**Dear Editor Associated and Reviewer**

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

**RC2**: 'Comment on egusphere-2026-1902', Anonymous Referee #2, 06 Jun 2026

The manuscript addresses an important and regionally relevant topic, and the proposed WHI could be useful for wildfire hazard monitoring in the Andean and Amazonian regions of Peru. However, the Introduction, terminology, and methodology require clarification.
The Introduction provides useful background on wildfire activity, drought, vegetation conditions, and agricultural fire use, but the progression from the broad regional context to the specific research gap is not yet sufficiently sharp. The authors should state more clearly what is missing in the existing literature, why current wildfire hazard indices are insufficient or not directly transferable to the Peruvian Andean-Amazonian context, and what is novel about the proposed WHI compared with previous approaches. The manuscript requires clearer and more consistent terminology. The authors frequently use the term “risk” throughout the manuscript, including in the abstract, but the analysis does not explicitly account for the additional components of risk beyond hazard, namely exposure and vulnerability. Therefore, the use of “risk” appears inappropriate unless these components are properly incorporated or discussed. Moreover, the term “hazard” may also be problematic in this context. In wildfire science, “fire hazard” is often associated with relatively static assessments of ignition and spread potential, fuel conditions, and potential fire behaviour. By contrast, the dynamic component of fire-prone conditions, particularly when driven by short- to medium-term environmental variability, is more commonly referred to as “fire danger.” The analysis presented by the authors seems to be more closely aligned with this latter concept (see for example the discussion at:

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

These distinctions are important because the proposed WHI combines static and dynamic environmental variables with an anthropogenic fire-use proxy, and is validated against wildfire emergencies and MODIS hotspots, which represent observed fire activity rather than hazard or risk itself. As a result, the terminology used in the manuscript should be revised carefully. This issue appears throughout the manuscript, which is why I have not highlighted every occurrence individually. The authors should systematically review the use of terms such as “risk,” “hazard,” “danger”, ensuring that each term is used consistently and in line with the actual scope of the analysis. In the methodological section, several aspects should be clarified in greater detail. This applies especially to some choices related to the indices, such as their rescaling to the 0-3 range and the thresholds used to assign values within this range. Although these choices may be plausible, they should be better justified and, where relevant, explicitly related to the Peruvian context. This would make the methodology more robust, transparent, and potentially replicable. Similarly, the final choice of weights assigned to the different components of the index should be more clearly justified, as noted in a more specific comment. Addressing these issues would substantially improve the conceptual clarity, reproducibility, novelty statement, and scientific robustness of the proposed index. I added some specific comments in the attachment.

Thank you very much for your important help regarding the definitions

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

To avoid ambiguity in the use of terms such as *hazard* and *danger*, we have consistently used the term *danger* throughout the manuscript. Accordingly, the Wildfire Hazard Index (WHI) has been renamed the Wildfire Danger Index (WDI). In contrast, the term *risk* is used when referring to the probability of impacts on human life or when explicitly designated as a *wildfire risk index* in previous studies.

INTRODUCTION

Row 31: The Introduction is too broad at the beginning. It starts with global wildfire-regime changes, tropical rainforest loss, Brazil deforestation, and South American wildfire crises. These points are relevant, but the transition to the specific Peruvian Andean-Amazonian problem could be faster and more focused.

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).

Row 37: The sentence defining “wildfire” interrupts the logical flow of the Introduction. If the authors wish to retain this definition, it would be better placed at the very beginning of the Introduction; otherwise, it could be shortened or removed.

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.

Row 41: Which “wildfire indices” are intended, hazard indices? Risk indices? Specify.

Many thanks, It was specified

Row 49-50: This sentence is broadly relevant, but its placement is not fully convincing. After discussing agricultural and livestock fire use as a primary driver, connection with the previous sentence should be clarified.

Ok, the paragraph was reformulated as follow:

