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Human Settlement Evaluation in Mountain Areas Based on Remote Sensing, GIS and Ecological Niche Modeling

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Abstract: The Qinghai–Tibet Plateau is the world's highest and largest plateau. Due to increasing demands for environment exploration and tourism, a large transitional area is required for altitude adaptation. Hehuang valley, which locates in the transition zone between the Loess Plateau and the Qinghai-Tibet Plateau, has convenient transportation and relatively low elevation. Our question is whether the geographic conditions here are appropriate for adapted stay before going into the Qinghai-Tibet Plateau. Therefore, in this study, we examined the potential use of ecological niche modeling (ENM) for mapping current and potential distribution patterns of human settlements. We chose the Maximum Entropy Method (Maxent), an ENM which integrates climate, remote sensing and geographical data, to model distributions and assess land suitability for transition areas. After preprocessing and selection, the correlation between variables and spatial auto-correlation input data were removed and 106 occurrence points and 9 environmental layers were determined as the model inputs. The threshold-independent model performance was reasonable according to 10 times model running, with the area under the curve (AUC) values being 0.917 ± 0.01, and 0.923 ± 0.002 for test data. Cohen's kappa coefficient of model performance was 0.848. Results showed that 82.22% of the study extent was not suitable for human settlement. Of the remaining areas, highly suitable areas accounted for 1.19%, moderately for 5.3% and marginally for 11.28%. These suitable areas totaled 418.79 km², and 86.25% of the sample data was identified in the different gradient of suitable area. The decisive environmental factors were slope and two climate variables: mean diurnal temperature range and temperature seasonality. Our model showed a good performance in mapping and assessing human settlements. This study provides the first predicted potential habitat distribution map for human settlement in Ledu County, which could also help in land use management.

Keywords: Human settlement; Remote sensing; Suitability assessment; Ecological niche modeling

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Introduction

The Qinghai-Tibet Plateau is the highest and largest plateau in the world, with an average elevation exceeding 4,500 meters and an area of 2,500,000 square kilometers. There is increasingly effort on exploring the Qinghai–Tibet Plateau due to its significant role in local and global environment and climate change studies, such as atmosphere-land interaction observations, rangeland degradation, inland lake area and wetland landscape changes, snow cover monitoring, air temperatures on soil thermal and hydrologic processes, etc (Qiu et al. 2009; Lu et al. 2011; Ma et al. 2009; Li et al. 2011; Bai et al. 2012; Immerzeel et al. 2009). However, the numbers of observation sites on the plateau, which require suitable human habitats, are quite limited (Lu et al. 2011). The tourism industry of Qinghai-Tibet Plateau, on the other hand, has been greatly promoted since the Qinghai-Tibet Railway was put into operation (Liu et al. 2006). Additionally, urban population in China has more than tripled in the past three decades with an accelerating rate of urbanization (Gong et al. 2012). To feed its 1.3 billion population with a per capita cultivated land far below the global mean, China is facing a great challenge of land scarcity (Chen 2007). The Qinghai–Tibet Plateau, therefore, could be a potential suitable settlement for human. However, it's not easy for people living in the low elevation areas to adapt to the abrupt elevation changes from plain to the Qinghai-Tibet Plateau, most people need a "step-by-step" adaptation process (Liu et al. 2006). Hehuang valley, located in the transition zone between the Loess Plateau and the Qinghai-Tibet Plateau, has convenient transportation and relatively low elevation. Our question is whether the geographic conditions here are appropriate for adapted stay before going into the Qinghai-Tibet Plateau.

Many researchers have paid their attention to human settlement assessment in costal zones (McGranahan et al. 2007; Small et al. 2003), which have the greatest population density and are the most suitable areas for human settlement. Little attention was paid to the plateau, which might become a suitable area for human settlement with the increasing temperature and changing precipitation patterns from climate change. The popular way to map historic and current human settlement patterns is the remote sensing techniques (Lu et al. 2008; Seto 2009. Feng et al. estimated the human settlement suitability in China (Feng et al. 2008) using index model in 1km resolution, but there is no higher resolution analysis.

In this study, we assess the suitability of human settlements in the transition zone between the Loess Plateau and the Qinghai-Tibet Plateau. In the transition zone, the human activities depend greatly on environmental conditions, where the "human species" has its niche. We applied ecological niche modeling (ENM) in mapping the current and potential distribution of human settlement patterns. Compared with other ecological niche models, the maximum entropy method (Maxent) (Phillips et al. 2006) is one of the best models in suitability modeling, especially for presence-only modeling (Elith et al. 2006; Townsend et al. 2007). Strong gradients in climate variables in the transition zone and spatially refined information on landscape and vegetation heterogeneity provided by remote sensing data can be readily incorporated in models to predict human settlement distribution. We also predict the future suitability for human settlement under climate change by replacing the current climate data with future climate simulation data. The contribution and significance of environmental variables in determining the suitability were also discussed.

