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Comprehensive Assessment of Geopolitical Risk in the Himalayan Region Based on the Grid Scale

Shihai Wu [1], Yili Zhang [2,3,4] and Jianzhong Yan [1,*]

1 College of Resources and Environment, Southwest University, Chongqing 400716, China
2 Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
3 University of Chinese Academy of Sciences, Beijing 100049, China
4 CAS Center for Excellence in Tibetan Plateau Earth Sciences, Beijing 100101, China
* Correspondence: yanjzswu@126.com

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Abstract: The Himalayan region serves as a land bridge between China and South Asia but is vulnerable to geopolitical factors. It is important to conduct geopolitical risk assessments to facilitate the restoration and construction of traditional trade routes in the Himalayan region. Based on multi-source natural, political, and socioeconomic data, we selected 12 indicators, including topographic relief, landslide risk, multi-hazard index, population density, territorial disputes, conflict risk, corruption perception index, transboundary water disputed risk, night light index, GDP, accessibility, and economic freedom, to assess these risks. A comprehensive assessment of the geopolitical risk in the Himalayan region is presented using the random forest (RF) model, analytic hierarchy process (AHP), entropy weight method, and AHP-entropy weight method. The results indicated that the geopolitical risk in the Himalayan region is generally high in the north and low in the south, with high level of risk primarily concentrated in the Kashmir valley and south, south-central Nepal and southern Tibet, and low level of risk mainly concentrated in the Bhutan and Tibet border areas of China. The high likelihood of natural risk is largely concentrated in the Indian states of Himachal Pradesh and Uttarakhand, Nepal, southeastern Bhutan, and southern Tibet. Significant political risk is mostly confined to the Kashmir valley and its south, while economic risk is mostly concentrated in Khyber-Pakhtunkhwa of Pakistan, Pakistani-administered regions of Kashmir, and Nepal. Geopolitical risk assessment based on the grid scale can better reveal and portray the spatial distribution of geopolitical risk in the Himalayan region and provide a basis for the restoration and construction of traditional trade routes in this region. According to the results of the geopolitical risk assessment, it is recommended that priority be given to construction in areas of relatively low risk, such as those close to Burang Country and Mustang, and that integrated planning be carried out for the restoration and construction of the predominantly low-risk trade routes between China and Bhutan, with further comprehensive analysis of each route conducted in conjunction with field surveys and proposed construction and control strategies.

Keywords: geopolitical risk; comprehensive assessment; grid scale; traditional trade routes; Himalayan region

1. Introduction

As the center of gravity of the global geopolitical game shifts to the Asia-Pacific region, China's neighbors and the areas along the Belt and Road are the frequent sources of shatter belts, facing huge geopolitical risks [1,2]. Political instability, intervention by major powers, economic vulnerability, terrorism, religious extremism, and ethnic conflicts are prominent. Due to a lack of awareness of geopolitical risks in neighboring countries and regions, the series of neighboring corridors promoted by China in recent years, such as the China-Pakistan Economic Corridor and the Bangladesh-China-India-Myanmar Economic Corridor, have suffered substantial losses [3]. Accurately assessing and coping with geopolitical risks in China's neighborhood and the areas along the Belt and Road has become a key issue to be addressed in corridor construction [4,5].

The Himalayan region is a natural barrier between China and India for building frontier security, as well as a hub connecting mainland China through South Asia to the Indian Ocean and even Central and West Asia, and it has important geostrategic value [6]. With the rise of two great powers, China and India, the Himalayan region has become central to the Sino-Indian game and the efforts of the United States to contain China. Historically, numerous traditional trade routes were formed along the transverse valleys and passes of the Himalayas through which people on both sides of the mountains traded and made religious pilgrimages, contributing to the socioeconomic prosperity and development of the Himalayan region [7]. However, the 1962 Sino-Indian War disrupted almost all of the Himalayan region's traditional trade routes, blocking long-established socioeconomic ties and forcing the region to transform itself from a gateway area into a remote and unsophisticated region far from the economic center. With the rapid development of economic globalization and the improvement in Sino-Indian relations, traditional trade routes were gradually restored and developed. In particular, in the context of China's "opening up to the West" and "the Belt and Road Initiative", China's central and local governments have proposed strategies such as the South Asia Corridor, the Trans-Himalayan Connectivity, the China-Nepal-India Economic Corridor, and the Trans-Himalayan Economic Zone of Cooperation to give full play to the economic and trade complementarities between China and South Asia and promote the development of the region [8]. However, a lack of understanding of the unique natural environment of the Himalayan region, territorial disputes, intervention by foreign powers, religious conflicts, nationalism, terrorism, other factors, and the risks of their interactions has, to a certain extent, led to the implementation of the restoration and construction of the traditional trade routes falling far short of expectations. For this reason, it is important to strengthen the identification and assessment of geopolitical risks to facilitate the restoration and construction of traditional trade routes in the Himalayan region.

To cope with the geopolitical risks of overseas investment and construction, domestic and foreign scholars have researched geopolitical risks from different perspectives. In the 1960s, foreign scholars first constructed an assessment framework based on the macro national scale and the micro enterprise scale from the domestic political, economic, and social aspects of the host country and used the Delphi method and the integrated risk index method to conduct a comprehensive assessment of political risk [9–12]. Then, with 9/11 and the 2008 financial crisis, non-traditional security issues such as terrorism and religious extremism came to the fore, and risks arising from geopolitical issues became a key factor affecting overseas investment and construction [13]. As a result, foreign scholars have further constructed a comprehensive geopolitical risk index from the perspectives of geopolitics, international relations, and finance based on data such as news media and socioeconomic statistics and methods such as textual analysis [14] and econometric models [15] to comprehensively assess global geopolitical risk, risk of energy, and mineral resource supply [16–18].

Nevertheless, domestic scholars have started their research relatively late, and by drawing on the research of foreign scholars, they have mainly explored the qualitative and quantitative assessment of geopolitical risks from the perspectives of geopolitics, international relations, international politics, and geography. In terms of qualitative analysis, the geopolitical risks and countermeasures faced by China's oil and gas resource investment in Central Asia [19], railway construction in Africa [20], overseas engineering contracting [21], and "the Belt and Road" construction in the Indian Ocean and other regions [22,23] have been analyzed. For quantitative analysis, a comprehensive evaluation index system was constructed based on different scales of international, regional, domestic, and project scales, including the geographical environment and socioeconomic, cultural, religious, political, and diplomatic aspects, and then the expert scoring method, entropy weighting method, AHP, and fuzzy comprehensive evaluation method were combined, and countries were adopted as evaluation units to assess the geopolitical comprehensive risks faced by the Belt and Road in investment and construction in Southeast and South Asia [3], Indochina Peninsula [24], Central Asia [25], Latin America [26], and Sub-Saharan Africa [27,28]. At the same time, some scholars also have assessed the geopolitical risks of corridor construction, such as the China-Pakistan Economic Corridor and the Arctic route [29,30]. As research progresses, a small number of scholars started to combine geographic big data and machine learning to conduct a comprehensive assessment of geopolitical risks in South Asia [31].

