Article

Analysis of the Impacts of Environmental Factors on Rat Hole Density in the Northern Slope of the Tienshan Mountains with Satellite Remote Sensing Data

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Abstract: Understanding the impacts of environmental factors on spatial–temporal and large-scale rodent distribution is important for rodent damage prevention. Investigating rat hole density (RHD) is one of the most effective methods to obtain the intensity of rodent damage. However, most of the previous field surveys or UAV-based remote sensing methods can only evaluate small-scale RHD and its influencing factors. However, these studies did not consider large-scale temporal and spatial heterogeneity. Therefore, we collected small-scale and in situ measurement records of RHD on the northern slope of the Tien Shan Mountains in Xinjiang (NTXJ), China, from 1982 to 2015, and then used correlation analysis and Bayesian network (BN) to analyze the environmental impacts on large-scale RHD with satellite remote sensing data such as the GIMMS NDVI product. The results show that the built BN can better quantify causality in the environmental mechanism modeling of RHD. The NDVI and LAI data from satellite remote sensing are important to the spatial–temporal RHD distribution and the mapping in the future. In regions with an elevation higher than 600 m (UPR) and lower than 600 m (LWR) of NTXJ, there are significant differences in the driving mechanism patterns of RHD, which are dependent on the elevation variation. In LWR, vegetation conditions have a weaker impact on RHD than UPR. It is possibly due to the Artemisia eaten by the dominant species Lagurus luteus (LL) in UPR being more sensitive to precipitation and temperature if compared with the Haloxylon ammodendron eaten by the Rhombomys opimus (RO) in LWR. In LWR, grazing intensity is more strongly and positively correlated to RHD than UPR, possibly due to both winter grazing and RO dependency on vegetation distribution; moreover, in UPR, sheep do not feed Artemisia as the main food, and the total vegetation is sufficient for sheep and LL to coexist. Under the different conditions of water availability of LWR and UPR, grazing may affect the ratio of aboveground and underground biomass by photosynthate allocation, thereby affecting the distribution of RHD. In extremely dry years, the RHD of LWR and UPR may have an indirect interactive relation due to changes in grazing systems.

Keywords: NDVI; GIMMS; SRTM; Rhombomys opimus; Lagurus luteus

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1. Introduction

Grassland rodent communities are important model systems in the study of community ecology and have received considerable attention. Natural and anthropogenic factors can directly or indirectly lead to changes in the habitats of rodents and can impact the spatial and temporal distribution of populations. Likewise, rodent communities can also have an impact on numerous abiotic and biotic environmental conditions in the areas in which they live. For example, on the northern slope of the Tien Shan Mountains (NTXJ) in Xinjiang, China, rodent damage has significantly harmed the health of the arid grasslands. It has been shown that high rat hole density (RHD) can negatively affect the health of the soil and vegetation in the region [1].

The northern slope of the Tien Shan Mountains belongs to a typical mountain–oasis–desert (from high land to low land) ecosystem [2,3] in the arid regions of Central Asia. The distribution of flora and fauna is strongly dependent on elevation variation. In NTXJ, rodent damage mainly occurs in grasslands and deserts and is primarily caused by Lagurus luteus (LL), which is mainly distributed in low mountain grassland, and Rhombomys opimus (RO), which is mainly distributed in the low desert. While the spatial and temporal distributions of RHD for both of these species are influenced by natural factors such as terrain [4], precipitation [5], temperature [6], soil texture [7,8], and vegetation [9], they may also be influenced by anthropogenic factors in the area, such as sheep grazing [10,11]. However, The temporal and spatial distribution of RHD and its complex driving mechanism remain uncertain. Although some ground in situ investigation and UAV-based approaches [4,12] have been used to measure the local or small-scale RHD within NTXJ and to analyze the relationships between RHD and environmental variables, there are numerous difficulties in extrapolating these local relationships to large-scale spatiotemporal mapping. The relationships between RHD and environmental variables' data may vary by scale, which, for example, may be caused by the difference in the vegetation information provided at the field-scale of local studies and the pixel-scale of satellite remote sensing data. Additionally, the information provided by local studies is not sufficient for spatiotemporal mapping. Therefore, the lack of comprehensive analysis and modeling of the relationships between large-scale RHD and various environmental factors (both natural and anthropogenic) has limited the prospect of the spatiotemporal mapping of RHD (Figure 1). Satellite remote sensing data have been widely used to develop long-term large-scale datasets of vegetation such as the GIMMS NDVI product [13], meteorological data [14], and other variables, which may be effective in providing large-scale environmental factors' data in the long time series. In addition, remote sensing data at the monthly scale may also help us understand the seasonal and monthly variation in the relationship between RHD and environmental factors. Further research in this area is crucial for the future prevention and control of damage caused by rodents.

Novel large-scale analysis and modeling may also be used to investigate the indirect interactions between RHD and ecosystems across elevation gradients. To date, machine learning approaches (e.g., random forest) have proven to be more effective in modeling the relationship between plant/animal communities and environmental factors [15] than traditional multiple regression analysis [16], especially when the volume of variables or data is large. They are also especially effective at estimating species distributions [17,18]. Bayesian network (BN) is a machine learning approach based on probability measures [19,20] that can quantify the complex, causal relationships between variables. This approach has advantages over other machine learning approaches in integrating expert knowledge and causal explanation. It can be used for probabilistic inference, diagnostic analysis, and decision support. BNs have also been used in species distribution studies [21] and proven effective in other ecological studies [22–26].
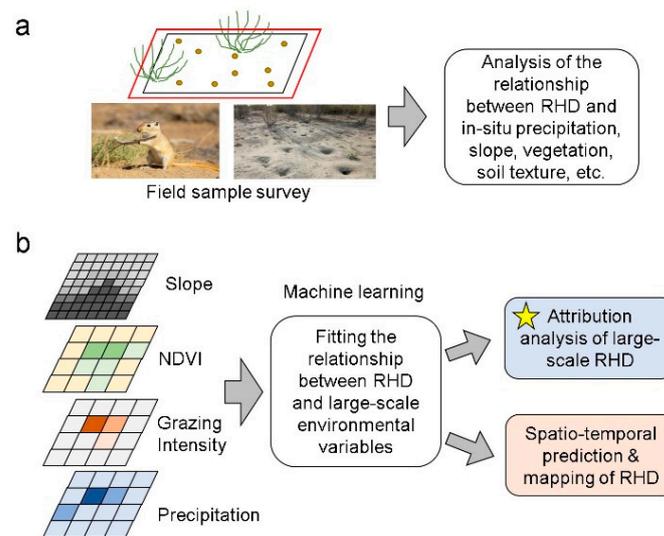
Figure 1. Conventional field-scale investigation of RHD and analysis (**a**) and prospect toward the large-scale spatiotemporal RHD mapping and the analysis of the impacts of environmental factors (**b**).

