ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-3/W1-2022
14th GeoInformation for Disaster Management (Gi4DM 2022), 1–4 November 2022, Beijing, China

RISK ASSESSMENT OF HIGH VOLTAGE POWER LINES CROSSING FOREST AREAS - A CASE STUDY OF WILDFIRES

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KEY WORDS： Risk assessment, Power line inspection, Fire risk index in transmission corridor, Analytic hierarchy process, Interpretative structural modeling.

ABSTRACT:

This study aims to introduce new methods for assessing risk of wildfires around power transmission line corridors(PTCs) using multiple sourced active monitoring data. The proposed approach starts from fire analysis using interpretative structural modeling(ISM) from historical data of fire-caused transmission line(TL) fault, which emphasizes on the fire regimes and the fire factors. The ISM illustrates the sequence and relationships among fire factors. The main influencing factors are then ranking using analytic hierarchy process (AHP) to distinguish each relative importance. FRP, a high-resolution fire risk index conducting fire risk around PTCs, was constructed considering these factors as a series of assessment criterion. Variable meteorological-type factors such as maximum temperature and minimum relative humidity, less variable basic elements such as surface conditions, and human activity elements are all weighed and considered in FRP. The risk of this line can be obtained by calculating the collected monitoring data from TLC. Moreover, the safety risk level can be analyzed based on this assessment and the risk map of the power corridor can be used to help the power department to improve the maintenance plan of the power corridor.

1. INTRODUCTION

Power transmission maintenance is an essential part of power industry at the present industrial age. The electrical power service could be interrupted by natural disaster such as wildfire around transmission line corridor (Upreti et al., 2019). As one kind of disaster, wildfire is a vital factor disturbing the power transmission system in the forestry area, which plays a role as a potential hazard to power transmission system and as a result of the transmission failure. One of the routine jobs of risk management by power companies is inspection and fire surveillance. However, the use of large-scale fire warning for power safety protection fails to address fire hazards around transmission corridors in a timely and accurate manner. Traditionally, inspections and early warming of high voltage (HV) PTC mainly rely on laborious and dangerous human work using aerial- and ground-based devices (Huang et al., 2021). Those monitoring techniques are not efficient nor effective in terms of data capturing and mining. To improve the disaster prevention and resilience capability of the power grid, it is also necessary to conduct a detailed understanding and assessment of the environmental risk conditions around the line before the occurrence of wildfires, hence raising the accuracy of early warning of the power grid.

The occurrence of wildfires is closely related to the meteorological environment. According to the research on wildfire, it can be seen that in different regions, wildfires are related to relative humidity or minimum relative humidity, maximum temperature or daily temperature difference, average or maximum wind speed, precipitation or continuous non-precipitation days. Factors such as land cover stage and vegetation index often have a significant linear correlation, and the related objects are generally a single factor or a combination of several factors (Ferreira et al., 2020; Jolly et al., 2015; Wang et al., 2016; Gallardo et al., 2016; Tian et al., 2014; Shen, et al., 2019). In addition, it calls for research on local "micro-meteorology" of the power grid corridor. People need to obtain the accurate weather forecast of one section or even a few towers for the safety precaution areas, so as to realize the early warning of the corridor fire disaster caused by the meteorological station (Chen et al., 2014; Yang et al 2019). Due to the low accuracy of the fire risk assessment model, Liu et al. selected a variety of wildfire factors and used BP neural network to establish a transmission line fire risk model. Taking the main wildfire factors as input, it can automatically explain the factor relationship and output the wildfire risk (Liu et al., 2017). Xu et al. studied the historical law of fire points during the Chinese Qingming Festival, and established a monthly fire risk model to forecast the fire risk in power corridor by combining precipitation, surface type, and normalized vegetation index. Their result shows that this evaluation system has high accuracy in Hubei power grid (Safwanah et al., 2017).

Faced with the situation that it is difficult to accurately assess and predict the fire risk in high-voltage transmission corridors, the meteorological environment, surface vegetation condition, historical fire patterns and human activity characteristics are analyzed as profiles of wildfire. The FRP (fire risk around power-lines) is proposed in terms of these characteristics. The

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model is constructed and solved by ISM and AHP, and then validated by practical instances.

