y=1801.188-17.015*TCAI-3+8.815*CLAND-6	0.548	0.526
Hulun buir	Y=466.73-0.052*CA-3	0.422	0.410
	Y=489.315-0.086*CA-3+0.047*MCA-3	0.536	0.515
	Y=500.683-0.141*CA-3+0.097*MCA-3+0.119*CASD-3	0.609	0.583
	Y=630.986-0.132*CA-3+0.092*MCA-3+0.106*CASD-3-1.642*TCAI-6	0.649	0.616

Based on the above regression equations in Table 2, we used the precipitation data collected at the meteorological stations in the regions to verify the predicted values calculated by the regression equations. The results showed that the p values were less than 0.05, which indicates that the model and the selected optimal landscape metrics were appropriate. The R2 value of Hulun Buir is the largest of the regions; this illustrates that the measured values agreed with the predicted values (Figure 6).

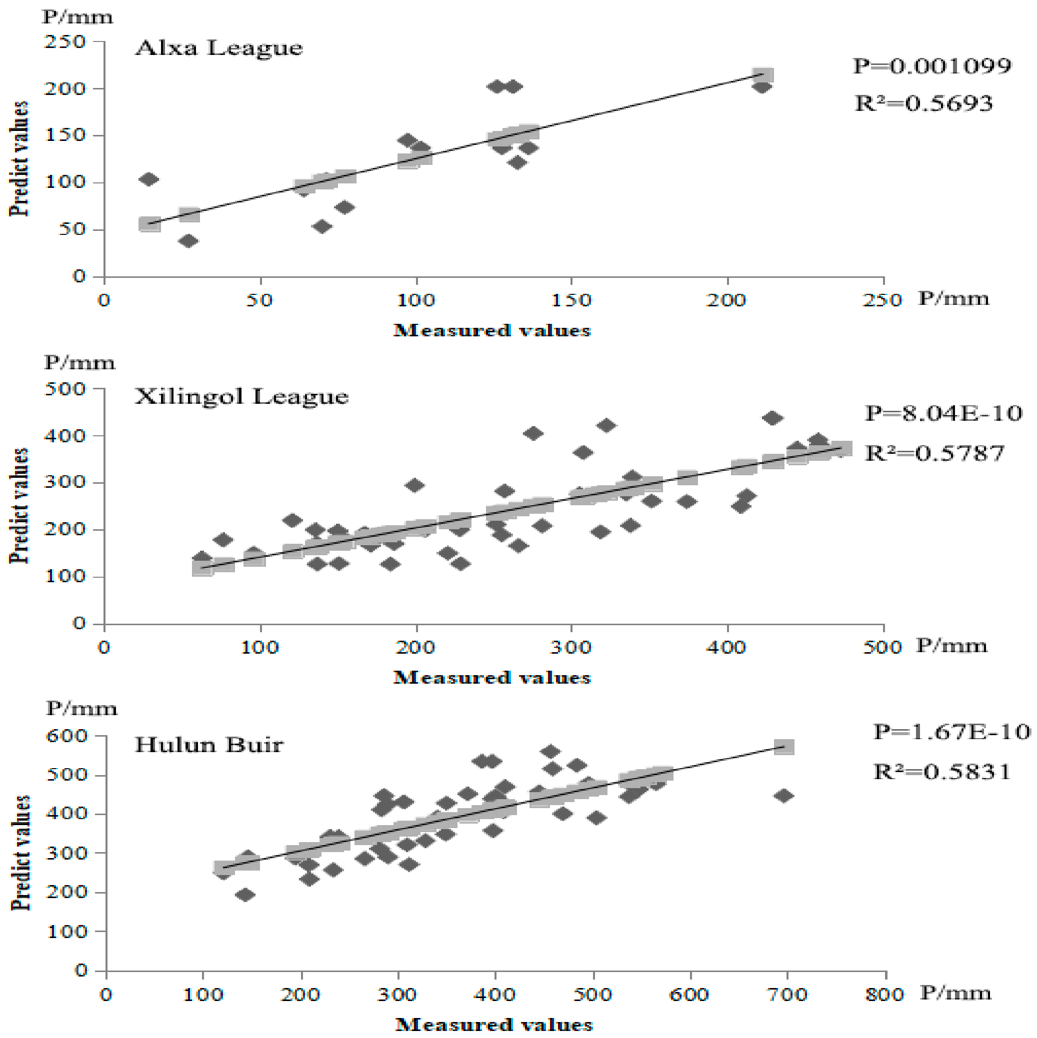


Figure 6. The Linear regression of the field measured values (x-axis) and predicted values (y-axis) for annual precipitations in three sub-climatic regions.

