Dear Editor Associated and Reviewer

We thank you for your helpful comments on the article. Your comments have been taking account point by point.

RC1: 'Comment on egusphere-2026-1902', Anonymous Referee #1, 29 May 2026

General Comments:

The manuscript addresses a relevant and timely topic: the assessment of wildfire hazard in the Andean and Amazonian regions of Peru, where fire activity has important ecological, social, and operational implications. The proposed Wildfire Hazard Index (WHI) has potential value for regional wildfire monitoring and early warning applications.

The study is clearly motivated and uses datasets that are broadly appropriate for this type of regional hazard assessment. The attempt to develop an interpretable index, rather than relying only on complex data-driven methods, is also a positive aspect, particularly for operational use in data-limited regions.

1. However, the manuscript would benefit from substantial revision before publication. In particular, the methodological choices behind the construction of the WHI, its weighting scheme, hazard classification, and validation need to be explained more clearly and justified more rigorously (I don't think "calibration" is the best word to describe what you did).

The manuscript was revised and improved. Some sections were improved and reformulated. For better understanding, Wildfire hazard index in now Wildfire danger index in the manuscript.

Concepts used, source : https://jgpausas.blogs.uv.es/2017/08/05/fire-danger-fire-hazard-fire-risk/

2. I also recommend reorganizing the Results section so that the model outputs are first presented as results of the proposed WHI, followed by a separate section dedicated to model validation or evaluation. This would make the distinction between model results and model performance clearer.

Okay. The results section has been reorganized, the optimized parameters (w_n) were presented first, at the beginning of the results section. The validation results are then displayed.

3. Overall, the manuscript has potential and addresses an important regional gap, but its scientific robustness and presentation need to be strengthened. I therefore recommend

major revisions. I'll go over the specific comments (in the attachment). I know they might seem like a lot (or a bit long), but it's just to explain why I think the way I do, and also to have a little "discussion" of ideas among us.

Ok, thank you very much

Specific Comments:

Abstract:

Line 22: The abstract should avoid overly general or circular statements such as "lower WHI values correspond to lower wildfire hazard." This is expected by definition and does not add much scientific information. The space could instead be used to summarize the main regional or seasonal findings of the study.

Ok, the sentence was removed

Introduction:

Line 30: The Introduction provides a broad and relevant overview of wildfire activity and wildfire hazard assessment. However, the opening paragraphs are somewhat general and could be more focused on the specific motivation of the study. I recommend streamlining this section to guide the reader more directly from the broader wildfire problem to the specific need for a wildfire hazard index for the Andean and Amazonian regions of Peru.

Ok, the paragraph was reformulated as follow:

Tropical regions of South America are characterized by high moisture levels and air temperatures, extreme rainfall, and ecosystemic biodiversity exceeding that of any other biome on Earth (Espinoza Villar et al., 2009, Spotlight on South America, 2017). South America's tropical rainforests are one of the world's largest carbon sinks, with the greatest potential for carbon sequestration (Blanton et al., 2024). The interaction among this carbon availability, anthropogenic land use change, and other factors has led to an increase in the vulnerability of its different ecosystems (Pivello et al., 2021). In the last decade, South America faced an unprecedented wildfire crisis, with Andean and Amazon Forest among the hardest-hit ecosystems (Béllo Carvalho et al., 2025). For instance, 10,897 km² of forest were cleared, and cumulative forest loss in the Brazilian Amazon reached 820,000 km² by 2020 (INPE, 2021). Meanwhile, in the Andean region of Peru, in western South America, the frequency of wildfires, which mainly affect forests, shrublands, and herbaceous grasslands, has increased sharpky (400%), outstripping the government's ability to respond (Zubieta et al., 2021).

Line 39: The manuscript introduces the concept of wildfire hazard and refers to wildfire indices and wildfire occurrence. However, the distinction between wildfire hazard, fire occurrence, fire activity, and wildfire risk should be clarified early in the manuscript. Since the proposed WHI does not explicitly include exposure or vulnerability, it should be consistently framed as a hazard or fire-prone conditions index rather than as a risk model.

Ok, the paragraph was reformulated. To avoid confusion with other concepts, "wildfire danger" has been defined in this section.

Overall, wildfires constitute a latent problem in various regions of the world (Ferreira et al., 2023: Berchtold et al., 2025; Barua et al., 2026). Wildfires in forested areas of South America can be considered environmental disasters, often triggered by anthropogenic activities (Alvarez et al., 2025; Pivello et al., 2021; Taboada-Hermoza and Martínez, 2025). In recent decades, wildfire regimes have undergone significant changes worldwide (Keeley and Syphard, 2021; Li et al., 2026; Schmidt and Eloy, 2020). Given this problem, prevention tools that characterize wildfire danger on a spatial and temporal scale can be crucial for warning of wildfire conditions. Wildfire danger can be defined as a sum of the factors affecting initiation, spread, and resistance to control in a given area, which is typically expressed as a semi-quantitative index (e.g., from very high to very low) (Zacharakis and Tsihrintzis, 2023). This danger also depends on weather and other factors and it is usually reported by meteorological agencies (weather-based fire danger). Wildfire danger has been extensively studied since 1925, incorporating various static and dynamic factors, both cumulative and non-cumulative (Bradshaw et al., 1984; Burgan, 1988; Van Wagner, 1987). These studies have led to the development of numerous wildfire danger indices at different spatial scales (Chen et al., 2023; Laneve et al., 2020; Soto et al., 2015; Xofis et al., 2020). However, the reliability of these danger indices varies considerably in space and time, and only a subset has been shown to be effective through validation against actual wildfire occurrences.

Line 44: The authors discuss several factors influencing wildfire hazard, including fuel moisture, meteorological conditions, topography, drought, vegetation conditions, and agricultural fire use. This discussion is relevant, but it should be more explicitly connected to the variables later used in the WHI. This would help justify the selection of the input variables.

Ok, the paragraph was reformulated as follow.

Overall, wildfires constitute a latent problem in various regions of the world (Ferreira et al., 2023: Berchtold et al., 2025; Barua et al., 2026). Wildfires in forested areas of South America can be considered environmental disasters, often triggered by anthropogenic activities (Alvarez et al., 2025; Pivello et al., 2021; Taboada-Hermoza and Martínez, 2025). In recent decades, wildfire regimes have undergone significant changes worldwide (Keeley and Syphard, 2021; Li et al., 2026; Schmidt and Eloy, 2020). Given this problem, prevention tools that characterize wildfire danger on a spatial and temporal scale can be crucial for warning of wildfire conditions. Wildfire danger can be defined as a sum of the factors affecting initiation, spread, and resistance to control in a given area, which is typically expressed as a semi-quantitative index (e.g., from very high to very low) (Zacharakis and Tsihrintzis, 2023). This danger also depends on weather and other factors and it is usually reported by meteorological agencies (weather-based fire danger). Wildfire danger has been extensively studied since 1925, incorporating various static and dynamic factors, both cumulative and non-cumulative (Bradshaw et al., 1984; Burgan, 1988; Van Wagner, 1987). These studies have led to the development of numerous wildfire danger indices at different spatial scales (Chen et al., 2023; Laneve et al., 2020; Soto et al., 2015; Xofis et al., 2020). However, the reliability of these danger indices varies considerably in space and time, and only a subset has been shown to be effective through validation against actual wildfire occurrences.