In addition, some research institutions monitor and assess global geopolitical risk dynamically by constructing geopolitical risk indices based on countries. For example, the Fragile State Index (FSI, https://fragilestatesindex.org/ (accessed on 5 March 2022)) is published annually by the US Fund for Peace, the Country Risk Index (CRI, https://www.fitchsolutions.com/ (accessed on 6 March 2022)) is provided by Fitch Solution, and the Report of Country-Risk Rating of Overseas Investment from China is published annually by the Chinese Academy of Social Sciences [32].

Based on the analysis of the above literature, relevant scholars and research institutions have conducted a large number of studies on geopolitical risk assessment which has laid a good foundation for this study, but there are still some shortcomings, mainly as follows: (1) the studies mainly take countries as the unit of analysis, which is not enough to reveal the geopolitical risks within countries and even cross-border areas; (2) the research areas are mainly concentrated along the Belt and Road, but not enough attention is given to connected peripheral areas, especially in the Himalayan region; and (3) the research data are mainly based on statistical data, and the methods are mainly used to create a comprehensive assessment of geopolitical risk by constructing an evaluation index system and combining textual analysis, entropy power method, hierarchical analysis, and fuzzy comprehensive evaluation method, which are more subjective and struggle to reveal the influence of geopolitical factors on risk. With the rapid development of geographic big data and GIS technology, a large amount of fine-grained spatial and temporal geographic data on natural, economic, political, and other elements closely related to geopolitical research provide favorable conditions for fine-scale geopolitical risk assessments [33].

Therefore, this paper conducted a comprehensive assessment of the geopolitical risk in the Himalayan region and revealed the spatial differentiation characteristics of geopolitical risk based on multiple sources of geographic big data, including natural, political, and socioeconomic elements, and a combination of the RF model, AHP method, entropy weight method, and AHP-entropy method using GIS software with a 1 km $\times$ 1 km grid size as the evaluation unit in order to provide a scientific basis for the restoration and construction of traditional trade routes in the Himalayan region.

2. Analytical Framework

Risk and risk analysis is multidisciplinary research and have developed different risk concepts in various disciplines and research practices, such as business risk, economic risk, environmental risk, financial risk, technological risk, policy risk, and security risk [34]. Risk is usually defined as the possibility of something having adverse consequences [35]. In climate change research, the concept of risk in the IPCC Sixth Assessment Report considers risk as resulting from potential impacts of climatic change and human response to climatic change, with adverse consequences including impacts on lives, livelihoods, social and cultural assets and investments, health and well-being, economy, infrastructure, and ecosystems and species [36]. In geopolitical studies, there are two main perceptions of geopolitical risk: one defines geopolitical risk as the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations [14]; the other sees geopolitical risk as the risk arising from geopolitical elements, including political and economic risks [23]. Based on these two perspectives, scholars have assessed geopolitical risk by using publicly available relevant indices or geopolitical event data derived from the news media, with countries as evaluation units. However, geopolitical risks include not only the adverse effects of geopolitical conflict but also the natural risks arising from complex natural environments, including sudden or gradual natural disasters; political risks arising from armed conflict events, violence, or competition for power between geopolitical actors; and economic risks arising from global or regional economic and financial shocks [4,37]. Overall, geopolitical risk can be decomposed into three components: natural environmental risk, political risk, and economic risk, which interact with each other to have a systematic impact on geopolitical risk.

Natural environment risks mainly include risks caused by complex topographical conditions and natural disasters such as landslides, mudslides, and earthquakes. The natural geographical environment is the basis for people's survival and development. Complex topographic conditions not only trigger people's competition for development space but also induce natural disasters. Natural disasters such as landslides, earthquakes, and mudslides not only directly lead to death, property damage, environmental destruction, and resource shortage but also trigger social conflicts and contradictions that can lead regions into long-term social unrest and political instability [38,39]. Political risks mainly include risks arising from emergencies (armed conflict, social unrest, terrorism, etc.), government governance capacity, regime stability, government corruption, ethnic and religious conflicts, boundary and territorial disputes, and transboundary water resource development and utilization [3]. An unstable regime, inefficient governance, and corruption in the host country often expose investors to the risk of "nationalization" [40]; internal armed conflicts and terrorism pose huge obstacles to investors [41]; ethnic and religious conflicts easily lead to social conflicts and incidents of vandalism and burning, which bring huge risks to investment and construction [42]; and border and territorial disputes, transboundary water resources, and other issues seriously affect political and economic exchanges between countries [29]. Economic risks mainly include those arising from economic turmoil, inflation, the state of transportation infrastructure, and economic freedom [43]. The worse the level of economic development of a country and the higher the rate of inflation, the more exposed investors are to the risk of huge economic losses [44]; at the same time, the worse the condition of transportation infrastructure, the more constant the increase the cost of investment and construction; and economic freedom allows a country or enterprise to be more flexible and free to invest and build, promoting the free flow of economic factors and reducing economic risks [45]. Political risks trigger economic risks such as trade sanctions, disruption of economic and trade cooperation, reduction in trade and investment, and economic recession, while economic risks further stimulate political risks such as armed conflicts, corruption, and political unrest between or within regions [46].

To this end, this paper built an analysis framework from the three aspects of natural risk, political risk, and economic risk based on geographical elements and combined the simulation and prediction advantages of geopolitical events in risk assessment [47] to comprehensively evaluate geopolitical risk in the Himalayan region. The analysis framework is shown in Figure 1.

Figure 1. Analysis framework.

3. Materials and Methods

3.1. Study Area

The Himalayan region refers mainly to the Himalayas and their surrounding areas. Scholars have defined the scope of the Himalayan region from different perspectives, among which physical geographers have mainly adopted the physical geography of the Himalayas, i.e., the narrow arc of approximately 2400 km from the Nanga Parbat in Kashmir in the west to the Namcha Barwa at the Great Bend of the Yarlung Tsangpo River in the east [48]. International political scholars have mainly defined the Himalayan region from a cultural perspective as a transitional zone where Buddhist and Hindu cultures meet between the Tibetan Plateau and the Indian plains [49]. Other scholars have also used the constructs of the region around the Himalayas [50], including the Pan-Himalayas [51], the Trans-Himalayan Economic Zone of Cooperation [8], and the Hindu Kush Himalayan region [52], to define and study the scope of the Himalayan region. In general, Chinese scholars have mainly focused on the Tibetan border areas north of the Himalayas [53], while foreign scholars have mainly focused on the areas south of the Himalayas [54]. Based on the research of relevant scholars, this paper defines the Himalayan region as the Himalayas and its surrounding areas that extend from the Hindu Kush in the west to the Hengduan Mountains in the east and lie between the Tibetan Plateau and the plains of South Asia, including the northern parts of the Khyber-Pakhtunkhwa of Pakistan, Kashmir, the northern Indian states of Himachal Pradesh and Uttarakhand, Nepal, Bhutan, Sikkim, the border areas of the Tibet Autonomous Region of China, and the Aksai Chin region of the Xinjiang Autonomous Region (Figure 2).