Our objective is to examine the relationship between RHD and ecosystems across elevation gradients and to determine their corresponding mechanisms when RHD and local conditions are influenced by the same environmental factors. This is particularly important to examine within NTXJ because local climate patterns have changed significantly [3], and precipitation in the mid-mountain region has increased due to oasis expansion and increased irrigation [27]. Thus, furthermore, the distribution and intensity of grazing may also be influenced by climate change and vegetation dynamics [28]. These environmental and anthropogenic factors can indirectly affect the large-scale distribution of RHD, but the spatial variability of these factors has rarely been considered in previous site-scale studies. Therefore, we analyzed the impacts of environmental factors on the large-scale RHD using satellite remote sensing data and BN. The training data are derived from in situ measured RHD investigations in NTXJ.

2. Methodology

2.1. Study Area

The terrain of NTXJ has a decreasing elevation gradient from the south (approximately 5000 m in the mountains) to the north (approximately 200 m at the edge of the desert) (Figure 2). The central region of NTXJ has a temperate continental arid climate, which is characterized by arid and hot summers and cold and windy winters. The annual average temperature ranges from <2 °C in the mountains to 8 to 10 °C in the plains. The precipitation season varies significantly, with the maximum precipitation concentrated in May and June, and the minimum amount in February. The annual precipitation gradually decreases from south to north, with annual precipitation in the southern mid-mountain region of 500 to 1000 mm, about 200 mm in the central plains, and about 100 mm in the northern desert [29]. The vertical distribution of its natural conditions (Figure 3) is a typical mountain-basin landform pattern. Different vertical elevation zones correspond to different landscape types and ecosystems. The unique natural conditions of NTXJ make it a typical representative of large-scale mountain–oasis–desert ecosystems in temperate arid regions of Central Asia [30].
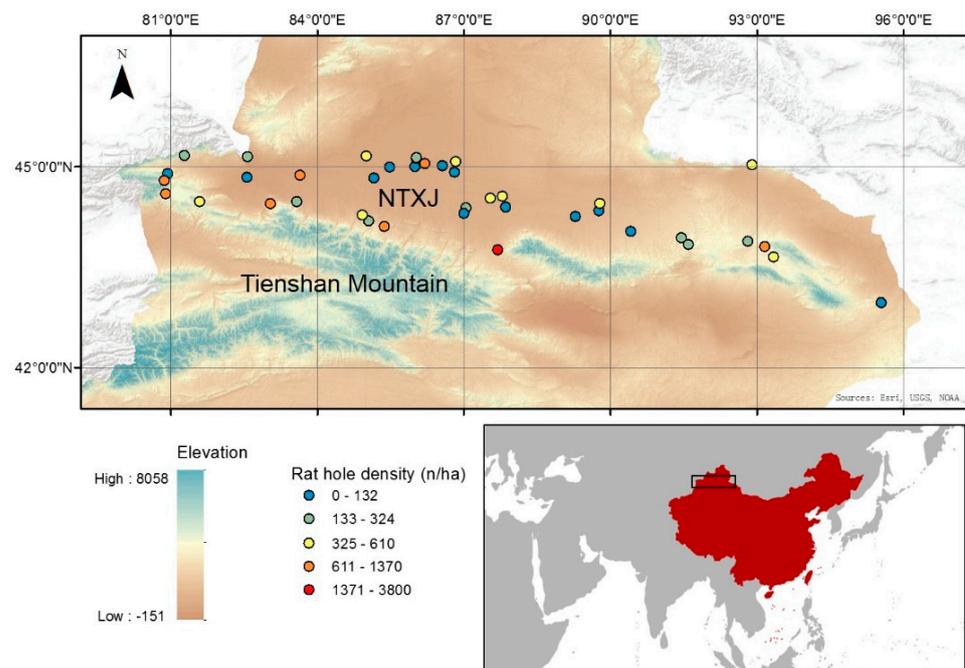
Figure 2. The location of the study area NTXJ (on the northern slope of Tien Shan Mountains in Xinjiang, China) and the spatial distribution of the collected rat hole density data in this study. This map is made based on the base map service GS (2016)1613 of China.
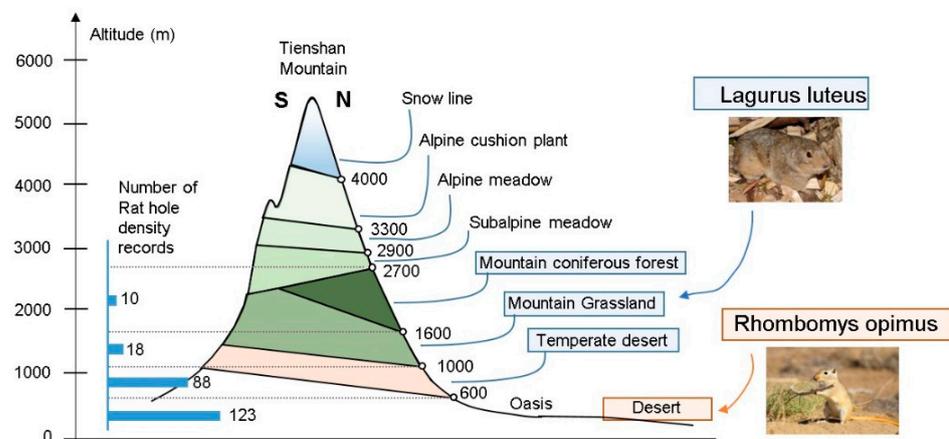

Figure 3. Vertical distribution of the vegetation types and the numbers of the collected rat hole density (n/ha) records on the northern slope of Tien Shan Mountains at Bogda Peak section. Different vertical elevation zones correspond to different landscape types and ecosystems.