Line 70: The manuscript states that wildfire hazard indices have been applied in several South American countries, but that their applicability to the Andean- Amazonian regions of Peru has not yet been rigorously evaluated. This is an important motivation, but the scientific gap should be stated more explicitly. The authors should clarify whether the main gap is the lack of a Peru-specific index, the limited validation of existing indices in Peru, the absence of short-term operational hazard products, or the need to incorporate anthropogenic fire-use information.

Ok, the paragraph was reformulated as follow.

However, applicability of fire danger indices to the Andean–Amazonian regions of Peru has not yet been rigorously evaluated and validated in the scientific literature. This South American region lacks a specific and validated wildfire danger index, and there is insufficient knowledge about how danger levels modulate in these types of ecosystems at spatial and temporal scales. Research is needed to develop a short-term danger index based on operational climatic and vegetative products that incorporate data on anthropogenic fire use. This study aims to propose a simplified model to assess the potential for wildfire danger under the influence of climatic factors, vegetative conditions, combustible material and anthropogenic fire use for the Andean and Amazonian regions of Peru.

Line 75: The objective of the study should be stated more precisely. The final sentence refers to climatic and vegetation-related factors, but the proposed WHI also includes anthropogenic and fuel-related components. The objective should therefore reflect all major components of the index and clearly state what distinguishes the proposed approach from existing wildfire hazard or fire weather indices.

Ok, the objective of the study was stated more specifically.

This study aims to propose a simplified model to assess the potential for wildfire danger under the influence of climatic factors, vegetative conditions, combustible material and anthropogenic fire use for the Andean and Amazonian regions of Peru.

Study area:

The Study area section would benefit from a summary table describing the main biophysical characteristics of each of the nine regions used in the analysis. Such a table could include, for example, elevation range, dominant land-cover or vegetation types, precipitation regime, main fire-prone ecosystems, and the relative importance of agricultural activity. This would help readers understand why the regionalization is relevant for wildfire hazard modelling and interpretation.

Ok. One table was added

Table 1: Characteristics of areas of analysis

	Study region	Surface (km^2)	Elevation (masl)	Average precipitation (mm)	Predominant ecosystems	Approximate agricultural area (%)
1	North Coast	58626	308	312	Dry savanna forest, Dry mountain forest, Coastal desert	15
2	Central Coast	17365	538	127	Coastal desert, Cactus patch	10
3	South Coast	62523	1131	82	Coastal desert, Cactus patch	5
4	Northern Andes	51184	2743	688	Shrubland, Andean grassland	32
5	Central Andes	143956	3634	611	Shrubland, Andean grassland	10
6	Southern Andes	173909	4094	630	Andean grassland, Shrubland, High Andean area with sparse vegetation	10
7	Northern Amazon	472973	404	2566	Low hill forest, Floodplain forest, Low terrace forest	6
8	Central Amazon	165197	654	2102	Low hill forest, Basimontane mountain forest.	10
9	Southern Amazon	146345	937	2397	Low hill forest, Basimontane mountain forest.	2

Line 91: The description of precipitation and elevation gradients could be expanded to include a more harmonized discussion of the western and eastern Andean slopes. Since the Pacific slope, eastern Andean slope, and Amazon basin have distinct climatic, vegetation, and fire-regime characteristics, the manuscript should more explicitly explain how these physiographic contrasts influence wildfire hazard and the interpretation of the WHI across regions.

Thank you for your comment. The figure has been improved, and an additional table has been added to the manuscript.

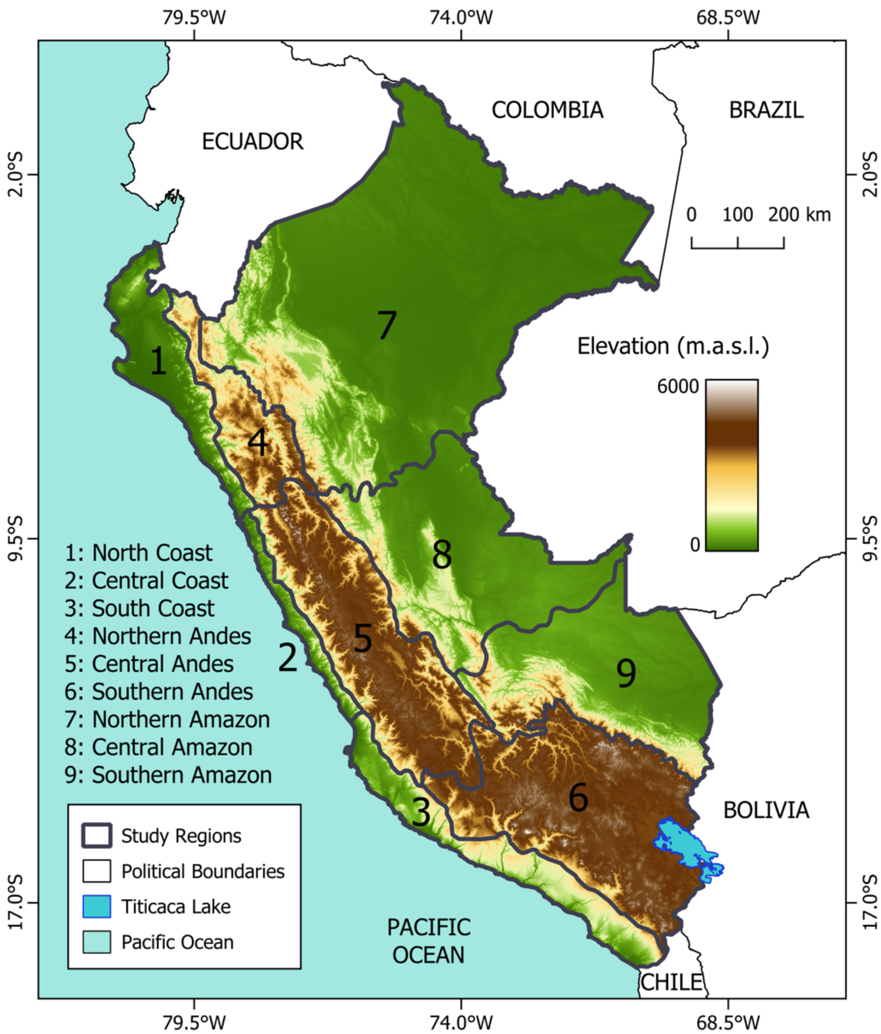

Figure 1: Study area and proposed areas of analysis.

Annual precipitation patterns vary markedly across the country; for example, there is almost no precipitation in the coastal region (valleys and deserts) (Table 1). The highest precipitation (exceeding 1000 mm/year) occurs predominantly in the tropical forests of eastern Peru, while the Andean region experiences lower values (around 600 mm/year) (Espinoza Villar et al., 2009). Under climate change scenarios, an increase in extreme precipitation events is expected to coincide with more frequent and intense meteorological droughts, characterized by reduced precipitation and increased evapotranspiration in the Peruvian Andes (Potter et al., 2023; Zubieta et al., 2021a). Extreme drought events, such as those recorded in 2005, 2010, 2016, 2020, and 2022, have been strongly associated with more frequent wildfire occurrence in Peru, with increases ranging from 400% to 700% compared to historical averages (Zubieta et al., 2019, 2023b).

