Novel GIS-Based Methodology to Quantify the Risk of Wildfires in Overhead Transmission Lines - A Case Study

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***Abstract*—Wildfires are among the most significant events that can present a considerable risk to power systems, so a proper evaluation of the associated risk is necessary to ensure the resilience and economic value of the system. This work aims to showcase a new geoprocessing methodology that is based on the Getis-Ord Gi* Hotspot spatial analysis to classify the risk of wildfires in overhead transmission lines (OHTL). The method was applied to 354 line spans of a 500 kV transmission line installed in the Brazilian Savanna in Northern Brazil. For validation, the results were compared with another methodology proposed by Berredo et al. that was developed for the same biome. The performance of the new method was validated via Kernel density estimation. The results show positive performance with the proposed method to quantify the risk of wildfires and suggest that the reference model might be excessively conservative.**

***Index Terms*—Overhead Transmission Lines, Reliability, Risk of Wildfire, System Planning, Vegetation Management.**

I. Introduction

SEVERE weather events present considerable risks to power systems and can negatively impact their resilience and economic value [1]–[6]. Under such extreme weather conditions, accidents caused by faults in overhead power lines have been reported more frequently [7]. Among such events, wildfires are one of the main causes of damage and interruptions of overhead lines worldwide. It accounts for the second leading cause of outages in the Brazilian interconnected power system with an estimated 3.9 thousand momentary and permanent failures from 2012 to 2022 [8]. In addition to operational impacts, wildfires may result in significant physical damages, such as the burning of support structures and conductors, and contamination of insulators. Furthermore, wildfires under conductors can degrade the dielectric strength of air resulting in wildfire-induced flashovers.

The impacts of wildfires can be prevented on new overhead lines by choosing less exposed routes and by designing compatible and hardened circuits. For example, lattice steel structures are more resilient to wildfires compared to wood structures. Additionally, increasing the clearance distance may prevent the conductors to be engulfed by flames and reduces the probability of severe damages (e.g., aluminum annealing and loss of tensile strength), and wildfire-induced flashovers. Conversely, existing lines exposed to wildfires may be doomed to intense and costly vegetation and fire management, or to structure and conductor modifications that are financially unfeasible.

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The environment and technical characteristics of the transmission line may also pose additional challenges. Design shortcomings very often result in impacts on the grid and the environment in the surroundings of the installations. Congested rights of way with highly loaded circuits may initiate wildfires due to circulating currents from electromagnetic induction into grounded components. The insulating performance of overhead transmission lines can be heavily impacted by the clearance distances adopted. Nevertheless, heretofore there are no standards establishing design or maintenance protocols to evaluate and address the risks imposed by wildfires, and mitigation methods.

In this work, a novel geoprocessing-based methodology based on Getis-Ord Gi* hotspot analysis is proposed for assessing the risk of wildfires in overhead line corridors. A reference methodology and the novel approach are applied to a case study notably exposed to wildfires in Northern Brazil and the results are compared [6]. The results show that the novel methodology may be used to:

- Enhance line routing and structure siting.
- Specify compatible line components (e.g., support structures and conductors).
- Hardening of existing assets.
- Apply vegetation management effectively.

New contributions in this work include the following:

- Use of a single data source for assessing the risk of wildfire in overhead line corridors, which will reduce the amount of required data.
- Attention to hotspot spatial resolution.

Compared to the reference methodology [9], the proposed approach is new in the following aspects:

- Use of a single data source for assessing the risk of wildfire in overhead line corridors.
- Use of established hotspot spatial analysis.
- Quantitative assessment based on probability and statistical significance.

The remaining sections of this paper are organized as follows. Section II describes the characteristics of the OHTL and Section III discusses the biome in which the asset is installed. Section IV discusses the methodology for the proposed approach and details the mathematical equations governing the modeling for the case study. The reference model regarding the risk of wildfire, called Berredo et al. [9], is described in Section IV-A and the proposed novel methodology is explained in Section IV-B. The case study and results are discussed in Section V, before the conclusions in Section VI.

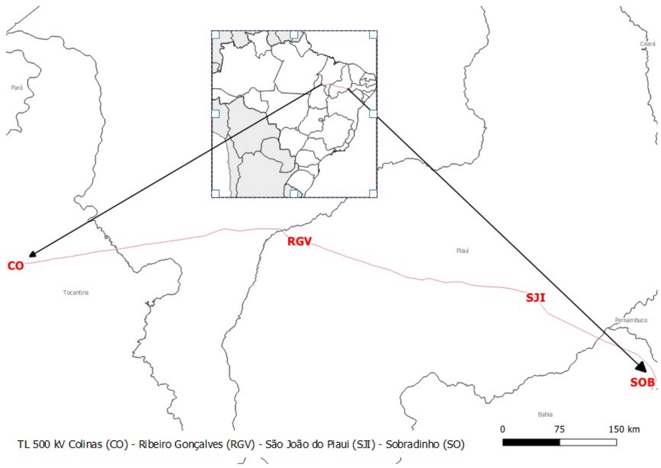


Figure 1. General Map of the OHTL.