2. RELATED WORK

Major failures such as tripping and shutdowns are often caused by lightning fires, wildfires, burning and other natural or typical meteorological disasters near the PTC. In recent years the number of fires caused by transmission faults is increasing, and wildfires contributed transmission faults are also on the rise, while line tripping reclosing rate is low, whose failure time is long (Millera et al., 2017). Accurate assessment of mountain fire disaster risk in power corridors, effective prediction of affected power corridor sections in case of mountain fire and provide corresponding early warning are the major needs and basic aspects of disaster prevention and safety maintaining in power corridors. At present, researchers are focusing on the use of multi-source remote sensing data, human activity range data and historical disaster data for fire risk assessment and regional fire dangerous classification, and the use of probability and statistical theory to analyze the risk level of transmission failures experiencing wildfires based on historical detection and disaster conditions. For the former, there are a large number of fire risk zoning and mapping in and around PTCs and studies on fire risk factors and fire occurrence patterns near TLs (Xu et al., 2016; Millera et al., 2017; CÁCERES, 2011). While most of the latter studies utilize neural networks, hierarchical analysis, APRIORI algorithm, random forest, genetic algorithm, logistic regression, fuzzy models, and other methods to predict fire risk, to build fire meteorological risk assessment models that predicting failure rates due to wildfires (Wang et al., 2016; Shen et al., 2019; Frost et al., 2012; França et al., 2014; Mitchell, 2013; Ziccardi et al., 2019). A precise model to associate PTC fire risk is still needed. In this report, a high-voltage transmission corridor is defined as a strip with a certain width (about 2-3km) formed by the overhead TLs, pylons, terrain, vegetation and other objects. The risk assessment data of TLC on the mesoscale and small scale would be applied to prevent the wildfire risk in TLC. The purpose of this research is to serve the safe operation of power grids, to improve the pertinence and system efficiency of TL inspection, and to provide data support and suggestions for protection of power transmission against disasters. The risk assessment of wildfire in power corridor was deeply explored in this dissertation.

3. PROPOSED METHOD

Figure 1 schematically illustrates the overall workflow of the subsequent processes in which three major components, fire impact factor selection, FRP construction and FRP mapping and high risk warning are proposed in this study.

