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Snow Disaster Early Warning in Pastoral Areas of Qinghai Province, China

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Academic Editors: Claudia Notarnicola, Soe Myint and Prasad Thenkabail
Received: 15 March 2017; Accepted: 9 May 2017; Published: 12 May 2017

Abstract: It is important to predict snow disasters to prevent and reduce hazards in pastoral areas. In this study, we build a potential risk assessment model based on a logistic regression of 33 snow disaster events that occurred in Qinghai Province. A simulation model of the snow disaster early warning is established using a back propagation artificial neural network (BP-ANN) method and is then validated. The results show: (1) the potential risk of a snow disaster in the Qinghai Province is mainly determined by five factors. Three factors are positively associated, the maximum snow depth, snow-covered days (SCDs), and slope, and two are negative factors, annual mean temperature and per capita gross domestic product (GDP); (2) the key factors that contribute to the prediction of a snow disaster are (from the largest to smallest contribution): the mean temperature, probability of a spring snow disaster, potential risk of a snow disaster, continual days of a mean daily temperature below −5 °C, and fractional snow-covered area; and (3) the BP-ANN model for an early warning of snow disaster is a practicable predictive method with an overall accuracy of 80%. This model has quite a few advantages over previously published models, such as it is raster-based, has a high resolution, and has an ideal capacity of generalization and prediction. The model output not only tells which county has a disaster (published models can) but also tells where and the degree of damage at a 500 m pixel scale resolution (published models cannot).

Keywords: snow disaster; risk assessment; early warning; artificial neural network; pastoral area

1. Introduction

Snow disasters in pastoral regions are meteorological disasters that affect animal husbandry because of heavy snow, sustained low temperatures, and prolonged snow cover. These disasters are serious threats to animal production and lives in pastoral regions because pastures are covered by snow, which makes livestock foraging difficult and can result in livestock deaths [1–3]. Snow disasters generally begin in October and end in April of the following year in the Tibetan Plateau [4]. Spatially, snow disasters mainly occur in high-elevation and high-latitude areas, as well as in rich natural grasslands, especially in Inner Mongolia, Xinjiang, Qinghai, Tibet, and other places [5]. Qinghai Province is located on the northeastern part of the Tibetan Plateau and often receives heavy snowfall in the winter and spring because of the influence of the plateau's specific geographic environment and climatic conditions. These conditions threaten the personal safety of herdsmen and their personal properties. In addition, heavy snow restricts the normal process of animal husbandry [2,5–7]. Therefore, it is important to construct accurate risk assessments of snow-caused disasters and pre-disaster early warning systems to prevent and reduce these disasters.

In recent years, many experts and scholars have examined various aspects of snow disaster prediction (by calculating the probability of a snow disaster occurrence during a certain time and in a specific area according to the existing data) and potential risk assessment (by simulating the geographic position, spatial distribution, and hazard degree of a snow disaster that has not yet occurred according to the simulation data) using remote sensing (RS) and geographic information system (GIS) technologies. The studies mainly focused on snow disaster monitoring methods [8–10], spatiotemporal analyses of the disaster-causing factors [7,11,12], snow disaster risk zoning and evaluation [12–18], and snow disaster early warning modeling and hazard assessment [1,3,18–22]. Many of these studies are both qualitative and quantitative and span from hazard evaluations of snow disasters to spatiotemporal early warning systems for snow disasters, as well as from single-factor models to multi-factor models. These various methods provide a theoretical basis for snow disaster early warning and hazard evaluation. Snow disaster early warning includes the probabilistic prediction of the hazard area and intensity of a snow disaster that is most likely to occur in the near future. Some studies only focused on assessing prior snow-caused disasters for the factors that caused the disasters and the associated damages [2,7,18,23], the vulnerability and resilience of a hazard-bearing body [17,24] and multi-factor, comprehensive early warning models [3,21,25]. However, only a few studies intended to combine potential risk assessments of a certain area into an early warning model for snow-caused disasters. The existing results of modeling a snow disaster for early warning purposes have some inherent weaknesses. For instance, some models do not consider the effects of factors outside the grassland animal husbandry system on snow disasters [26] and the effects of human intervention on the degree of damage of snow disasters [21]. They also ignored the effects of herding, meteorological factors, and other factors on snow disaster hazards [3]. The previous results of the simulation did not agree with the actual situation [19] and did not evaluate deviations in estimated snow disaster levels [25]. In summary, the existing models of snow disaster are generally associated with certain limitations, and no study has provided raster-based temporal-spatial predictions of snow disasters using machine learning methods.

Therefore, a study is presented in this paper using RS and GIS technologies combined with the statistic and climatic data of the Qinghai pastoral area with the following objectives: (1) to construct a logistic regression model of the potential risk for snow disasters; (2) to establish a back propagation artificial neural network (BP-ANN) early warning model for snow disasters; and (3) to assess the accuracy of the snow disaster early warning results using known snow disaster cases. Through this study, we hope to provide theoretical support for scientific early warning of snow disasters, disaster prevention and reduction schemes, post-disaster rescue strategies, and post-disaster recovery plans.

2. Study Area and Data

2.1. Study Area

Qinghai Province (31°09′ N–39°19′ N, 89°35′ E–103°04′ E) is located on the northeastern edge of the Qinghai-Tibet Plateau. The province has an average elevation of above 3500 m and an area of 721,200 km^2. The topography and landforms in the area are complex. Notably, many mountainous and low-lying terrain areas are located in the eastern part of the study area, and numerous plateaus and basins exist in the northwest (Figure 1). Qinghai is characterized as a typical plateau continental climate with low temperatures, large temperature variations between day and night, low and concentrated rainfall, long hours of sunshine, and high solar radiation with large regional differences and significant vertical variations. The grassland types are mainly alpine meadow and alpine steppe and account for 81% of the total pasture area in the study area [27]. Grassland utilization is mainly dominated by fenced grazing and four-season rotational grazing.