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For comparative purposes, this study defines the Andean region as reference areas located above 1500 meters above sea level (masl) (Zubieta et al., 2021b), while the Amazon region is considered to comprise lowlands up to 1500 masl on the eastern slopes of the Andes (Fig. 1). Official wildfire records from the Peruvian government, supported by data from the Civil Defense Institute (INDECI), indicate that 80–90% of wildfire occurrences are concentrated in the Andean region, particularly between 1500 and 4000 masl (Zubieta et al., 2021b). Andean grasslands constitute the ecosystem at greatest danger of wildfire in high-altitude regions (Ccanchi, 2021; Zubieta et al., 2021b), where the accumulation of highly flammable vegetation could significantly increase wildfire danger, especially during the dry season (June–August) and the onset of the wet season (September–December). The agriculture sector, in which fire use is common, employs the largest proportion of the Peruvian workforce (27.5%) (UP, 2022). Despite that economic importance, the danger associated with fire use in agriculture and livestock production has received relatively limited scientific attention (Alvarez et al., 2025; Taboada-Hermoza and Martínez, 2025). A recent study highlights that wildfires—officially recognized as emergencies by government authorities—in the Andean region of Cusco (southern Peru) primarily occur near rivers and roads (Zubieta et al., 2023a).

Line 109: The final paragraph of the Study area section introduces the availability of climate and satellite datasets. While this information is relevant, it overlaps with the following Data and Methodology section. The authors could either shorten this paragraph or use it more explicitly to explain why the selected datasets are suitable for this study area. If not, it should be included in the next section.

You are right. For better understanding, this paragraph was moved to the Data and Methodology section, as follow:

The spatial and temporal availability of climate datasets in Peru, including observational data (Aybar et al., 2020; Huerta et al., 2022), satellite-based precipitation products (Huffman et al., 2023), and vegetation spectral indices derived from satellite observations (Ccanchi, 2021; Zubieta et al., 2021b), among others, provides a valuable opportunity to analyze wildfire danger and develop new wildfire danger monitoring methodologies (Ambadan et al., 2020; Laneve et al., 2020; Talukdar et al., 2024). Taking advantage of large-scale data available for Peru, datasets were selected and prioritized as described below:

Figure 1: The cartographic presentation of the study-area map should be improved. In particular, the elevation map would be easier to interpret if a more intuitive colour scale were used, ranging from green for lower elevations to brown for higher elevations. The elevation legend should also be displayed vertically, which would make the altitudinal gradient clearer. In addition, the ocean should be represented with a distinct colour from the neighbouring countries, to avoid confusion between marine areas and land outside the study area.

Ok, study map was improved

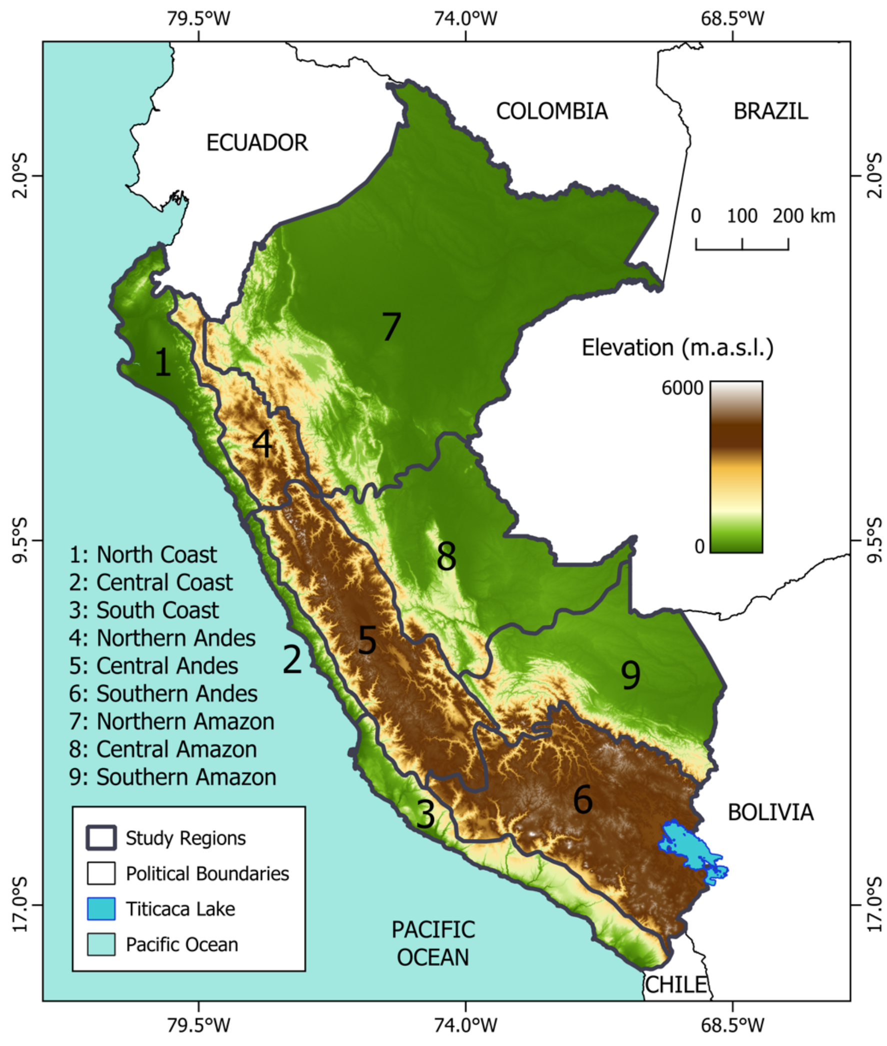

Figure 1: Study area and areas of analysis proposed.

Methodology:

Line 120: The historical data should be described in more detail. The authors should clarify the time period covered, the definition of a "wildfire event" or "wildfire emergency", the spatial precision of the records, and whether these data represent ignition points, affected locations, administrative reports, or emergency declarations. This is particularly important because these data are later used for model evaluation.

Thanks, it was adjusted in data and methodology, respectively.

Historical data on wildfire event locations (2000-2024) were compiled from the Ministry of the Environment of Peru. These datasets were constructed from emergency technical reports of wildfire and validated by using Sentinel satellite images (MINAM, 2025). Each wildfire report represents a georeferenced point set in a geographic information system. These datasets were used for temporal and spatial validation of the level of wildfire danger. MODIS surface reflectance data (MOD09A1 product) were obtained at a spatial resolution of 500 m and a temporal resolution of 8 days.

To ensure the consistency and reliability of the validation analysis, the historical wildfire records compiled by the Ministry of the Environment (MINAM) for the 2019–2024 period were used. This period represents the most reliable phase of the national wildfire database, reflecting substantial improvements in the coverage and accuracy of emergency reports provided by INDECI (CENEPRED, 2020). To further strengthen model verification, satellite-derived active fire (hotspot) data for the 2016–2024 period were also incorporated, including the 2016 wildfire season, which was declared a national emergency in Peru due to the severity of wildfire events (PCM, 2016).

Line 145: The choice of input variables is reasonable, but the manuscript should better justify why these four components were selected and why other potentially relevant factors were excluded, such as, temperature, relative humidity, slope, aspect, etc. This is particularly important because the Introduction mentions topography and meteorological conditions, but these are not fully represented in the WHI.

Okay. In the introduction section, topography is no longer mentioned and the focus has shifted to variables used in this paper. Moreover, to justify a previous paragraph, it was structured in the aforementioned line.