2.2. Data

The data used in this study include published records of RHD in NTXJ and environmental factors. The RHD data were collected from published literature, which was mainly obtained from the China National Knowledge Infrastructure (CNKI) and in Chinese. We collected 239 RHD records with spatiotemporal information from published articles on the investigation of RHD within NTXJ. These records spanned from 1982 to 2015. Most of these raw data records were obtained from RHD surveys of small regions based on quadrats and UAV remote sensing. In addition to the temporal and spatial information of RHD, spatially averaged data of the environmental factors (Table 1) were extracted with raster data in each shapefile averaged in ArcGIS, including precipitation, temperature, soil texture, topography, shortwave radiation, and grazing intensity.

Table 1. Description of data on environmental factors that affect RHD.

Environmental Factors	Explanation	Raw Dataset Source	Spatiotemporal Resolution
Elevation		SRTM DEM dataset in China (2000) [31]	90 m
Slope		SRTM DEM dataset in China (2000) [31]	90 m
Aspect		SRTM DEM dataset in China (2000) [31]	90 m
Sand	Percentage of sand content in topsoil	Harmonized World Soil Database	
Silt	Percentage of silt content in topsoil	Harmonized World Soil Database	
Clay	Percentage of clay content in topsoil	Harmonized World Soil Database	
P_yr	Annual precipitation	1 km monthly precipitation dataset for China (1901–2017) [32]. The dataset was made through a fusion of remote sensing products, a reanalysis dataset, and in situ observation data at weather stations.	1 km, yearly
P_3mon_lag_pre	Precipitation in the three months before the survey	1 km monthly precipitation dataset for China (1901–2017) [32]	1 km, monthly
T_avg_yr	Annual average temperature	1 km monthly mean temperature dataset for china (1901–2017) [33]	1 km, yearly
T_max_yr	Monthly maximum temperature	1 km monthly maximum temperature dataset for China (1901–2017) [34]	1 km, monthly
T_min_yr	Monthly minimum temperature	1 km monthly minimum temperature dataset for China (1901–2017) [35]	1 km, monthly
T_mon	Monthly average temperature	1 km monthly mean temperature dataset for china (1901–2017) [33]	1 km, monthly
NDVI	Normalized vegetation index	NOAA Global Inventory Monitoring and Modeling System (GIMMS), version number 3g.v1	8 km, monthly (Maximum Value Composites with 15-day raw data) from 1981 to 2015
LAI	Leaf area index	NOAA Climate Data Record (CDR) of Leaf Area Index (LAI) and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), Version 4	8 km, monthly (mean value of daily raw data) from 1982 through the present
Grazing intensity	Grazing intensity (number of livestock per hectare)	FAO (http://www.fao.org/livestock-systems/en/, last accessed: 10 November 2021), field data in 2015, Xinjiang statistical yearbook [10,11]	0.08333°, yearly
Shortwave radiation		China meteorological forcing dataset (1979–2018) [14]	0.1°, monthly (mean value of 3-hour raw data)

2.3. Bayesian Network

The BN [19] is a directed acyclic graph model. Its nodes represent the probability distribution of variables, and the directed edges represent the causal correlations given the conditional probability table. By combining prior knowledge and observational data, we obtain the conditional probability distribution of the network nodes. The expectation–maximization algorithm [36] is used to iteratively calculate the expectation and maximum

likelihood estimation of the parameters and implement the optimization process for the missing data.

To simulate the causal relationship between RHD and environmental factors with a BN, we processed the multi-dimensional data collected from the articles into a training dataset with RHD as the target variables and environmental variables as the independent features (Figure 4). Based on empirical knowledge and preliminary correlation analysis, we chose suitable variables as nodes of BN and determined the directional causal link between nodes and the status discretization (Table 2) of each variable node to reduce the computational complexity of the joint probability distribution. The different numbers of intervals and segmentation points in the discretization process may have an impact on the performance of the model and the prior knowledge obtained from expert knowledge. Therefore, in this paper, the discretization of data was synchronized with the setting of prior knowledge, and expert knowledge and the actual data distribution guided the discretization procedure. Further, the BN was parameterized by the training data with the joint probability calculated.
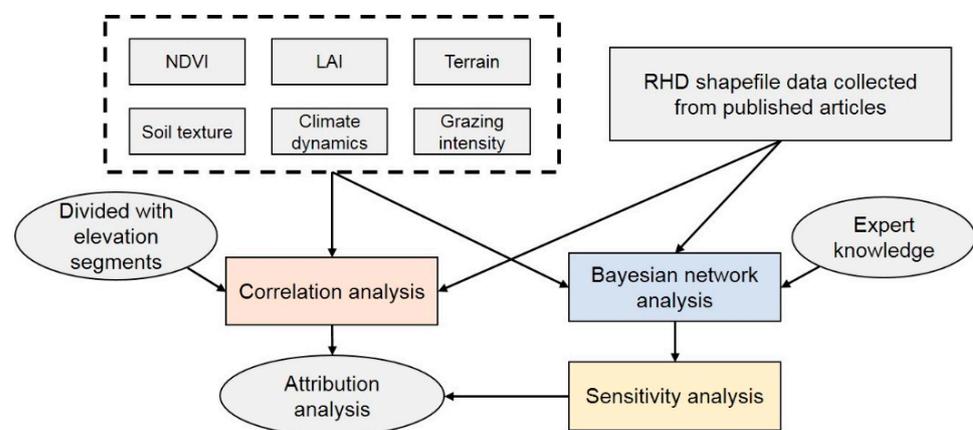

Figure 4. Flowchart of the analysis.

Table 2. Discretization of the status of the included variables as nodes of the BN.

Variables	Status Levels	Unit
RHD	0 to 300, 300 to 800, 800 to 4000	n/ha
Elevation	200 to 600, 600 to 1000, 1000 to 1600, 1600 to 2500	m
P_yr	0 to 150, 150 to 250, 250 to 600	mm
T_avg_yr	−3 to 8, 8 to 10, 10 to 12	°C
P_3mon_lag_pre	0 to 10, 10 to 30, 30 to 60	mm
NDVI	0 to 0.1, 0.1 to 0.2, 0.2 to 0.6	
LAI	0 to 0.15, 0.15 to 0.3, 0.3 to 1	
Slope	0 to 2, 2 to 10	°
Sand	0 to 40, 40 to 55, 55 to 100	

A BN is composed of random variables $(X_1, ., X_n)$ with their joint probability distribution [20] calculated as

$$P(X) = P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | pa(X_i)) \tag{1}$$

where $pa(X_i)$ is the value of the parent node of the child node X_i. With expert knowledge integrated, we can obtain the prior conditional probability table (CPT) of the BN. An

expectation–maximization (EM) algorithm [36] was used to incorporate the observational data to calculate the posterior CPTs.