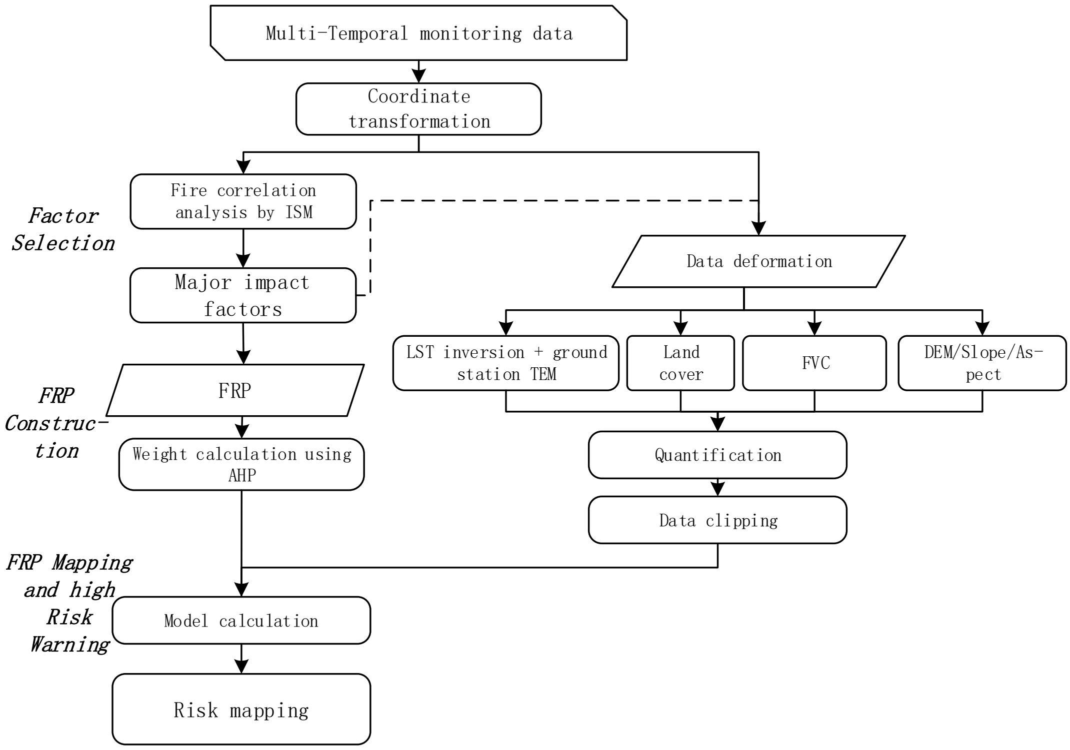


Figure 1. Overall workflow for FRP modelling and evaluating of PTC.

3.1 Factor selection

Facing the frequently occurred wildfires around the forestry PTC, the risk assessment methodology of wildfire in the long large-scale transmission area was studied, to accurately assess the risk of wildfires. ISM and SPSS are used in the analysis of data during 18 years from Shaoguan, China, to be concluded that the wind, humidity, temperature, precipitation, terrain, seasonal change, and human activity have a greater impact than the factors.

Correlation analysis was established using historical fire spots and ground-based meteorological station monitoring data, topographic data, and surface vegetation observation data f for 18 consecutive years from 2001-2018 in Shaoguan City. The data used mainly include:

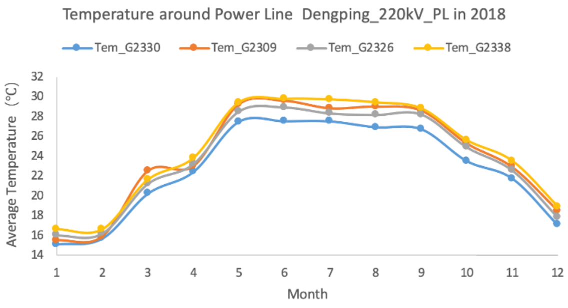
[1] hot spot detection data from MCD14ML (Global Monthly Fire Location Product) from 2001-2018. Surface hotspots with

confidence levels greater than 70 in the March fire were selected as a sample data.

[2] Meteorological data. Ground-based meteorological station monitoring data from 2001-2018 were selected, and March of each year was used as the observation value (Figure2, 3).

[3] Terrain. Three types of terrain data, elevation, slope and slope direction, were used.

[4] Surface vegetation. Two types of data, surface type and vegetation cover, were used.



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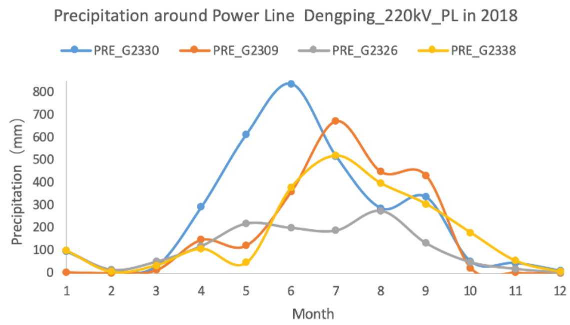

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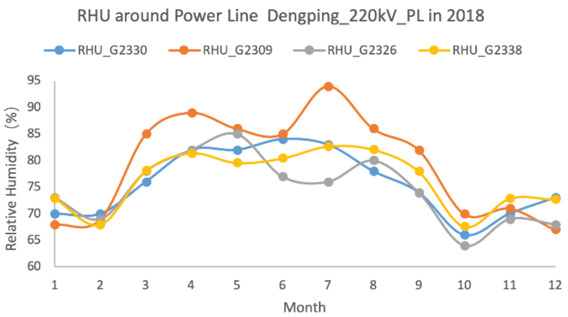

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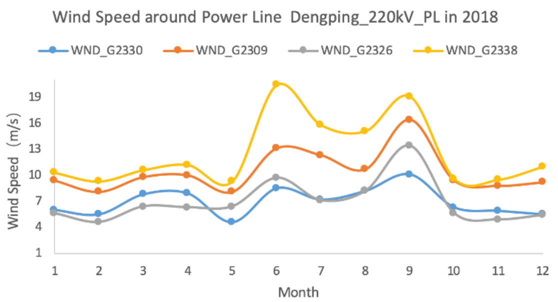