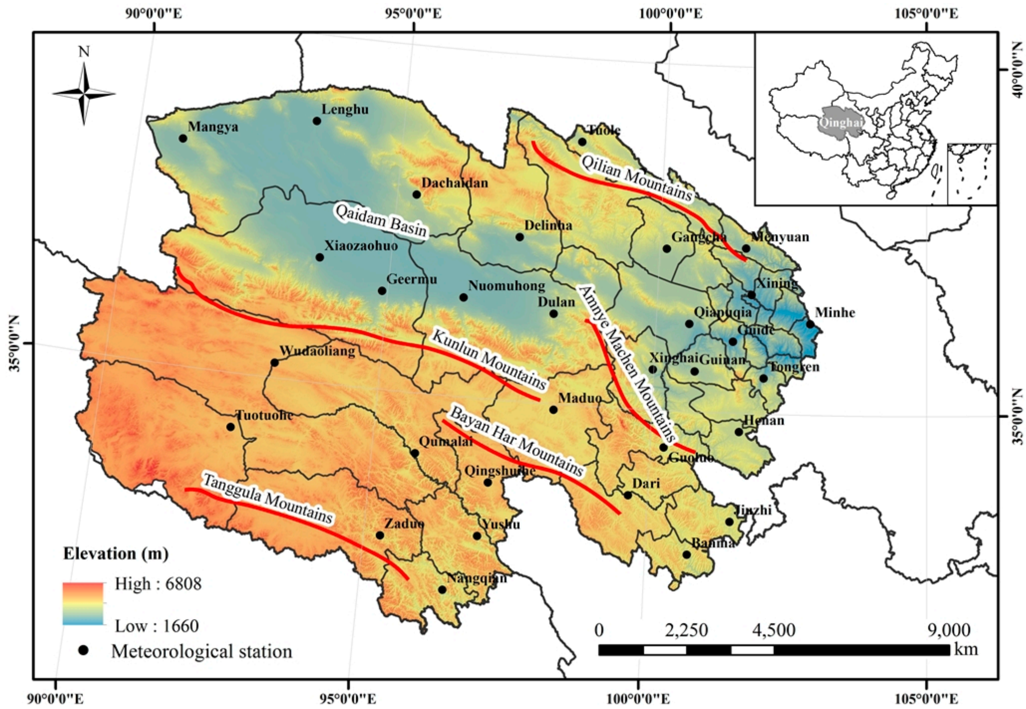

Figure 1. The topography of the Qinghai Province and locations of meteorological stations.

2.2. Data

2.2.1. Remote Sensing Data

This study uses Moderate Resolution Imaging Spectroradiometer (MODIS) daily snow cover products (MOD10A1 and MYD10A1) (500 m resolution) from the Terra and Aqua satellites between 2001 and 2015 and the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) daily snow water equivalent (SWE) products (25 km resolution) and snow depth data (25 km resolution), which are derived from the long-term snow depth dataset of China developed by Dr. Che Tao [28] from 1979 to 2014 (*Heihe Planning Data Management Center*) [29].

2.2.2. Meteorological Observation Data

Daily temperature, precipitation, snow depth, and wind speed data were collected at meteorological stations and were obtained from the Chinese Meteorological Data Sharing Service System (CMDS) [30] between 2000 and 2015. This study uses the widely applied ANUSPLIN 4.3 software [31,32], which was developed by Hutchinson (2004) [33] based on the thin plate spline theory for climate data surface fitting to spatially interpret the observation data from meteorological stations to obtain five indexes (continual days of mean daily temperature below 0 °C, continual days of mean daily temperature below −5 °C, continual days of mean daily temperature below −10 °C, mean temperature, and total precipitation) of weather conditions during a disaster with a spatial resolution of 500 m.

2.2.3. Statistical Data

Statistical population and livestock data (i.e., quantity of livestock at the beginning of the year and end of the year), socioeconomic data (i.e., per capita gross domestic product (GDP) and per livestock GDP), and other data from each county-level administrative district in the Qinghai Province from 2000 to 2015 were obtained. The data were collected by the Statistics Bureau of Qinghai Province and were interpolated into raster data (500 m resolution) using spatialization methods.

Data from 33 typical cases (from *China's Meteorological Disaster Volume (Qinghai)*) [34] were selected from the snow disaster records in Qinghai Province from 2001 to 2007 as a sample set to train the BP-ANN model. Accuracy evaluations of the early warning model were conducted based on two additional snow disaster cases in 2008 and 2015 (Table 1). According to the statistics on meteorological disasters, a spatial database was established containing the probability of a winter snow disaster (from October to January of the next year), the probability of a spring snow disaster (from February to May), and the mean annual probability of a snow disaster over 50 years (from 1961 to 2010).

Table 1. Typical cases of snow disasters in Qinghai.

Case Category	Year	Location	Number of Events
Machine Learning cases	2001	Tongde county	1
	2002	Tongde county	1
	2004	Delinha, Henan, Tianjun, Wulan, Xunhua, Zeku, Dulan, and Tongde counties	10
	2005	Banma, Chindu, Dari, Datong, Gangcha, Gonghe, Huangyuan, Qumalai, Tianjun, Tongde, Tongren, Xinghai, Yushu, and Zeku counties	16
	2006	Tongren and Dulan counties	3
	2007	Delinha and Xunhua counties	2
Validation cases	2008	Three Rivers Headwater Region	1
	2015	Dulan and Wulan counties	1

2.2.4. Others

Digital elevation model (DEM) data with 90 m spatial resolution were obtained from the U.S. Geological Survey (USGS) [35], and the slope data were extracted to analyze the effects of topographic factors in the grazing region. Administrative division, grassland type, and seasonal grassland utilization data in the study area were analyzed to remove the impacts of non-grassland and summer pasture areas from the early warning results of snow disasters.

3. Methodology

3.1. Process of a Snow Disaster Early Warning Model

A flow chart of a snow disaster early warning model is shown in Figure 2. We first construct a logistic regression model to evaluate the potential risk associated with a snow disaster and calculate the potential snow disaster risk using a correlation analysis, principal component analysis (PCA), and other methods based on 33 typical snow disaster cases from 2001 to 2007 in Qinghai Province. Then, based on a number of historical statistical factors, pre-disaster snow condition factors, and meteorological factors during the disasters, key early warning factors of the snow disasters are selected as network input parameters using the mean impact value (MIV) variable selection method. Finally, livestock mortality is set as a network output parameter to train the BP-ANN early warning model of snow disasters. Furthermore, we use the two verified snow disaster cases in mid-February 2008 and late February 2015, to evaluate the early warning model. In each county-level administrative district, livestock mortality (M) can be represented as follows:

$$M = Q_d / Q_r \quad (1)$$

where Q_d is the quantity of dead livestock in each snow-caused disaster and Q_r is the quantity of livestock at the beginning of the year.

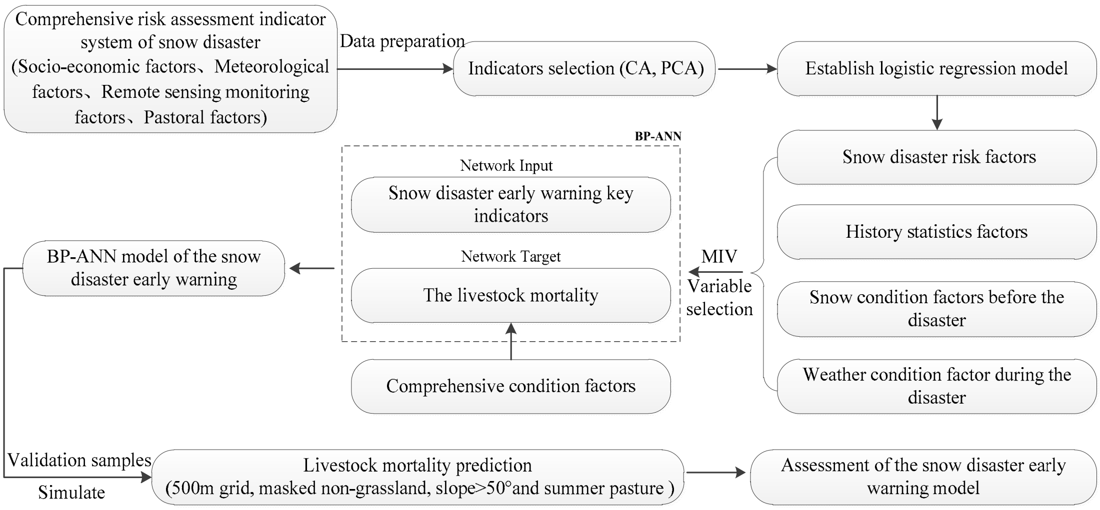

Figure 2. Flow chart of the snow disaster early warning model.