II. Power Grid Characteristics

The case study focuses on a compact 500 kV overhead transmission line (OHTL) installed in Northern Brazil that interconnects the north and northeast Brazilian transmission subsystems (see Fig. 1). The OHTL interconnects four substations: Colinas (CO), Ribeiro Gonçalves (RGV), São João do Piauí (SJI) and Sobradinho (SO).

The circuit is mainly supported by compact cross-rope lattice steel guyed structures, resulting in a very lightweight circuit, but with a large 70 m wide right-of-way footprint. The design conceived a compact line geometry aiming to achieve lower surge impedance to increase the surge impedance loading. The OHTL's environmental permit allows vegetation management in only 28 m of the 70 m width. Thus, the vegetation on the remaining 21 m strip at each side of the right-of-way (ROW) is left intact. This characteristic may reduce the environmental footprint. However, it contributes to increasing the risk of outages as a significant amount of fuel remains in the right-of-way. The intact vegetation on the ROW sides may result in higher flames, increasing the risk of damages and wildfire-induced flashovers by decreasing the clearance distance or filling the gap between conductors and the ground.

One advantage of wider vegetation management is the firebreak characteristic. A firebreak is a strip of land without vegetation, set with the purpose of controlling fire spread. A fast-spreading grass fire may breach a narrow-managed right-of-way, especially in the presence of trees [10].

The Brazilian standard states that vegetation management should be performed in trim levels fashion. The closer to the line axis, the more trimmed should be the vegetation. The utility's OHTL spans are divided into five trim levels, limited to the 28 m strip established in the environmental permit. The vegetation is trimmed at 10 cm high in the three primary critical trim levels where the conductor sag is closer to the ground. Those three levels are typically comprised of grass and short shrubs as vegetation management is performed on a yearly basis. The 10 cm trim also prevents soil erosion. The trimmed grass is left on the ground and small limbs and branches are laid out at the boundaries of the right-of-way to prevent additional fuel under the conductors.

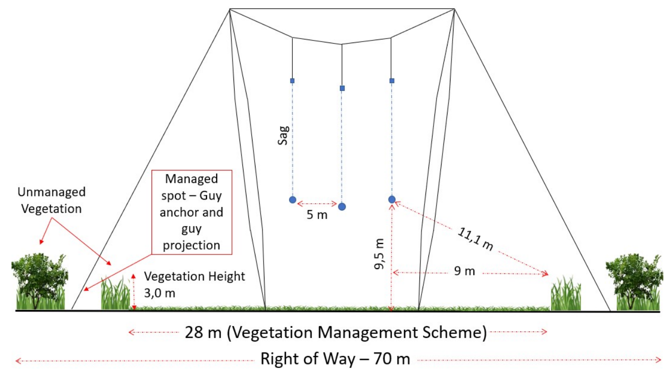


Figure 2. Main Structure, Clearance Distances, and ROW Dimensions.

Fig. 2 and Table I present details and relevant characteristics of the OHTL.

Table I
Overhead Transmission Line Main Characteristics

Characteristic	Value
Nominal Voltage	500 kV
Total Length	923.4 km
Number of Structures	1,871
Circuit Configuration	Horizontal
Average Span Length	450 m
Right-of-Way Width	70 m
Sag at Maximum Operating Temperature	20.73 m
Minimum Vegetation Clearance Distance (MVCD)	9.5 m
Distance between conductors	5 m
Current	2,736 A per phase
Operating Temperature - Long Duration	60 °C
Surge Impedance Loading (SIL)	2,369 MVA

III. Environment Characteristics

The Brazilian territory is classified into 6 very different land biomes. Each biome provides different climate, topographic and social characteristics that contribute to wildfire occurrence. The studied OHTL is installed in the Cerrado and Caatinga biomes. While the Caatinga biome covers the greatest semiarid region in Northeast Brazil and consists primarily of small, thorny trees that shed their leaves seasonally, the Brazilian Cerrado is a complex of tropical grassland (campo limpo), savanna (campo sujo, campo cerrado, and cerrado sensu stricto), and seasonal forest (cerradão) [11]. It is the largest savanna region in South America [12] and the focal region for the expansion of Brazilian agriculture.

The Cerrado is the second-largest Brazilian biome and contains 31.4% of the Brazilian transmission system. Regular wildfires occur in the dry season, mainly caused by people hunting, preparing land for cultivation, improving the quality of grazing for livestock, and controlling the spread of woody plants, while lightning contributes mainly at the beginning of the rainy season [13]. Thus, Brazilian utilities perform vegetation management of OHTLs installed in those biomes before the dry season. Tropical savanna wildfires are surface fires with average flame heights of 2.8 m, ranging from 0.5 m to 5 m when back and head fires are taken into account [13].

The spread rate will depend on several aspects such as wind speed, topography, and moisture content of the fuel.