4.3.3. Multiple Correlations among Landscape Metrics and Precipitation

RDA figures indicate that landscape pattern has almost the same effect on precipitation, and only differs across types and strengths across three regions (Figure 7). The landscape metrics of grasslands have nearly the same negative effects across the three regions, which suggests that grasslands have a greater impact on precipitation than the other types. Some research suggests that conversion to built-up lands has a greater effect on surface morphology, radiation, and heat, thus altering the local precipitation of an urban area [32]. In this study, the proportion of built-up lands is relatively small, at less than 0.5% in the three regions. Therefore, its impact on precipitation in the regions is negligible.

In the Alxa League, the metrics of CACoV in grasslands and TLA in non-irrigated croplands are negatively related to precipitation, meaning that the larger the variation in core grassland area and the greater the area of cropland, the smaller the precipitation amount. In the Xilingol League, the amount of core area in grasslands is negatively related to precipitation, and the proportion of water area is significantly positively related to precipitation. This illustrates that waters play an important role in regional precipitation in the Xilingol League. In the Hulun Buir region, the optimal landscape metrics obtained via a regression model demonstrates a negative relationship with precipitation. Since different sub-climatic regions have different climatic backgrounds, correlations between landscape pattern and precipitation varied from region to region. Therefore, there is no model that can be applied to all regions.

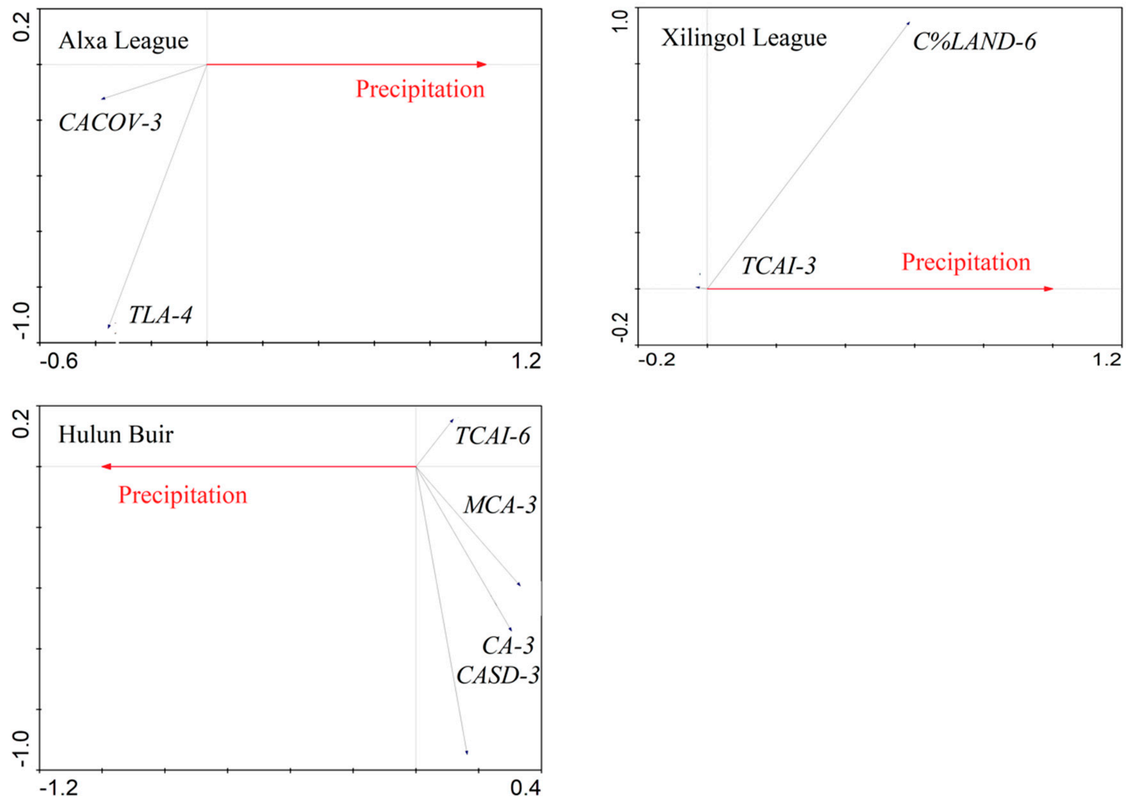


Figure 7. RDA between landscape metrics and annual precipitation in three sub-climatic regions.