3.2. Integrated Snow Cover Products

Based on snow cover products and SWE products as well as various composite rules and algorithm models [36–38], we produce the composite MOD10A1 and MYD10A1 obtained at different times to reduce some cloud cover based on characteristic cloud movement. Then, we mask the cloud pixel through an adjacent temporal composite (i.e., if the pixel for a given day is classified as a cloud but in the previous and following days, it is snow, then, the pixel is classified as snow; if the cloud pixel in the previous and following days is land, the pixel is classified as land). Then, we use the snow line approach (SNOWL), which is a method based on the aforementioned theory to assign and reclassify the cloud pixel based on its elevation compared with snow and land in a given elevation zone [37]. Finally, a daily cloud-free snow cover product (500 m resolution) in Qinghai Province (2001 to 2015) is produced by taking advantage of both the MODIS high spatial resolution and cloud transparency of the downscaling AMSR-E SWE product (500 m resolution). For example, the cloud-free snow cover product on 15 February 2008 and on 25 February 2015 in Qinghai Province is shown in Figure 3. We re-sample the original SWE data using the neighbor interpolation method in the ArcGIS 10.2. In addition, the fractional snow-covered area, snow-covered area, snow-covered days, and other factors are calculated. The snow depth is one of the snow disaster early warning factors; we use a resampling method to interpret it and obtain downscaling snow depth data with a 500 m spatial resolution.

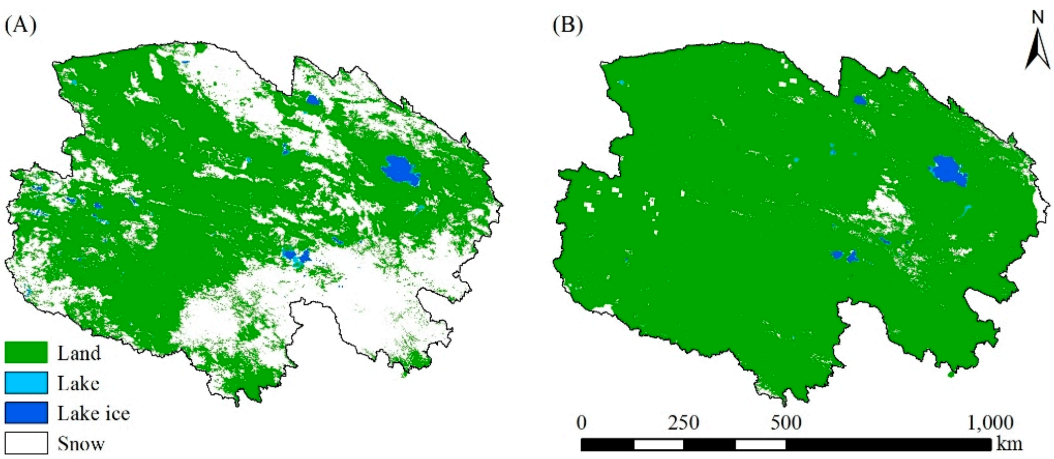

Figure 3. The cloud-free snow cover product on 15 February 2008 (**A**) and on 25 February 2015 (**B**) in Qinghai Province.

3.3. Potential Risk Assessment

This study collects 19 factors (average value of the 7 years (2001–2007)) about socioeconomic factors, meteorological factors, remote sensing monitoring factors, and pastoral factors that influence a snow disaster that occurs in Qinghai Province based on available research experience [12,13,15,17,39]. Then, the study determines the representation and operability (i.e., spatialization) of each factor and constructs an indicator system of the snow disaster potential risk assessment (Table 2).

In this study, a logistic regression model is used to evaluate the potential risk of snow disasters in pastoral regions of Qinghai Province based on existing studies [12,40]. The logistic regression model was used to avoid subjectivity when the weight of each index was determined. Another advantage of a logistic model is that independent variables can be either continuous, discrete, or non-normally distributed [41,42].

If P is the probability of a snow disaster occurrence ranging from 0 to 1, then $1 - P$ is the probability of a snow disaster not occurring. The natural logarithm of $P/(1 - P)$ $(\ln(p/(1-p)))$ and the associated linear regression equation are as follows:

$$Logit\,(P) = \ln(p/(1-p)) = \alpha + \beta_1\chi_1 + \beta_2\chi_2 + \ldots\ldots + \beta_n\chi_n \tag{2}$$

or

$$p = \frac{\exp\,(\alpha + \beta_1\chi_1 + \beta_2\chi_2 + \ldots\ldots + \beta_n\chi_n)}{1 + \exp\,(\alpha + \beta_1\chi_1 + \beta_2\chi_2 + \ldots\ldots + \beta_n\chi_n)} \tag{3}$$

where P is the probability of a snow disaster occurrence; $\alpha$is a constant; $\beta_1, \beta_2, \ldots, \beta_n$ are logistic regression coefficients; and $\chi_1, \chi_2, \ldots, \chi_n$ are key factors of the snow disaster risk.

Table 2. The indicator system of the potential risk assessment of a snow disaster.

Variable Type	Code	Variable Name	Unit
A. Socioeconomic factors	A1	Per capita gross domestic product	Yuan
	A2	Gross regional domestic product	Yuan
	A3	Net income of farmers and herdsmen	Yuan
	A4	Density of population	No./km^2
	A5	Highway density	km/km^2
B. Meteorological factors	B1	Precipitation	mm
	B2	Average wind speed	m/s
	B3	Annual mean temperature	°C
	B4	Slope	°
	B5	Probability of anterior winter snow disaster	%
C. Remote Sensing Monitoring factors	C1	Maximum depth	cm
	C2	Mean snow depth	cm
	C3	Number of snow-covered days	d
	C4	Percentage of snow-covered grassland	%
	C5	Percentage of snow-covered area	%
D. Pastoral factors	D1	Livestock stocking rate	Su/ha
	D2	Inventories at the beginning of the year	No.
	D3	Inventories at the end of the year	No.
	D4	Area ratio of farmland	%

3.4. Snow Disaster Early Warning

Based on the 33 typical snow disaster cases from 2001 to 2007 in Qinghai Province, 13 snow disaster early warning factors (Table 3) are chosen based on previous studies, data availability, and the results of risk evaluation in the study area. They include three historical statistical factors (V2–V4), four snow condition factors (V5–V8) before snow disasters occur, and five meteorological factors (V9–V13) during snow disasters. The snow disaster risk factor (V1) is the P value (Equation (3)), the probability of a snow disaster occurrence, obtained based on the logistic regression model in Section 3.3. V1 is also one of the five key factors used for the BP-ANN model for a snow disaster early warning (Section 3.4).

Table 3. Factors of a snow disaster early warning.