Spatial and temporal distribution of wildfire danger can be influenced by other factors, including vegetation and climatic conditions, among others (Rothermel, 1972; Van Wagner, 1987). A primary cause is the use of fire in agricultural and livestock practices (Alvarez et al., 2025; Taboada-Hermoza and Martínez, 2025). Monitoring of wildfire danger is therefore essential for preventive management and constitutes a critical component of early warning systems (Zubieta et al., 2023a; Mestre and Manta, 2014). This is particularly relevant in tropical regions, where climate variability plays a significant role in wildfire regime and there is a lack of tools for seasonal wildfire prevention. Climate variability has contributed to an increase in the frequency of droughts in Andean and Amazonian ecosystems of South America, highlighting their vulnerability to future climate change (Acevedo Ortiz et al., 2026; dos Reis et al., 2021; Zubieta et al., 2019), particularly in terms of wildfire impacts on flora and fauna (Mosquera-Guerra et al., 2024). This is the case in Peru, where the Andean and Amazonian regions exhibit exceptionally high forest diversity (Fearnside, 2017; Fadrique et al., 2026). Alterations to these ecosystems underscore the urgent need to preserve their integrity at large spatial scales to maintain local tree diversity. However, the increasing frequency of wildfires over the past two decades poses a significant threat to the conservation of tree species in both the Andes and the Amazon (Pivello et al., 2021; Zubieta et al., 2021a). This increase has been linked to factors such as droughts and extreme wind events in these regions (Ccanchi, 2021; Toledo et al., 2024; Zubieta et al., 2023b), which contribute to moisture loss and heightened exposure of vegetative fuels.

Row 61: The phrase "burns from escalating into wildfires" is potentially misleading, as it suggests that wildfire is simply a later stage of a burn. Moreover, the issue of agricultural fire use is better introduced in the previous paragraph. I would suggest linking the discussion more clearly.

Thanks, this was corrected:

To prevent burns conducted in agricultural and livestock activities from turning into wildfires, continuous monitoring of climatic conditions that influence wildfire spread is crucial (Carta et al., 2023).

Row 63-69: This paragraph is partly necessary, but in its current form it feels redundant and unfocused. Fire Weather Index is mentioned, but the paper does not use FWI.
Dry conditions are mentioned as important for wildfire hazard, but then many other factors not related to dry conditions are mentioned. Topographic factors such as elevation are mentioned, but topography is not clearly included in the WHI. Fuel treatment effectiveness seems less relevant for the Peruvian regional hazard-index model. Temporal and spatial patterns of fire occurrence are more related to validation or historical fire analysis, not directly to the input variables.

Thanks, this was corrected

To characterize wildfire danger, an initial approximation has been developed using indices that include climatic variables at large spatial scales (Chandler et al., 1983; Van Wagner, 1987). To improve their effectiveness in different ecosystems, research has also prioritized additional analyses to incorporate a greater number of variables or parameters, not only related to climate but also to vegetation obtained from satellites (Yebra et al., 2013; Qadir et al., 2021; Castel-Clavera etal., 2025), in addition to technical parameters related to forest load (Fernandes, 2009; Hood et al., 2022).

Row 71-76: Important paragraph, but the research gap and novelty should be stated more clearly. “Their applicability” is ambiguous.

Ok, it was specified

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.

STUDY AREA

Row 107-108: It is not clear whether this information is actually relevant to the argument being developed. In its current form, it appears somewhat disconnected from the surrounding discussion and should either be better integrated into the text or removed.

Ok , you are right. This sentence was removed

Row 111: Instead of “prevention methodologies” it would be better to say “wildfire hazard monitoring methodologies”, you can use for example “hazard assessment tools.”

Ok, this was considered

Row 112-113: Beyond punctuation, the sentence also feels conceptually incomplete. I would suggest to rephrase or better introduce the concept.

Ok , you are right. To avoid confusion, this sentence was removed

DATA AND METHODOLOGY

Row 160: Why were this index, the other component indices, and consequently the overall WHI rescaled to the 0-3 range? The authors should justify this choice, explaining whether this range has a methodological basis, follows previous studies, or was selected for interpretability/classification purposes.

Thanks, you are right. A justification was inserted or improved.

The four components of the WDI share a common range from 0 to 3, ensuring comparability within the WLC framework. This range is determined by the categorical nature of the model components. Fuel load (M_fuel) and agricultural fire use (Agr_fire use) are assigned discrete ordinal values ranging from 0 to 3, representing increasing levels of fuel combustibility and agricultural fire-use intensity, respectively. To avoid potential bias in the weighting process, the continuous drought P_drought) and vegetation (Veg_dry) components were also normalized to the same 0–3 range using the historical percentile-based scaling functions described above. This procedure is described in detail in the Methodology section as follows:

**Input variables to wildfire danger modeling**

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).

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.