A justification of the model components was added also:

Various studies that use large-scale fire danger modeling (Chen et al., 2023; Laneve et al., 2020; Soto et al., 2015; Xofis et al., 2020) suggest the high relevance of vegetative and climatic factors for analyzing wildfire danger, which is mainly characterized by the interaction of the state and type of available forest fuel (Hardy, 2005) and the effect of climatic conditions (e.g., droughts) on that fuel during the dry period (Manta et al., 2018). Based on this context and various regional scientific investigations conducted in Peru, which propose monitoring parameters linked to these factors to characterize the continuous severity of drought (Espinoza et al., 2016; Saavedra and Zubieta, 2024) and water stress of vegetation (Zubieta et al., 2021b; Zubieta et al., 2023b), parameters linked with vegetation development (vegetation type and vegetation index derived from remote sensing) and droughts (accumulation of dry days) were selected. These parameters can be considered suitable for representing the vegetative and climatic factors of wildfire danger in Andean-Amazonian areas (Fig. 2). Finally, to represent the anthropogenic role as an ignition factor in wildfires, priority was given to analyzing regional agricultural activity (cultivated areas of Peru) in the danger modeling, as fire is most likely to be used in agricultural activity (Fig. 2).

We selected a water stress indicator (climatic parameter of wildfire danger model), which is assessed through the accumulation of Dry-Day Frequency (DDF) over the previous 30 days (Espinoza et al., 2016; Saavedra and Zubieta, 2024), because the dry season plays a cumulative role in reducing vegetation moisture (Zubieta et al., 2021b). For this purpose, daily precipitation data from the GPM-IMERG Late Run product were used (Huffman et al., 2023). A “dry day” is operationally defined as a day with accumulated precipitation below 1 mm (Espinoza et al., 2016), a criterion also applied in studies conducted in the Peruvian Andes (Zubieta et al., 2021b; Ccanchi, 2021).

Line 153: The normalization of Dry-Day Frequency using the 75th and 99th percentiles should be justified more rigorously for the study region.

Ok. The explanation was improved.

A period of severe water stress (prolonged dry days) in the Amazon region can be considered a period of normal dry days in the Andean region. To limit the spatial and temporal variability of the cumulative number of dry days in the most recent dry days in Andean and Amazonian zones, percentiles (P_n) were estimated from the DDF data series. This spatial and seasonal adjustment using percentiles ensures that the thresholds reflect local climatological conditions rather than absolute values. To standardize the response of this parameter within the model, the DDF data series were normalized using the historical 75th percentile (P_{75}: threshold for the onset of anomalous conditions that would increase the danger of wildfires (Lenderink and van Meijgaard, 2010) and 99th percentile (P_{99}: threshold of extreme drought conditions (Galeano et al., 2017) of the 2002–2024 time series. P_{75} can be considered the threshold for the onset of significant drought conditions, separating standard climate variability from periods where dry day accumulation exceeds normal levels, while P_{99} can be considered as the upper bound for extreme drought conditions, following statistical criteria widely applied to identify high-intensity, low-probability climate events (Galeano et al., 2017). This approach enables the definition of a danger scaling (last 30 days) function ranging from 0 to 3 for each pixel derived from GPM-IMERG data, as described below:

$$P_{drought} = \begin{cases} 0 & \text{if } DDF_{t,i} \leq P_{75} \\ 3 \times \frac{DDF_{t,i} - P_{75}}{P_{99} - P_{75}} & \text{if } P_{75} < DDF_{t,i} < P_{99} \\ 3 & \text{if } DDF_{t,i} \geq P_{99} \end{cases} \quad t = 1 : 46 \,;\ \mathrm{i} = \ 1{:}\,30 \tag{1}$$

Where $P_{drought}$ represents the climatic parameter in the model, DDF denotes the cumulative number of dry days at time *t*, calculated for each day *i* over the preceding 30-day period. "*t* " refers to the annual MODIS availability; "*i*" refers to the last 30 days.

Line 169: The NDVI normalization procedure should be clarified. The use of the April historical maximum as the reference for peak vegetation vigour may not be equally appropriate across all regions of Peru, given the strong climatic and phenological differences between the coast, Andes, and Amazon. The authors should justify this choice and explain whether regional or pixel-specific seasonality was considered.

Ok. The explanation was improved.

To ensure comparability per pixel within the model, NDVI was also normalized on a scale from 0 to 3 using the historical time series for the period 2002–2024. The normalization procedure compares current vegetation vigor with the historical maximum average value ($NDVI_{max}$) observed in April, because April (the period of peak vegetative vigor) can be considered a reference month for the end of the rainy season or period of greater humidity in the vegetation in both the Andean and Amazonian regions of Peru (Espinoza et al., 2016; Zubieta et al., 2021b; Ccanchi y Zubieta, 2023). For example, values above the maximum NDVI identified in April would not imply a greater danger of wildfire. However, the danger would begin to increase when the NDVI progressively drops below this threshold value. A critical wilting threshold, defined as the 1st percentile (P_1) of the historical NDVI distribution, is also considered. P_1 was selected to represent the lower bound of historically observed extreme low vegetation conditions, where only 1% of the historical record falls below this level, consistent with the use of low-order percentiles to characterize extreme states in vegetation time series (Forkel et al., 2013) as described below:

$$Veg_{dry} = \begin{cases} 0 & \text{if} \quad NDVI_t \geq NDVI_{max} \\ 3 \times \frac{NDVI_{max} - NDVI_t}{NDVI_{max} - P_1} & \text{if} \quad P_1 < NDVI_t < NDVI_{max} \quad t = 1:46 \\ 3 & \text{if} \quad NDVI_t \leq P_1 \end{cases} \qquad (2)$$

Where $Veg_{\ dry}$ represents the vegetation-related parameter of the model, and NDVI (average of the last 4 images), *t* denotes the spectral index at time *t.*

Line 179: The anthropogenic fire-use component assumes a link between planting intentions and agricultural burning. This is plausible, but the authors should provide stronger justification and discuss its limitations. Planting intention does not necessarily mean fire use, and the timing of burning may vary by crop, region, altitude, and local practice.

You are right, the explanation was improved.

In Peru, fire use has been documented in Andean communities, where the period of agricultural burning coincides with the preparation of land for temporary crops (such as corn, potatoes, barley and wheat, among others) between July and December (Alvarez et al., 2025; Taboada-Hermoza and Martinez, 2025). In Amazonian communities, fire use occurs between July and December, coinciding with the period of agricultural burning to prepare for new crops, with greater intensity between August and September (Torres Paredes, 2025). Anthropogenic fire use in the agricultural and livestock sectors (ignition agent) ($Agr_{fire\ use}$) was incorporated as a monthly dynamic variable (Fig. 2). This variable is directly linked to the planting calendar, which typically involves the use of fire to clear and prepare land prior to sowing (Alvarez et al., 2025). Planting intentions can be defined as the result of the assessment in agricultural units of the probable areas to be planted; taking into account available areas, inputs for production, climate and phytosanitary conditions, which may directly or indirectly affect the agricultural season (MIDAGRI, 2025b). Planting intentions can be used as an approximation of agricultural burning activity at a regional scale, because short-cycle crops require periodic land preparation and clearing through the use of fire. This is important since 97% of agricultural units in Peru are carried out by small farmers (INEI, 2012; Zegarra, 2024). For estimating the anthropogenic role and its subsequent use in the model, the planned area of monthly seasonal crops for the 2020–2025 seasons at the district level was used (MIDAGRI, 2025b). The planting data series was also normalized to a scale from 0 to 3 using the 33.3% and 66.6% terciles of the historical distribution for each district. This classification criterion was used to establish a neutral and equitable threshold for a variable representing a complex cultural practice. In the agricultural component, a value of 0 corresponds to no planting, a value of 1 to low intensity, a value of 2 to moderate intensity, and a value of 3 to high intensity.