Variable Type	Variable Code	Variable Name	Notice
Snow disaster risk factor	V1	Potential snow disaster risk	Spatial resolution of 500 m
Historical statistical factors	V2 V3 V4	Probability of a winter snow disaster Probability of a spring snow disaster Mean annual probability of a snow disaster	These factors were calculated according to the yearly records of meteorological disasters from 1951 to 2000
Snow condition factors before a disaster	V5 V6 V7 V8	Fractional snow-covered area Snow-covered days (SCDs) Snow depth Snow-covered area	These factors were calculated from 15 days before the disaster to the day of the disaster
Weather condition factors during a disaster	V9 V10 V11 V12 V13	Continual days with the mean daily temperature below 0 °C Continual days with the mean daily temperature below −5 °C Continual days with the mean daily temperature below −10 °C Mean temperature Total precipitation	These factors were calculated from the day of the disaster until 15 days after the disaster

BP-ANNs are multilayer, feed forward networks trained by back propagation error algorithms. The first BP-ANN was originally proposed by Werbos in 1974 [43], and BP-ANNs were popularized by Rumelhart in 1986 [44]. Currently, it is one of the most widely used neural network models in the medical, environmental, and technological fields, among others [45–52]. The method uses gradient descent to continuously adjust the network's weight and threshold value through back propagation, which minimizes the network error. The topological structure of a BP-ANN model includes an input layer, hidden layer, and output layer. Additionally, a network can contain multiple hidden layers capable of dealing with the problem of linear inseparability [53]. In this paper, the BP neural (Back-propagation neural network) program for computing was Matlab 6.5 software.

The MIV method is used to select variables in this study and to determine the input terms that have significant impacts on the results. Dombi et al. (1995) [54] and others suggested using the MIV method to reflect the change in the weight matrix of a neural network. Additionally, the MIV method is considered one of the best indexes for evaluating the variable correlation in a neural network [55], and it has been used to determine the effects of the input neuron on the output neuron. The sign of the output neuron represents the relevant direction, and the absolute value represents the relative importance. The calculation process is as follows:

(1) Train the model. After training is finished, every input variable P_j (j = 1, 2, 3, ... , n) from the training samples P would increase or decrease by 10% *P to obtain two new training samples P_{j1} and P_{j2}.
(2) Use the two new cases as the simulation samples in the well-trained model. This yields two new middle-stage variables A_{j1} and A_{j2}. Then, calculate the difference between A_{j1} and A_{j2} to account for the impact value of the input variables.
(3) Next, the MIVs are obtained using the impact values divided by the number of samples n.
(4) Finally, sort the input variables from large to small according to the sizes of their absolute values and choose the first m independent variables as input feature variables according to Equations (4) and (5) for usage in the BP-ANN (in the next step).

$$\eta_m = \sum_{i=1}^{m} |MIV| / \sum_{i=1}^{n} |MIV| \tag{4}$$

$$\eta_m > 85\% \tag{5}$$

where η_m is the cumulative contribution rate of each independent variable; m is the number of variables selected; and n is the total number of variables.

3.5. Hazard Evaluation Standard for Snow Disasters

Based on Guo et al. (2012) [56], we classify snow disasters into four levels: light, moderate, severe, and extremely severe disasters (Table 4).

Table 4. Standards of snow disaster levels (Guo et al., 2012).

Level	Snow Disaster Level	Livestock Mortality (%)
1	Light disaster	<5
2	Moderate disaster	5–20
3	Severe disaster	20–30
4	Extremely severe disaster	>30

4. Results

4.1. Potential Snow Disaster Risk in Qinghai Province

After principal component analysis of the 19 parameters (Table 2), five key factors (maximum snow depth, slope, SCDs, annual mean temperature, and per capita GDP) that influence snow disasters are selected. A logistic regression model is ultimately obtained to comprehensively evaluate the potential risk of snow disasters in Qinghai and the parameters of the model (Equation (3)) are shown in Table 5.

Table 5. The parameters of a logistic regression model (Equation (3)).

Model Parameters	Value	Factors	Factor Name
α	−12.60	χ_1	slope
β_1	0.60	χ_2	Snow-covered days (SCDs)
β_2	2.54	χ_3	annual mean temperature
β_3	3.07	χ_4	maximum snow depth
β_1	1.72	χ_5	per capita GDP
β_1	7.84		

Figure 4 shows the spatial distribution of various risk factors related to snow disasters in the study area. As shown in Figure 4A, large slope areas are mainly concentrated around mountains in Qilian, Kunlun, Tanggula, Bayan Har, and Amnye Machen of Qinghai Province. Figure 4B shows that the annual mean SCDs is generally low in the study area and high in some localized areas (especially Delingha and Tianjun). As shown in Figure 4C, eastern Qinghai Province, the Qaidam Basin and its surrounding area have high annual mean temperatures between 0 °C and 9.27 °C. Other areas have low annual mean temperatures between −13.97 °C and 0 °C. Figure 4D shows that the areas with deeper snow cover (between 10 mm and 26 mm) in Qinghai are mainly distributed in Tianjun, Qilian, Yushu, Nangqian, Zaduo, Gande, and Dulan counties, while the snow depths in Haixi Prefecture, Golmud City, and the eastern agricultural regions are shallow (between 0 mm and 10 mm). Additionally, Figure 4E shows that the per capita GDP levels in the southern and southeastern parts of Qinghai Province are low, while the GDP levels in Haixi Prefecture are high.

The probability of a snow disaster in the study area is calculated according to Equation (3) and Table 5 and classified using the natural breaks (Jenks) method. Because of the very low probability of snow disasters occurring in non-grassland areas and areas with slopes greater than 50°, these areas are removed from the final results of the snow disaster risk (Figure 5). Overall, the comprehensive results of snow disaster risk in Qinghai suggest that the risk is higher in the south and lower in the north. High-risk areas ($P > 0.17$) are mainly concentrated in southern Qinghai, especially in the southeastern Yushu Prefecture and the central Guoluo Prefecture. At the county scale, the snow disaster risk is high in Golmud and Delingha cities and Chenduo, Yushu, Nangqian, Dari, Gande, Maqin, Dulan, and Menyuan counties. Based on the topographic and geomorphic conditions, the snow disaster risk in the Qaidam Basin in northwestern Qinghai and the agricultural areas in eastern Qinghai are low (0.03 < *P* < 0.08), while the risks in the Qilian Mountains, Kunlun Mountains, Tanggula Mountains, Bayan Har Mountains, Amnye Machen, and other high mountain areas are high. The risk in other areas are intermediate (0.08 < *P* < 0.17).