The effects of drought and reduced precipitation on vegetation were assessed using the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974). We selected NDVI as vegetative parameter of the wildfire danger model, which is derived from MODIS remote sensing data (MOD09A1 MODIS product) (Fig .2). NDVI enable continuous updating of danger levels based on vegetation response (Ccanchi, 2021; Zubieta et al., 2021b, 2023b). This vegetation-related component enables the identification of water stress and reductions in biomass vigor, which are key factors influencing the flammability of live fuels during periods without rainfall (Zubieta et al., 2021b). To account for the cumulative effects of recent climatic conditions on vegetation, the NDVI incorporated into the model was computed as the mean of the four previous 8-day composite images for each time step, corresponding to an effective temporal integration period of 32 days. This approach smooths short-term fluctuations and provides a more robust representation of vegetation phenology, including canopy structural responses to sustained water stress (Ccanchi, 2021; Zubieta et al., 2021b, 2023b).

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.*

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).

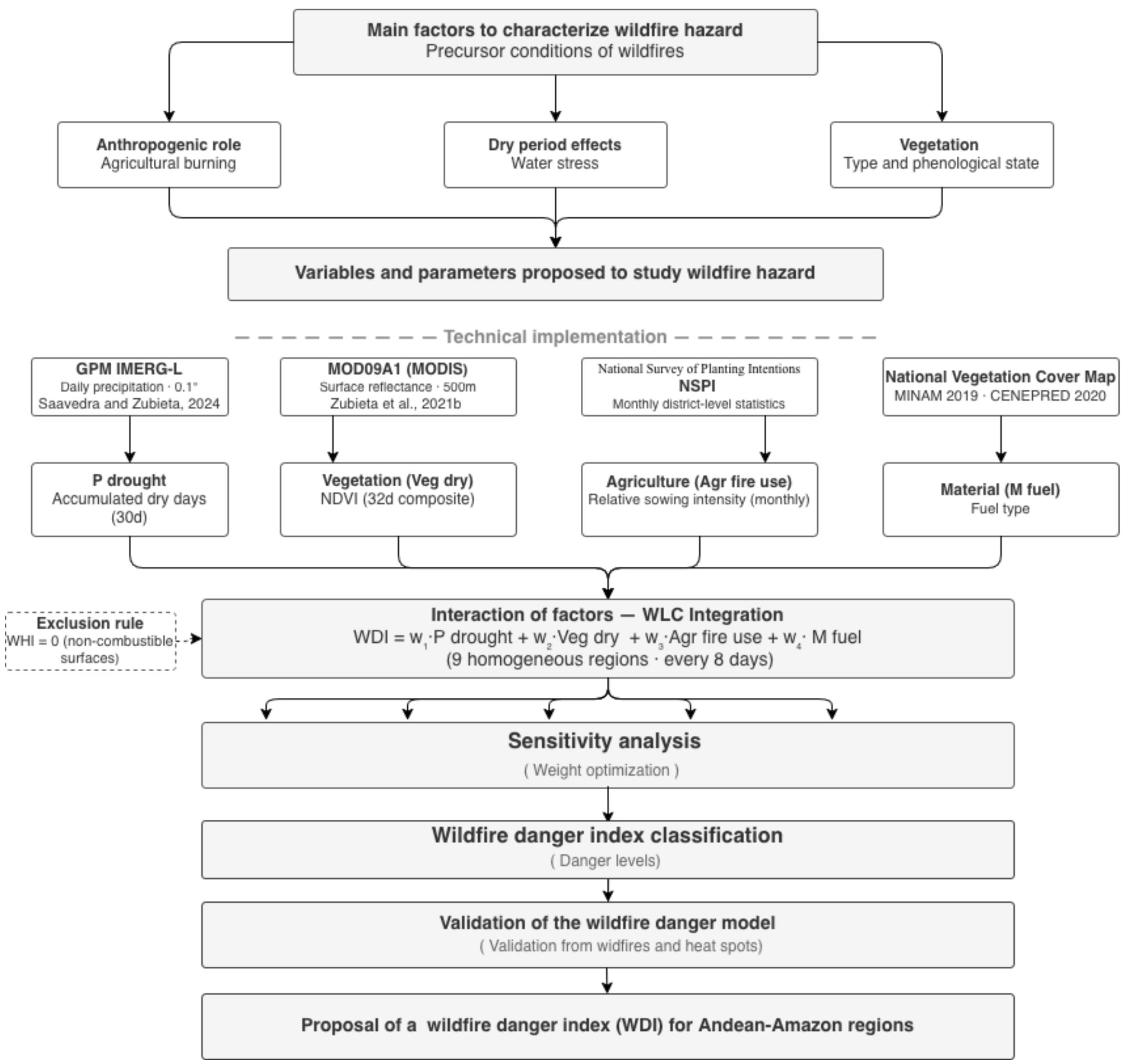


**Figure 2: Simplified flowchart of the proposed Wildfire Danger Index algorithm.**

Finally, to represent the fuel component ($M_{fuel}$), defined as the combustible vegetation material, the spatial distribution of vegetation cover was derived from the National Vegetation Cover Map (CENEPRED, 2020) (Fig. 2). Based on the forest fuel load and combustibility ($M_{fuel}$), four ordinal categories were proposed with discrete values from 0 to 3 (four levels). Value 0 corresponds to non-combustible surfaces, bodies of water, urban areas, value 1 corresponds to tree cover, value 2 corresponds to shrublands, and finally value 3 corresponds to grasslands. This component remains constant over time and serves as a spatial contextual factor that modulates the influence of dynamic climatic and vegetation conditions on the final danger index. Finally, the four components $\left(P_{Drought}, Veg_{Dry}, Agr_{fire\ use}, M_{fuel}\right)$ share a common range of 0 to 3, which guarantees their comparability with each other (Fig. 2).

Row 164: The statement that "t refers to the annual MODIS availability" is rather vague. Only later in the manuscript is it clarified that the model has an 8-day temporal resolution; therefore, I assume that t refers to this 8-day time step, or to a quasi-weekly temporal unit. This should be clarified from the beginning of the model description, so that the temporal structure of the analysis is immediately understandable.

Thanks, it has been specified in methodology section, as follow:

To account for Peru's diverse climatic regions, the study was structured using a regional sectorization adapted from the SENAMHI (National climate service of Peru) climate classification, dividing the country into nine homogeneous regions across the Coast, Highlands, and Rainforest (Cubas, 2021) (Fig. 1). Anthropogenic, climatic, and vegetation-related datasets were selected as input variables for the wildfire danger model. Their temporal resolutions ranged from static datasets to products updated every 8 days, with the 8-day interval defining the model's temporal resolution. All input variables