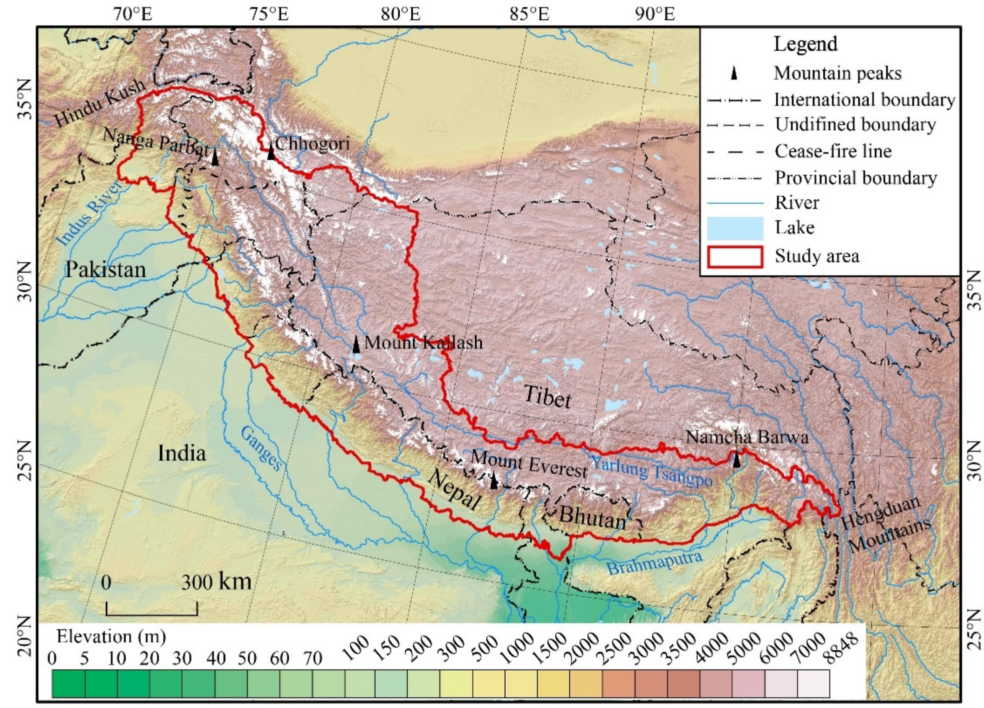

Figure 2. The location map of the study area.

We chose the Himalayan region as our study area for several reasons. First is the complex physical geography of Himalayan region. The Himalayan region is in the collision zone between the Eurasian Plate and the Indian Plate, with a complex geological environment and frequent geological disasters such as earthquakes, landslides, and mudslides [54]. Additionally, the region has rich and diverse vegetation types which create a global biodiversity hotspot. Furthermore, the region, known as the "Asian Water Tower", possesses rich glacial resources, which are the birthplace of Asia's major rivers (Indus, Ganges, Yarlung Tsangpo River, etc.) that provide water for production and living for nearly one billion people downstream [55]. In the context of global climate change, the Himalayan region has become one of the most significant areas of global climate change, and the interaction of various factors, such as increasing regional population, rapid socioeconomic development, and interference from great powers outside the region, continues to exacerbate problems such as regional water conflicts and transboundary water use [56]. Secondly, the Himalayan region is characterized by a unique human geographical environment. Hinduism, Buddhism, Islam, and many tribal cultures meet and collide in the Himalayan region, and the many sacred mountains and lakes in the Himalayan region are valued as communal areas of spirituality by different religions and cultures. Throughout history, the transverse valleys along the Himalayas have developed into routes of human and commercial exchange linking the Tibetan Plateau and the South Asian plains [7]. Thirdly, the Himalayan region is constantly subject to the intervention and influence of great powers in the interaction of its complex physical geography and unique human geography, which continue to exacerbate the complexity and vulnerability within the region, exposing the region to substantial geopolitical risks.

3.2. Data Sources and Processing

3.2.1. Data Sources

The original data in this paper consisted mainly of vector and raster data. To ensure the uniformity of the data, firstly, all data projections were converted to Lambert azimuthal equal area projection by using ArcGIS software. Secondly, the conversion tools were used to convert the vector data into raster data with a spatial resolution of 1 km, and the resample tool was used to resample the raster data with different resolutions to a 1 km spatial resolution.

(1) Geopolitical event data

Geopolitical event data include armed conflict data and landslide data. Armed conflict data were derived from the Armed Conflict Location and Event Data Project (ACLED, http://www.acleddata.com/ (accessed on 12 March 2022)). This database is a real-time database dedicated to recording the location, date, people, fatalities, and type of political violence and protest events reported across the globe, including six event types: battles, explosions/remote violence, violence against civilians, riots, protests, and strategic developments. Landslide data were sourced from the Global Landslide Catalog (GLC) database [57].

(2) Natural element data

Natural element data include slope, elevation, topographic relief, average temperature, average precipitation, multi-hazard frequency, and land cover. Slope and elevation are generated from the DEM dataset, which was derived from NASA SRTM data (https://lpdaac.usgs.gov/products/srtmgl3v003/ (accessed on 13 March 2022)) with a spatial resolution of 90 m. Topographic relief was extracted from the elevation data. Referring to the study by Feng et al. [58], the best domain window was first determined to be 18×18 using the mean variable point method, and then the topographic relief of the study area was calculated based on the optimal domain window. The average temperature and average precipitation were obtained from WorldClim (https://worldclim.org/data/worldclim21.html (accessed on 14 March 2022), v2.1) at a spatial resolution of 1 km. The multi-hazard frequency was derived from the NASA Socioeconomic Data and Applications Center's Global Multi-hazard Frequency and Distribution (https://sedac.ciesin.columbia.edu/data/set/ndh-multihazard-frequency-distribution (accessed on 15 March 2022), v1) with a spatial resolution of $2.5'$. Land cover data were from GlobeLand30 in 2020 (http://www.globallandcover.com (accessed on 16 March 2022)).

(3) Social-economic and political element data

Socioeconomic elements include GDP, night-time light, urban accessibility, distance to a major navigable river, distance to a major navigable lake, and economic freedom. GDP data were obtained from Kummu et al. [59], with a spatial resolution of 1 km. Night-time light data were from the National Oceanic and Atmospheric Administration (NOAA) DMSP-OLS dataset (https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html (accessed on 20 March 2022), v4) at a spatial resolution of 1 km. Urban accessibility was from Weiss et al. [60] at a spatial resolution of 1 km. The distance to a major navigable river and distance to a major navigable lake were obtained from Yale University's geographically based economic data (G-Econ 4.0, http://gecon.yale.edu/ (accessed on 22 March 2022)) at a spatial resolution of $0.1°$. Economic freedom was derived from the Heritage Foundation's Global Economic Freedom Index 2021.

Political elements include population density, transboundary water resources, territorial disputes, ethnic distribution, and corruption perceptions. Population density data were obtained from the 2018 LandScan Global Population database (https://landscan.ornl.gov/ (accessed on 25 March 2022)) at a spatial resolution of 1 km. Ethnic distribution data were obtained from the GeoEPR 2021 dataset (https://icr.ethz.ch/data/epr/geoepr/ (accessed on 26 March 2022)). Transboundary water resource data were obtained from the Transboundary Freshwater Dispute Database (TFDD) (https://transboundarywaters.science.oregonstate.edu/content/transboundary-waters-assessment-programme-river-basins-component (accessed on 27 March 2022)).

Territorial disputes cover several countries. The India-China territorial disputes were obtained by vectorizing the accompanying map in the Combat History of Self-defense Counterattack on the Sino-Indian Border [61]. The Bhutan-China territorial disputes were obtained by vectorizing the surveying and mapping records of the Tibet Autonomous Region [62]. The India-Nepal territorial disputes were from the website https://thedarjeelingchronicle.com/india-nepal-border-controversy/ (accessed on 30 March 2022). Corruption perceptions were derived from the Global Corruption Index 2021 published by Transparency International.