In terms of density of wildfires, the Cerrado biome presents the second highest rate, with 2.45 hotspots/km^2 in the analyzed period between 2012 and 2022 (see Fig. 3) [14]. Furthermore,

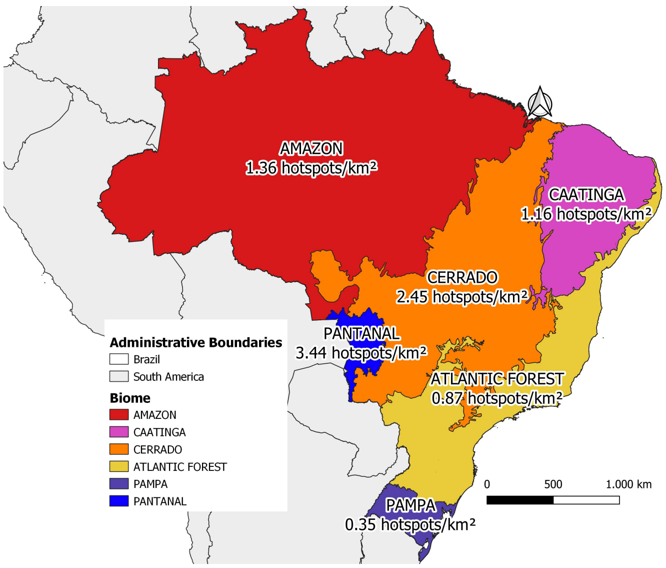


Figure 3. Number of wildfire events (hotspots) per km^2 for each biome.

Fig. 4 shows the relationship between the density of wildfires, biome territory area, and percentage of the total length of OHTLs per biome in Brazil for the same period of analysis. The chart is sorted by the density of wildfires (hotspots/area). It is interesting to highlight that the largest density of wildfires, 3.44 hotspots per km^2, occur in the Pantanal biome. However, since only 0.2% of the total extent of the bulk grid is currently installed in that region, the impacts on the power grid are less noticeable. Of considerable interest, 31.4% of the grid is installed in the Cerrado biome, second in wildfire density with 2.45 hotspots per km^2. This shows the importance of the wildfire risk analysis to the reliability of the bulk grid.

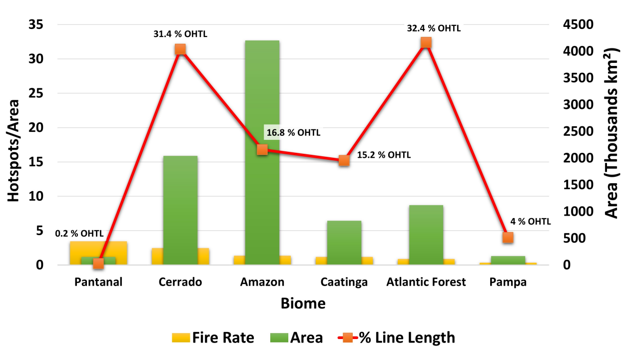


Figure 4. Fire rate versus territory area.

IV. Methodology

This section presents the methodology adopted to analyze the performance of the novel model of risk of wildfire. Two models of risk of wildfire are applied to the case study and the results are compared. The reference model used in this research was proposed in Berredo et al. [9] in 2016.

The software QGIS was used to perform the spatial analysis of the risk of wildfires. QGIS is a free and open-source geographic information system licensed under the GNU General Public License, with development led by the Open Source Geospatial Foundation (OSGeo) [15]. In addition, the analysis used the scikit-learn module in Python [16] to compare the quality of the output using a confusion matrix.

The proposed new approach classifies the probability and the standard deviation of occurrence of wildfires in one single model using hotspot spatial analysis of a historical hotspots GIS layer. The rationale behind this simplified approach is that it may be sufficient to determine the current probability of wildfire occurrence in a given location if wildfires are detected there over time.

One of the operational challenges of modeling fire ignition and spreading is the requirement of heavy processing of satellite images. Mathematical calculations using various electromagnetic spectrum wavelengths can be used to identify and classify patterns like vegetation coverage. As a result, satellite images can be altered to produce products such as polygon shapes representing various land coverages (e.g., forests, urban spread, land occupation, encroachment, etc.). The more GIS layers that are required in the model, the more computing and labor-exhausting the work will be to process.

A. *Reference Model of Risk of Wildfire - Berredo et al.*

Berredo et al. proposed a complete methodology to classify the risk of outage of overhead lines due to wildfire-induced flashovers. To achieve the specific end, the methodology determines the risk of wildfire using two GIS models (i.e., risk of ignition of fire and risk of propagation of fire). The risk of wildfire is the outcome of a matrix containing the results of risks of ignition and propagation. Berredo et al. used Albini's spotting model [17], Rothermel's surface fire spread model [18] [19] and Chuvieco [20] to classify the risks of ignition and propagation (spreading) of wildfire, tailored for the Brazilian tropical savannas (i.e., Cerrado and Caatinga biomes).

The result of the risk of wildfire is compiled into one GIS layer and included in the classification of the line vulnerability to wildfire-induced flashovers. In total, the Berredo et al. method requires 13 GIS layers to generate the risk of ignition and six layers for the risk of propagation, of which five layers are new (see Table II. The GIS inputs are analyzed for a 10 km wide strip along the overhead line route.

As Albini and Rothermel's models are implemented into modules of the FlamMap GIS software [21], the Berredo et al. method is implemented via a plugin for the QGIS software [22] called CQFS (Criticidade a Queimadas em Faixa de Servidão - *Criticality of wildfires in Rights of Way*) to identify line spans located in the Brazilian savanna likely to flashover in the scenario of a wildfire [23]. The QGIS plugin developed to support the methodology provides four results:

- Map of risk of fire ignition.
- Map of risk of fire propagation.