1 Study Area

Our study region (between 102°09'E -102°47'E and 36°N-36°40'N) is located in the northeast of Qinghai Province, China, and covers the whole the Ledu County. The study region has 12 tributary streams of the Yellow River, with a total length of about 322 km (Figure 1).

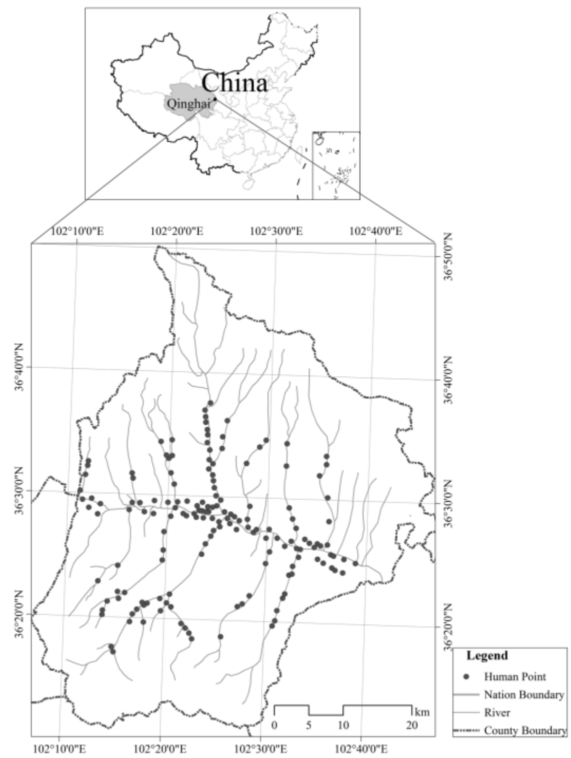

Figure 1 Study area and current human settlements in Qinghai Province, China

Ledu County is located in the typical region of the transition zone between the Loess Plateau and Qinghai-Tibet Plateau, covering three types of geographical conditions. The River Valley Region is suitable for plant growth with altitude between 1,850 and 2,400 m a.s.l., annual precipitation less than 350 mm, annual temperature above 6°C, annual radiation over 145 kcal/cm^3, and frost-free season 140-155 days. The Loess Hilly Region has less precipitation and more evaporation with altitude between 2,000 and 2,600 m a.s.l., annual precipitation 360 to 450 mm, annual temperature 3 to 6°C, annual radiation 130-145 kcal/cm^3, and frost-free season of 107 to 137 days. The Rock Mountain region has an altitude of over 2,600m, annual precipitation 460-500 mm, annual temperature 1-3°C, annual radiation 130 kcal/cm^3, frost-free season of 99-57 days. Abundant rainfall in the region is suitable for the growth and development of forest vegetation, but growing season is shorter because of the lack of heat.

2 Data Collection and Analysis

The current human settlement map was provided by local government and digitalized in ArcGIS 9.3 Desktop (ESRI) environment. These original 288 points were mapped according to the administrative division. We modified them to the geographic patterns based on registered HJ images and GPS points recorded in field survey. Only 160 of them were geographically positioned inside the patterns (Figure 1). We selected these locations larger than 0.09 km^2, which was supposed appropriate for human settlement. The rest 128 villages were too small to be identified in satellite images, so they were ignored in the model training in our 30 m scale study.

The precision of these samples was verified by high-resolution remote sensing images in Google earth. Here we hypothesized that the settlement pattern had the same attribute and ecological niche, this validation only make sure that the training data were exactly inside the patterns.

2.1 Environmental data

2.1.1 Climate data

Climatic tolerance is likely to be an important driver for the distribution of human settlements. We thus used the spatially explicit climatic data available from the WorldClim, version 1.4 database (Hijmans et al. 2005), downloaded from website (http://www.worldclim.org/). The WorldClim data was interpolated using ANUSPLIN model based on observing data from 47,554 meteorological sites globally, which has a spatial resolution of 1 km. The pixel value in China was averaged from data between 1955 and 2000. The WorldClim dataset contained 19 bioclim variables which represent the variation trend, seasonality and extreme limiting factors. These bioclim variables have significant biological meanings and were widely used in ecology niche modeling (Peterson AT and Vieglais DA 2001, Peterson AT 2003). The 19 bioclim variables were the Annual Mean Temperature (AMT), Mean Diurnal Range (MDR), Isothermality (IS100), Temperature Seasonality (TS100), Max Temperature of Warmest Month (MTWM), Min Temperature of Coldest Month (MTCM), Annual Temperature Range (ATR), Mean Temperature of Wettest Quarter (MTWT), Mean Temperature of Driest Quarter (MTDT), Mean Temperature of Warmest Quarter (MTW), Mean Temperature of Coldest Quarter (MTC), Annual Precipitation (AP), Precipitation of Wettest Month (PWM), Precipitation of Driest Month (PDM), Precipitation Seasonality (PS), Precipitation of Wettest Quarter (PWT), Precipitation of Driest Quarter (PDT), Precipitation of Warmest Quarter (PW), Precipitation of Coldest Quarter (PC), respectively (Table 1).