To evaluate the impacts of various environmental factors on RHD, we applied a sensitivity analysis based on mutual information (MI) [37,38]. This represents the entropy reduction in the child node given the status of the parent node. The higher the MI value is, the higher is the sensitivity of the child node to the parent node for the stronger causality. MI is calculated as follows:

$$MI = H(Q) - H(Q|F) = \sum_q \sum_f P(q, f) \log_2 \left(\frac{P(q,f)}{P(q)P(f)} \right) \tag{2}$$

where H represents the entropy, Q represents the target node, F represents the set of other nodes, and q and f represent the status of Q and F.

To understand the environmental driving mechanism of high RHD based on the built BN, we performed a diagnosis analysis [19] and obtained the posterior probability change in the environmental nodes given the specific status of the RHD node.

3. Results

3.1. Correlation Analysis of Environmental Factors Affecting RHD

The correlation analysis (Figure 5) shows that RHD throughout NTXJ as a whole is significantly positively correlated with elevation, slope, NDVI, LAI, annual precipitation, and precipitation in the three months before the survey, and is significantly negatively correlated with temperature variables. However, based on the difference of the landscape divided by the elevation, the correlations show significant differences between regions with an elevation higher than 600 m (UPR) and regions with an elevation lower than 600 m (LWR) (Figure 6), while the correlations are mostly not significant with an elevation higher than 1000 m. In LWR, RHD is significantly correlated with most environmental variables. The seven main differences of the relationships between RHD and environmental variables in LWR and UPR include the following: (1) In LWR, RHD is significantly negatively correlated with slope, while in UPR, it is significantly positively correlated. This feature is just the opposite for aspect; (2) in LWR, RHD is significantly positively correlated with the sand content in the soil. This shows that RO may prefer to live in sandy areas. In UPR, the correlation is weak, possibly because the sand content is lower at higher altitudes; (3) in LWR, RHD has a significantly positive correlation with longitude, while in UPR, it has a significantly negative correlation; (4) in LWR, the negative correlation between RHD and temperature variables is stronger than in UPR; (5) in LWR, the positive correlation between RHD and precipitation is weaker than in UPR; (6) in LWR, RHD is significantly positively correlated with grazing intensity and shortwave radiation, while in UPR, the correlation is weak.

3.2. Sensitivity Analysis of Environmental Factors Affecting RHD Based on the BN

In addition to the linear correlation analysis above, the causal and individual impacts of these variables on RHD are not clear, due to the collinearity between environmental variables (e.g., in NTXJ, temperature and precipitation are highly correlated with elevation). The sensitivity analysis (Table 3) is based on the built BN (Figure 7) and shows that RHD throughout NTXJ as a whole is most sensitive to LAI, followed by NDVI, slope, and sand. The sensitivity of RHD to these variables shows significant differences in regions of various elevation ranges. The sensitivity of RHD to LAI is much higher in UPR than in LWR, which indicates that vegetation types at various elevation range significantly affect RHD. Furthermore, the sensitivity of RHD to NDVI above and below 600 m is not highly differentiated. It may be caused by the fact that the remote sensing NDVI data are not very effective in monitoring the growth and underground biomass of Haloxylon ammodendron, since RO takes the tender roots and twigs of Haloxylon ammodendron as the main food in the lower plain desert area of LWR. Moreover, in each elevation interval, the sensitivity of

RHD to LAI is higher than that of NDVI. When compared with NDVI, LAI may be a better indicator of vegetation for measuring RHD in NTXJ.
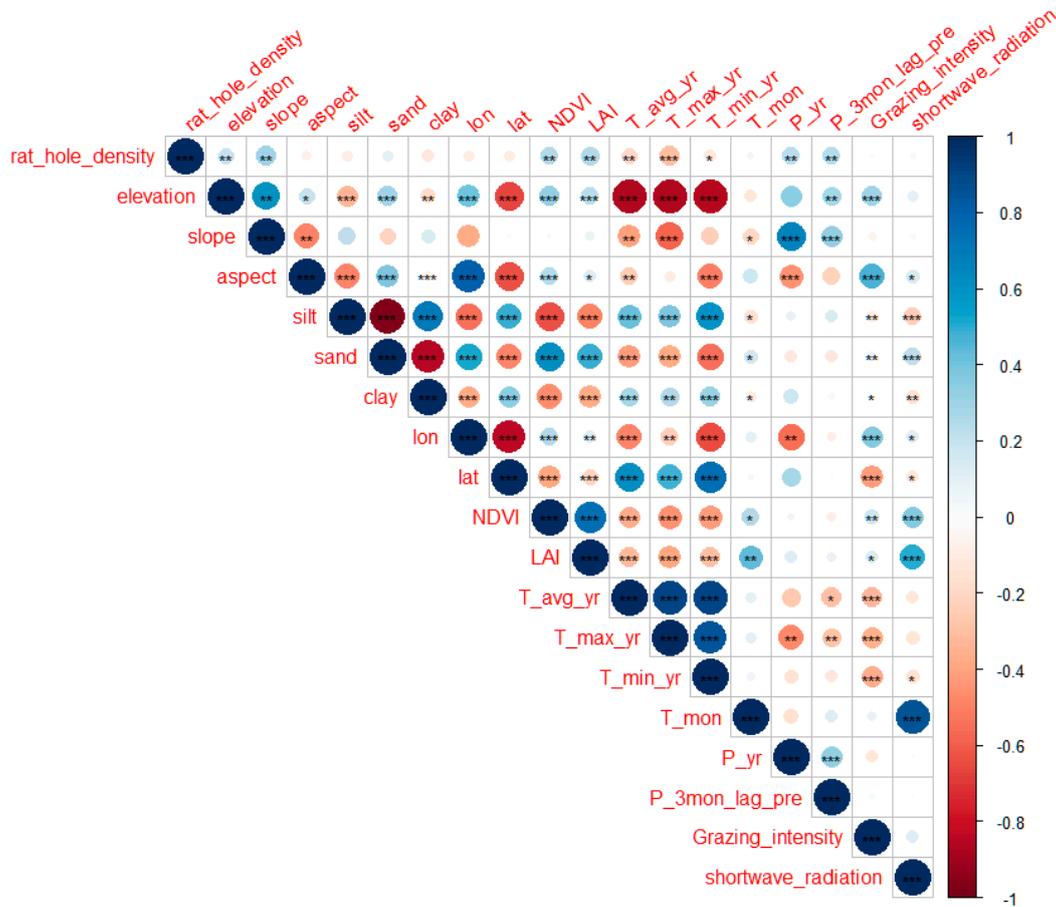

Figure 5. Correlation coefficient matrix of factors affecting rat hole density throughout NTXJ. (***), (**), and (*) represent the significance level of *p*-value < 0.01, 0.05, and 0.1, respectively.