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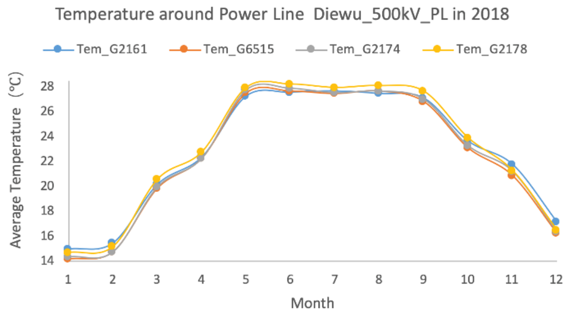
Figure 2. Meteorological observation around Dengping_220kV HV TL: (a) daily average temperature in each month, (b) daily average precipitation from 20:00 to 20:00 in each month, (c) daily average minimum relative humidity in each month, (d) daily average maximum wind speed in each month.



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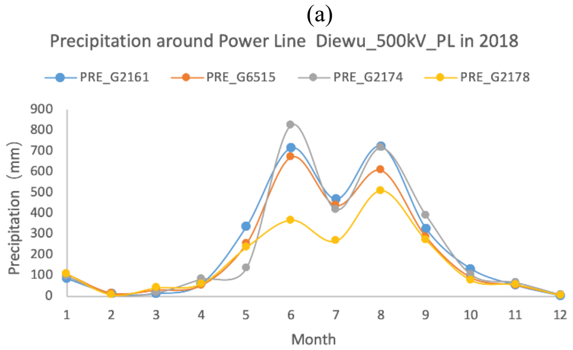

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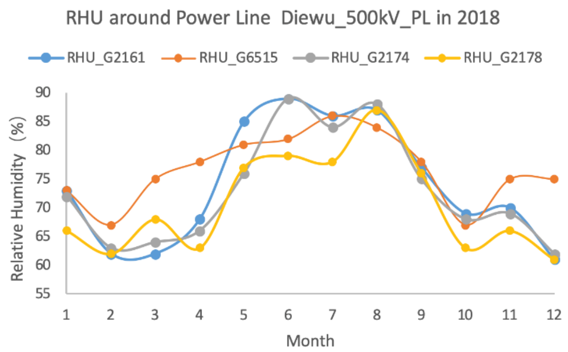

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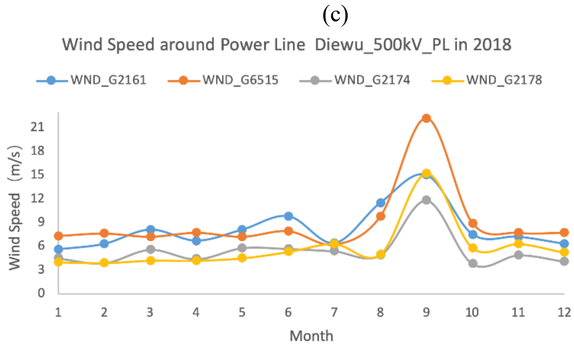

(d)

Figure 3. Meteorological observation around Diewu_500kV HV TL: (a) daily average temperature in each month, (b) daily average precipitation from 20:00 to 20:00 in each month, (c) daily average minimum relative humidity in each month, (d) daily average maximum wind speed in each month.

The results of the correlation analysis between the factors and the number of fire points prove that nine indicators can be selected to characterize the influence of three types of fire risk factors, namely, maximum temperature, minimum relative humidity, precipitation, wind speed, vegetation index, average slope direction, average slope, average elevation and ground cover type, on fire risk in power corridors.

Relevance	Max TEM	Min RH	PRE	WND	Vegetation Index	Average SLP	Average ASP	Average Altitude	LC
Pearson	0.455	-0.667	-0.782	0.315	0.458	0.320	0.36	0.357	0.44
Significance	0.190	0	0	0.272	0.061	0.220	0.251	0.187	0.199
N	28	28	28	28	28	28	28	28	28

Table 1. Relevance analysis between fire frequency and impact factors.