2.1.2 Remote sensing data

DEM data was derived from ASTER GDEM Version 2. The Ministry of Economy, Trade and Industry of Japan (METI) and the National Aeronautics and Space Administration (NASA) of the USA are collaborating on a project to develop ASTER Global Digital Elevation Model (ASTER GDEM), a DEM data which is acquired by a satellite-borne sensor "ASTER" to cover all the land on earth. The raster DEM was 30 m resolution.

NDVI data was calculated from multi-spectral HJ-1 A/B CCD images launched in China, 2008, with a spatial resolution of 30 m. The CCD images contain Blue, Green, Red and NIR bands, with a revisit period of 2 days. The images were geometrically and atmospherically corrected (Zheng et al. 2011). The calculation formula was NDVI = (Band NIR – Band Red) / (Band NIR + Band Red).

Land Use and Cover Change (LUCC) and river distribution data was acquired from local government (Table 1).

Table 1 Environmental variables

Variable	Data source	Input
AMT	WorldClim	No
MDR	WorldClim	Yes
IS100	WorldClim	Yes
TS100	WorldClim	Yes
MTWM	WorldClim	No
MTCM	WorldClim	No
ATR	WorldClim	No
MTWT	WorldClim	No
MTDR	WorldClim	No
MTW	WorldClim	No
MTC	WorldClim	No
AP	WorldClim	No
PWM	WorldClim	No
PDM	WorldClim	No
PS	WorldClim	Yes
PWT	WorldClim	No
PDT	WorldClim	Yes
PW	WorldClim	No
PC	WorldClim	No
DEM	ASTER GDEM	No
Slope	ASTER GDEM	Yes
Aspect	ASTER GDEM	Yes
LUCC	Local government	No
DTR	Local government	Yes
NDVI	CRESDA	Yes

Notes: Annual Mean Temperature (AMT), Mean Diurnal Range (MDR), Isothermality (IS100), Temperature Seasonality (TS100), Max Temperature of Warmest Month (MTWM), Min Temperature of Coldest Month (MTCM), Annual Temperature Range (ATR), Mean Temperature of Wettest Quarter (MTWT), Mean Temperature of Driest Quarter (MTDT), Mean Temperature of Warmest Quarter (MTW), Mean Temperature of Coldest Quarter (MTC), Annual Precipitation (AP), Precipitation of Wettest Month (PWM), Precipitation of Driest Month (PDM), Precipitation Seasonality (PS), Precipitation of Wettest Quarter (PWT), Precipitation of Driest Quarter (PDT), Precipitation of Warmest Quarter (PW), Precipitation of Coldest Quarter (PC)

2.2 Data preprocessing

The input 25 environmental variables (Table 1) were projected to the same coordinate, then resample to 30 m resolution. The variables were extracted by county boundary to make sure that all inputs had the same extent. Then they were standardized from -1 to 1. This standardization was only applied in data selection, the model input was the original environmental data, because Maxent model could tolerant the large different range of input data, and we need to further analyze variable response. Prior to modeling, the correlation of the set of variables were examined to avoid bias in modeling. We used the Spearman correlation coefficient to test the relationship between variables rather than Pearson Correlation Coefficient. The absolute values of pair-wise correlations are considered. The variable with the largest mean absolute correlation (e.g. higher than 0.9) would be removed.

We sampled each variable with the occurrence data, then examined the spatial auto-correlation using Moran's I index. If they did have high spatial auto-correlation, we divided our study area as a 2 km × 2 km fishnet, and selected only one occurrence point in one square, to make sure the input presence data was not clustered.

2.3 Ecological niche modeling

In the transition zone between loess plateau and the Qinghai-Tibet Plateau, human activities largely depend on environmental conditions. We used the Maxent algorithm to map the distribution. Maxent is a general-purpose method for making predictions or inferences from incomplete information and high stability to run with presence-only point occurrences (Phillips et al. 2006). The input data includes the environmental layers for a geographical region and the species occurrence data inside that region. We selected 75% occurrence points as samples, the rest 25% points as test, and run the model 10 times with default parameters (Lozier et al. 2009) in the support of the "Maxent" Version 3.3.3k software, provided by (Phillips et al. 2004), to evaluate the performance and robust of our model.