Table 3. Sensitivity of RHD to environmental variables for the whole NTXJ and the subregions divided by elevation.

| Environmental Variables	NTXJ	Plain Desert (200 to 600 m)	Desert & low Mountain (600 to 1000 m)	Grassland & Low Mountain (1000 to 1600 m)	Grassland/Coniferous Forest & Mid Mountain(1600 to 2500 m)
Elevation	0.01215	no value	no value	no value	no value
LAI	0.06445	0.03561	0.08259	0.07575	0.08313
NDVI	0.03974	0.02737	0.05708	0.01535	0.00865
Sand	0.02447	0.03586	0.02840	0.00477	0.00398
Slope	0.02698	0.02163	0.05088	0.00481	0.00454
P_yr	0.01492	0.00236	0.02017	0.02246	0.00046
P_3mon_lag_pre	0.01062	0.01160	0.01405	0.00807	0.01112
T_avg_yr	0.00739	0.00912	0.00142	0	0
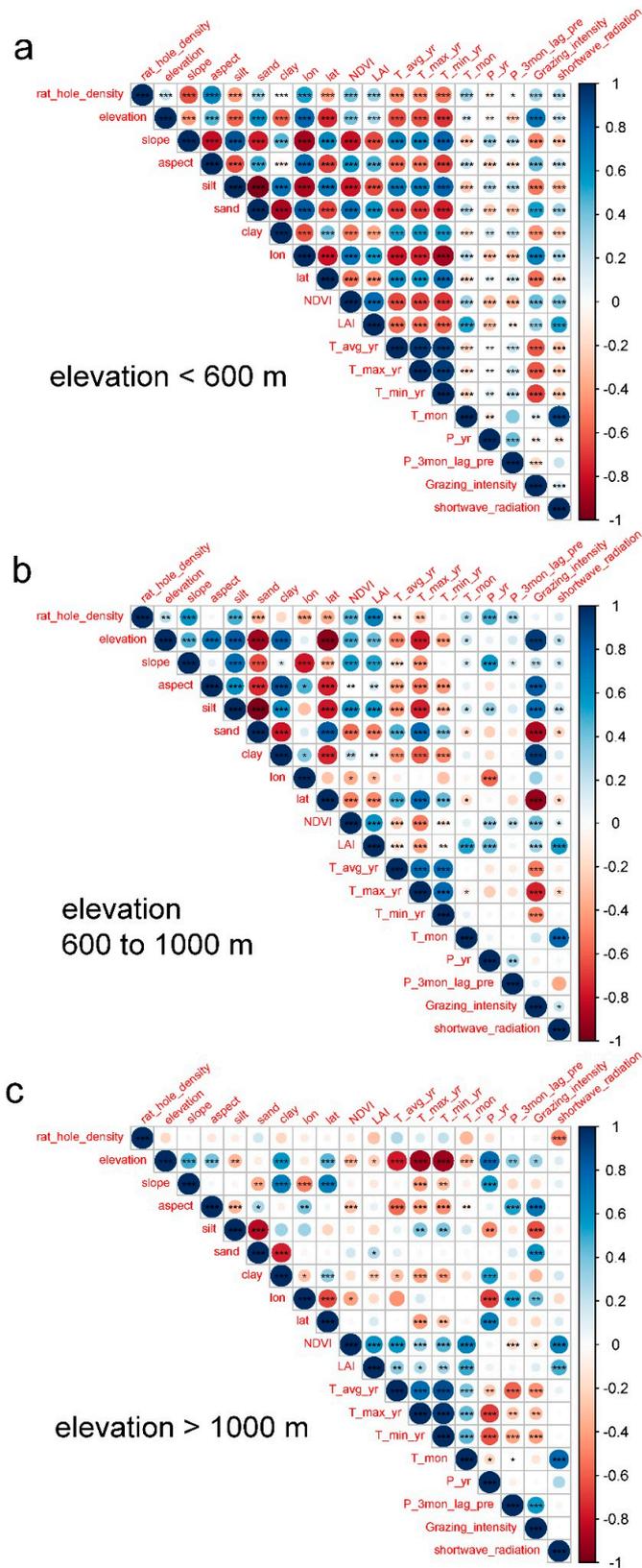
Figure 6. Correlation coefficient matrix of the factors affecting rat hole density in plain deserts with an elevation lower than 600 m (**a**), low mountain temperate deserts with an elevation of 600 m to 1000 m (**b**), and mountain grasslands with an elevation higher than 1000 m (**c**). (***), (**), and (*) represent the significance level of *p*-value < 0.01, 0.05, and 0.1, respectively.
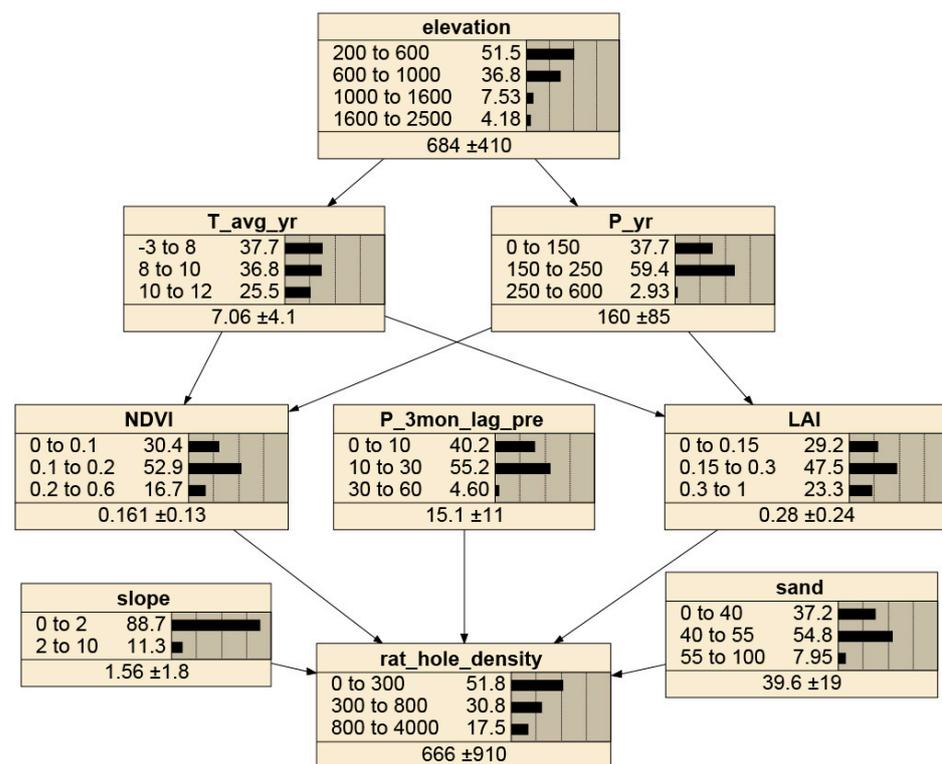
Figure 7. The Bayesian network of causality among natural environmental factors influencing rat hole density. In each node, the black histogram represents the probability distribution, the values before and after the "±" indicate the mean and standard deviation of the distribution, respectively.