3.2.2. Data Processing

(1) RF model

RF is a decision tree-based machine learning method proposed by Breiman in 2001 [63]. The model uses a bootstrap random sampling method, which draws multiple samples from the original sample, performs decision tree modeling on each bootstrap sample, and then combines the decision tree models to produce a final prediction by voting [64]. In contrast to traditional algorithms, the RF model does not need to set indicator weights or classification criteria in advance, and the weight and classification criteria are implied in the internal characteristics of the data [65]. In addition, due to the advantages of insensitivity to multicollinearity, the ability to handle both continuous and categorical variables, better tolerance of outliers and noise, and higher prediction accuracy, the RF model is now widely used in disaster risk assessments and terrorism predictions [66–68].

The operating principle of the RF model is summarized as follows (Figure 3). Firstly, the bootstrap sampling method is used to select K samples from the original training set in a put-back manner, with each sample having the same size as the original training set. The samples not drawn are called out-of-bag (OOB) samples and can be used to evaluate the performance of the model, called OOB estimation. Secondly, K decision tree models are constructed according to the drawn K sample training sets. Thirdly, each record is voted on to decide its final classification according to the K classification results.

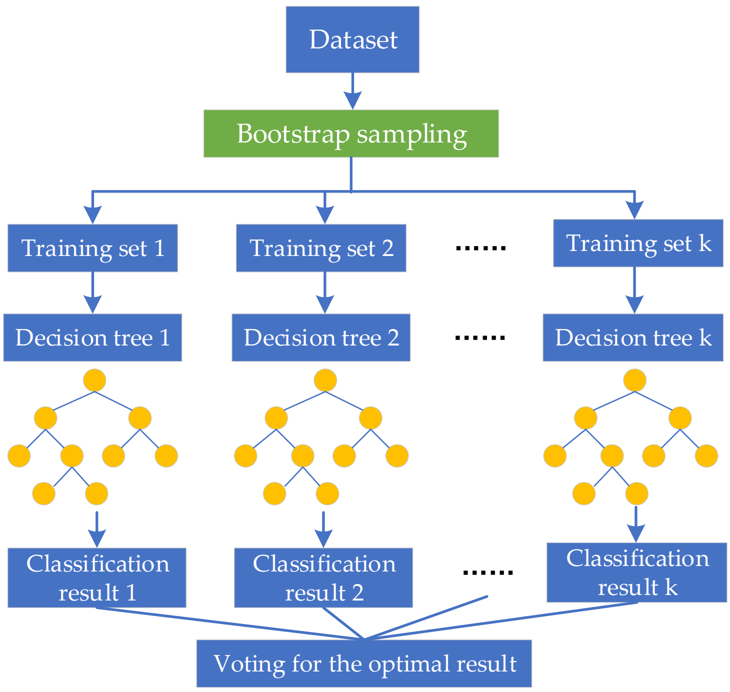

Figure 3. The flowchart of the RF model.

The following describes the determination of model parameters and validation of accuracy. Firstly, mtry and ntree are two key parameters in the random forest model, where mtry represents the square root of the number of factors and ntree represents the number of decision trees. These two parameters are mainly determined based on the OOB error rate generated during the construction of the RF model. In accordance with the principle of minimizing the error rate as the model parameter setting, the values of ntree and mtry were finally determined through several attempts until the OOB error remained stable. Secondly, the receiver-operating characteristic (ROC) and area under the curve (AUC) were used to comprehensively evaluate and validate the simulation effect of the model. the AUC value is between 0 and 1. The closer the value is to 1, the better the model is and the more accurate it is. If the AUC value is less than 0.5, the model is considered invalid [69].

Based on the 'RandomForest' package in the R statistical language, the two indicators of conflict risk and landslide risk in geopolitical risk assessment were calculated through RF model by selecting relevant variables. Firstly, using the armed conflict data in geopolitical events as the dependent variable, combined with the research of related scholars [47,68], 12 indicators of slope, elevation, average temperature, average precipitation, multi-hazard frequency, GDP, night-time light, urban accessibility, distance to a major navigable river, distance to a major navigable lake, ethnic distribution, and population density were selected to simulate and predict the conflict risk. Secondly, using landslide data from geopolitical events as the dependent variable and combining with the research of related scholars [54], six indicators, including slope, elevation, topographic relief, average precipitation, average temperature, and land cover, were selected to simulate and predict landslide risk.

The specific steps for conflict risk are as follows. First, based on the armed conflict data of the study area, a 1 km × 1 km grid was constructed using ArcGIS software, and the grids with armed conflict were assigned a value of 1, representing the conflict samples, while the rest of the grids were assigned a value of 0, representing the nonconflict samples. Second, the same number of grids was randomly selected from the grids with a value of 0 as the nonconflict samples, and a total of 7012 samples were finally obtained (3016 conflict samples and 3016 nonconflict samples). Third, 75% of the samples were randomly selected from the sample data as the training set and 25% of the samples as the test set, and the ntree and mtry parameters in the model were set to 2 and 3000, respectively, using the cyclic variable method. Finally, the model was constructed to simulate and predict the conflict risk, and the model's simulation effect was comprehensively evaluated and validated using the receiver operating characteristic (ROC) and area under the curve (AUC).

The specific steps for landslide risk are as follows. First, based on the landslide data of the study area, a 1 km × 1 km grid was constructed using ArcGIS software, and the grids with landslide were assigned a value of 1, representing the landslide samples, while the rest of the grids were assigned a value of 0, representing the non-landslide samples; second, the same number of grids was randomly selected from the grids with a value of 0 as the non-landslide samples, and a total of 2936 samples were finally obtained (1468 landslide hazard samples and 1468 non-landslide samples). Second, 75% of the samples were randomly selected from the sample data as the training set and 25% as the test set, and the ntree and mtry parameters in the model were set to 5 and 3000, respectively, using the cyclic variable approach. Finally, the model was constructed for landslide risk simulation and prediction, and the results were validated using the receiver operating characteristic (ROC) and area under the curve (AUC).

(2) Extremum normalization

As the evaluation indicators have different units and represent different practical meanings, they cannot be directly calculated and compared, so they need to be normalized. Based on a related reference [70], an extremum normalization method was used to normalized the indicators. Among the indicators selected for this paper, the multi-hazard frequency, topographic relief, population density, transboundary water resources, territorial disputes, and corruption perceptions are positive indicators, while the economic freedom, night-time light, urban accessibility, and GDP are negative indicators. The specific formulae are as follows.

$$\text{Positive indicators}: y_{ij} = (x_i - \min(x))/(\max(x) - \min(x)) \quad (1)$$

$$\text{Negative indicators}: y_{ij} = (\max(x) - x_i)/(\max(x) - \min(x)) \quad (2)$$

where y_{ij} is the standardized value of indicator j at region i, and its value range is from 0 to 1; x_i is the original value of region i, and $\max(x)$ and $\min(x)$ are the maximum and minimum values of indicator j, respectively.