We explored receiver-operating characteristic (ROC) plots, from which the area under each curve (AUC) were derived. The main advantage of ROC analysis is that area under the ROC curve (AUC) provides a single measure of model performance, independent of any particular choice of threshold (Phillips et al. 2006). The AUC is considered as an effective indicator of model performance. The larger the AUC, the highest is the sensitivity rate and the lower is the 1-specificity rate (Cantor et al. 1999). Usually AUC values of 0.5–0.7 are taken to indicate low accuracy, values of 0.7–0.9 indicate useful applications and values of > 0.9 indicate high accuracy (Manel et al. 2001). We also evaluated Cohen's kappa, a measure of inter-rater agreement of variables, the proportion of all possible cases of presence or absence that are predicted correctly after accounting for chance effects. For kappa, values of 0.0–0.4 are considered in medical applications to indicate slight to fair model performance, values of 0.4–0.6 moderate, 0.6–0.8 substantial and 0.8–1.0 almost perfect (Manel S et al. 2001).

Response curve and contribution of each variable were also derived from the modeling to evaluate the importance of each variable and explain how it affects the model performance. We used a jackknife (also called 'leave-one-out') procedure, in which model performance is assessed based on its ability to predict the single locality that is excluded from the 'training' dataset.

2.4 Suitability assessment

Our Maxent model outputs the occurrence probability, which represents the geographically suitability of the human settlement. We divided the possibility (0.0-1.0) into four classes, including the highly (0.75-1.0), moderately (0.5-0.75), marginally (0.25-0.5) and not suitable (0.0-0.25), respectively. Explanation of the classes was described in Table 2.

3 Results

3.1 Data preprocessing

After standardization and correlation analysis, highly correlated variables were removed. Furthermore, the PDM with homogeneous attributes in our study extent were also deleted. Finally, the selected 9 input variables were NDVI, Slope, Aspect, Distance to River, MDR, IS100, TS100, PS, PDT, respectively. The Moran's I index was 0.47, 0.28, 0.89, 0.06, 0.96, 0.82, 0.96, 0.51, 0.86, respectively (Figure 2).

Table 2 Suitability classes

Class	Description
Class 1 Highly suitable	Land having no significant limitations to human settlement, or only minor limitations that will not significantly reduce benefits and will not raise inputs above an acceptable level.
Class 2 Moderately suitable	Land having limitations which in aggregate are moderately severe for human settlement; the limitations will reduce productivity or benefits and increase required inputs to the extent that the overall advantage to be gained from the use, although still attractive, will be appreciably inferior to that expected on Class 1 land.
Class 3 Marginally suitable	Land having limitations which in aggregate are severe for human settlement and will reduce productivity or benefits, or increase required inputs, that this expenditure will be only marginally justified.
Class 4 Not suitable	Land having severe limitations which are not appropriate for human settlement.

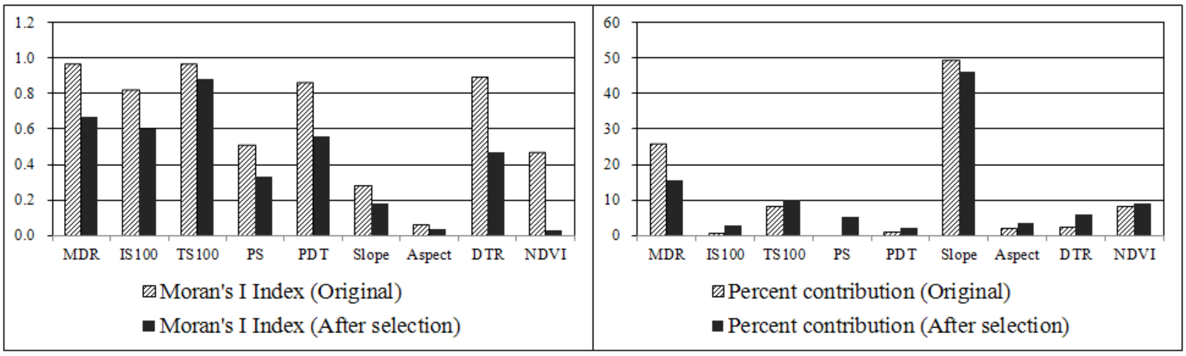

Figure 2 The Moran's I index of the original input data and the spatial auto-correlation of the selected data (left), the percent contribution of the original input data and the remove spatial auto-correlation selected data (right).