Table II
INPUT DATA - BERREDO ET AL. MODELS OF IGNITION AND PROPAGATION OF WILDFIRE.

Risk of Ignition	Risk of Propagation
Transmission Line	Transmission Line
Sun Irradiance	Slope Orientation
Maximum Temperature	Hypsometric Curve
Census	Land Use
Land Use	Highway
GNDVI	Watershed Orientation
NDVI	
Basal Area	
Density	
Volume	
Hotspots	
Altitude	
Wind Speed	

- Map or risk of fire (result from ignition and propagation).
- Map of vulnerability to flashover.
- Map of criticality (result from risk of fire and vulnerability to flashover).

Mapping the criticality of outage is the ultimate goal of that methodology.

B. Novel Methodology of Risk of Wildfire

This paper presents an alternative model to classify the risk of wildfire. Instead of a two-step model approach, such as those proposed in previous work [9], [19]–[21], which requires identification of both risks of ignition and propagation of fire to obtain the results of risk of fire, the new method looks exclusively into statistically significant hotspots generated from a large dataset of active fire obtained by satellite imagery and resolves the probability, standard deviation, and confidence level of the risk of wildfire for every line span.

Since the density of hotspots alone cannot tell if the cluster is statistically significant, the novel model exploits the Getis-Ord Gi* spatial statistic GIS method to identify wildfire patterns by resolving Z-Scores and P-Values of statistically significant hotspots within neighboring events. Getis-Ord Gi*, which has been used for hotspot analysis with related applications (e.g., earthquake hotspots, traffic safety management) [24]–[26], compares the local sum of a cluster of hotspots and its neighbors to the sum of all wildfire events. When the local sum is very different from the expected result, and when that difference is too significant to be the result of random chance, a statistically significant Z-Score results [27]. The standard score (Z-Score) for Getis-Ord Gi* is given by (1) [24], [25],

$$Z(Gi^*) = \frac{\sum_{j=1}^{N} w_{ij}x_j - \bar{z}\sum_{j=1}^{N} w_{ij}}{s\sqrt{\frac{N\sum_{j=1}^{N} w_{ij}^2 - \left(\sum_{j=1}^{N} \cdot w_{ij}\right)^2}{N-1}}} \tag{1}$$

where w_{ij} is the spatial weight between observations i and j, $\bar{z} = \frac{\sum_{j=1}^{N} x_j}{N}$, and $s = \sqrt{\frac{\sum_{j=1}^{N} x_j^2}{N} - \bar{z}^2}$. $w_{ij} = 1$ if observation j is within a threshold distance d of observation i and 0 otherwise. N is the total number of line spans in the analysis area (line section). x is a weight associated with each region.

The Z-Score measures the statistical significance, the distance from a particular line span to the mean value (μ) of the entire hotspot dataset, in standard deviations (σ). The model also provides the probability (P-Value) that a given hypothesis will occur for every line span analyzed. A statistically significant cluster of hotspots should have a high value and be surrounded by other events with high values. A span classified with a high risk of wildfire will have a positive standard deviation (Z-Score), which means that the more intense the clustering of wildfires in a line span, the higher the Z-Score will be. Line spans with medium to low risk of wildfires will result in Z-Scores below zero.

Every line span is populated with the standard deviation (Z-Score), and probability (P-Value) that a fire event will occur. The quantitative results represented by ranges of Z-scores and P-values were translated into risk classes as listed below:

- **Low risk of wildfire** - insignificant risk of wildfire represented by a Z-score over -0.28
- **Medium risk of wildfire** - up to 10% confidence level represented by Z-scores ranging from -0.28 to 0.124.
- **High risk of wildfire** - up to 50% confidence level represented by Z-scores ranging from 0.125 and 0.673.
- **Very high risk of wildfire** - confidence level above 50% represented by Z-scores above 0.674.

The translation from quantitative to qualitative results was necessary to enable the comparison of the results with the methodology proposed in [9]. Interpretation of results requires both Z-Score and P-Value. The combination of very high or very low Z-Scores, associated with very small P-Values, are found in the tails of the normal distribution. When a feature pattern analysis yields small P-Values and either a very high or a very low (negative) Z-Score, this indicates it is very unlikely that the wildfire represents a null hypothesis. Fig. 5 shows the Gaussian distribution for the proposed model.

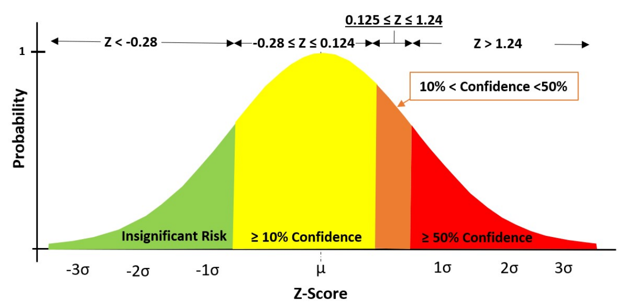


Figure 5. Gaussian curve for Enhanced Berredo et al.