3.3. Methods

Based on the analytical framework, the geopolitical risk assessment of the Himalayan region was realized through the following steps: (1) constructing a geopolitical risk evaluation index system from the three aspects of natural risk, economic risk, and political risk; (2) adopting the RF model to simulate and predict the conflict risk and landslide risk triggered by armed conflict events and landslide events, respectively; (3) adopting the AHP method and entropy weighting method to determine the weight of each indicator; (4) adopting the extremum normalization method to standardize each indicator; and (5) adopting the comprehensive index method to calculate the geopolitical risk, then using the natural breaks method in ArcGIS software to classify the geopolitical risk index into very high risk, high risk, medium risk, low risk, and lower risk.

3.3.1. Weight Determination

(1) Analytic hierarchy process method

Analytic hierarchy process (AHP) is a combined qualitative and quantitative approach to decision analysis proposed by American operations researcher Thomas L. Saaty in the 1970s [71]. This method determines the weight of each element by decomposing a complex problem into different levels and different constituent elements and then comparing the elements in two to determine their importance; it is a subjective weighting method and has been widely used to determine the weight of evaluation indicators [72]. The calculation steps are (i) establish a hierarchical structure model; (ii) construct a judgment matrix and invite experts in related fields to compare and quantify two-by-two indicators using the scaling method of 1~9 and its reciprocal; (iii) calculate the weights of each indicator; and (iv) use the ratio CR of the consistency indicator (CI) and average random consistency indicator (RI) to conduct a consistency test [73].

(2) Entropy weight method

Entropy weighting is an objective weighting method that determines the weight of each indicator by calculating the information entropy [74]. The calculation steps are (i) assume that there are m cells and n evaluation indicators in the study area and construct a judgment matrix as $T = (t_{ij})_{m\times n}$; (ii) define the information entropy of each indicator; and (iii) calculate the entropy weight of each indicator r_j. The calculation formula is as follows.

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{m}\left[\left(y_{ij}/\sum_{i=1}^{m} y_{ij}\right) \times \ln\left(y_{ij}/\sum_{i=1}^{m} y_{ij}\right)\right] \quad (3)$$

$$r_j = (1 - E_i)/\sum_{j=1}^{n}(1 - E_i) \quad (4)$$

(3) Linear combination weighting

To fully combine the advantages of subjective and objective assignments, the linear combination method was used to synthetically determine the weights of the indicators in geopolitical risk evaluation based on the results of the weight calculation of the AHP method and the entropy weight method [75]. The calculation formula is as follows.

$$w_j = \alpha s_j + \beta r_j \quad (5)$$

$$\begin{cases} d(s_j, r_j)^2 = (\alpha - \beta)^2 \\ \alpha + \beta = 1 \end{cases} \quad (6)$$

$$d(s_j, r_j) = \sqrt{\frac{1}{2}\sum_{j}^{n}(s_j - s_j)^2} \tag{7}$$

where w_j is the combination weight of indictor j, s_j is the subjective weight calculated by the AHP method, r_j is the objective weight calculated by the entropy method, α and β are the distribution coefficients of subjective and objective weights, respectively, and $d(s_j, r_j)$ is the distance function between subjective and objective weights. The final linear combination weighting was obtained by calculation (Table 1).

Table 1. Weight of geopolitical risk index.

Subsystem Level	Index Hierarchy	Weight		
		AHP	Entropy Weight	AHP-Entropy Weight Method
Economic risk (0.2424)	Economic freedom	0.1344	0.9971	0.2523
	GDP index	0.4621	0.0001	0.3989
	Night light index	0.3008	0.0026	0.2601
	Accessibility index	0.1027	0.0002	0.0887
Political risk (0.4735)	Population density index	0.0367	0.5809	0.1737
	Corruption perceptions index	0.0708	0.0296	0.0604
	Territorial disputes risk	0.2721	0.3108	0.2818
	Transboundary water disputed risk	0.1349	0.0172	0.1053
	Conflict risk	0.4855	0.0615	0.3788
Natural risk (0.2841)	Topographic relief index	0.2970	0.1132	0.2218
	Landslide risk	0.1634	0.3436	0.2371
	Multi-hazard index	0.5396	0.5432	0.5411

3.3.2. Composite Index Measurement

Based on the results of the linear combination weighting calculation (Table 1), the composite index method was used to multiply each indicator by its combination weight and then they were added together to obtain the composite index of geo-risk in the Himalayan region. It is calculated as follows.

$$Z_i = \sum_{j=1}^{n} y_{ij} \times w_j \tag{8}$$

where Z_i denotes the geopolitical risk composite index of cell i, with higher values indicating higher risk; w_j is the combination weight of indicator j; and y_{ij} is the standardized value of indicator j.

4. Results

4.1. Natural Risk

The indicators of natural risk in the Himalayan region include topographic relief (Figure 4(a1)), landslide risk (Figure 4(a2)), and multi-hazard frequency (Figure 4(a3)). Among them, landslide risk was obtained by RF model analysis, and the ROC curve results showed that the AUC value of the test data was 0.894, indicating the high accuracy of the RF model in simulating and predicting landslide risk sample data. The high landslide risk areas are distributed along the southern slopes of the Himalayas in an arc-shaped strip; the topographic relief decreases from north to south along the Himalayan ridgelines, and the topographic relief near the ridgelines reaches over 1200 m. Due to factors such as topographic fragmentation, landslides and mudslides are frequent in the southern slopes of the Himalayas, and the multi-hazard frequency was high, with the multi-hazard frequency in northwest India being the largest, affected by at least three hazards, and Nepal and other parts of northwest India being affected by at least two hazards (Figure 4(a3)). The natural risks in the Himalayan region were calculated using the raster calculator tool of ArcGIS software (Figure 4(a4)).