To incorporate the $Agr_{fire\ use}$ component as a spatial variable into the wildfire danger model, exclusively agricultural areas were prioritized. To do this, a map of agricultural land (MIDAGRI, 2025a) was overlaid, resulting in 12 maps per year, which characterize possible fire danger zones associated with agricultural activity (fire use). The spatial restriction to agricultural areas applies only to the component $Agr_{fire\ use}$., which is implemented as a spatial filter using geographical information systems, limiting the calculation of this component exclusively to agricultural areas (pixels defined as crops).

Line 199: The AHP weighting procedure is not sufficiently transparent. The authors should provide the pairwise comparison matrices, the final weights for each region or scenario, and the consistency ratio (in the Results).

The explanation has been clarified and improved. The Analytic Hierarchy Process (AHP) was initially applied (Saaty, 1977); however, the resulting model performance was not satisfactory. Therefore, a Weighted Linear Combination (WLC) approach was subsequently adopted to integrate climatic factors ($P_{drought}$), vegetation condition ($eg_{\,dry}$), *anthropogenic influences* ($Agr_{fire\ use}$), and fuel load (M_{fuel}).

Wildfire Danger Index (WDI)

Integration of climatic factors ($P_{drought}$), vegetation condition ($Veg_{\,dry}$), anthropogenic influences ($Agr_{fire\ use}$), and fuel load (M_{fuel}) was performed using a Weighted Linear Combination (WLC) approach (Fig. 2). The relative importance obtained for each variable is consistent with (a) findings from previous wildfire research (Alvarez et al., 2025; Ccanchi, 2021; Espinoza et al., 2016; Zubieta et al., 2021b, 2023b), and (b) the authors' expertise regarding Peru's environmental conditions and biodiversity. Unlike data-driven models that require extensive training datasets, this knowledge-driven approach ensures physical interpretability and remains robust in regions with limited historical records. The general mathematical formulation of the model proposed is defined as follows:

$$WDI = \left(w_a \cdot P_{Drought}\right) + \left(w_b \cdot Veg_{Dry}\right) + \left(w_c \cdot Agr_{fire\ use}\right) + \left(w_d \cdot M_{fuel}\right) \qquad (3)$$

Where the coefficients w_n represent the relative weights assigned to each factor.

For a better adjustment of the scenarios, the weight allocation was performed using a sensitivity analysis based on 22 systematic weighting scenarios, grouped according to the dominant factor into five categories (balanced weights, climate dominance, phenological dominance, anthropogenic dominance, and fuel dominance), with dominant factor weights ranging from 0.40 to 0.70 (Fig. 2). Sensitivity analysis is widely recognized as a methodologically sound approach for the calibration and validation of Multi-Criteria Evaluation (MCE) models used in danger assessment (Chen et al., 2001; Chen et al., 2010). For each of the nine regions (Fig. 3), the optimal weighting scenario selected was the one that maximized the Area Under the Curve (AUC) of the success rate curve, a standard metric for comparing and selecting danger and susceptibility models (Verde and Zêzere, 2010; Rahman et al., 2022). The success rate curve is constructed by ordering the territory from highest to lowest WDI danger level and plotting the cumulative percentage of area on the X-axis against the cumulative percentage of fire events captured on the Y-axis. The AUC was calculated using the trapezoidal rule over the six points defined by the index danger levels. An AUC value of 1 indicates that all fire events are concentrated in the highest danger areas, while a value of 0.5 corresponds to a random distribution (Fig. 3). The model was implemented at an 8-day temporal resolution, consistent with the MODIS data, while non-combustible surfaces (e.g., sparse vegetation, water bodies, deserts, and urban areas) were excluded from the WDI modeling (Fig. 2).

The resulting WDI values range continuously from 0 to 3 and are classified into six danger levels to facilitate operational interpretation (Table 2). Equal intervals of 0.6 were adopted as the classification criterion because of their simplicity and operational interpretability, which are desirable characteristics for an expert knowledge-based index designed for regional monitoring. To empirically verify that the intervals defined by the WDI effectively discriminate danger categories with different wildfire occurrence densities, the ratio between the proportion of wildfire events captured within each danger level and the proportion of the study area occupied by that danger level was calculated for each region, following the rationale of the frequency ratio method commonly applied in wildfire susceptibility studies (Arca et al., 2020; Das et al., 2023):

Line 213: The WHI classification into six hazard levels appears to use equal intervals from 0 to 3. The authors should explain why these thresholds were used.

Ok a description was added.

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$$R_i = \left(\frac{F_i}{F_{total}}\right)/\left(\frac{A_i}{A_{total}}\right)$$

Where R_i is the frequency ratio for danger level i; F_i and F_{total} denote the number of wildfire events in danger level i and the total number of wildfire events, respectively; and A_i and A_{total} represent the area of danger level i and the total modeled area, respectively. The results of the frequency ratio analysis are presented in Table 3.

Table 2: Classification of Wildfire Danger index (WDI).

WDI Interval	Danger class	Level	Description
0	Very low	0	Sparse or no vegetation.
>0 & <=0.6	Low	1	Forest, shrub, and herbaceous ecosystems with high vegetative vigor near the historical maximum, minimal dry day accumulation, and little to no agricultural activity.
>0.6 & <=1.2	Moderate	2	Forest, shrub, and herbaceous ecosystems with near-average vegetative vigor and ongoing dry day accumulation. Probable presence of agricultural activity.
>1.2 & <=1.8	High	3	Forest, shrub, and herbaceous ecosystems with limited vegetative vigor and a significant dry day accumulation that has severely reduced moisture, primarily in herbaceous ecosystems. High probability of active agricultural activity.
>1.8 & <=2.4	Very High	4	Predominantly herbaceous and shrub ecosystems with very low vegetative vigor, a dry day accumulation exceeding the average level, and severe impact on vegetative moisture. Very high probability of agricultural activity.
>2.4 & <=3	Extreme	5	Herbaceous, shrub, and forest ecosystems with extremely low vegetative vigor, a dry day accumulation above historical levels, and severe water stress in the vegetation. Very high probability of agricultural activity. Seasonal conditions associated with a prolonged drought.

Note: The descriptions for each class reflect the most frequently observed conditions. Predominant ecologi conditions vary between regions depending on the dominant vegetation cover and the intensity of seaso agricultural activity

Figure 2: The flowchart is useful for summarizing the proposed WHI framework, but the final steps should be clarified. The last two blocks, currently referring to “Uncertainty analysis - WHI classification” and “Proposal for a wildfire hazard index (WHI)”, appear to mix model construction with model evaluation. Since the comparison with wildfire emergencies and MODIS hotspots is used to assess model performance, these steps should be explicitly labelled as model validation or model evaluation, or with another consistent terminology adopted by the authors. This would make the workflow clearer by distinguishing the construction of the WHI from its subsequent evaluation.