were harmonized onto a common spatial grid with a resolution of 0.1° (approximately 10 km). Historical wildfire records from the Ministry of the Environment (MINAM, 2025), which incorporate emergency reports from the INDECI for the 2019–2024 period, were used for model development and validation. In addition, active fire (hotspot) data were preprocessed to remove false positives associated with glaciers, volcanic activity, and urban areas. A schematic overview of the modeling framework is presented in Figure 2.

Row 169: Does the NDVI rescaling account for vegetation type or land-cover class? Using a single maximum value over the entire study area may be misleading, especially given the land-cover heterogeneity described earlier. Different vegetation types are unlikely to share the same NDVI variability range. The authors should clarify whether the rescaling is performed globally or separately by vegetation/land-cover class, and justify this choice accordingly.

Thank you, a more detailed explanation was prioritized

The effects of drought and reduced precipitation on vegetation were assessed using the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974). We selected NDVI as vegetative parameter of the wildfire danger model, which is derived from MODIS remote sensing data (MOD09A1 MODIS product) (Fig .2). NDVI enable continuous updating of danger levels based on vegetation response (Ccanchi, 2021; Zubieta et al., 2021b, 2023b). This vegetation-related component enables the identification of water stress and reductions in biomass vigor, which are key factors influencing the flammability of live fuels during periods without rainfall (Zubieta et al., 2021b). To account for the cumulative effects of recent climatic conditions on vegetation, the NDVI incorporated into the model was computed as the mean of the four previous 8-day composite images for each time step, corresponding to an effective temporal integration period of 32 days. This approach smooths short-term fluctuations and provides a more robust representation of vegetation phenology, including canopy structural responses to sustained water stress (Ccanchi, 2021; Zubieta et al., 2021b, 2023b).

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:

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

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.*

Row 182: The authors should justify the choice of normalizing agricultural activity using the 33.3% and 66.6% terciles. It is currently unclear why this classification scheme was selected and whether it has a methodological or empirical basis. They should explain whether these thresholds are supported by previous studies, by the distribution of the data, or by a specific rationale related to agricultural use patterns.

Ok a more detailed explanation was prioritized

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.

Row 183: It is unclear in what sense the analysis is restricted to agricultural areas. Does this restriction apply only to this specific index, or does it affect other parts of the analysis as well? In addition, the meaning and role of the 12 maps mentioned afterwards are not sufficiently clear. Overall, the use of this variable is difficult to follow and should be clarified, including how it is calculated, where it is applied, and how it contributes to the final model.

Ok, it was clarified

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).