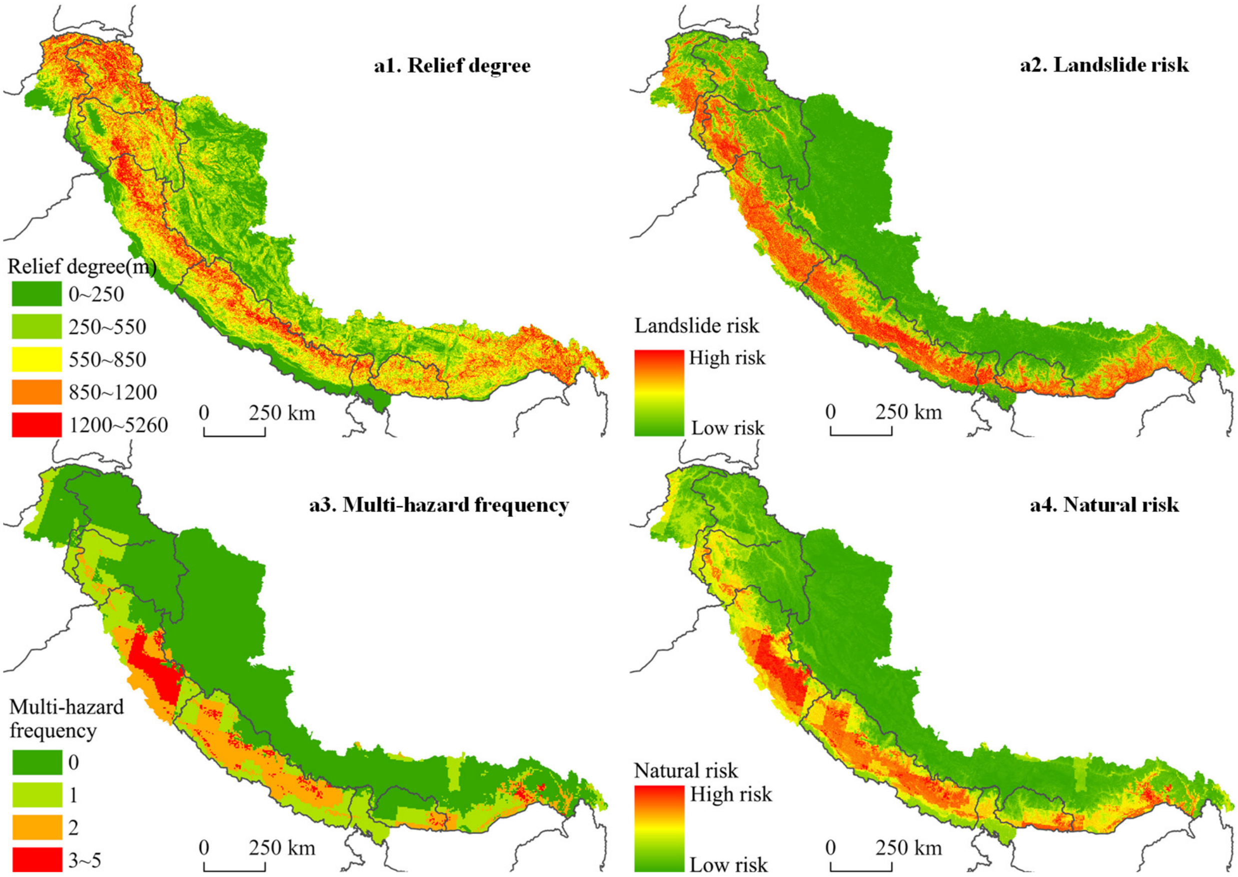

Figure 4. Spatial distribution of the natural risk index in the Himalayan region.

Overall, under the combined influence of complex topography and multiple hazards, such as landslides, mudslides, and floods, the Himalayan region showed two high concentrations of natural risk in northwest India and Nepal. In addition, southeastern Bhutan and the areas on both sides of the Yarlung Tsangpo River in southern Tibet also present high risks. Southern Kashmir and other areas in southern Tibet are relatively low risk. Tibetan border areas on the northern slopes of the Himalayas have the lowest natural risk.

4.2. Political Risk

The political risk indicators include population density (Figure 5(b1)), territorial disputes (Figure 5(b2)), conflict risk (Figure 5(b3)), corruption perceptions index (Figure 5(b4)), and transboundary water disputed risk (Figure 5(b5)). Among them, conflict risk was obtained through the analysis of the RF model, and the results of the ROC curve showed that the AUC value of the test data was 0.983, indicating the high accuracy of the random forest model in simulating and predicting the conflict risk sample data. The simulation results of conflict risk showed that the south-central region of Nepal, the Kashmir valley and its south, the southwestern region of Khyber-Pakhtunkhwa of Pakistan near the Indus plain, and the southwestern region of Himachal Pradesh in India face the highest conflict risk, while the Tibetan border region, Bhutan, and the northeastern region of India near the Tibetan border of China face the lowest conflict risk (Figure 5(b3)). In terms of other indicators, the population of the Himalayan region is mainly concentrated in the Kathmandu Valley on the southern slopes of the Himalayas, the Kashmir Valley, and the southern belt near the plains of India (Figure 5(b1)). Territorial disputes have become a major factor affecting the volatile situation in the Himalayan region, including India-Pakistan Kashmir, the western, central, and eastern sections of the Sino-Indian border, the Yadong section, the Baiyu area, and Merag-Sagteng near the Sino-Bhutan border (Figure 5(b2)). The corruption perception index was more severe in Pakistan and Nepal, relatively low in India and Bhutan, and lowest in China (Figure 5(b4)). The Himalayan region is known as the water tower of Asia, and the development and use of transboundary water resources have constantly led to instability in the region, with the Yarlung Tsangpo and Indus river basins having the highest risk (Figure 5(b5)).

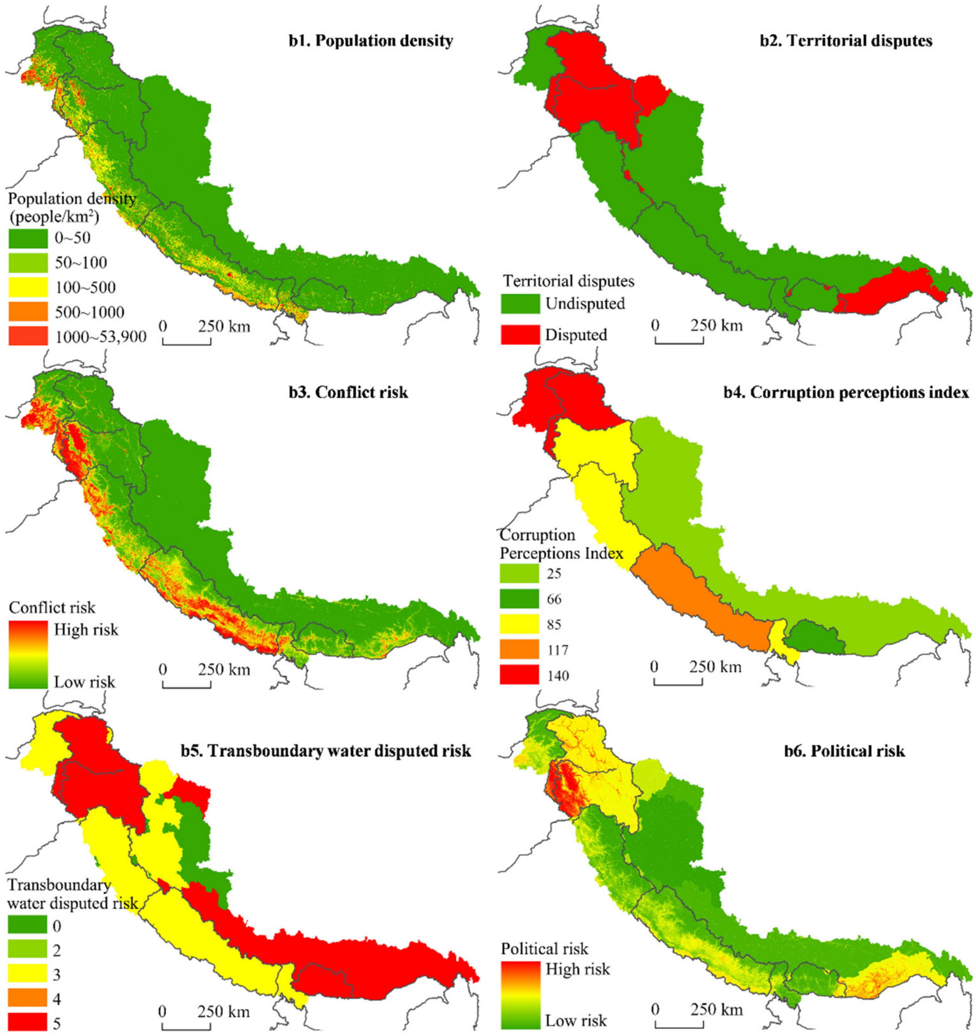

Figure 5. Spatial distribution of the political risk index in the Himalayan region.