In areas below an elevation of 1000 m, RHD is more sensitive to soil sand content. Without temporal variations, the soil sand content is primarily used to only explain the spatial variation of RHD. The sensitivity of RHD to soil sand content is even comparable to LAI; this is especially the case in LWR. This indicates that the distribution of RHD may be higher in areas with high sand content that are below the elevation of 1000 m. The sensitivity of RHD to the slope is highest in the range of 600 to 1000 m, followed by LWR, and lowest in areas above 1000 m. These findings indicate that the impacts of slope on RHD are limited to the low mountain regions and LWR.

However, an important consideration for these results is that the coarse-scale of the RHD data may not have captured the influence of small topographic characteristics throughout the study region. These findings may be impacted by the variation in the slope in conjunction with the variation of land cover types (from low mountain desert to oasis, to low plain desert), and as a result, RHD is more distributed in low mountain desert and plain desert. The sensitivity of RHD to annual precipitation is more sensitive in the elevation ranges of 600 m to 1000 m and 1000 m to 1600 m. This may be due to the high temporal and spatial heterogeneity of precipitation in these two altitude zones and the higher consequent impacts on vegetation growth. There is little difference across elevation ranges in the sensitivity of RHD to precipitation in the three months before each survey. RHD is more sensitive to the average annual temperature in LWR than in UPR, which may be because the vegetation condition of UPR is not as sensitive to temperature as that of LWR.

3.3. Causal Diagnosis of High RHD and Evaluation of the Potential Ecological Amplitude of Rats in LWR and UPR Based on the BN

Using the diagnostic analysis function of the BN, we analyzed the driving factors of severe and extremely severe rodent damage, which are determined by the high RHD (800 to 4000 n/ha) indirectly in LWR and UPR. As the high-value status of the RHD node

is determined (Figure 8), the posterior probability distributions of other environmental variables consequently change (Table 4). In LWR, severe and extremely severe rodent damage is most likely caused in areas of medium soil sand content (+13.4%), high slope (+9.6%), and high LAI (+6.1%) when compared with the average level of rodent damage. In UPR, severe and extremely severe rodent damage is most likely to occur in areas of high NDVI (+16.2%), high LAI (+12.5%), high slope (+12.5%), and medium annual precipitation (+11.2%) when compared with the average level of rodent damage. Therefore, areas with the above environmental conditions may be the focus of future rodent damage control in NTXJ.
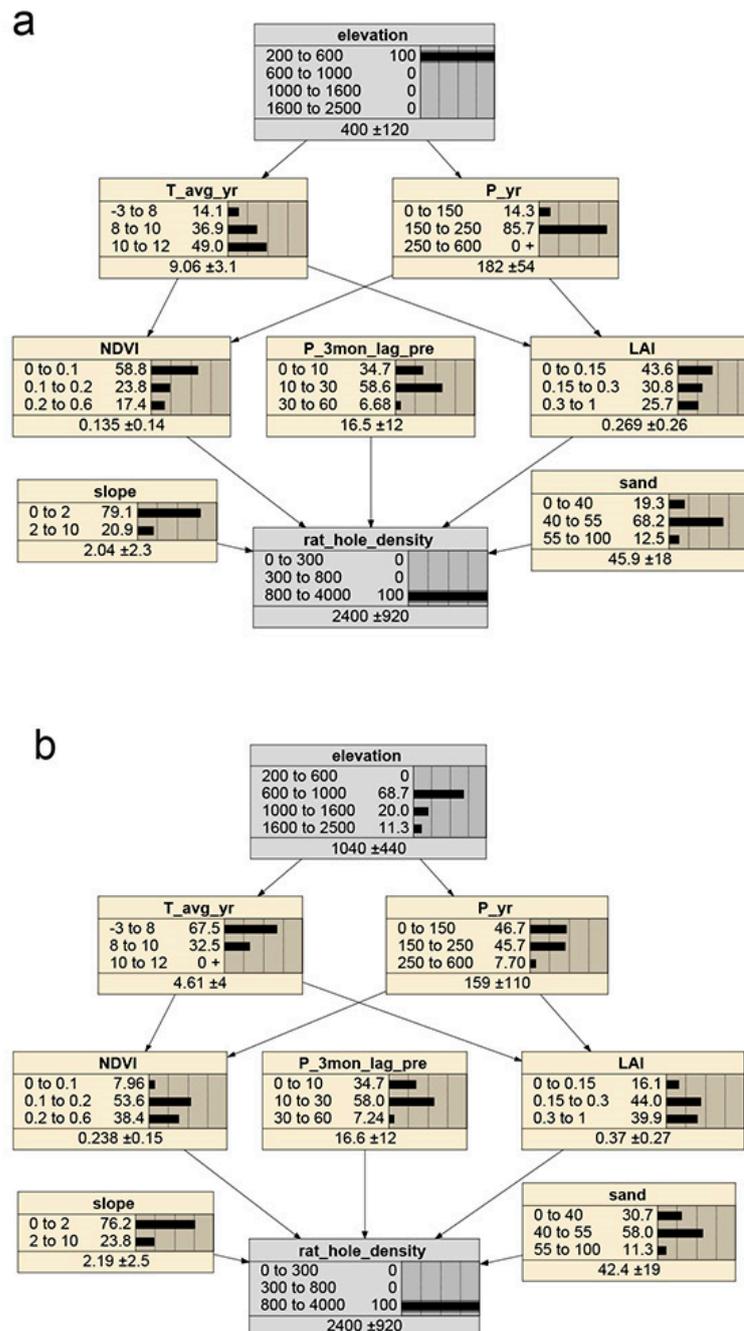