Notes: MDR — Mean Diurnal Range, IS100 — Isothermality (P2/P7) (* 100), TS100 — Temperature Seasonality (standard deviation *100), PS — Precipitation Seasonality (Coefficient of Variation), PDT — Precipitation of Driest Quarter, DTR — Distance to Rivers, NDVI — Normalized Difference Vegetation Index).

All input variables were significantly spatial auto-correlated. After the random selection of presence data, the Moran's I index was 0.03, 0.18, 0.04, 0.47, 0.67, 0.60, 0.88, 0.33, 0.56, respectively (Figure 2). The data cluster was significantly reduced, and the input data was 106 points.

3.2 Evaluation results

Maxent model was generated using the georeferenced locations as occurrence data, and climate, topography, ecological variables at 30m spatial resolution.

The input data includes 9 environmental layers for a geographical region (Table 1) and 106 species occurrence data inside that region. We selected 81(75%) occurrence points as samples, the rest 25(25%) points as test.

For all data partitions and test data, the AUC values were 0.917±0.01 and 0.923±0.002, respectively (Figure 3), across 10 replicate runs. Both of the AUC values were close to maximum value 1, and significantly better than random (0.5). This high accuracy means the Maxent-derived results were a close approximation of the probability distribution which represents the reality. Therefore, the Maxent model was capable in predicting the potential geographic distribution of human settlement. The Cohen's kappa coefficient of model performance was 0.848, which means we correctly predict the extent of occurrence at rates, better than chance expectation.

The classified geographic distribution of human settlement suitability was mapped as in Figure 3. 82.22% of the study area was classified as the unsuitable class. The ratio of the highly, moderately and marginally area was 1.19%, 5.3%, and 11.28%, respectively. These suitable areas were 418.79 km^2 large. 86.25% of the sample data was identified in the different gradient of suitable area. The suitable areas are located along with the Huangshui River. This river valley has relatively flat terrain surface, small variation between maximum and minimum temperature, wet atmosphere and humid soil (Figure 4).

3.3 Role of variables

To further demonstrate the role of environmental data in human settlement prediction, we analyzed the contribution and response curve of each variable. The most important environmental layer was slope, percent contribution of 46.1%. In the second place was MDR and TS100 with 15.4% and 10.1% contribution. The Maxent model's internal

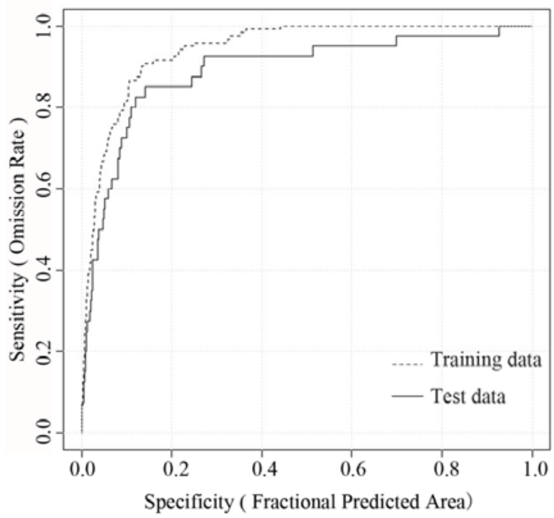

Figure 3 The Maxent output ROC curve

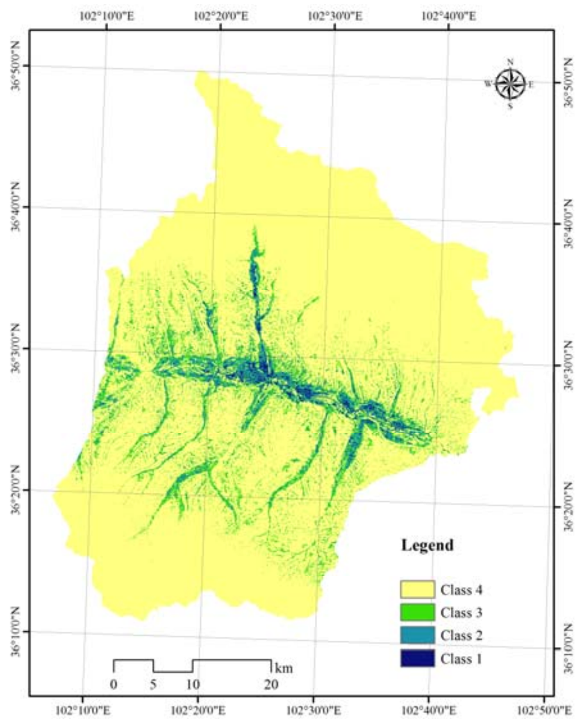

Figure 4 Classified suitability map

Notes: Class 1 Highly Suitable, Class 2 Moderately Suitable, Class 3 Marginally Suitable, Class 4 Not Suitable, respectively, as described in Table 2.

jackknife test of variable importance showed that Slope and TS100 were the two most important predictors of human settlement's habitat distribution (Figure 5). Accordingly, the most suitable area for human settlement usually had lower topographic irregularity and relatively high annual and seasonal temperature ranges (Figure 6).