Ok, it was considered

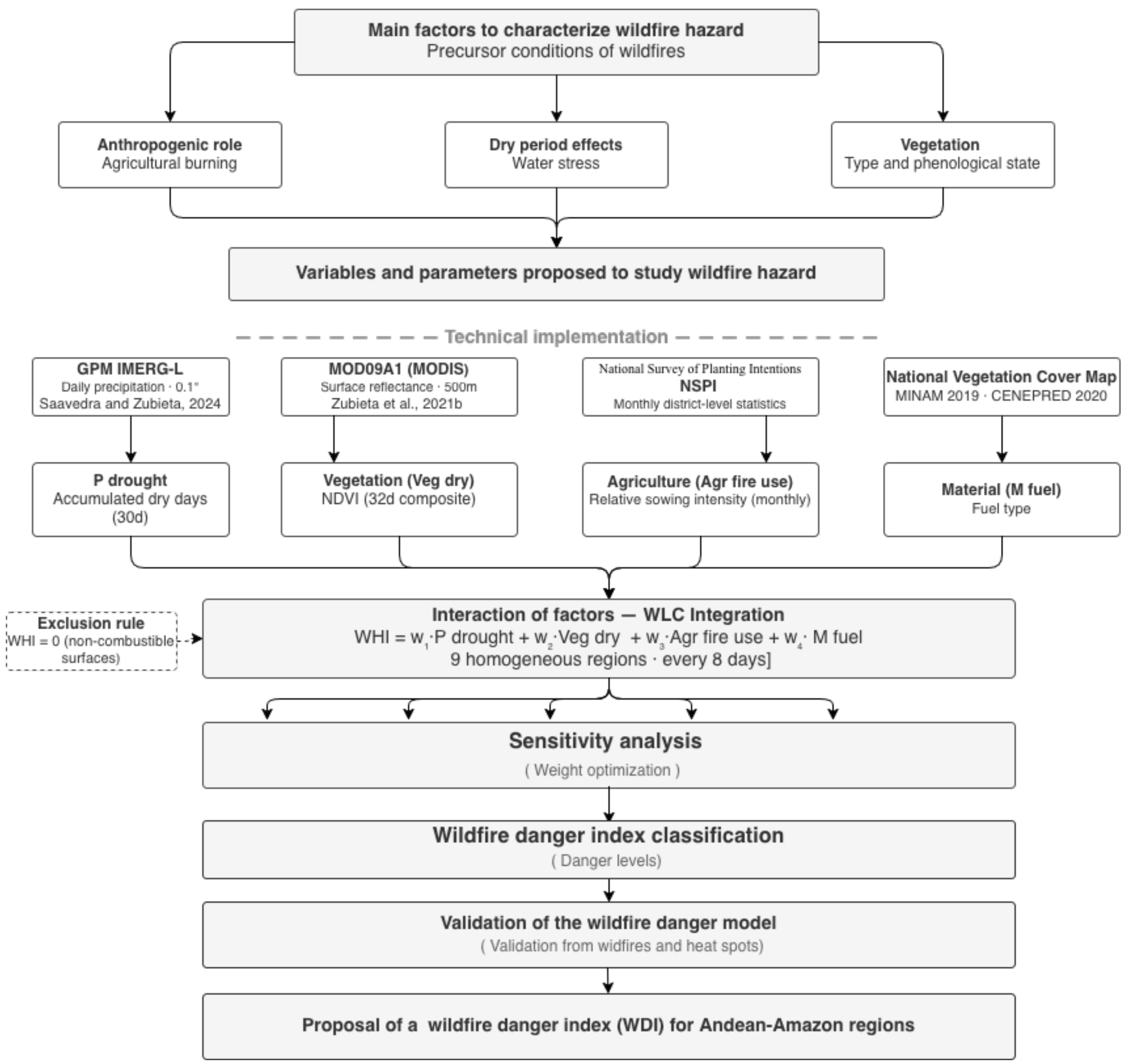

Figure 2: Simplified flowchart of the proposed Wildfire Danger Index algorithm.

Results:

• The Results section needs to be reorganized. The main objective of the manuscript is to develop and propose a new Wildfire Hazard Index (WHI); however, the Results section starts directly with model performance and comparisons with reported wildfire events and the CFOI product, before clearly presenting the WHI model outputs themselves. I recommend that the authors first present the final AHP-derived weights and/or optimized parameters, followed by the spatial, seasonal, and regional patterns produced by the WHI. Only after this should the manuscript include a separate subsection dedicated to model evaluation or validation against observed fire activity, including reported wildfire emergencies, MODIS-derived hotspots, and the CFOI product. This structure would make the contribution of the proposed model clearer and would avoid giving the impression that the results are mainly focused on the validation datasets rather than on the WHI itself.

Okay. The results section has been reorganized. The optimized parameters (w_n) were presented first, at the beginning of the results section. The validation results are then displayed.

• Some methodological aspects currently appear for the first time in the Results section and should be moved to, or explained more fully in, the Methodology. For example, the calculation of Success Rate Curves, AUC values, correlation coefficients, significance levels, and the procedure used to select the optimized parameters should be described before the results are presented. The Results section should report the outcomes of these analyses rather than introduce the methods used to calculate them.

Thank you, for your recommendations. Those paragraphs were now located and/or adjusted in the methodology section.

• Some parts of the Results section are written more like interpretation or discussion than as a presentation of results. For example, statements claiming that the model "can effectively represent and distinguish seasonal wildfire pattern – line 294 to 296" or "These findings suggest that the model effectively captures – line 281 to 282" should be moved to the Discussion, or at least clearly separated into a model evaluation subsection (other example, Line 276 to the discussion (limitations)). The Results section should, for example, first present the observed patterns and statistical outputs, while the Discussion should interpret why the model performs differently between the Andean and Amazonian regions.

Okay, you're right, to improve these expressions, the paragraphs were reformulated to express qualitative and quantitative results to remain in the results section.

These findings shows that the model effectively captures periods of highest wildfire occurrence in Andean regions when extreme danger levels are analyzed (Fig. 5d–f).

The proposed model effectively represents seasonal wildfire patterns in Amazonian regions when very high and extreme danger levels are considered (Fig. 6h–i). Moreover, stronger model performance is observed in the Andean regions ($r \approx 0.78$; $p < 0.01$) (Table 4).

). The correlation coefficients indicate that in Amazonian regions, the combined use of danger levels 4 and 5 is more significant for identifying periods of increased wildfire danger (Fig. 8g–i), although detection remains less robust than in the Andes. Improved consistency between hotspots and model outputs is observed when both danger levels are considered, particularly in the central ($r \approx 0.80$; $p < 0.01$) and southern Amazon regions of Peru ($r \approx 0.84$; $p < 0.01$) (Table 4).

Discussion:

The Discussion should be more clearly separated from the Results. Several statements in this section repeat results that were already presented earlier, particularly regarding regional model performance, the difference between Andean and Amazonian regions, and the use of hazard level 5 versus levels 4 and 5 combined. The Discussion should focus less on restating the results and more on explaining why these patterns occur and what they imply for wildfire hazard modelling in Peru.

Thanks, you are right. To avoid unnecessary additions to the paper, some fragments were moved to the introduction section or removed.

Line 374 and 378 (for example): Part of the Discussion reads more like background or state-of-the-art material than interpretation of the study results. For example, the paragraph discussing the use of satellite data to capture vegetation moisture, vegetation response to precipitation, and the integration of GPM and MODIS products would be more appropriate in the Introduction, where it can help justify the methodological approach. In the Discussion, the authors should instead focus on what the use of these satellite-derived products revealed in this study, how it affected WHI performance across regions, and what limitations remain when applying MODIS and GPM data in complex Andean and Amazonian environments. And you can use this example, for other parts of the discussion.