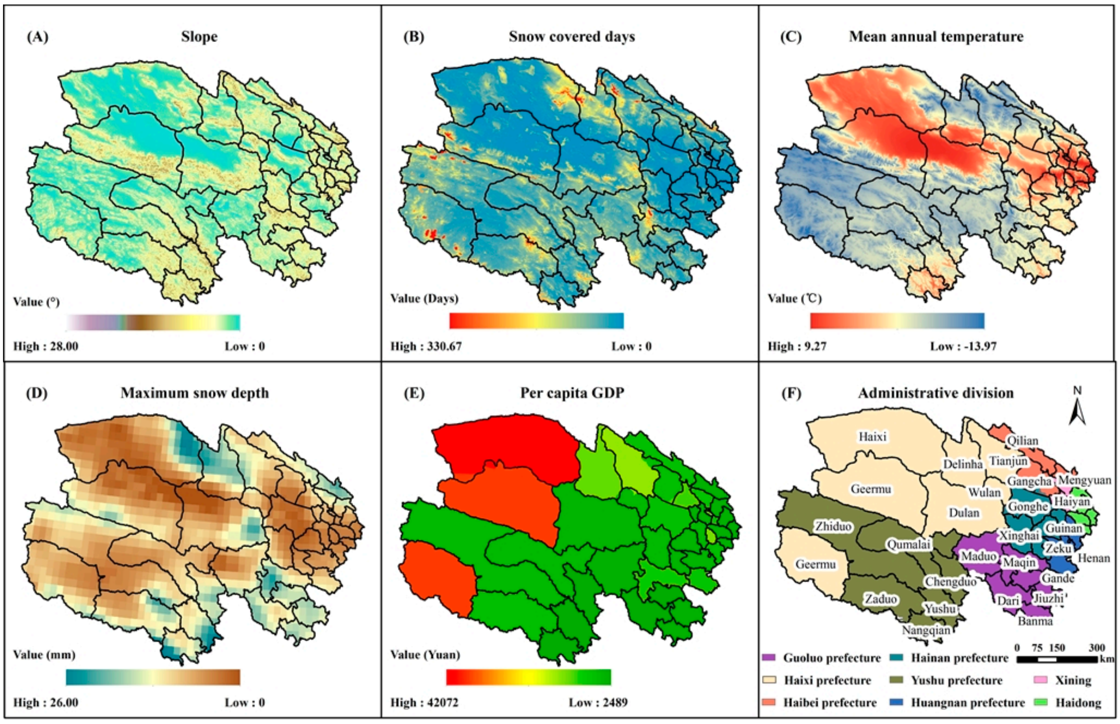

Figure 4. The spatial distributions of risk factors: slope (**A**); snow-covered days (**B**); mean annual temperature (**C**); maximum snow depth (**D**); and per capita GDP (**E**); as well as the administrative divisions in Qinghai Province (**F**).

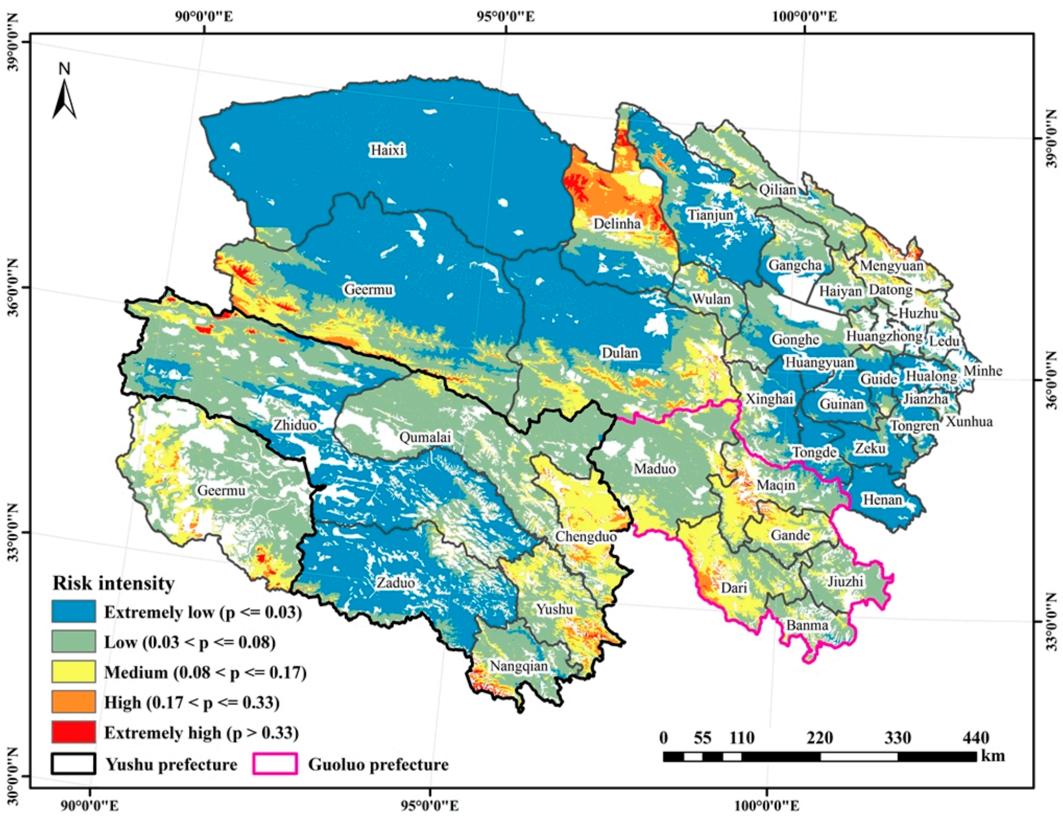

Figure 5. Potential snow disaster risk at 500 m pixel scale resolution in Qinghai (white spaces are non-grassland areas and slopes >50°).

4.2. Snow Disaster Early Warning Model Based on the BP-ANN

This study uses the MIV method (Section 3.4) to calculate the MIVs (Table 6) of 13 independent variables (Table 3) by using the livestock mortality as the dependent variable. The first five independent variables (V12, V3, V1, V10, and V5) whose cumulative contribution to absolute values of MIVs are greater than 85% are used as input factors for the BP-ANN training, testing, and validation. Livestock mortality is used as the only network output. The model also includes ten hidden layers based on empirical equations [57]. The most suitable structure of the BP-ANN model for predicting livestock mortality was believed to be the 5-10-1 structure. The transfer function of the hidden layer is a log-sigmoid function and the function of the output layer is a purelin function. The adopted network training algorithm is the Levenberg-Marquardt algorithm (trainlm).

BP-ANN modeling results (simulated livestock mortality) are compared with the actual livestock mortality in three different datasets: training (23 samples), testing (5 samples), and validation (5 samples), as shown in Figure 6a–c, respectively. It is found that the actual livestock mortality and simulated livestock mortality exhibit high determination coefficients (0.90, 0.64, 0.45, respectively) and small root mean square error (RMSE) values (0.0269, 0.0238, 0.0877, respectively). If all samples are used to build the BP-ANN model, a similar good result can be achieved (R^2 of 0.66 and RMSE of 0.0419, Figure 6d). In BP-ANN, the validation dataset is a set of examples used to determine the network structure or control the complexity degree of the model, and the fitting capability of the validation dataset (Figure 6c) did not influence the performance capability of the BP-ANN model. The training dataset is a set of examples used for learning and the testing dataset is a set of examples used only to assess the generalization performance of a model. Based on an evaluation of R^2 and RMSE of the training dataset and testing dataset, the BP-ANN model is a good predictor of the livestock mortality with ideal certainty, as expected. Overall, the five key variables are used to build a reasonable and effective BP-ANN model for the study area.

Table 6. Selection of the back propagation neural network variables.