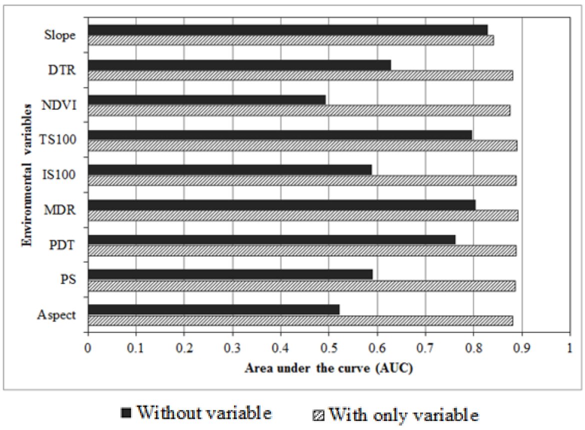

Figure 5 Results of jackknife evaluations of relative importance of predictor variables for human settlement Maxent model

Notes: MDR — Mean Diurnal Range, IS100 — Isothermality (P2/P7) (* 100), TS100 — Temperature Seasonality (standard deviation *100), PS — Precipitation Seasonality (Coefficient of Variation), PDT — Precipitation of Driest Quarter, DTR — Distance to Rivers, NDVI — Normalized Difference Vegetation Index).

In the next place were NDVI, DTR and PS with values of 8.9%, 5.8% and 5.3%, respectively. The topographic factor determines the fundamental human settlement distribution. The surface configuration impacts the distribution rather than the absolute elevation. The climate factors (MDR, TS100) also have large influence on human settlement distribution, which means temperature variation and temperature seasonality are suitable for human settlement. Thus, considering the climate change, the suitability of human settlement would be changed in the future.

4 Discussion

The habitat of each species has its niche in the ecology system, so does the human being. Despite the natural conditions, human settlement was affected by social and economic factors. In the discussion of sustainable urban development, we consider these factors in one system. Here, the area we examined was dominantly affected by natural resources and limitations. Thus, our assessment only focused on the natural benefits and disadvantages which defined the human settlement distribution. Therefore, when selecting the prediction variables, we only considered the environmental factors, such as climate, topography, vegetation, rivers, etc., rather than socio-economic variables such as railway, roads.

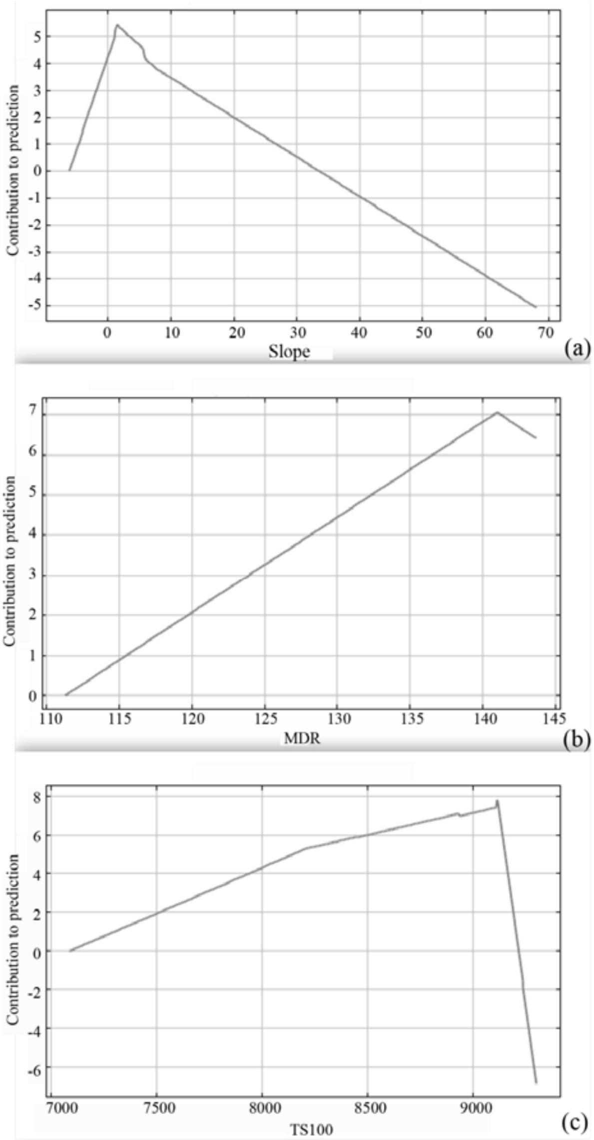

Figure 6 Response curve of three most important variables. (a), (b), (c) represent the variable affections of Slope, MDR, TS100 in Maxent prediction, respectively.