Spans with a large absolute value of Z-Score and a small value of P-Value are probably too insignificant. Unusual scenarios could represent interesting situations, though, as land use may change over the years. For instance, a forest could change into agricultural land. This model used ten years of data (2012 to 2022) obtained from the Fire Information for Research Management System (FIRMS) [14] website that is managed by NASA.

Compared to Berredo et al., this method uses a higher resolution fire data. While Berredo et al. adopts post-processed fire data with 1 km spatial resolution from the satellite MODIS, the novel method uses 375 m spatial resolution fire data obtained from the Polar-orbiting Active Fire Detection of the satellite VIIRS Suomi NPP/NOAA-20. This is of high importance since the pixel size represents the size of the hotspot. Each hotspot is located in the center of a pixel containing one or more fire sources, including thermal power plants or volcanoes. A hotspot detected by the MODIS sensor will measure 1 km x 1 km, while the hotspot obtained by the VIIRS will measure 375 m x 375 m [28]. A large wildfire will be sensed as a sequence of aligned hotspots where each one is located in the center of each pixel.

The new model results in confidence intervals, translated into qualitative risk classes of wildfire. Confidence levels of 10% and under, 10% to 50%, and above 50% of occurrence of fire represent low, medium, and high risk of wildfire, respectively. Considering uncertainties (e.g., the spatial accuracy of the remote sensing) and fire spread influencing factors, the model accounts for hotspots in a 2 km wide buffer along the line route. Therefore, to provide normalized means of comparison with the new model, the original 10 km buffer adopted in Berredo et al. was reduced to 2 km. Fig. 6 shows the dimensions of the buffer (2,000 m) and the right-of-way (70 m) of the case study hit by hotspots (red dots).

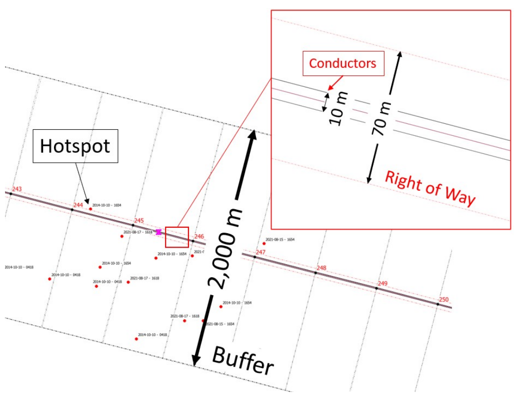


Figure 6. Physical boundaries for the classification of risk of wildfire.

Fig. 7 and Fig. 8 show the detection and post-processing of several wildfire events in a line section of the ATE 2 OHTL. Note the spatial resolution of 375 m x 375 m (green squares in Fig. 7) and the related hotspot coordinates in the center of the quadrants (red points). The new method assumes the number of hotspots in a span as the maximum value of eight overlapping squares in the slice of buffer corresponding to the line span (see Fig. 8). The maximum number of overlapping squares in a span is populated in the attribute table of each span buffer and used as an input parameter for the spatial statistic tool to perform the hotspot analysis.

V. Case Study Results and Discussions

This section explains the calculation steps and results of the risk of wildfire proposed in Berredo et al. [9], in the new methodology based on Getis-Ord Gi*, and the comparative results of both methods.

A. Test Scenario A - Berredo et al.

Berredo et al. adopts two models (i.e., risk of ignition of fire and risk of propagation of fire) to determine the risk of

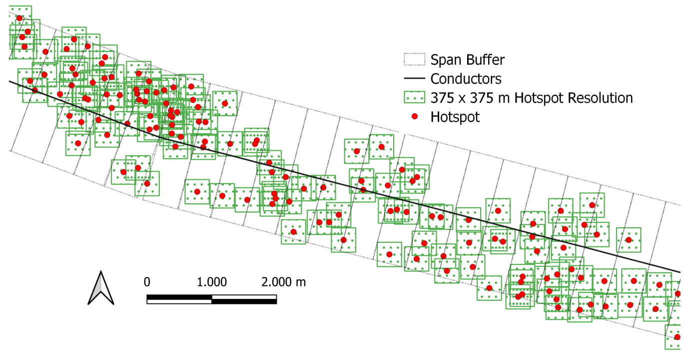


Figure 7. Hotspot detection size (375 m x 735 m).

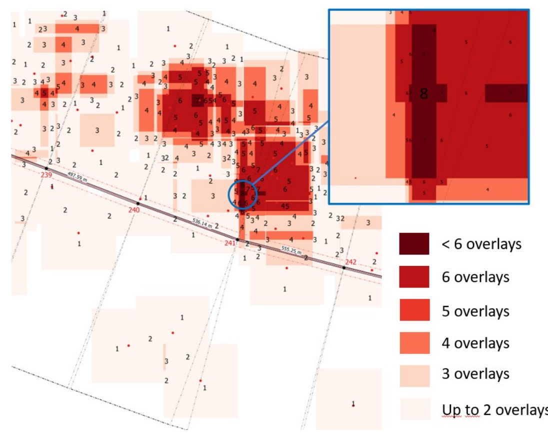


Figure 8. Hotspot overlapping.

wildfire. The risk of wildfire is classified into five ranges of dimensionless values translated into five risk levels according to Table III.