Figure 8. The BN-based diagnostic analysis of the occurrence of high RHD (800 to 4000 n/ha) in LWR (**a**) and UPR (**b**). The values before and after the "±" indicate the mean and standard deviation of the distribution, respectively.

Table 4. Potential changes in the probability of the status of environmental variables corresponding to the occurrence of high RHD (800 to 4000 n/ha) in LWR and UPR.

Environmental Variables	Probabilistic Changes in the Status of Environmental Variables Due to the Determination of the High RHD Status in LWR (%)			Probabilistic Changes in the Status of Environmental Variables Due to the Determination of the High RHD Status in UPR (%)		
	Low	Medium	High	Low	Medium	High
LAI	+2.6	−8.7	+6.1	−0.5	−12.0	+12.5
NDVI	+5.6	−11.6	+6.0	+1.8	−18.0	+16.2
Sand	−17.9	+13.4	+4.5	−6.5	+3.2	+3.3
Slope	−9.6	no value	+9.6	−12.5	no value	+12.5
P_yr	−2.8	+2.8	0	−12.8	+11.2	+1.6
P_3mon_lag_pre	−5.5	+3.4	+2.1	−5.5	+2.8	+2.7
T_avg_yr	+1.1	−0.5	−0.6	+3.7	−3.7	0

Note: "low", "medium", and "high" represent the low-, medium-, and high-value status of the nodes, respectively.

4. Discussion

4.1. The Effectiveness of a BN in the Attribution Analysis of RHD Distribution in NTXJ

Since BNs have been used extensively in ecological studies [23–26], especially for the expression of expert knowledge and cause and effect, it was an appropriate method for the attribution analysis of RHD in this study. The environmental variables used in this study inherently have a high linear correlation, so it was important to reduce the interference of collinearity between the variables. This enabled us to obtain a more accurate understanding of the effect of each environmental factor and to determine whether these factors directly or indirectly affect RHD. When compared with conventional correlation analysis or some non-causal machine learning methods such as random forest, a BN may have advantages in deepening the understanding of causal mechanisms because expert knowledge can be integrated. As ecosystem types in NTXJ are primarily determined, we focused on the vertical differentiation within various elevation ranges to be considered in the BN. Additionally, the dynamic diagnostic analysis function of the BN and the visualization of the ecological amplitude in this study enabled us to focus our analysis on the differential driving mechanisms of RHD under various environmental condition combinations. These results can enrich our knowledge and enable decision makers to make informed decisions regarding rodent damage control. Results derived from the BN can also be used for the probabilistic inference of RHD if environmental variables are given. These findings demonstrate the potential advantages of BN in decision support for rodent damage control.

However, a BN may also have limitations in studies such as this. One potential disadvantage is the lack of consideration of interaction relationships within the network. Since the relationship between BN nodes needs to be directional, some interaction relationships and feedbacks may be ignored [39]. For example, vegetation conditions affect the food sources of rats and thus affect RHD, but at the same time, high RHD will affect vegetation condition and soil physical–chemical properties [40,41]. Thus, the relationship between RHD and vegetation conditions may be reversed. If these relationships are not considered, our understanding of the interactive effects of vegetation and RHD may be limited. Furthermore, if the influence of predator populations, such as foxes [42], on RHD is included in this BN, the interaction relations will be more complicated and should thus not be ignored. Therefore, future studies should consider how to better incorporate the impacts of such interactions when such machine learning methods are used.

4.2. Uncertainties and Limitations Concerning the Driving Environmental Mechanisms of RHD in NTXJ

Previous studies have mostly analyzed small-scale and local RHD within NTXJ, but the study of large-scale RHD remains limited. The new findings of this study provide information in the quantitative relationship between large-scale RHD and environmental variables, and analyses on the different patterns of RHD across elevation ranges. Additionally, this study focused on the impacts of environmental factors on the temporal and spatial distribution of RHD, rather than the feedback of RHD on environmental factors (e.g., the impacts on vegetation degradation and soil texture) [43]. Our findings are constrained primarily by the directional limitation [39] between the BN nodes, but also because the environmental factor data obtained from the survey of surface soil texture may not be applicable to the feedback effect of RHD on local soil texture.

Given the results of the correlation analysis and the BN-based analysis, we found that vegetation condition is an important factor that affects the large-scale temporal and spatial distribution of RHD in NTXJ. Of all the other natural factors that were considered, this factor was significantly more important. This relationship can be attributed to the fact that vegetation is the most important food source for rats in NTXJ, and the temporal and spatial distribution of food sources heavily influences the distribution of rat populations. The differences in the relationships between RHD and LAI or NDVI may be influenced by the different types of vegetation that are consumed by RO in LWR and LL in UPR. Haloxylon ammodendron is the main food source for RO, whereas and LL primarily consumes Artemisia spp. Other factors (e.g., precipitation, temperature, grazing intensity) may also indirectly affect RHD through their effects on vegetation. However, the use of the coarser spatial resolution of NDVI and LAI data may bring uncertainty to such analyses, especially in desert areas with low vegetation coverage. This may lead to an underestimation of the impact of spatial vegetation variability on RHD. Due to the use of a monthly temporal resolution, the effects of temporal (i.e., interannual, seasonal) variability of the vegetation condition on RHD may have been considered to be a greater influence than the spatial variability. Furthermore, the 90 m resolution of terrain variables may not be a fine enough scale to capture the impacts of small-scale terrain factors (e.g., sand dunes with a scale below 20 m) on RHD [4]. In this case, the small-scale terrain factors obtained by UAV remote sensing [4] can be value-added because the extracted values from shady slopes and sunny slopes can be more accurate. Therefore, the guiding significance of the terrain-related variable analysis in this study for rodent damage control may only be effective at the regional scale, rather than the scale smaller than 90 m. In LWR, the major anthropogenic factor of grazing intensity is significantly positively correlated with RHD. One possible explanation for this relationship is that although grazing may threaten the food supply of RO, grazing in LWR occurs mostly in winter. This grazing period is staggered within the breeding season of RO (spring and summer), and the distribution of both RO and grazers depends on the synchronous distribution of vegetation. Thus, there may be positive correlation between grazing intensity and RDH. In UPR, the weak correlation between grazing intensity and RHD may be because grazing sheep do not feed on Artemisia spp. as their main food source, and the total vegetation in the area is sufficient for sheep and LL to coexist.