3.2 FRP construction

3.2.1 AHP construction: Considering various factors relevant to the fire risk (Figure 4), including surface vegetation condition, topography, humanity, season, meteorology and their correlation with the occurrence of wildfire, FRP, a fire risk index of power-lines, is designed to quantitatively evaluate and determine the areas and time periods getting high risk of fire in the whole corridor and to judge areas that need urgent inspection. In practice, the multi-source data was fused to be archiving and standardized.

Data fusion needs to solve the problem of spatial and temporal consistency and the unification of resolution. Data standardization includes two aspects: numerical index and descriptive index data quantification. More, an improved AHP method is proposed to calculate the weight of each factor. FRP is described as:

$$\mathrm{FRP} = x_1 \sum_{i=2}^{n} w_i x_i + c \tag{1}$$

where w_i = weight of each index in lowest layer.
$x_i (i = 2,3,\cdots,10)$ = fire indexes
x_1 = seasonal suppressor factor
c = absolute term

The default value of c is 0.1, to which added that ensuring a positive RFP value. In view of these factors, Equation (1) can be described as:

$$\mathrm{FRP} = \alpha_0(\delta_1 RHU + \delta_2 TEM + \delta_3 PRE + \delta_4 WDI + \delta_5 Height + \delta_6 Slope + \delta_7 ASP + \delta_8 LC + \delta_9 FVC) + \tau \tag{2}$$

3.2.2 Weight calculation: indicators are classified as numerical (positive, formula 1, negative, formula 2, moderate, formula 3) and descriptive. Numerical indicators are standardized in the following way.

$$y_i = \begin{cases} 1 & x_i \geq max_i \\ \frac{x_i - min_i}{max_i - min_i} & max_i > x \geq min_i \\ 0 & x_i < min_i \end{cases} \tag{3}$$

$$y_i = \begin{cases} 1 & x_i < min_i \\ \frac{max_i - x_i}{max_i - min_i} & max_i > x_i \geq min_i \\ 0 & x_i > max_i \end{cases} \tag{4}$$

$$y_i = \begin{cases} \frac{x_i - min_i}{o_i - min_i} & min_i \leq x_i < o_i \\ \frac{max_i - x_i}{max_i - o_i} & max_i > x \geq o_i \\ 0 & x > max_i \end{cases} \tag{5}$$

where x = value of ith element
min_i = the minimum value of ith element
max_i = the maximum value of ith element
o_i = the optimal of the element belonging to moderate criteria.

The standardization of descriptive indicators is based on the classification of the corresponding attribute descriptions of the indicators, and the scoring is based on the impact of different attribute categories on the occurrence of hill fire. The descriptive indicators include surface type and seasonal indicators, and the specific quantitative results are shown in Table 2.

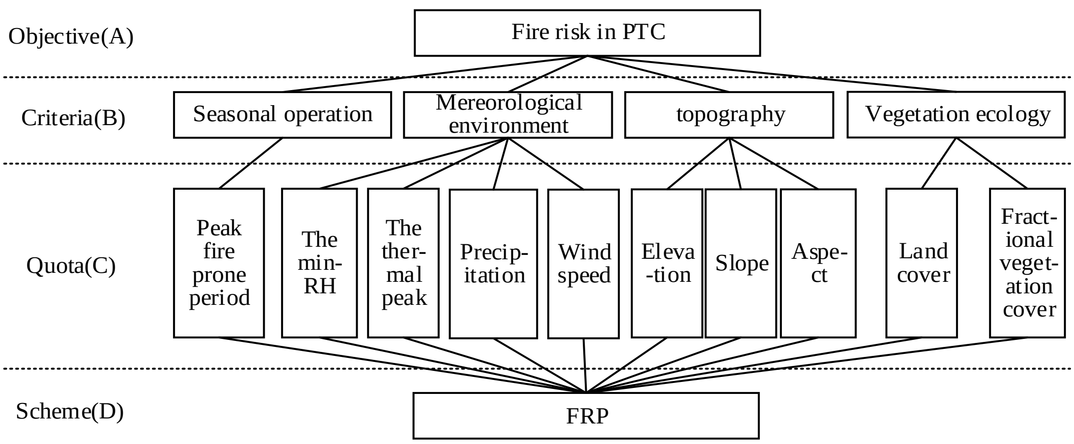

Figure 4. The general hierarchical structure constructed by ahp.