5. Discussion

5.1. Landscape Metrics Selection

Landscape metrics have been developed to describe patch edge, shape, diversity, evenness, and interspersion of landscapes [41,42]. They may be closely associated with various ecological processes such as the hydrologic cycle [43]. Unfortunately, the calculation of these metrics is hampered by the difficulty of replicating large-scale experiments and the complicated responses of the metrics to changes in spatial scale and pattern [34]. The utilization of landscape metrics is also limited by their capabilities, sensitivities, and methods of derivation [39,41]. In addition, it can be very challenging and even misleading to represent particular landscape patterns by setting specific landscape metrics [44]. As a result, it is essential to select the correct landscape metrics in which interpretation can be highly or perfectly connected to one specific ecological function. These metrics can be ecosystem and species specific because they have not been explicitly used to ensure that the simulated pattern is best fitted to the actual ones [35,45]. Most metrics exhibit a specific behavior, and there also exists a domain of the scale effect [46]. Therefore, in this paper, we used the Pearson correlation analysis for primary selection, and the stepwise linear regression for further filtering the 266 metrics at the class and landscape levels to screen the significant metrics of the three sub-climatic regions for 1995, 2005, and 2015, at the 0.01 and 0.05 levels.

5.2. Distinguish the Impacts of Natural Climatic Variation and Landscape Pattern

Changes in the landscape pattern alter the underlying conditions of the atmosphere, eventually feeding back into and influencing the climate. The observed precipitation is also an effect of natural climatic change [12]. The means, to distinguish between the impacts of climate change and landscape pattern on local precipitation is crucial for ecosystem management and the development of land use policies. Atmospheric circulation affects large territories in the highest magnitude by determining precipitation, and local landscape patterns can also have a permanent influence on the precipitation, which differs spatially. Further, the variability of precipitation is mostly related to variations in the large-scale atmosphere circulation. Therefore, under the climate change background, the variation in circulation regimes may cause a difference in precipitation in different regions. For instance, surface warming results in greater convection, and therefore, the convective precipitation increases [47]. The changes occurring in the surface parameters, including emissivity, albedo, and roughness, when areas are converted from natural vegetation to farmland, may have important climatic implications [48]. In the present study, we improved the method to determine the relative effects of natural climatic variations and landscape pattern changes on precipitation in the three sub-climatic regions. We standardized data to eliminate the influence of latitude, elevation, and other localized factors. This will help us in the detection and attribution of landscape and climate changes, and in the projection of future precipitation changes under different land use scenarios. The results of our present study also show the same trends as those determined in previous studies [47,48].

5.3. Contribution of Landscape Pattern

Landscape pattern (including configuration and composition) has significant effects on many ecological processes [49,50]. In this study, different landscape patterns for the same land use type were found to have different influences on precipitation, but the area-related landscape metrics of grasslands all had negative relationships with precipitation in the three regions. As for water, it was the largest proportion of the total landscape area and the main contributor to precipitation in the Xilingol League. Yet, in the Hulun Buir region, the number of water core patches was negatively related to precipitation. Therefore, the influence of landscape pattern on precipitation is different in different regions under various climatic backgrounds. Moreover, the indices of landscape pattern that are related with precipitation are more significant at the class level than at the landscape level, which means that the metrics of main land use have closer relationships to precipitation than those of land use mosaics. Thus, a suitable pattern of grasslands and waters in semi-arid areas can considerably regulate local precipitation. In fact, landscape patterns should be taken into full account in land use planning and management in order to minimize the possible harmful impacts of global climate change.

6. Conclusions

This study examined the relationship between landscape patterns and annual precipitation in three sub-climatic regions in Inner Mongolia using the daily precipitation observation data from the Meteorological Administration of China, the spatial interpolation precipitation data from Data Center for Resources and Environmental Sciences, and the well-classified landscape data for 1995, 2005, 2010, and 2015. Through the use of standardized data, the contribution ratios of natural climatic variations and landscape pattern changes on precipitation were calculated, respectively, and the Pearson correlation analysis, regression models, and redundancy analysis were used to determine which landscape metrics are most influential and how they influence precipitation. The contribution ratio of landscape pattern was higher in the Alxa League and Xilingol League than in Hulun Buir, since landscape pattern changes in less vegetated arid desert regions can modify evapotranspiration and have associated latent heat partitions, more than those in the densely vegetated forests and grassland regions. Regression analysis was carried out on the three regions to develop regression models on precipitation. The proposed models, based on key landscape metrics, were proven to be able to accurately predict annual precipitation, by using 2010 data for validation. Through RDA, key metrics demonstrated different relations to precipitation, as well as within metrics. Generally, landscape metrics, mainly core area and proportion of grassland, have negative relationships with precipitation; areas with water have significantly positive relationships with local precipitation in semi-arid regions. Correlations between landscape patterns and precipitation varied from region to region; there is no model that can be applied to all regions.

Management of land uses in arid and semi-arid areas to sustain precipitation would require optimizing land use, as suggested by the current study. Landscapes that encompass a variety of land uses, such as small grasslands, croplands, land with a relatively large proportion of forests, and land with shrubs or ponds, and occupy an area within a 4 km-radius, are proposed as ideal for enhancing local precipitation in arid and semi-arid regions in Inner Mongolia. For other arid and semi-arid areas on Earth, this case study may present a clue on how to recognize suitable landscape patterns and spatial scales to potentially enhance precipitation, thus providing useful information for weakening the global drying tendency and improving the sustainable landscape administration.