To improve the understanding of this section of the paper, the entire discussion section was revised and adjusted as follow.

Discussion

Wildfire danger indices must be adapted to the specific characteristics of each region, particularly in countries with high biodiversity and diverse climatic regimes. This is true in Peru, where coastal (desert) zones, mountain (Andes) zones and extensive tropical forests (Amazonian zones) are present. Our findings indicate that the model does not adequately capture the spatial or temporal patterns of wildfire danger in coastal regions (below 1500 masl). This limitation suggests reduced model performance in areas dominated by sparse vegetation and prolonged dry periods without rainfall. Although the coastal region lies within tropical South America, it is characterized by arid conditions, with precipitation occurring mainly during El Niño events, when extreme rainfall conditions may develop (Woodman and Takahashi, 2014).

Methodologies initially proposed for any region are not necessarily transferable to other areas, as wildfire regimes vary according to local environmental and climatic conditions (Adab et al., 2013; Castel-Clavera et al., 2025; Srock et al., 2018). Therefore, the regional variability in optimal weighting scenarios proposed in this paper could reflect the ecological heterogeneity of the Peruvian territory in detecting the spatial distribution of wildfire danger. To enhance the performance of wildfire danger indices, recent approaches have also incorporated factors related to ignition sources and anthropogenic influences (Adab et al., 2013; Bisquert et al., 2014; Di Giuseppe et al., 2025). Accordingly, the wildfire danger model developed in this study integrates datasets representing fuel characteristics (MINAM, 2019) and cultivated areas across Peru to account for human-induced fire activity. On average, the higher weighting assigned to Veg_{Dry} suggests that the role of climate on vegetation and its dynamics can be considered the most relevant variable for estimating wildfire danger (Zubieta et al., 2021b; Zubieta et al., 2023b).

The results of the wildfire danger model proposed in this study demonstrate an adequate capability to detect the seasonal occurrence of wildfires between 2019 and 2024 when extreme danger levels (level 5) are considered in Andean mountain regions. However, the Amazonian region is not adequately represented when only extreme danger is analyzed. To improve danger assessment in Amazonian areas, the combined use of danger levels 4 and 5 (very high and extreme) is recommended. This could be because of the role that vegetation (forest fuel) plays in tropical regions. For example, at the regional level for the Andean regions, vegetation conditions and fuel load would concentrate the highest weights, with high-altitude grasslands representing the structural component that determines the baseline danger level, while vegetation water stress acts as a dynamic modulator during drought episodes (Zubieta et al., 2021b; Ccanchi, 2021). In the Northern and Southern Amazon, however, the dominance of vegetation conditions indicates that seasonal phenological dynamics are the main predictor of wildfire danger in these ecosystems.

Extreme environmental conditions—such as high temperatures and reduced precipitation—play a critical role in altering vegetation and are key determinants of fuel conditions and wildfire occurrence (Chen et al., 2023). In Peru, such conditions are reflected in the declaration of (a) states of emergency due to wildfires in multiple regions (PCM, 2016, 2024a), and (b) states of emergency due to water deficits associated with prolonged dry periods (PCM, 2024b). The spatial distribution of the WDI indicates that extreme danger is primarily associated with higher vegetation loads in Andean forests and Andean–Amazonian forests, consistent with emergency declarations triggered by increases in difficult-to-control wildfires in 2016 and 2024 (PCM, 2016; PCM, 2024a). The spatial extent of extreme danger identified by the WDI model for November 2016 along the Andes may be attributed to a prolonged dry season, or a period of below-normal rainfall lasting between 5 and 7 months, as documented for Andean and Amazonian regions of South America (Jimenez et al., 2021). A similar scenario of extreme danger was observed in September 2024, characterized by a high number of wildfires, during which the dry season in Amazonian regions of Peru extended until November 2024 (IGP, 2024b), also leading to the declaration of a state of emergency due to water scarcity in November 2024 (PCM, 2024b). These findings suggest that the effectiveness of wildfire danger alerts based on the WDI model proposed in this study is closely linked to the accurate estimation of the duration and severity of meteorological drought in the Andean and Amazonian regions. In summary, the results of the study suggest that the model can adequately represent the spatial and temporal distribution of wildfires at a regional scale when very high and extreme danger are also analyzed.

Moreover, the results corroborate that the danger model is also effective in representing fire activity, as reflected by thermal anomalies (hotspots) derived from MODIS satellite data, at both regional and national scales. Hotspots are particularly useful for characterizing fire activity when burned areas range between 50 and 100 hectares in Andean zones (Zubieta et al., 2023a). The findings show a consistent detection of seasonal hotspot patterns between 2016 and 2024, particularly under very high and extreme wildfire danger conditions in both Amazonian and Andean regions. For operational wildfire monitoring, the use of satellite data—given its high spatial and temporal resolution—combined with hotspot observations, provides a valuable tool for continuous validation and improvement of danger models.

The wildfire danger model proposed in this study has the potential to contribute to the development of wildfire prevention systems in Peru, where such systems remain limited. Existing wildfire information systems, whether developed by governmental agencies (Araújo et al., 2025) or researchers, are typically based on indices (Delgado et al., 2022; Ziccardi et al., 2020). For example, the Canadian Forest Fire Danger Rating System is based on the Fire Weather Index (FWI) (Forestry Canada, 1992; Van Wagner, 1987). In South America, Argentina uses the Forest Fire Danger Index (CONAE, 2026), derived from the Australian system developed by McArthur (1967), while Brazil uses the Nesterov Ignition Index (INM, 2026), a cumulative index for classifying wildfire danger on a daily basis (Nesterov, 1949).

In the context of climate change and evolving drought regimes, wildfires are likely to pose an increasing threat to tropical ecosystems in the coming decades (González et al., 2025). As in other regions of South America, where climatic patterns strongly influence fire activity (Silva et al., 2025), the seasonal increase in wildfire frequency in the Andean–Amazonian region of Peru is being modulated and intensified by the frequency, duration, and severity of drought periods (Zubieta et al., 2021b, 2023b). Operational monitoring of vegetation dynamics and drought impacts is therefore essential, as these factors directly influence the seasonal and intra-seasonal variability of wildfire danger.

An important avenue for improving danger prediction models lies in the application of artificial intelligence techniques (Bountzouklis etal., 2023). In this context, data quality should be prioritized, as it is fundamental to achieving significant advances in fire activity forecasting, particularly regarding the spatial and temporal dynamics of forest fuel (Andrianarivony and Akhloufi, 2024). Indeed, data quality may be more critical than model complexity in enhancing the predictive performance of artificial intelligence approaches applied to wildfire danger (Di Giuseppe et al., 2025).

This study proposes a new wildfire danger index for the Amazonian and Andean regions of Peru in South America, integrating observational data (estimation of crop areas and forest fuel) with satellite-derived products such as GPM (Huffman et al., 2023) and MODIS (Vermote et al., 2002). This is consistent with short-term wildfire risk indices, which are typically developed using variables associated with climatic conditions—such as temperature, relative humidity, wind speed, and precipitation (McArthur, 1967a; Van Wagner, 1974, 1987)—or parameters that reflect the influence of climate on vegetation and fuel characteristics (Goodrick, 2002; Sharples et al., 2009).

Some limitations are mentioned but not fully connected to their implications for operational use. For example, the use of district-level planting intentions as a proxy for agricultural fire use, the absence of multiple variables,etc. The authors should explain how these limitations may influence the interpretation and operational application of the WHI.