Variable	Mean impact values(MIVs)	Abs (MIVs)	Cumulative Contribution Rate (%)	Variable	MIVs	Abs (MIVs)	Cumulative Contribution Rate (%)
V12	−0.0189	0.0189	20.4	V4	−0.0020	0.0020	94.9
V3	−0.0166	0.0166	38.3	V9	−0.0012	0.0012	96.2
V1	0.0160	0.0160	55.6	V8	0.0011	0.0011	97.4
V10	0.0148	0.0148	71.6	V11	0.0010	0.0010	98.5
V5	−0.0123	0.0127	85.4	V2	0.0010	0.0010	99.5
V7	−0.0045	0.0045	90.2	V6	−0.0008	0.0008	100
V13	0.0023	0.0023	92.7				

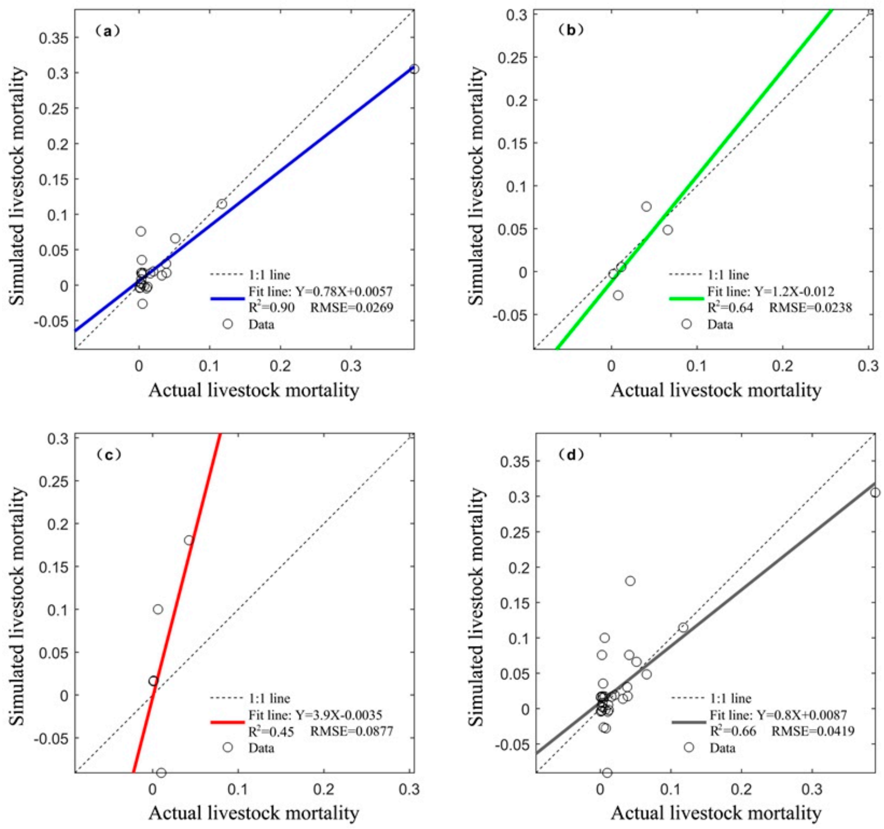

Figure 6. Back propagation artificial neural network (BP-ANN) simulated versus actual livestock mortalities: (**a**) simulation based on the 23 training samples; (**b**) test simulation of the established model using the five testing samples; (**c**) validation simulation of the established model using the five validation samples and (**d**) simulation based on all 33 samples.

4.3. Accuracy Assessment of the Snow Disaster Early Warning Simulation

To assess the accuracy of the established BP-ANN early warning model, two additional snow disaster cases in 2008 and 2015 are used (i.e., the five key factors V12, V3, V1, V10, and V5 of each case) to obtain corresponding network outputs (livestock mortality values). These outputs are the predicted values and are compared with the corresponding actual livestock mortality of each case. Figures 7 and 8 are the model outputs of the livestock mortality (at 500 m pixel size) of the 2008 and 2015 cases, respectively, according to the standard levels of snow disaster classification given in Table 3.

The levels of snow disaster simulation results in the 2008 (Figure 7) case suggest that the severe disaster area was relatively small (5294 km^2) and concentrated locally in Zeku and Dari counties. This area accounted for 2.48% of the total pasture area in the winter and spring in the study area. The moderate disaster level was mainly distributed in the Three Rivers Headwater Region (especially in southeastern Yushu Prefecture, northwestern Guoluo Prefecture, and northwestern Huangnan Prefecture), with a hazard area of 42,390 km^2, accounting for 19.84% of the total pasture area in the winter and spring of the study area. The area of light snow disaster was 165,985 km^2 and was mainly concentrated in southwestern Yushu Prefecture, eastern Haixi Prefecture, and eastern Qinghai Province. This area accounted for 77.67% of the pasture area in the winter and spring of the study area.

Overall, moderate and light snow disasters areas were prevalent in the Three Rivers Headwater Region, and the simulated results agreed well with the reported actual hazard scenario. According to the disaster volume records and the relevant literature data, during this 2008 snow disaster event, heavy snowfall mainly affected the three Prefectures of Yushu, Guoluo, and Huangnan, and killed 181,500, 116,700, and 40,600 domestic animals, respectively, in each prefecture [58]. In addition, according to the Landsat 7 TM false color image (Figure 9A) of a snow disaster in mid-February 2008, most areas in southern Guoluo Prefecture were covered by snow; this could verify the simulated results of the snow disaster on a small scale as well.

Based on the simulation results in 2015 (Figure 8), the area of severe snow disasters was small and mainly concentrated in northern Dulan County and some areas of Wulan County, encompassing a hazard area of 9124 km^2, which accounted for 5.04% of the total pasture area in the winter and spring in the study area. Moderate snow disasters mainly occurred in central Hainan Prefecture and eastern Haixi Prefecture, with a hazard area proportion of 8.96%. The area of light snow disasters was the largest with an area of 155,556 km^2, and accounted for 85.99% of the total pasture area in the winter and spring. This level was mainly distributed in southeastern Yushu Prefecture, northeastern Guoluo Prefecture and most areas of Huangnan Prefecture. Based on the overall analysis of the study area, the damage caused by the snow disaster was still mainly classified in the light disaster level with some moderate and severe snow disasters mainly distributed in Dulan and Wulan counties.

Overall, the simulation results agreed well with the actual snow disaster scenario. According to a government report, the 2015 heavy snowfall occurred in the eastern region of Haixi Prefecture and caused severe snow disasters in the local areas of Wulan County and Dulan County. These disasters affected more than 8000 herdsmen in the six villages and towns of Dulan County and killed more than 20,000 domestic animals [59]. In addition, according to the Landsat 8 OLI false color image (Figure 8B) of a snow disaster in late February 2015, partial areas in Dulan County were covered by snow, and this could verify the simulated results of the snow disaster on a small scale as well.

To further validate the accuracy of the simulation results, actual livestock mortality reported in the three Prefectures (Guolu, Yushu, and Huangnan) of the 2008 case and the two counties (Dulan and Wulan) of the 2015 case are compared with the simulated livestock mortality in the corresponding prefecture or county (Table 7). For the 2008 and 2015 cases, the model accuracy was 76% and 85%, respectively, with an overall accuracy of 80%.

Table 7. Accuracy assessment of the simulated livestock mortality from the snow disaster early warning model.