Author Contributions: Y.P. conceived and designed the study; Y.P. and Q.W. collected and analyzed the data; Q.W., M.F., Z.Z., and Q.C. performed the field survey; Q.W. prepared the paper draft and Y.P. reviewed and revised the paper.

Acknowledgments: The study was financially supported by the National Key Research and Development Program of China (Project No. 2017YFC0505606); the Top Discipline and First-class University Construction Project (Yldxxk201819) of Minzu University of China; the Undergraduate Research and Training Program (URTP2017110024) of Minzu University of China.

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

Appendix A

Table A1. The landscape metrics used in this study.

Landscape metrics name	Scale	Description
Mean nearest index (MPI)	class/landscape	≥0, measuring the proximity of the same type of patches and the fragmentation of the landscape or class
Mean nearest neighbour distance (MNN)	class/landscape	0–1, indicating landscape fragmentation or patch distance increase
Interspersion juxtaposition index (IJI)	class/landscape	0–100, describing the landscape spatial pattern and measuring the interspersion of each patch in the landscape or class
Number of patches (NumP)	class/landscape	≥1, the total number of patches in the landscape or class
Mean patch size (MPS)	class/landscape	>0, indicating the degree of fragmentation and presenting an average condition in the landscape or class
Patch size coefficient of variation (PSCoV)	class/landscape	Coefficient of variation of all patches size
Patch size standard deviance (PSSD)	class/landscape	Patch size standard deviation of all patches

Table A1. *Cont.*

Landscape metrics name	Scale	Description
Total edge (TE)	class/landscape	Total edge of the landscape or class
Edge density (ED)	class/landscape	Amount of edge relative to the landscape or class area
Mean shape index (MSI)	class/landscape	Measuring the shape complexity
Area-weighted mean shape index (AWMSI)	class/landscape	≥1, it equals 1 when all patches are regular
Mean patch fractal dimension (MPFD)	class/landscape	Measuring the shape complexity
Area-weighted mean patch fractal dimension (AWMPFD)	class/landscape	1–2, it equals 2 when all patches are complex and irregular, the usual upper limit of its value is 1.5
Shannon diversity index (SDI)	landscape	≥0, measuring the relative patch diversity
Shannon evenness index (SEI)	landscape	0–1, measuring the patch distribution and abundance
Total core area (TCA)	class/landscape	The total area of disjunctive core patches
Total landscape area (TLA)	Class/landscape	The total area of landscape
Core area density (CAD)	class/landscape	The relative number of disjunctive core patches relative to the landscape or class area
Mean core area (MCA)	class/landscape	The average area of disjunctive core patches
Patch core area standard deviation (CASD)	class/landscape	Patch area standard deviation of core patches
Patch core area coefficient of variation (CACoV)	class/landscape	Coefficient of variation of core patch area
Total core area index (TCAI)	class/landscape	Measuring the amount of core area in the landscape or class
Disjunctive core area coefficient of variation (CACV1)	class/landscape	Coefficient of variation of disjunctive core patch area
Disjunctive core area standard deviation (CASD1)	class/landscape	Patch area standard deviation of disjunctive core patches
Largest patch index (LPI)	class/landscape	0–100, the percentage of the total landscape or class
Landscape shape index (LSI)	class/landscape	Reflecting the complexity of the landscape or class
Mean core area index (MCAI)	class/landscape	The average percentage of a landscape or class patch that is core area
Mean core area per patch (MCA1)	class/landscape	The average core area per patch
Number of core areas (NCA)	class/landscape	The number of core patches in the landscape or class
Modified Simpson's diversity index (MSIDI)	landscape	Measuring the patch diversity, it equals zero when there is only one patch in the landscape and increases as the number of different patch types increases and the area among patch types becomes more equal
Patch richness (PR)	landscape	≥1, the number of different patches within the landscape
Patch richness density (PRD)	landscape	Patch richness is divided by the total area of landscape
Simpson's evenness index (SIEI)	landscape	Measuring the distribution of area among patch types
Modified Simpson's evennessIndex (MSIEI)	landscape	An even distribution of area among patch types in maximum evenness, when it equals 1, the distribution of area is exactly even
Class area (CA)	class	>0, the total area of class
Percent of landscape (%LAND)	class	0–100, the percent of class area in the total landscape
Core area percent of landscape (C%LAND)	class	0–100, the percent of core class area in the total landscape
Double log fractal dimension (DLFD)	class/landscape	Measuring the shape complexity

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