Row 210: The weighting procedure requires more transparency. The authors state that an AHP-based pairwise comparison and sensitivity analysis were used, but the manuscript should provide the pairwise comparison matrices and the criteria used to select the final optimized weights for each region. Without these details, the weighting process is difficult to reproduce and appears partly subjective. Then, it is not clear in the Results section which set of weights was used to produce the results shown. Are these the weights reported in Table 3? If so, I would suggest presenting Table 3 earlier in the manuscript, before the results are discussed, so that the reader can more easily understand the basis of the analysis.

Table 3 has been moved to an earlier position in the manuscript, before the model results are discussed.

**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:

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

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):

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

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

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). To examine the relationship between wildfire occurrence and the modeled danger, Pearson correlation coefficients were calculated (significance level:

$p < 0.01$) between the number of wildfire events and the percentage of area corresponding to each WDI danger level. The results of this analysis are presented in Table 4.

Figure 3 presents Success Rate Curves (SRC) illustrating the performance of the wildfire danger model, using the Area Under the Curve (AUC). The AUC was estimated by comparing the cumulative percentage frequency of reported wildfire emergencies with the cumulative percentage frequency of the modeled surface area, calculated from the total number of pixels in the wildfire danger index maps (generated every 8 days) during the study period. Danger levels were grouped as follows: 1 (low), 2 (moderate), 3 (high), 4 (very high), and 5 (extreme) (Table 2), for the nine regions of Peru described in Figure 1.