Political risk was obtained by overlaying individual elements using the raster calculator tool of ArcGIS software (Figure 5(b6)). The results showed that the Kashmir valley and its south face the highest political risk, northeastern Kashmir and southern Tibet face higher risk, and the Bhutan and Tibet border areas face the lowest risk. The Kashmir Valley and its south are affected not only by the Kashmir territorial disputes but also by a combination of issues such as corruption perceptions of local government, armed conflict, the development and use of transboundary water resources in the Indus basin, and religious conflict between Hinduism and Islam, resulting in high levels of political risk. Northeastern Kashmir and southern Tibet are mainly affected by territorial disputes and the transboundary water resources of the Yarlung Tsangpo River, showing high-risk characteristics. Nepal is affected by armed conflict and corruption due to the unrest in the country and presents a medium-risk level.

4.3. Economic Risk

The economic risk indicators include the night light index (Figure 6(c1)), GDP (Figure 6(c2)), accessibility (Figure 6(c3)), and economic freedom index (Figure 6(c4)). High values of the night-time light index were concentrated in the southern part of Pakistan, northwestern India, and Sikkim (Figure 6(c1)). High values of GDP were concentrated in Nepal, with relatively high levels of GDP in the Shigatse of Tibet and Bhutan (Figure 6(c2)). Accessibility was higher on the southern slopes of the Himalayas, most of which can be reached within 5 h, while the accessibility of the Ngari Prefecture of Tibet and areas near the national borderline on the northern slopes of the Himalayas was poor, requiring at least 1 day to reach (Figure 6(c3)). Economic freedom was the worst in Nepal and Pakistan and better in China and Bhutan (Figure 6(c4)).

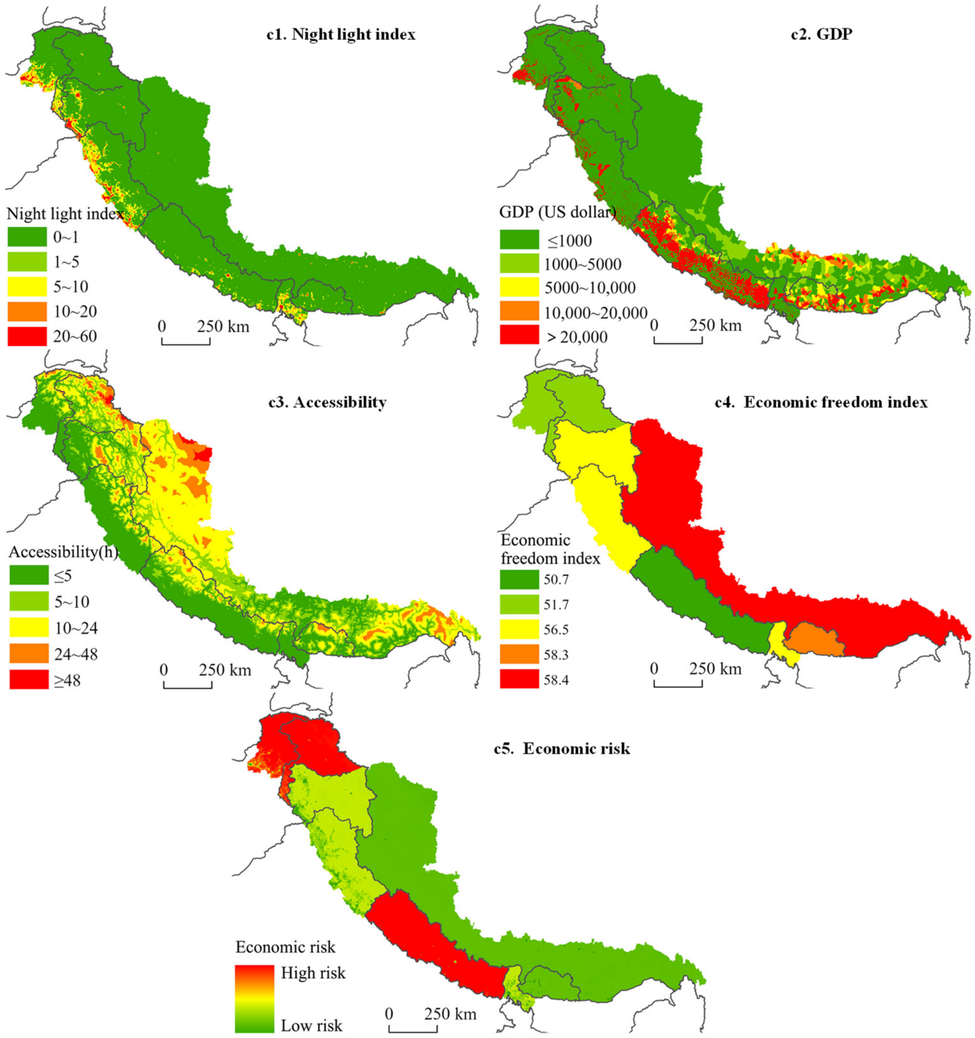

Figure 6. Spatial distribution of the economic risk index in the Himalayan region.

The economic risk for the Himalayan region was calculated using ArcGIS software's raster calculator analysis tool (Figure 6(c5)). Overall, economic freedom had a greater impact on economic risk in the Himalayan region, with Nepal and Pakistan having the lowest economic freedom index, a poorer economic environment, and the highest risk exposure; northwest India and Sikkim have relatively low risk, and Tibet and Bhutan have the lowest risk.

4.4. Geopolitical Risk

According to Formula (8) of the comprehensive index method, each index was multiplied by the corresponding combination weight to obtain the comprehensive index of geopolitical risk based on the AHP-entropy weight method. The natural breaks of ArcGIS software were used to classify the geopolitical risk composite index into five levels: very high risk, high risk, medium risk, low risk, and lower risk. The results are shown in Figure 7.

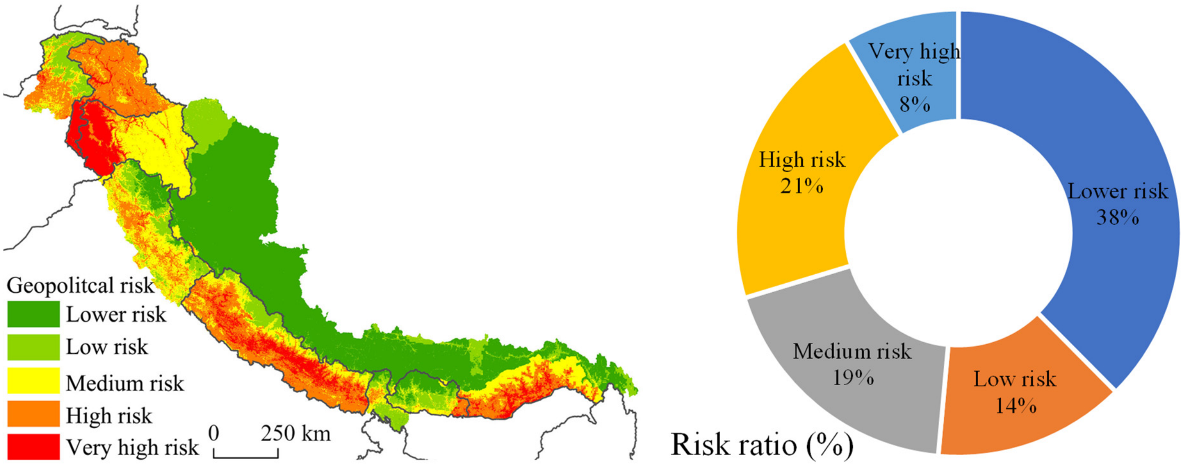

Figure 7. Spatial distribution of the geopolitical risk index in the Himalayan region.