Criteria	Factors	Land usage	Value $f_i(x)$	Type
Vegetation Ecology	land cover (LC)	shrub, forest	1	descriptive index
		grass	0.8	
		country land, Farmland	0.6	
		tundra	0.3	
		urban land, impervious surface	0.1	
		waters, ice and snow, bare land	0	
	fractional vegetation coverage (FVC)		(0,1)	positive
Meteorology	precipitation(PRE)		(0,1)	negative
	max wind(WND)		(0,1)	positive
	highest temperature(TEM)		(0,1)	positive
	min relative humidity (RHU)		(0,1)	negative
Topology	elevation(DEM)		(0,1)	negative
	slope(SLP)		(0,1)	positive
	aspect(ASP)	schattenseite[1] half shady [2] half sunny[3] sunny slope [4]	(0,1)	moderate
Season	seasonal fire peak	Jan., Feb., Mar., Apr., Sep., Oct., Nov., Dec.	1	descriptive index
		May., Jun., Jul., Aug.	0.8	

Table 2. Index quantification.

By equivalence interval division, FRP was classified to be five grades (table 3). When the FRP in a region was identified as high, the regions would be marked and got an alarm signal, so as to providing corresponding data support and implementation suggestions for transmission line inspection and maintenance. This would provide accurate data for the further routine inspection, and lay a good foundation for the early warning of the potential disaster of vegetation obstacles.

FRP grade	Value	Description
Low	< 0.2	yellow green
Normal	0.2 - 0.4	little green
Moderate	0.4 - 0.6	yellow
Important	0.6 - 0.8	brown
Extra important	> 0.8	red

Table 3. FRP grades.

4. EXPERIMENTAL RESULTS

The TLCs run through the north-south, across the east and west, forming a multi-level transmission and distribution network that have different voltage levels in China. Multi-source remote sensing data and weather monitoring data were obtained in some areas of Southern Power Grid, China. By experimental analysis (Figure 5), the weights of each parameter in FRP model are calculated by factor analysis, entropy weight method and AHP respectively. The comparison of these methods shows that the weight obtained by the AHP is slightly heavy but basically average. Using this method to calculate the weights of the FRP model can comprehensively and clearly perform a hierarchical analysis of all factor relationships, and achieve a good quantitative result according to the importance between each factors classes and within classes.

In terms of the weights of these influencing factors, the weight of "meteorological factors" was higher among the three criterion layers analyzed. While, the topographic factors and vegetation-ecological factors were relatively balanced, with the latter slightly dominant. In order to verify the weighting results, the FRP factor weights were calculated using factor analysis, entropy weighting method and AHP, and the results were compared as shown in Table 4. Through the comparison, it is found that the factor analysis method emphasizes the correlation between several main influencing factors and the evaluation target. When all the indicators are analyzed together, it cannot reflect the relative relationship between factors in a more detailed way, but tends to weaken some factors that are not significant enough. For example, factors like "slope", "aspect" that got low weights, may lead to the reduced applicability of the model in different voltage or varying scenarios. The entropy weighting method lacks reliance on the internal relationships of each factor. Although the calculation process is more objective, it is impossible to know the significance of each factor because it is weighted with factor uncertainty, and it is impossible to know which fire factor is really referred to an indicator or another. In contrast, the AHP focuses on the intra-class relative importance, parent-child importance, and inter-type importance of each factor in each type, and focuses on the equalization of the weight assignment of each factor, resulting in a slightly over weighted but basically even of each weights. Therefore, using the AHP method to solve the index weights of FRP can provide a more comprehensive and clear hierarchical analysis of all factor relationships, and achieve a quantitative result based on inter-class and intra-class importance. The weighting result would not over-rely on some of the strongly correlated factors and are able to exploit the role of short-term changes in meteorological factors on the corridor fire risk. Further, it does not fully combine the spatial variability of other factors, which makes the evaluation better applicable.