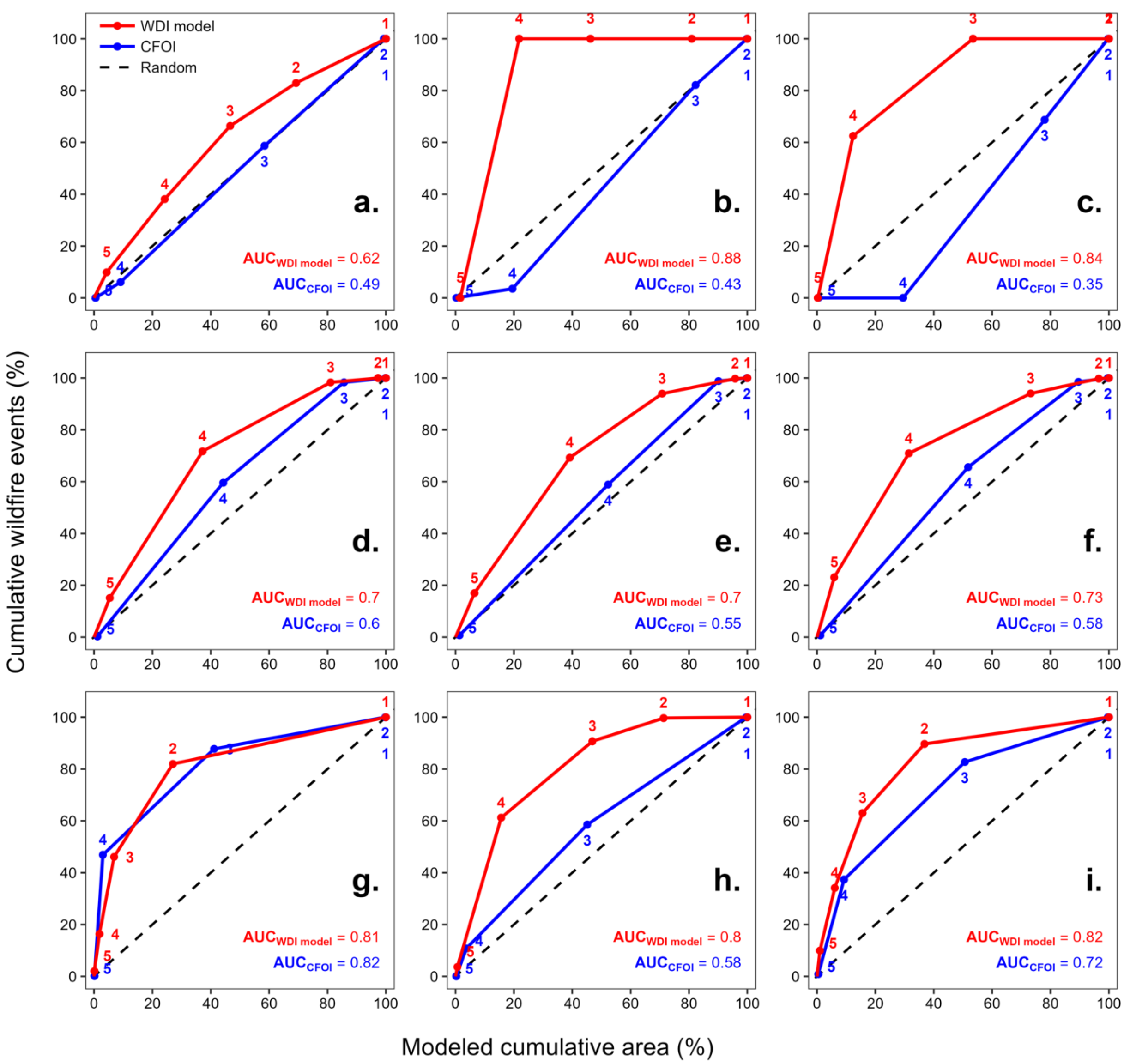


**Figure 3: Success Rate Curves (SRC) for WDI and CFOI (MINAM, 2025) models, showing the Area Under the Curve (AUC). Danger levels are referred to as: 1 (low), 2 (moderate), 3 (high), 4**

**(very high), 5 (extreme) for nine regions of Peru: a) North Coast (1), b) Central Coast (2), c) South Coast (3), d) Northern Andes (4), e) Central Andes (5), f) Southern Andes (6), g) Northern Amazon (7), h) Central Amazon (8), i) Southern Amazon (9). The location of the regions can be seen in Fig. 1.**

## Results

The equidistribution line (dashed black line in Fig. 3) represents a scenario in which wildfire occurrences are uniformly distributed across space (danger classes) and time (months). Results from the Index of Favorable Conditions for Fires in Vegetation (CFOI) provided by MINAM (2025) tend to be more evenly distributed in terms of wildfire occurrence (%) across danger classes (%) compared to the WDI model proposed in this study (Fig. 3). It is important to note that SRC curves that closely follow the equidistribution line indicate limited model performance, as they fail to adequately capture the influence of key climatic, vegetation or anthropogenic factors on wildfire danger. This limitation is observed in the CFOI results for several Andean (Fig. 3d–f) and Amazonian regions of Peru (Fig. 3h). The central and southern coasts do not necessarily reflect optimal performance (Fig. 3a-c). The results of the proposed model exhibit a more heterogeneous detection pattern across both space and time (Fig. 3a–i). For example, approximately 20% of wildfire events recorded between 2019 and 2024 correspond to about 5–10% of the Andean region affected by extreme wildfire danger (level 5) during drought periods (Fig. 3d–f). This pattern is consistent with years characterized by high wildfire frequency, such as 2020 (Zubieta et al., 2023b), and with 2024, when a state of emergency was declared because of the severity and frequency of wildfires (PCM, 2024b).

In the Andean region, the model primarily identifies level 5 (extreme danger) as representative of seasonal periods with the highest wildfire occurrence, particularly during events that exceeded the response capacity of government agencies in 2024. In contrast, results for the Amazon region indicate that severe seasonal wildfire conditions are better captured by danger levels 4 (very high) and 5 (extreme), as these categories encompass a larger proportion of wildfire events (Fig. 3g–i). For example, between 10% and 60% of wildfire events during 2019–2024 correspond to approximately 5–10% of the Amazonian region affected by high to extreme wildfire danger (levels 4 and 5) during peak fire seasons (Fig. 3g–i).

**Table 3: Optimized parameters ($w_n$), Area Under the Curve (AUC), and correlation coefficients between the percentage of modeled area (levels 5 and 4+5) and the percentage of wildfires and hotspots for the periods 2019–2024 and 2002–2024, respectively.**

| Region | Wa | Wb | Wc | Wd | AUC | Wildfire | Hotspots |
|---|---|---|---|---|---|---|---|

| | | | | | | (5) | (4+5) | (5) | (4+5) |
|---|---|---|---|---|---|---|---|---|---|
| North Coast | 0.10 | 0.10 | 0.60 | 0.20 | 0.62 | - | | 0.79 | 0.49 |
| Central Coast | 0.15 | 0.15 | 0.50 | 0.20 | 0.88 | - | - | - | - |
| South Coast | 0.15 | 0.15 | 0.20 | 0.50 | 0.84 | - | 0.89 | - | 0.04 |
| Northern Andes | 0.10 | 0.40 | 0.10 | 0.40 | 0.70 | 0.55 | 0.75 | 0.92 | 0.86 |
| Central Andes | 0.15 | 0.50 | 0.15 | 0.20 | 0.70 | 0.91 | 0.82 | 0.96 | 0.82 |
| Southern Andes | 0.20 | 0.40 | 0.20 | 0.20 | 0.73 | 0.90 | 0.79 | 0.95 | 0.61 |
| Northern Amazon | 0.10 | 0.60 | 0.15 | 0.15 | 0.81 | 0.94 | 0.78 | 0.93 | 0.86 |
| Central Amazon | 0.15 | 0.15 | 0.50 | 0.20 | 0.80 | 0.97 | 0.65 | 0.94 | 0.87 |
| Southern Amazon | 0.10 | 0.60 | 0.15 | 0.15 | 0.82 | 0.64 | - | 0.84 | 0.86 |