Table III
Risk of wildfire, Berredo et al., risk classes.

Risk Class	Value
Very Low	Risk <=0.2
Low	0.2 < Risk <= 0.4
Medium	0.4 < Risk <= 0.6
High	0.6 < Risk <= 0.8
Very High	0.8 < Risk <= 1

Fig. 9 shows the results of the risk of wildfire for the reference model. From top to bottom, the first step shows the risk of ignition. The second step shows the risk of propagation. The third step shows the risk of wildfire that is the result of merging the risks of ignition and propagation. The risk of wildfire is classified in a grid of 500 m x 500 m cells. Thus, since a line span can intercept several cells, the final classification of risk of wildfire used the cell with the highest score intersecting the line span.

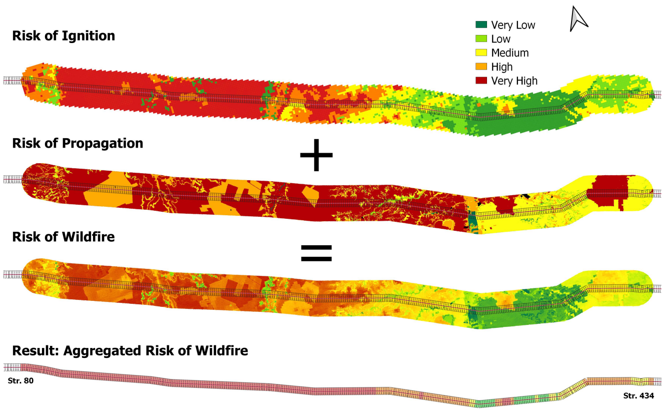
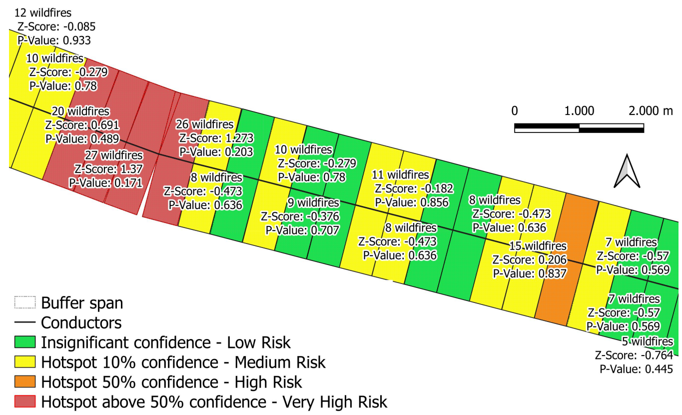


Figure 9. Classification of Risk of Wildfire according to Berredo et al. - structures 80 to 434.

(a) Classification of Risk of Wildfire according to the proposed method - Structures 80 to 434.



(b) Detailed classification displaying the standard deviation and probability of wildfire for each line span.

Figure 10. (a) Classification of risk of wildfire according to the proposed method - Structures 80 to 434, (b) Detailed classification displaying the standard deviation and probability of wildfire for each line span.

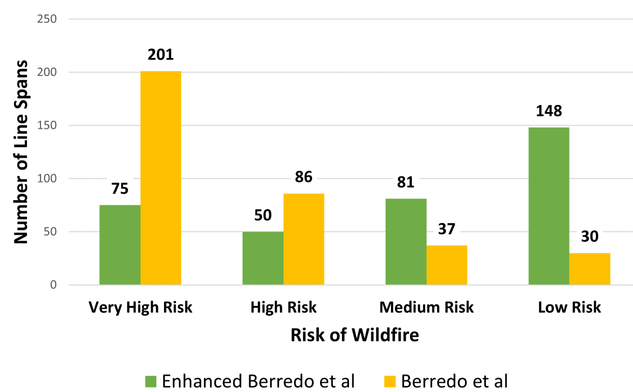


Figure 11. Results of the classification of risk of wildfire.

B. Test Scenario B - Enhanced Berredo et al.

This section presents the results of the proposed new model to classify the risk of wildfire by Hotspot Analysis based on Getis-Ord Gi* using a ten-year data collection. Instead of the three-step approach presented in the Berredo et al. method, this method relies exclusively on hotspot data to classify the risk of wildfire. The results of the Z-score measure the statistical significance, the distance from a particular line span to the mean value (μ) of the entire hotspot dataset, in standard deviations (σ). The model also provides the probability (P-Value) of occurrence for each of the line spans analyzed.

Fig. 10 shows the results of the classification of the risk of wildfire between structures 80 and 434 using the new method. The classification adopts the maximum value of cells overlapping each other in a line span. The cell size is 375 m x 375 m, corresponding to the spatial resolution of the remote sensing source.

C. Results and Comparison

In this section, the two methodologies of classification of risk of wildfire are compared and analyzed. GIS tools and a confusion matrix are used to analyze the results of feature classes. The comparison approach consisted in identifying spans matching risk levels. As previously mentioned in Section IV-B, the results of the proposed methodology were translated from Z-Scores to risk levels to make the confusion matrix possible. In practice, utilities can establish the risk levels based on ranges of standard deviation and probability to meet their risk management policies.