Notes: MDR — Mean Diurnal Range, TS100 — Temperature Seasonality (standard deviation *100).

Correlation between variables and spatial autocorrelation greatly affects linear models. Maxent could tolerant this but it doesn't help determine which variables are the main drivers in the model process. Therefore, prior to modeling, we need to examine the correlations to avoid bias. Because the variables were not normal distribution (Figure 7), we used the Spearman Correlation Coefficient rather than Pearson Correlation Coefficient. Here, we chose variables with Spearman Correlation Coefficient larger than 0.9, the high correlated variables were removed, meanwhile the reasonable number of variables were remained in modeling. Spatial autocorrelation could inflate accuracy measures like AUC values and the importance of some auto-correlated variables (Veloz 2009; Hawkins et al. 2007).

We also tested the spatial auto-correlation in model residuals using Moran's I coefficient. This index indicates the degree of similarity/ dissimilarity between the values of the residuals in this case. Distance classes for the correlogram were defined to maximize the similarity in the number of interactions between pairs of localities. There are several methods to remove spatial auto-correlation, such as GLMM, GEE, SEVM, et al. (Dormann 2007). It's said that without removing the spatial auto-correlation, the assumption of independently and identically distributed errors can be violated in standard regression models. Ensuring that training data not excessively clustered will provide a better assessment of prediction accuracy (Veloz 2009). Our random presence data selection could in some extent reduce the clusters of data, and the Moran's I coefficient dropped, (Figure 2). The clustered occurrence points increased the weight of some