Cases	**In Mid-February 2008**			**In Late February 2015**	
Disaster areas	**Guoluo Prefecture**	**Yushu Prefecture**	**Huangnan Prefecture**	**Dulan County**	**Wulan County**
Quantity of livestock at the beginning of the year (10^4)	200.6	270.3	212.5	23.6	144.3
Number of livestock deaths (10^4)	116.7	181.5	40.6	1.4	0.6
Actual livestock mortality (%)	0.0582	0.0671	0.0191	0.0593	0.0416
Simulated livestock mortality (%)	0.051	0.0414	0.0148	0.0709	0.0462
Average accuracy (%)		76		85	
Overall accuracy (%)			80		

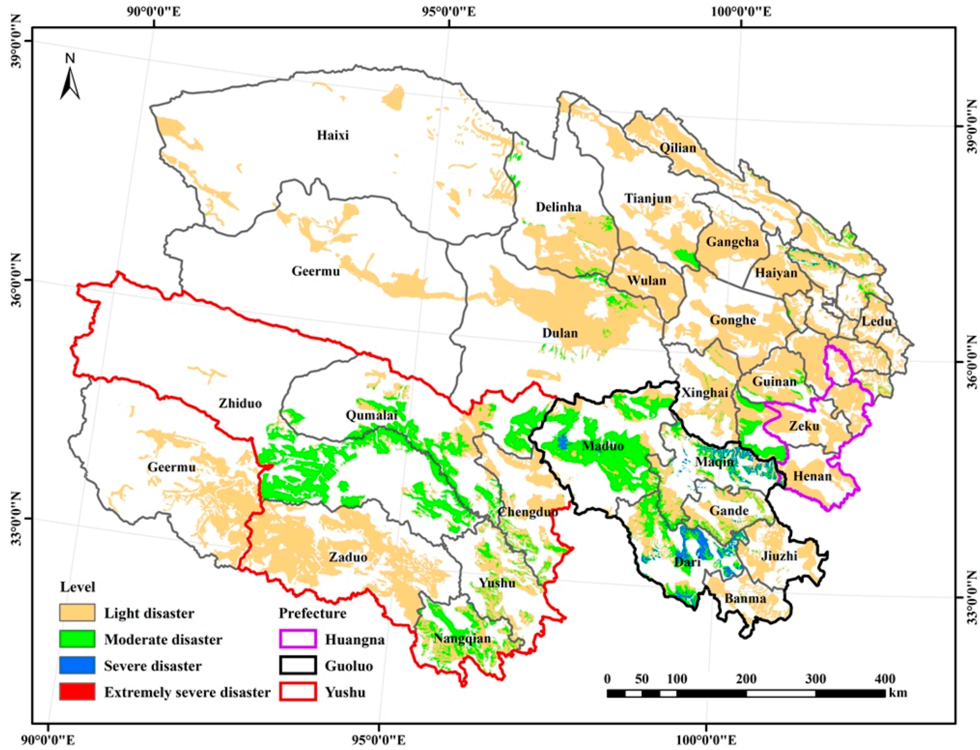

Figure 7. The simulation results of a snow disaster in mid-February 2008 in the winter and spring pastures in Qinghai Province (white spaces are non-grassland ages, slope >50°, and summer grazing grassland).

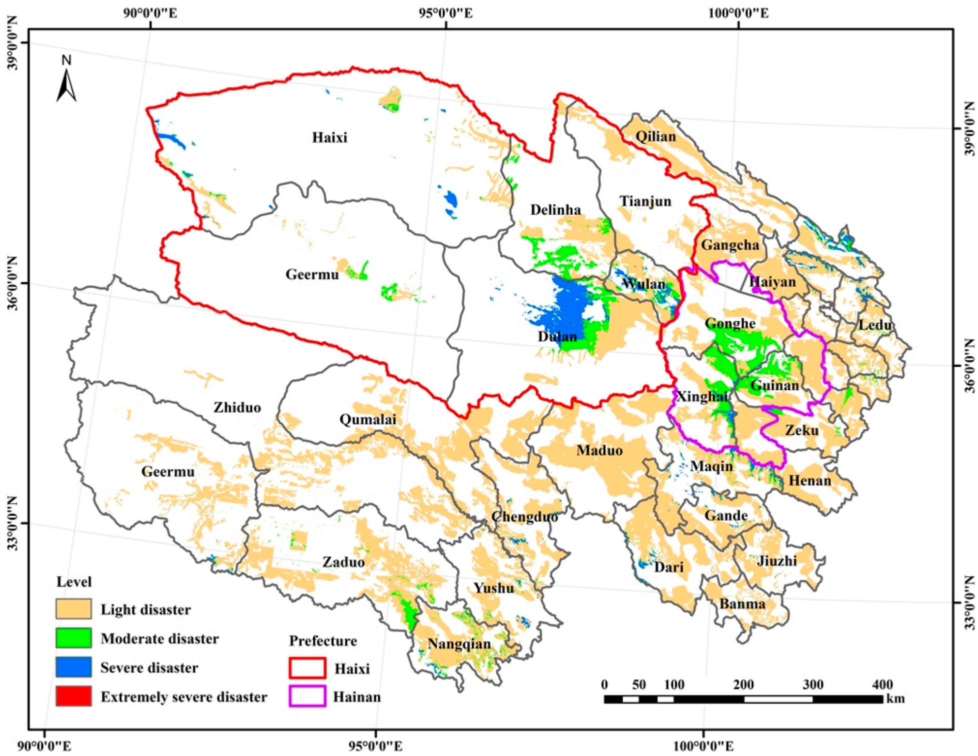

Figure 8. The simulation results of a snow disaster in late February 2015 in the winter and spring pastures in Qinghai Province (white spaces are non-grassland areas, slope >50°, and summer grazing grassland).

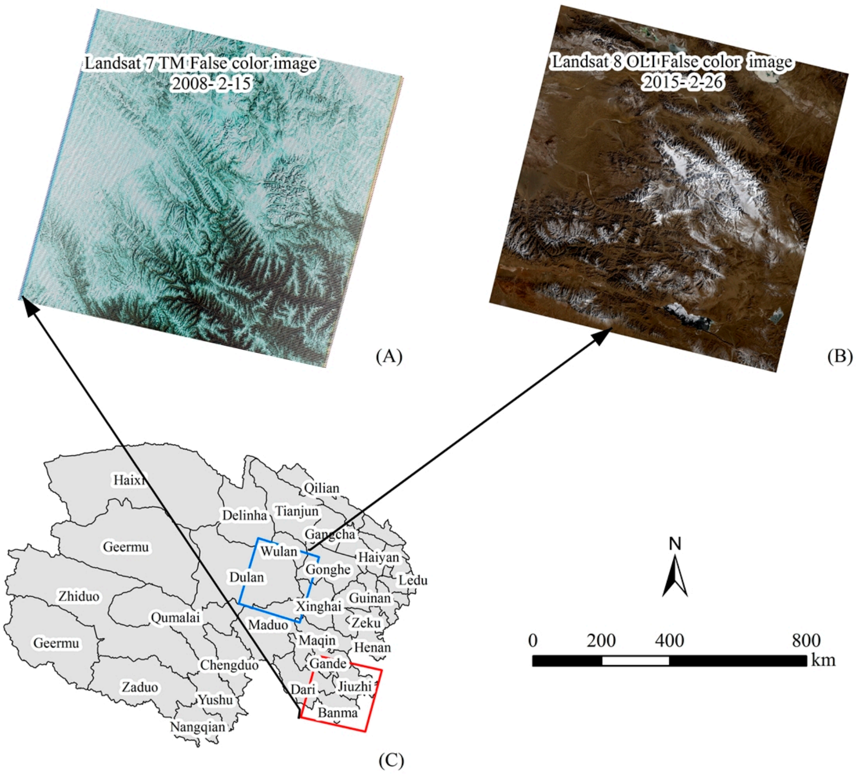

Figure 9. The Landsat 7 TM false color image of a snow disaster in mid-February 2008 (**A**) and the Landsat 8 OLI false color image of a snow disaster in late February 2015 (**B**), and the administrative divisions in Qinghai Province (**C**).