The results of the classification of the risk of wildfire for both analyzed methods are shown in Fig. 11. Note that whereas results from Berredo et al. concentrate most of the line spans in a very high risk of wildfire, the proposed new method concentrates most of the spans in a low risk of wildfire. For the new method, a very high risk of wildfire means that there is a minimum 50% confidence level that a wildfire will occur, based on the analysis of 20 years of hotspot events.

Fig. 12 shows the matching results between Berredo et al. (Predicted Label) and the new methodology (True Label). Only 83 out of 354 line spans (23%) presented identical results. The matching results are distributed as follows:

- 51 out of the total spans match results of very high risk level of wildfire.
- 15 out of the total spans match results of high risk level of wildfire.
- 6 out of the total spans match results of medium risk level of wildfire.
- 11 out of the total spans match results of low risk level of wildfire.

Fig. 13 shows the correlation of results between the risk levels classified in Berredo et al. and the results of Z-Score from Enhanced Berredo et al. Results matching are those inside the colored boxes. Results outside the colored boxes are those failing to match the risk.

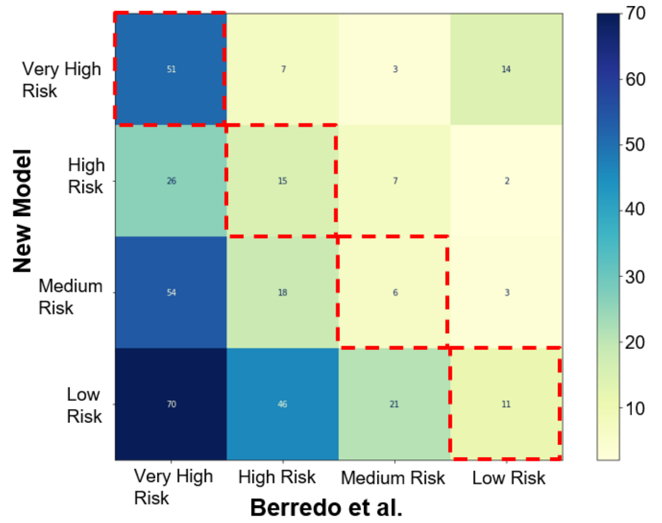


Figure 12. Confusion matrix between results of Berredo et al. and Enhanced Berredo et al.

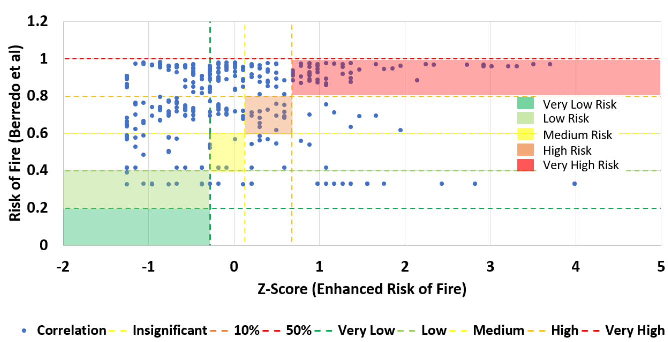


Figure 13. Correlation chart between results of Berredo et al. (Risk levels) and Enhanced Berredo et al. (Z-Scores).

Fig. 14 shows the comparison of results between Berredo et al., the proposed new method (Enhanced Berredo et al.), and a heatmap analysis using kernel density estimation based on the 20-year hotspot data. The kernel density estimation is a non-parametric method to estimate the probability density function of a random variable. In the GIS, kernel density estimation calculates the density of a given point feature.

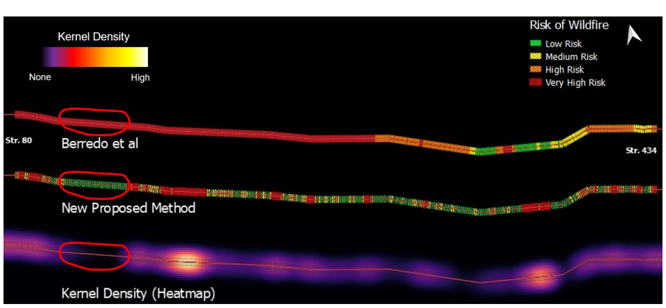


Figure 14. Comparison between Berredo et al., the new method, and kernel density estimation (heatmap).

The proposed method presents a strong visual correlation with the kernel density map shown in Fig. 14. Whereas denser sections of the heatmap (yellow-to-white color sections) match spans classified with a very high risk of wildfire (red color spans) in the proposed new method, regions with dispersed hotspots (dark blue-to-dark color sections) match low-risk spans (green color sections). This comparison evidences the effectiveness of the proposed new methodology for classifying the risk of wildfire. In addition, Fig. 14 indicates that the Berredo et al. method might result in an overly conservative risk of wildfire. The region marked in red color shows evidence of opposite results and how the proposed new method matches the kernel density estimation.