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1. 337.5-67.5°; 2. 292.5-337.5°, 67.5-112.5°; 3. 247.5-292.5°, 112.5-157.5°; 4. 157.5-247.5°

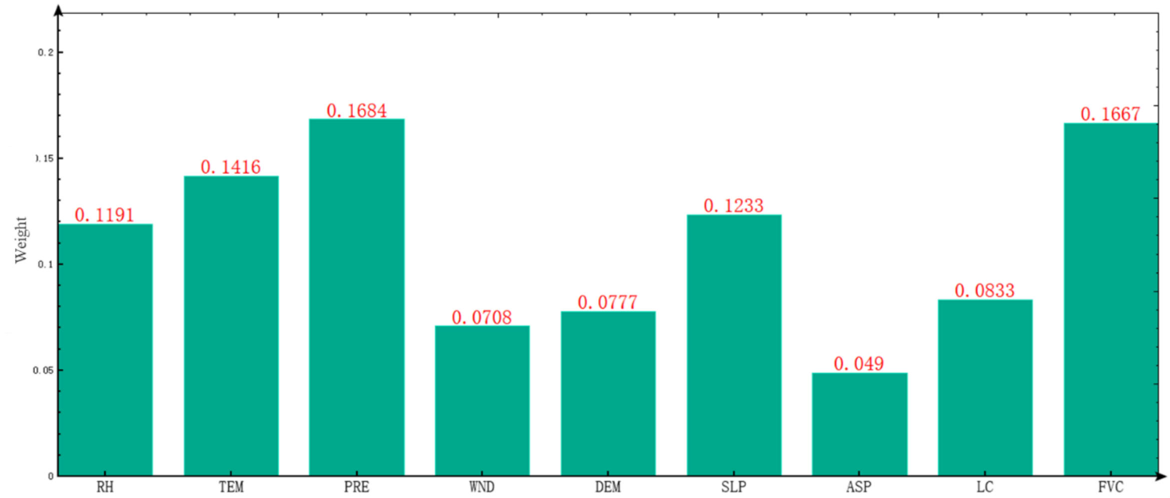
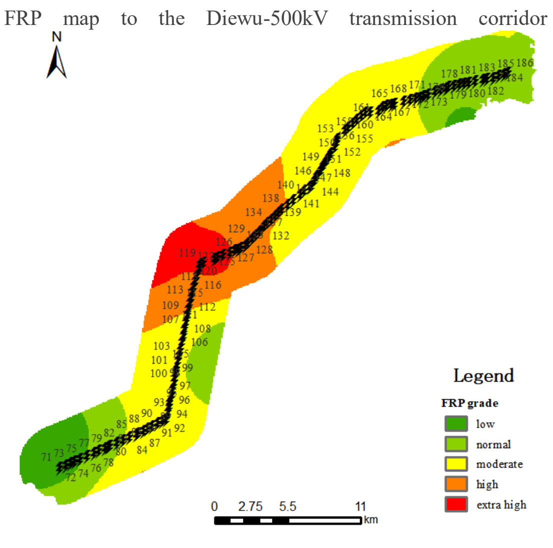


Figure 5. Experimental result by AHP.

Criteria	Indicator/factor	AHP	Factor analysis method	Entropy weighting method
Meteorological	PH	0.1590	0.0911	0.1704
	TEM	0.1191	0.1114	0.1981
	PRE	0.1605	0.1485	0.1055
	WND	0.0743	0.0756	0.1217
Topological	DEM	0.0915	0.1141	0.1302
	SLP	0.0891	0.0527	0.1013
	ASP	0.0438	0.0381	0.0905
Vegetation ecological	LC	0.1452	0.1487	0.0651
	FVC	0.1180	0.2181	0.0172

Table 4. Analysis of FRP weight calculation results.

FRP mapping was conducted using ArcGIS10.1, as shown in Figure 6. The risk level was rendered in different colors from light to dark, and from blue to red. The FRP contains 5 classes, including low, normal, moderately high and extra high. The experimental results distinguish and mark the high-level fire risk zones under different seasons. Therefore, certain sections with higher risk levels are proposed for timely and accurate inspection and safe clearance detection of the surrounding vegetation hazards. The research results can provide important data support for fire risk warnings of power transmission maintenance and power reliability operation analysis.