The uncertainty section of modeling was improved as follow:

Wildfire location data in Peru are approximate and primarily based on emergency reports (MINAM, 2025); their spatial and temporal distribution was used to evaluate the performance of the model in identifying wildfire danger levels. It is important to note that wildfire events reported by civil defense authorities are typically concentrated near roads and rivers (Zubieta et al., 2023a), suggesting that fire activity in remote or high-altitude regions may be underreported. The spatial and temporal distribution of wildfire events can be considered reliable because they were verified using a) news reports and b) identification of fire scars in Landsat and Sentinel satellite images (MINAM, 2025). In contrast, satellite-derived fire activity (hotspots) data provide a valuable complementary source for evaluating wildfire danger models at local and regional scales in Amazonian areas, where official records are limited.

The model relies on a climatic variable that is highly relevant for Andean regions, as demonstrated by Zubieta et al. (2021b) and Zubieta et al. (2023b), but not necessarily applicable to Amazonian regions. Nevertheless, estimation of model coefficients through a sensitivity analysis approach made it possible to classify danger functions at a regional scale using the Wildfire Danger Index (Table 3). The use of Dry-Day Frequency and NDVI, derived from remote sensing data, enables the detection of dynamic changes in rainfall deficits and vegetation conditions, respectively. In addition, a static variable representing fuel type (i.e., forests, shrublands, and grasslands) was incorporated to characterize combustible material. However, the primary ignition source in this region of South America is associated with fire use in agricultural and livestock activities (Alvarez et al., 2025; Roman et al., 2024; Taboada-Hermoza and Martínez, 2025).

The anthropogenic factor in WDI modeling is represented at the national scale solely through agricultural planting areas, which could be also considered a limitation, as it does not account for (a) the quantity and type of crop residue remaining after land clearing, (b) the use of fire for pasture renewal, and (c) variations in fire use within protected natural areas. For prevention, the short-term computational operability of the WDI model at a national scale is a priority. In this context, the influence of all the aforementioned factors and their interaction (climatic, vegetative, anthropogenic) can contribute in different ways to limitations of the model in representing wildfire danger, because of the great biodiversity and diverse hydroclimatic regimes. As result, the WDI model performance varies across regions when coastal, Andean, and Amazonian zones are analyzed independently. The application of region-specific functions, as proposed in this study, is therefore recommended to achieve optimal performance in Andean and Amazonian regions. This variability reflects the influence of fuel load across diverse ecosystems in South America (Fearnside, 2017), particularly in Peru, which exhibits high ecological diversity across its coastal, Andean, and Amazonian regions (Pulgar Vidal, 2014). The findings indicate that the model can adequately represent the probability of wildfire occurrence reported as emergencies (extreme danger level), achieving an approximate efficiency of 80% in Andean regions. Nonetheless, WDI model performance in Amazonian regions is decreased. To improve model performance, very high and extreme danger levels can be used jointly to achieve efficiency of approximately 60% for these Amazonian areas. It is important to note that model performance increases slightly (to approximately 64%) when analyzing hotspots (satellite thermal anomalies) within areas classified as very high and extreme danger in Amazonian regions. This suggests that the model is able to adequately identify wildfire danger in these regions when both danger levels are considered simultaneously. To improve the temporal resolution of the WDI model outputs to a daily timescale, one potential approach is to take advantage of the daily temporal resolution of the IMERG precipitation product by incorporating it as an input variable to the model.

To improve the performance of wildfire modeling and management of the data used in this modeling, an attractive alternative is to employ machine learning tools where an additional data series can also be evaluated. Beyond computational capacity and data availability, the selection of wildfire danger models using machine learning should be guided by region-specific characteristics (Ejaz and Choudhury, 2025). In Peru, potential improvements to model performance at regional and local scales coul include (a) incorporating crop type and phenological stages, and (b) integrating the spatial and temporal history of wildfires associated with controlled burns in livestock systems and protected areas. Recent advances also highlight the potential of deep learning approaches for wildfire danger assessment (Ejaz and Choudhury, 2025; He et al., 2024; Ismail et al., 2024; Xu et al., 2025).

Line 469: The final part of the Discussion introduces machine learning approaches, but this discussion feels somewhat disconnected from the main contribution of the manuscript. If retained, it should be better linked to the limitations of the current WHI and to specific future improvements.

Ok the paragraph was improved

To improve model performance, very high and extreme danger levels can be used jointly to achieve efficiency of approximately 60% for these Amazonian areas. It is important to note that model performance increases slightly (to approximately 64%) when analyzing hotspots (satellite thermal anomalies) within areas classified as very high and extreme danger in Amazonian regions. This suggests that the model is able to adequately identify wildfire danger in these regions when both danger levels are considered simultaneously. To improve the temporal resolution of the WDI model outputs to a daily timescale, one potential approach is to take advantage of the daily temporal resolution of the IMERG precipitation product by incorporating it as an input variable to the model.

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Conclusion:

Line 477: The Conclusions section should be more concise and more directly focused on the main findings of the study. The first part repeats general background information about wildfire frequency, drought, and agricultural burning, which has already been discussed in the Introduction and Discussion. The authors should instead begin by summarizing the main contribution and findings of the proposed WHI.

Line 484: The statement that the results demonstrate consistency between WHI outputs and fire activity should be made more specific. The authors should summarize the main evidence supporting this conclusion.

Line 485: The conclusion that the model "adequately captures the seasonal variability of wildfire hazard" should be phrased more cautiously. The Results show that performance varies between regions and hazard levels, so the conclusion should explicitly acknowledge that the model performs better in some regions than others. And this should also be taken into account in the results and discussion.

Thank you very much, the conclusions section has been reformulated and/or improved

> Peru is a highly diverse country; however, it lacks operational tools for monitoring wildfire danger. Accurate prediction of wildfire danger is therefore critical for enhancing the safety of local populations and firefighters. In this study, a Wildfire Danger Index (WDI) was developed based on Dry-Day Frequency (DDF), the Normalized Difference Vegetation Index (NDVI), cultivated area (CA), and forest fuel (FF). The proposed method enables the assessment of short-term wildfire danger (8-day intervals) in the Amazonian and Andean regions of Peru, where these indicators are often limited or unavailable. The input variables—NDVI, DDF, FF, and CA—are identified as key parameters for analyzing wildfire danger levels (very low, low, moderate, high, very high, extreme). The results demonstrate consistency between WDI outputs and fire activity, as represented by reported

wildfire emergencies and satellite-derived hotspots, with efficiency between 60 and 80% in Amazonian and Andean regions, respectively. The analysis suggests that the model can adequately represent the interannual variability of wildfire danger in some regions of Peru. To improve the differentiation between very high and extreme danger levels in Amazonian areas in relation to the Andes, both danger levels should be analyzed to alert to the severe increase in wildfire in these regions. Including more detailed climatic, vegetative, and anthropogenic factors can reduce the limitations of the WDI in representing the spatial and temporal distribution of wildfire danger. Our findings indicate that the proposed method can support danger classification and contribute to the development of regional wildfire early warning systems in the Amazonian and Andean regions. It can also be applied to generate short- and medium-term seasonal forecasts of wildfire danger, contributing to disaster risk management by governmental institutions. Finally, the integration of machine learning and deep learning approaches is recommended to further enhance the generation of wildfire danger maps in Andean–Amazonian regions.