Table 1: Although I fully understand the need to provide a descriptive interpretation of the final classes, the rationale behind each description is not sufficiently clear. Since the final value results from the combination of several components, it is unclear why the class descriptions emphasize only some of them. In addition, the descriptions seem to focus mainly on relatively static features, such as herbaceous ecosystems, whereas the proposed index is presented as dynamic. This aspect should be better explained and justified, clarifying how the different components contribute to each class and why specific characteristics are highlighted in the interpretation. Moreover, the basis on which the hazard classes were defined should be clearly explained.

Thank you for your comment, The table's features have been improved.

**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

RESULTS

Row 223: The opening paragraph of the Results section is too introductory and does not immediately present the study's results.

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.

Figure 8: I would suggest moving Figure 8 earlier in the manuscript, so that the reader can immediately understand what type of outputs are being discussed. Alternatively, the authors should at least provide an example of these maps before discussing the results in detail.

Okay. The results section has been reorganized. The optimized parameters ($w_n$) were presented first, at the beginning of the results section. Wildfire maps referring to extreme events were subsequently described as follow:

For prevention, this study proposes a set of optimized parameters ($w_n$) for monitoring wildfire danger in the Andean and Amazonian regions (Table 3). To analyze periods of high wildfire frequency, modeling from these optimized parameters, extreme scenarios associated with states of emergency decreed by the Peruvian government are described in Figure 4. This is the case of maps of Wildfire Danger Index for (a) 16–23 November 2016 and (b) 13–20 September 2024 (Fig. 4). The results indicate that the Andean region and the Andean–Amazon transition zone (1500–4000 m above sea level) are primarily exposed to extreme levels of wildfire danger at the onset of the rainy season (November) along the Andes (Fig. 3a). A similar spatial pattern of extreme fire danger is also observed at the end of the dry season, or period of minimal rainfall (September), across both Andean and Amazonian regions (Fig. 4b). In Peru, a marked increase in wildfire activity was identified in 2016 (Zubieta et al., 2021b) and 2024. These conditions were reflected in the declaration of states of emergency due to wildfires across multiple regions during these years (PCM, 2016, 2024a). Wildfire danger across Peru is adequately represented by the model when very high and extreme WDI levels (Levels 4 and 5, respectively) are analyzed (Fig. 3), as these categories correspond to critical vegetation conditions that are key determinants of fuel dryness and wildfire occurrence (Zubieta et al., 2021b; IGP, 2024).

For comparison, the number of MODIS-derived hotspots was also analyzed relative to the modeled danger area, and correlation coefficients were similarly computed for each danger level (Table 4). The results indicate that correlations are generally not significant for danger levels 1 (low), 2 (moderate), and 3 (high) across coastal, highland, and rainforest regions. However, the detection of extreme danger (level 5) in the Andean and Amazonian regions shows greater consistency, with statistically significant correlations at the 90% and 95% confidence levels (Table 4).

**Table 4: Correlation between percentage of reported events (using wildfires and hotspots) and percentage of surface area modeled for danger level 1 (Low), 2 (Moderate) , 3 (High), 4 (Very high) , 5 (Extreme) and 4+5 (Very high and Extreme) zones.**