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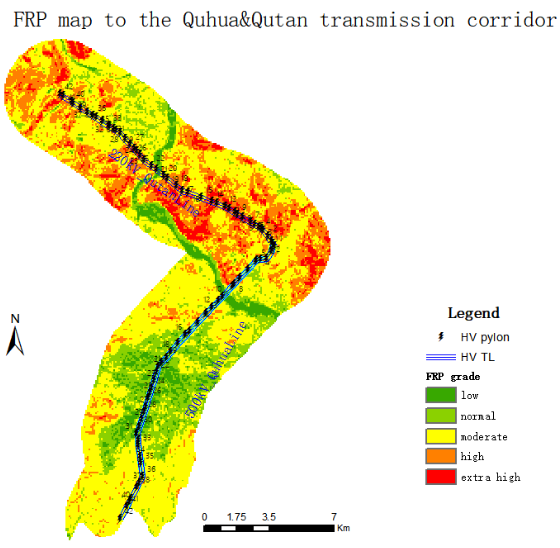

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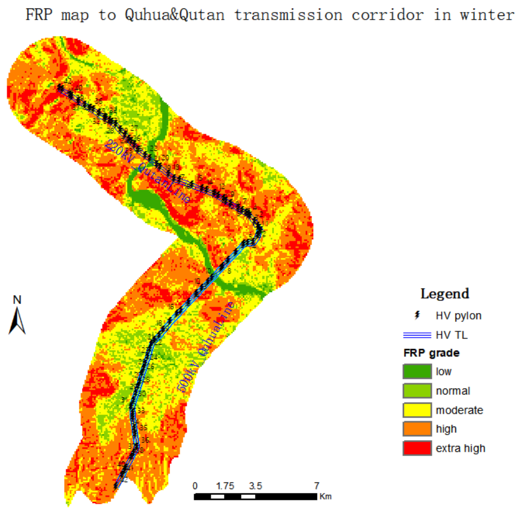

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Figure 6. FRP of HV power lines in 2018. (a) FRP map to the Diewu-500kV transmission corridor in June, (b) RP map to the Quhua & Qutan transmission corridor in September, (c) RP map to the Quhua & Qutan transmission corridor in January.

5. CONCLUSION

Experiments show that precipitation and vegetation cover are the most important influencing factors of FRP, while micro-environments (i.e. temperature, relative humidity and slope) near the TL often lead to the transmission facilities being exposed to hazards. In addition, the vegetation growth in transmission lines through forested areas often affects the fire risk, for example, dense (thick and lush) forestry areas usually result in a higher FRP. The proposed algorithm, unfortunately, has a few requirements on the data quality, such as the moderate weather stations around each corridor, so that the resolution of the FRP map is incapable of distinguishing each transmission pylon. When the data gap in the main direction of PLs is larger than 3km, the value will be affected in view of the scale of the FRP map. The research object of this paper is the high-voltage and ultra-high-voltage power corridors mainly in forestry areas, which are erected in the wild or on the highlands of mountains and forests, and rarely pass through populated areas. According to several statistics, as the population density around our study areas is less than 1 person/hm², this study does not calculate indicators for such factors related to human activities. As far as human activities are concerned, more people will appear in the distribution area around the corridor when a special solar term comes or when it is suitable for outdoor travel, which can otherwise be reflected by the indicators through seasonal or month factors.

There are still other factors affect wildfires in power transmission corridors. For example, vegetation moisture content is an important indicator to reflect the flammability of vegetation, but its value often requires field measurement or sampling analysis. Fortunately, vegetation moisture content is closely related to actual meteorological data such as precipitation, humidity and temperature, and to a certain extent, it can be indirectly reflecting by these above factors. Secondly, in the study of the characteristics of wildfire caused transmission faults, it was found that seasonal changes, dry weather, low humidity, high wind speed, low air pressure, and special topographical conditions are the most important signs of the frequent occurrence of wildfire faults. In addition, factors such as road network density, water system, residential area, and distance from nearby roads also have a certain impact on wildfires around the power corridor. Finally, for human activity factors, e.g., various human behaviors that affect the occurrence of wildfires and unnatural fire sources formed by artificial facilities, large wildfires often form, but this factor generally needs to be combined with the specific study area and through limited human behavior and festival customs information, that would be analyzed completely. Thus, more factors will be assessed to improve the accuracy in the future.

ACKNOWLEDGEMENTS

This research was funded by the National Natural Science Foundation of China, (grant number U19A2049) and Opening Foundation of Ministry of Education of Key Lab of Virtual Geographic Environment (Grant No. 2020VGE02).

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