Table IV
COMPARATIVE RESULTS OF DESCRIPTIVE STATISTICS

Information	Berredo et al. Dimensionless	New Method Z-Score
Number of Hotspots	2351	
Number of cells	354	
Average	0.779	-2.54^{-12}
Std Error	0.010	0.053
Median	0.865	-0.181
Mode	0.330	-1.248
Std Deviation	0.201	1.001
Variance	0.040	1.002
Minimum	0.327	-1.248
Maximum	0.980	3.989
Low Risk Spans	30	148
Medium Risk Spans	37	81
High Risk Spans	86	50
Very High Risk Spans	201	75

Table IV displays the results of descriptive statistics for both methods. Quantitative results should not be compared directly, since Berredo et al. is based on a dimensionless range of values, whereas the proposed new method uses ranges of standard deviations (Z-Scores) to establish the qualitative risk classes. Considering that the utility would perform vegetation management on one-third of the span length, here estimated in 500 m with a 28 m width, the new model would reduce the vegetation management area to 62.6%, or 2,268,000 m^2.

VI. CONCLUSIONS

In this paper, a new method to estimate the risk of wildfire applied to overhead transmission lines is presented. New contributions provided in this paper include a spatial analysis based on historical data of wildfires that can be used to design wildfire-resilient OHTL and prioritize vegetation management by identifying the locations with critical exposure to wildfires. First, the background information and need are discussed, including characteristics of the power grid and environment. Then, the proposed methodology is detailed. For validation, the new method is showcased and compared with another method for a case study of a 500 kV compact line. Results are presented in Fig. 14, 13, 11, and Table IV. Future work will focus on improving the proposed methodology by calibrating the buffer width to better address the risk associated with the risk of fire spread.

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ID: 2023-IASAM23-0122 (R1)
Title: Novel GIS-Based Methodology to Quantify the Risk of Wildfires in Overhead Transmission Lines - A Case Study

Response to the Reviews for the Manuscript

The authors would like to thank the Editors and the Reviewers for their insightful and constructive feedback. The manuscript has been revised in light of the reviewers' comments and concerns to improve the quality of the paper. The authors believe that all of the comments have been carefully addressed. For convenience, the original comments from each reviewer are included in this response letter. Below are notes on how we have responded and incorporated the comments in our revision. The reviews' comments are in red. The authors' responses are in black, as applicable.

The summary of the corrections are as follows:

- Changes are incorporated to improve the quality of the manuscript, as applicable.
- The existing figures have been modified, as indicated in this response document.
- The paper has gone through a proofreading process.

Contents

1. Editors' Comments:

We are pleased to advise that your paper, "Novel GIS-Based Methodology to Quantify the Risk of Wildfires in Overhead Transmission Lines - A Case Study", 2023-IASAM23-0122, has been recommended for presentation in the IEEE Industry Applications Society Annual Meeting. Any comments to the author appearing below are intended for your information only.

Your paper has been through a formal peer-review process and has been recommended for Acceptance for presentation in the IAS Annual Meeting.

Associate Editor
Comments to the Author:
Please address the reviewers' comments in your final conference paper.

These are the Reviewer's comments to the author.

1.1. Response to Editors' Comments:

The authors would like to thank the Editors for the valuable suggestions and comments to improve the paper. As per your suggestions, all the questions and comments raised by the reviewers have been addressed in the revised paper. Both the revised version of the paper as well as the response sheet are attached for your reference. Thank you for your consideration.

2. Reviewer #1's Comments

Reviewer: 1

Comments to the Author
(There are no comments. Please check to see if comments were included as a file attachment with this e-mail or as an attachment in your Author Center.)

2.1. Response to: Reviewer #1's Comments

The authors would like to thank the Reviewer for the valuable suggestions and comments. We appreciate your time to review our paper.

3. Reviewer #2's Comments

Reviewer: 2

Comments to the Author
This paper presents a methodology for the quantification of wildfire risk under overhead transmission lines. The new methodology is compared against a previous one and a case study is presented and discussed. The paper is clearly written and easy to follow. It contributes to its research subject. Some minor comments follow:
• Does the presence of guys in the unmanaged part of the right of way affect the performance of the overhead line?
• Please check reference style for consistency with the template.
• Page 3, 2nd line: "…to 5 me…" correct to "…to 5 m…".
• Please check the caption of Fig. 3 against its content. The last to entries in the legend of the figure are not clear as well.

3.1. Response to: Reviewer #1's Comments

The authors would like to thank the Reviewer for the valuable suggestions and comments to improve the paper. We agree with your recommendations. As per your suggestions, the paper has been updated to improve the quality. Listed below are our specific responses to your comments:

Comment a: (Does the presence of guys in the unmanaged part of the right of way affect the performance of the overhead line?)

- The authors thank the reviewer for this comment and have updated the paper. Fig. 2 has been revised to improve clarity regarding the guy wire and vegetation.

Comment b: (Please check reference style for consistency with the template.)

- The authors thank the reviewer for this comment and have updated the paper to improve clarity, as requested. We updated the reference style for consistency.

Comment c: (Page 3, 2nd line: "…to 5 me…" correct to "…to 5 m…".)

- The authors thank the reviewer for this comment and have updated the paper to correct this item, as requested.

Comment d: (Please check the caption of Fig. 3 against its content. The last to entries in the legend of the figure are not clear as well.)

- The authors thank the reviewer for this comment and have updated the paper, as requested. The caption for Fig. 3 has been updated to improve clarity.