To predict the large-scale spatial and temporal distribution of rat population density, further considerations to the uncertainties and limitations should be made concerning the characteristics of the population. In this study, the seasonal changes in the rat population were mainly considered through the inclusion of monthly temporal variables (e.g., NDVI, temperature, and precipitation). However, for occasional occurrences of extremely high reproduction rates within the population, the predictive capability of these environmental variables may be limited significantly. Additionally, the sex ratio [6], age structure, and predator density for the rat population may also be important in predicting their density distribution. This should be a primary focus in future studies. These considerations may resolve the many limitations in generating accurate spatial and temporal maps of the

rat density distribution. Likewise, more accurate environmental variable data, such as the distribution of Haloxylon ammodendron and other desert plants [44,45] is critical to predicting RHD distributions in the future.

4.3. Other Potential Impacts of Grazing on RHD

Although we found that grazing in LWR and UPR have had significantly different impacts on RHD, the nature of this conspecific relationship remains uncertain. This is because grazing intensity data that are purely based on statistical data cannot accurately represent the temporal and spatial dynamics of the past and present grazing systems and grassland management practices. The significant differences in water availability and vegetation conditions between LWR and UPR may dominate the impacts of grazing on RHD. One possible reason for the variable conditions between elevation zones is due to the joint effect of low water availability and photosynthate allocation in local vegetation. Under grazing conditions, the root–shoot ratio increases, and under conditions of low water availability, more photosynthate can be allocated to roots [46–48]. In LWR vegetation, more photosynthate may be allocated to roots to decrease transpiration under low water availability conditions. Likewise, the underground biomass of plants may also increase to adapt to the disturbance of grazing [49]. Therefore, more food resources can be provided for RO and may lead to a positive impact of grazing on RHD in LWR.

In UPR, grazing may reduce ET and increase soil moisture, which, in turn, promotes grass growth at certain grazing intensities [50]. Thus, the impact of grazing on RHD can be insignificant due to weak food competition between livestock and LL when there are sufficient food resources. However, under extreme drought conditions, water availability and food resources in UPR may also decrease significantly. Intensive grazing in the summer and autumn may greatly decrease the aboveground biomass throughout grassland areas and may further perpetuate the negative effects on RHD. Under these drought conditions, the plant biomass in LWR is also lower. This may result in decreased grazing intensity in winter and spring due to insufficient food resources provided, thus further influencing RHD in LWR. These considerations indicate that across areas of different water availability conditions, grazing systems may indirectly influence RHD in UPR and LWR across different elevation ranges. As RHD data collected in this study are limited to areas below alpine grassland at 2700 m, the impact of grazing on RHD in higher elevation areas is limited. However, these considerations may be not significant in NTXJ because the grazing duration on alpine grassland is short, lasting only one to two months, and is often concentrated in summer [50]. However, compared with NTXJ, throughout other alpine meadows, or grassland areas in the world [51–53], longer grazing durations may indeed have a more significant impact on the population density of rodents. In addition, in alpine meadows, small rodents such as pika may spend the winter by eating yak feces [54], so the population density and grazing intensity may also show a positive correlation.

4.4. The Prospect of Combining Satellite Remote Sensing Data and RHD Modeling

Compared with studies to identify local rat hole numbers, which may require very fine resolution such as UAV images, the main innovation of this research is to establish a relation between satellite remote sensing (e.g., NDVI data of GIMMS, DEM data of SRTM, and meteorological dataset made through a fusion of remote sensing products, reanalysis dataset and in situ observation data at weather stations) and the RHD in local-scale studies. This has rarely been reported in previous studies. This study proved the effectiveness of using large-scale satellite remote sensing data to analyze the temporal and spatial changes of the population density of rodents. In addition, the data used in this paper, such as soil texture, precipitation, temperature, etc., have other corresponding alternative datasets produced by satellite remote sensing. Therefore, in future studies, we can use various remote sensing datasets to establish a correlation with RHD. This is more suitable for large-scale rodent population monitoring. It may contribute to the application prospects of satellite remote sensing in animal ecology studies.

5. Conclusions

This study compiled small-scale and in situ RHD data in NTXJ that were collected between 1982 to 2015. Correlation analysis and BN were used to study the relationship between RHD and corresponding environmental variables. The conclusions are as follows:

1. The BN can effectively quantify causality in the environment-driven mechanism modeling of RHD in NTXJ and support decision making.

2. The NDVI and LAI data from satellite remote sensing are important to the spatial–temporal RHD distribution and the mapping in the future.

3. In LWR and UPR within NTXJ, there are significant, patterned differences in the driving mechanism of RHD, which are dependent on the elevation.

4. In LWR, vegetation conditions have weaker impacts on RHD than in UPR, possibly because of the Artemisia spp. eaten by LL in UPR is more sensitive to the spatial–temporal variations in precipitation and temperature than the Haloxylon ammodendron eaten by the RO in LWR.

5. In LWR, grazing intensity has a stronger positive correlation to RHD than in UPR, possibly because winter grazers and RO both depend on vegetation distribution. In UPR, sheep do not feed Artemisia spp. as the main food, and the total vegetation is sufficient for sheep and LL to coexist.

6. Under differing conditions of water availability in LWR and UPR, grazing may affect the ratio of aboveground and underground biomass through photosynthate allocation, thereby affecting the distribution of RHD. In extremely dry years, the RHD of LWR and UPR may have an indirect interactive relationship due to changes in grazing systems.

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