| Region | Correlation coefficients - wildfires | | | | | |
|---|---|---|---|---|---|---|
| | r (level 1) | r (level 2) | r (level 3) | r (level 4) | r (level 5) | r (level 4+5) |
| North Coast | - | - | - | - | - | - |
| Central Coast | - | - | - | - | - | - |
| South Coast | - | - | - | | - | - |
| Northern Andes | - | 0.53 | - | 0.65 | 0.55 | 0.75 |
| Central Andes | - | 0.39 | 0.54 | 0.20 | 0.91 | 0.82 |
| Southern Andes | 0.45 | - | - | 0.54 | 0.90 | 0.79 |
| Northern Amazon | 0.13 | - | - | 0.71 | - | 0.78 |
| Central Amazon | 0.30 | 0.26 | 0.24 | 0.49 | - | 0.65 |
| Southern Amazon | - | 0.56 | - | - | - | - |
| Region | Correlation coefficients - hotspots | | | | | |
| | r (level 1) | r (level 2) | r (level 3) | r (level 4) | r (level 5) | r (level 4+5) |
| North Coast | - | - | - | 0.27 | - | - |
| Central Coast | - | - | - | - | - | - |
| South Coast | - | - | - | 0.23 | - | - |
| Northern Andes | 0.12 | 0.36 | - | 0.49 | 0.95 | 0.86 |
| Central Andes | | 0.23 | - | 0.66 | 0.96 | 0.82 |
| Southern Andes | 0.52 | - | 0.46 | 0.41 | 0.94 | 0.70 |
| Northern Amazon | | 0.41 | 0.55 | 0.86 | - | - |
| Central Amazon | - | 0.19 | - | 0.73 | - | 0.80 |
| Southern Amazon | - | - | 0.33 | 0.72 | - | 0.84 |

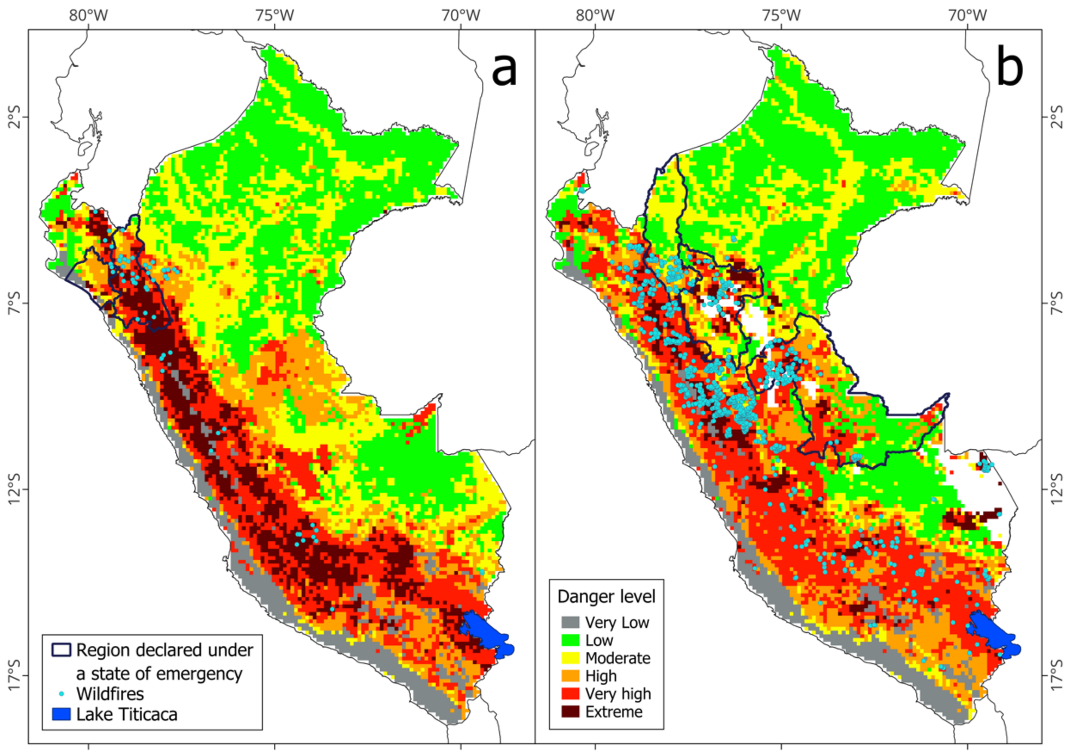


**Figure 4**: **Spatial distribution of wildfire danger levels for (a) 16–23 November 2016 and (b) 13–20 September 2024, corresponding to periods during which the Peruvian government declared states of emergency for wildfires.**

Figure 3: The procedure used to construct the ROC curves is not sufficiently clear. In particular, the manuscript should explain how the hazard classes were related to the observed fire occurrences in order to derive the ROC curves. I would recommend that the authors describe this step in more detail.

Ok. The explanation was improved

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 ($R_i$), following the rationale of the frequency ratio method commonly applied in wildfire susceptibility studies (Arca et al., 2020; Das et al., 2023).

DISCUSSION

Row 413: This statement does not seem to be adequately supported by the results, since no spatial analysis of the distribution of hazard classes across the study area is provided. Such an analysis could, however, be interesting and would help support this interpretation more robustly

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).