5. Discussion

An early warning of snow disaster plays an important supporting role in disaster prevention and reduction in pastoral areas. With the development of high-resolution earth observation systems, simulations of snow disasters for early warning has improved from analysis of a single hazard event to comprehensive evaluations of various concurrent or connected disasters. This study analyzes the key factors that affect the risk assessment of snow disasters in Qinghai Province. A logistic regression method is used to construct a regression model of risk evaluation of snow disasters. The BP-ANN network, which is based on historical statistics, grassland husbandry information, snow remote sensing, and meteorological observations of 33 typical snow disaster cases, was trained to establish a snow disaster early warning model. The network has ideal predictive capability and generalization capacity to meet the requirements of snow disaster simulation for early warning.

The results (Figure 5) show that the high-risk areas of a snow disaster in Qinghai are mainly concentrated in the southern part of the region (Chenduo, Yushu, Nangqian, Dari, Gande, Maqin counties, and other places). Additionally, the Kunlun Mountains, Bayan Har Mountains, and Amnye Machen area are prone to snow disasters (especially on both sides of the Bayan Har Mountains). These results agree with the results of Hao et al. (2006) [5]. The northwest Qaidam Basin and eastern agricultural regions are low-risk areas, and this finding agrees with previous results [12,13,17]. According to geographic and climate conditions, socioeconomic conditions, and snow monitoring in the study area, this study focused on 19 factors (Table 2) that affect snow disaster risk assessment to construct a logistic model for evaluating the snow disaster risk based on a raster (a 500 m cell size). The model can reflect the distribution of the potential risk of a snow disaster. This study uses the natural breaks (Jenks) grading method to determine levels of the snow disaster risk [12,13], and the method produces satisfactory results. Although the approach is based on inherent natural grouping in the data, it can appropriately group similar values, maximize the difference between categories, and accurately reflect the links between data. However, the method lacks general applicability; thus, the scientific grading method is suitable for snow disaster risk evaluation, but other applications must be explored in later studies.

In summary, existing models of a snow disaster generally have certain limitations [3,19,21,25,26]. The BP-ANN method is widely used in many fields and can approximate any nonlinear function while providing clear physical and conceptual results based on a flexible and changeable topological structure [44,46]. Additionally, the method is widely applicable and effective, and it provides a strong nonlinear mapping capacity. Thus, it is ideal for studies in the field of natural disasters [18,60–66]. The overall accuracy of the snow disaster early warning model based on the BP-ANN method in this study reached 80%. Compared to the multivariate model of nonlinear regression (accuracy of 86%) for snow disaster early warning in the pastoral areas on the Qinghai-Tibet Plateau [21] and the snow disaster multi-index evaluation model (accuracy of 76%) under natural conditions [26], the BP-ANN early warning model has a similar high accuracy, but the accuracies of these two studies [21,26] only considered two states: disaster or no disaster. Therefore, their accuracies are very qualitative, unlike this study, in which we use the livestock mortality, a quantitative assessment. In addition, in our model, the risk assessment factor (i.e., probability of a snow disaster occurrence) is one of the five key factors used for the simulation for an early warning. This, however, was not considered in these previous studies. The third improvement of our modeling is that our model is built totally on a grid (500 m in this case), unlike the previous studies that were only based on resolution at the county level. This greatly improves the resolution and accuracy of a snow disaster warning. In previous studies, one can only predict whether a county has a disaster or not, while in this study, we not only know which county has a disaster, but also know where it occurs and the degree of damage at the 500 m pixel scale.

All the advantages mentioned above do not mean that our model has no limitations and deficiencies. Notably, the approximation and generalization ability of the network model is closely related to the learning samples, which are particularly reflected in the neural network. If the set of samples is poorly representative with conflicting and redundant samples, the network may not perform adequately [52]. Furthermore, although detailed information from 71 cases of snow disasters from 1951 to 2008 were considered in the disaster level standards in Guo et al. (2012) [56], the degree of reduction in snow disasters was not considered. The overall degree of reduction in snow disasters in recent years was due to many factors such as policy support, technical development, increasing herdsman knowledge regarding disaster prevention, and improved infrastructure. Hence, the snow hazard rating standards (Table 3) used in this study must be further revised and improved. Due to current limitations on obtaining snow hazard information (i.e., where, when, and how many livestock died), the accuracy of our model is satisfactory for local areas, but assigning warning levels for the entire study area (such as at the Qinghai Province level) is still associated with a certain degree of uncertainty.

6. Conclusions

In this study, with the MODIS daily snow cover products (MOD10A1 and MYD10A1), the AMSR-E daily SWE products, and the long-term snow depth dataset, we first constructed 19 indicators of potential snow disaster risk and 13 indicators of snow disaster early warning by effectively integrating the correlative statistical data. Furthermore, based on a risk analysis and the factors that influence snow disasters in pastoral areas of the Qinghai Province, a snow disaster model for early warning based on the BP-ANN machine learning method at a 500 m spatial resolution is developed and validated. The main conclusions are as follows:

(1) The potential risk of snow disasters in Qinghai Province is overall high in the south and low in the north, with some exceptions. The crucial factors that affect the spatial distribution and the risk of a snow disaster are maximum snow depth, slope, SCDs, annual mean temperature and per capita GDP. Among these key factors, maximum snow depth, slope, and SCDs show similar spatial distribution as the potential risk map, while annual mean temperature and per capita GDP show the opposite distribution compared with the potential risk map of snow disasters.

(2) The key factors that influence the simulation of a snow disaster for early warning in the study area are the five factors listed in order: mean temperature (V12), probability of a spring snow disaster (V3), potential snow disaster risk (V1), continual days with the mean daily temperature below −5 °C (V10), and fractional snow-covered area (V5). Of these, the potential snow disaster risk (V1) is the output of the logistic regression modeling result. This is the first time that V1 is included in the simulation of snow disasters for early warning.

(3) Validation results suggest that the BP-ANN approach is an ideal method for simulating a snow disaster for early warning. Although the approach is better and more advanced than the previous approaches, this method has limitations and deserves further attention and improvements.

Acknowledgments: This study was supported by the National Natural Science Foundation of China (31372367, 31672484, 41671330) and part of the Program for Changjiang Scholars and Innovative Research Team in the University (IRT13019).

Author Contributions: All authors contributed significantly to this manuscript. Jinlong Gao and Xiaodong Huang designed this study. Jinlong Gao, Xiaofang Ma, Qisheng Feng, and Tiangang Liang were responsible for the data processing, analysis, and paper writing. Hongjie Xie made valuable revisions and editing of the paper.

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

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