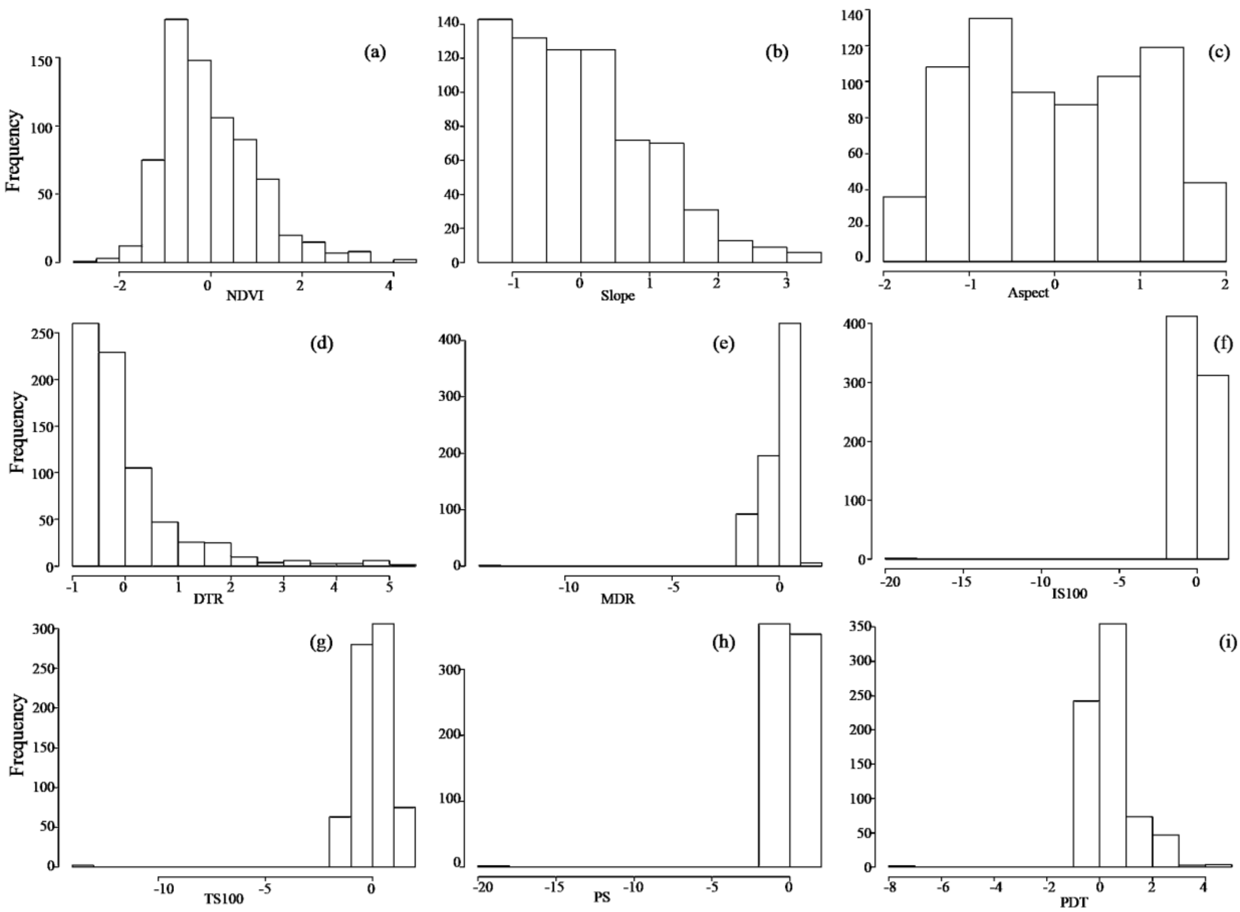

Figure 7 Distribution histogram of variables, (a)~(i) represent the value distribution of NDVI, Slope, Aspect, DTR, MDR, IS100, TS100. PS, PDT, respectively.

Note: MDR — Mean Diurnal Range, IS100 — Isothermality (P2/P7) (* 100), TS100 —Temperature Seasonality (standard deviation *100), PS — Precipitation Seasonality (Coefficient of Variation), PDT — Precipitation of Driest Quarter, DTR — Distance to Rivers, NDVI — Normalized Difference Vegetation Index).

factors which would mislead the explanation of environmental variable. After the processing, the contribution of each variable seemed more reasonable, the accuracy of model prediction was also improved, the AUC for test data increased from 0.884 to 0.924.

Maxent-derived results are a close approximation of the probability distribution which represents the reality. Models extrapolated the sensitivity developed by the training data from point localities and the environmental variables to a larger space. We tested model prediction statistically by its significant and consistent performance, which was better than a random prediction. This approach provided confidence in model predictions and in distribution patterns derived from environmental data. The distribution of patterns was meaningful and reasonable. Thus, we concluded that in examples used in our study, Maxent predictions were significantly different from random prediction and its performance was close to optimal. Thus, we could apply this method in larger extent, such as the whole Qinghai–Tibet Plateau and the nationwide to assess the human settlement suitability. This binding rivers and roads make this place a good place to stay and a convenient stage to go.

The highly suitable and moderately suitable areas were distributed in the river valley and along the Huangshui River. One reason was the limitation of natural condition. In the mountain areas we discussed here, people's living mainly depends on agriculture activities which were determined by water supply. Another reason was the infrastructure that the Qinghai-Tibet Railway and highway were across the river valley area, which helped in the urbanization along the Huangshui River valley. Meanwhile, the convenient transportation was a competitive factor in the decision making of step stay.

The importance of variables shows that the determining factor was the topography, which is coincidence with the basic geographic laws. Generally, this topographical factor would not be changed in the next decades except for some terrible geological disaster, thus the future suitability would be altered by the following contributing factors, the climate variables. As the IPCC reports, the different scenarios will lead to the different climate and environment changes. Here, we mapped and assessed the current human settlement distribution, so, where could we live in the 2050? What decisions could we make to make it better? These issues need further discussions.

The extent of the assessing area has a large effect on the results (Barve et al. 2011). The area of our study was limited, but it's typical. This area has various topography types, and diverse spatial distributions of temperature, precipitation, vegetation, soil, etc. Mountains are very different over short horizontal and altitudinal distances (Kuhle 2007; Xiao et al. 2010).

The natural environment suitability of human settlements in China showed that the suitable region accounting for 45% of the total land area. The transition zone was located in the marginally suitable area (Feng et al. 2008). By more precise evaluation, the marginally area had the suitable zone, even in mountain areas. Thus, human settlement suitability needs to be discussed in smaller scale, which would lead to different reorganization and understanding of human settlements.

5 Conclusion

Our Maxent model showed a good performance in mapping and assessing human settlements using occurrence records and limited environmental variables. The high AUC value and robustness of our model presented that it could be applied in quantifying human settlement distribution of other areas. This study provides the first predicted potential habitat distribution map for human settlement in Ledu County. Most of the assessed suitable area was located in the Huangshui river valley, along with roads and railway, where is an appropriate place for adaptive stay and a convenient stage to set off again. The potential habitat distribution map for human settlement can help in planning land use management.

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