In terms of the overall spatial distribution of geopolitical risks (Figure 7), the very high and high risks of geopolitical risks in the Himalayan region are mainly concentrated in three regions: Kashmir, the central and southern regions of Nepal, and southern Tibet. The medium risks are mainly concentrated in two regions: Himachal Pradesh and Uttarakhand in India and parts of northern Nepal near the Tibetan border in China. The low and lower risks are mainly concentrated in two regions: the Tibetan border region in China and Bhutan.

In terms of the proportion of geopolitical risk levels in different regions (Table 2), Nepal was dominated by very high-risk and high-risk levels, with high-risk areas accounting for 46.25% of the total area of Nepal and very high-risk areas accounting for 20.29%, mainly in the central and southern regions of Nepal. Bhutan was dominated by low-risk and lower-risk areas, with low-risk areas and lower-risk areas accounting for more than 34% of the total area of Bhutan, mainly in central, northern, and western Bhutan. Pakistan was dominated by high risk, with high-risk areas accounting for 59.36% of the total area of Pakistan, mainly in Pakistani-administered Kashmir. India was predominantly medium risk, with medium-risk areas covering 47.26% of the total area of the Indian region, mainly in the central and southern parts of Indian-administered Kashmir, Himachal Pradesh, and Uttarakhand. China was predominantly lower risk, with lower-risk areas covering 73.65% of the total area of the China region, mainly in areas other than Tibetan South and Aksai Chin.

Table 2. Ratios of geopolitical risk levels in the Himalayan region.

Risk Level	Lower Risk (%)	Low Risk (%)	Medium Risk (%)	High Risk (%)	Very High Risk (%)
Nepal	0.09	11.65	21.72	46.25	20.29
Bhutan	35.6	34.89	18.37	8.14	2.98
Pakistan	0	17.2	12.78	59.36	10.66
India	7.1	15.58	47.26	16.83	13.23
China	73.65	11.24	6.34	6.39	2.38

5. Discussion

This study provided a comprehensive assessment of geopolitical risk in the Himalayan region from a quantitative perspective, which provides a more comprehensive picture of the geopolitical risk characteristics in the Himalayan region than previous indirect assessments that have mainly focused on South Asia [3,31], the China-Pakistan Economic Corridor [29], and the Indian Ocean region [22] as study areas. Previous studies have mainly reflected the geopolitical risk situation in countries and parts of the southern slopes of the Himalayas, while the geopolitical risk in the southern Tibetan and Tibetan border regions of China on the northern slopes has not been adequately portrayed. The assessment of geopolitical risk in South Asia by Lin et al. [31] showed that the risks are higher in northern India and northwestern Pakistan, high in the southern part of Nepal bordering India, and lower in Bhutan, all of which are generally consistent with the assessment results of our study. However, the risks were shown to be relatively low in northern Kashmir, which is less consistent with the results of our study, mainly because their study analyzed the risks posed by terrorism and did not sufficiently consider territorial disputes, transboundary water resources, economic risks, etc. Northwest Pakistan, Kashmir, and northern India are affected not only by traditional security issues such as territorial disputes, arms races, military threats, and religious conflicts between Hinduism and Islam but also by nontraditional security issues such as terrorism, the development and utilization of transboundary water resources in the Indus basin, natural disasters, and organized crime abroad [29,56]. Hong et al. [3] used a country-based scale to construct an indicator system to assess the geopolitical risk of major projects in South Asia. The results showed that Bhutan, Nepal, and Pakistan are at medium risk and India is at high risk. Among them, the evaluation results of Nepal and Pakistan are not consistent with our study, mainly because their study emphasized the impact of elements such as the intervention of major powers and the alliance and confrontation relationship between China and the host country on project investment, while the armed conflict, natural environment, and economic differences within the country or region were not sufficiently portrayed.

This study attempted a comprehensive assessment of geopolitical risks in cross-border areas at the raster scale. Compared with the current macro geopolitical risk assessment, which is mainly based on the national scale [14,24,26], our study fully combined the advantages of geographic big data and methods to put the assessment and identification of geopolitical risks into a specific geographic space, which can provide a more fine-grained risk assessment for the construction of the corridor in the Himalayan region. Although the assessment based on the raster scale can better reveal the influence of geographical factors such as topography, natural disasters, accessibility, socioeconomic development, and armed conflicts on geopolitical risk, the lack of big data on other geographical elements at fine scales, such as the political stability, intervention of major powers, and foreign trade dependence [24,32], has led to insufficient portrayals of the geopolitical risk of these factors.

In the future, we need to further explore geopolitical risk assessment by combining the Global Database of Event, Language, Tone (GDELT) and the Chinese Global Investment Tracker (CGIT) with other geographic big data. Among them, GDELT data are updated every 15 min by collecting broadcast, print, and news reports in more than 100 languages around the world that cover social dynamic events related to politics, military, diplomacy, economy, etc. Compared to other data, GDELT data have a wider coverage [76] and are now being used by scholars for research on geopolitical relations [77], political risk [78], and social stability and unrest [79].

6. Conclusions

This study set out to conduct a comprehensive assessment of geopolitical risk in the Himalayan region at the raster scale based on data on physical geographic factors such as topography, climate and landslides, economic factors such as GDP, night-time light, and urban accessibility, and political factors such as armed conflict, territorial disputes, and transboundary water resources using the RF model, entropy weight method, AHP, and AHP-entropy weight method. The main results are as follows.

(1) The geopolitical risk in the Himalayan region as a whole showed a medium-high risk zone on the southern slopes of the Himalayas and a low-risk zone on the northern slopes.
(2) The geopolitical risks in the Himalayan region are influenced by a combination of natural, political, and economic risks. High risks of natural risks are concentrated in the Indian states of Himachal Pradesh and Uttarakhand, Nepal, southern Tibet, and southeastern Bhutan. High risks of political risks are concentrated in the Kashmir Valley and areas south of it, and medium risks are concentrated in Kashmir and southern Tibet. High risks of economic risks are concentrated in the Khyber-Pakhtunkhwa of Pakistan, Pakistani-controlled Kashmir, and Nepal.
(3) Raster-scale assessments can better characterize the spatial distribution of geopolitical risk and provide a basis for the restoration and construction of traditional trade routes in the Himalayan region.
(4) Given that China's investment and corridor construction in the Himalayan region are mainly concentrated in Nepal and Kashmir, which are mainly high-risk and very high-risk areas, a comprehensive study of risks is needed for future investment, planning, and construction. Priority should be given to the construction of relatively low-risk areas in northern Nepal near Burang County and Mustang. Based on the low-risk level in Bhutan, there is a need for integrated planning for the rehabilitation and construction of corridors between China and Bhutan. Further detailed analysis of the geopolitical risk of each traditional trade route in the Himalayan region in conjunction with field surveys should be done to identify the main constraints of the corridors and propose strategies for their construction and control.

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