https://doi.org/10.3126/banko.v35i2.73366 Banko Janakari, Vol 35 No. 2, 2025 Pp 45-54

GIS-Based Analysis of Wildfire Distribution Across Slopes in the Wadi Safsaf Watershed, Northeastern Algeria

Faicel Tout*, Nouh Rebouh, Yacine Benzid, Zakaria Zouak, Amer Zeghmar, Meriem Bourecherouche, Haythem Dinar and Sara Keblouti

Received: 31 December 2024 Revised: 27 July 2025 Accepted: 5 September 2025 Published: 30 September 2025

In recent decades, many regions of the world have been affected by wildfires. As a result, researchers have shown increasing interest in understanding the causes of these events, their patterns of spread, and the factors that influence their behaviour. This study aimed to investigate the distribution of wildfire affecting vegetation on slopes in the Wadi Safsaf watershed in Algeria using Geographic Information Systems (GIS). The research focused on analysing the relationship between slope and area affected by wildfires by comparing the Differential Normalised Burn Ratio (dNBR) with slope maps. The study also used the Normalised Difference Vegetation Index (NDVI) and the Land Use and Land Cover (LULC) map in additional stages to gain a deeper understanding of the results. Interestingly, the results showed that, contrary to initial expectations, areas with low slopes had the highest percentage of wildfire damage. Further analysis revealed that most of the affected areas were agricultural land that had been misclassified as burned by the (dNBR). The research underlines the importance of field verification and highlights the role of slope in increasing wildfire damage in forested areas. However, it also emphasises the complexity of the relationship between slope and wildfire spread, which is influenced by other factors. The study concludes by recommending the consideration of multiple environmental factors in the study of this phenomenon. It advocates the development of more accurate predictive models to support disaster management decision-making.

Keywords: Algeria, Forest, Slopes, Vegetation cover, Wadi Safsaf, Wildfires

Forest fires have become a significant concern, representing one of the most impactful threats to the environment and human settlements (Nájera De Ferrari et al., 2024; Soualah et al., 2024; Vogiatzoglou et al., 2024). As a result, numerous researchers worldwide have been working to find ways to mitigate and control them, making the investigation of their causative factors an essential endeavour (Paudel et al., 2024; Xu et al., 2024b).

These fires, which originate from diverse sources (Tout, 2023), can be exacerbated and intensified by several factors, including rising temperatures, strong winds, and generally arid conditions. Moreover, topographical features are among the contributing factors to the spread of fires (Makumbura et al., 2024; Paudel et al., 2024). These features have increasingly been considered as fundamental criteria in certain studies, particularly those utilising multi-criteria analysis to identify areas most susceptible to the occurrence and spread of these fires (Talukdar et al., 2024; Vergara et al., 2024).

Therefore, it is crucial to evaluate the role of slopes in facilitating fire spread and exacerbating damage rates (Butler et al., 2007; An et al., 2009; Shan et al., 2024). This understanding will help develop proactive and contingency plans that take this factor into account, enabling better control of fire spread and protection of priority areas.

A deep understanding of the relationship between slope and wildfires is crucial for effective fire management and policymaking, as slope significantly affects fire behaviour, spread, and intensity (Shan et al., 2024). Overlooking this factor can result in ineffective fire suppression, increased threats to human settlements, and severe ecological

Centre de Recherche en Aménagement du Territoire (CRAT), Campus Zouaghi Slimane, Route de Aïn El Bey, 25000 Constantine, Algérie. *Email: faicel.tout@crat.dz; Tel.: (+213)044956961

consequences. Therefore, integrating slope-related variables into fire prediction models (e.g., Fire Behaviour Prediction Systems), mitigation strategies (e.g., targeted fuel treatments on steep terrain), and emergency planning (e.g., slope-specific evacuation routes) is essential for strengthening wildfire resilience and response.

In this study, which focuses on the Wadi Safsaf Watershed in Algeria as the study area, we aim to understand the influence of slope on wildfires by analysing the distribution of areas affected by wildfires in different slope categories. Although the study of this topic may require the creation of a controlled environment to isolate other factors, such as wind, in order to examine the effect of slope as the sole factor in the spread of wildfires in vegetation cover, this paper attempts to analyse the affected areas using remote sensing techniques and commonly used indices for the detection of burned areas. We then evaluate their distribution among different slope classes within their natural environment.

It is worth noting that this research does not investigate the dynamics of wildfire spread along slopes, such as whether fires spread uphill or downhill, or the speed of their progression along these slopes. These aspects require real-time monitoring during wildfire events. Instead, this study focuses solely on identifying or demonstrating the relationship between slope gradients and increased wildfire damage.

Materials and methods

Study area

The Wadi Safsaf Watershed is located in northeastern Algeria (Figure 1) and represents sub-Watershed No. 09 of the Constantine Coastal Watershed No. 3, covering an area of approximately 1165 km². One of the primary reasons for selecting this area for the study is its distinctive forest cover and significant topography. The region has a Mediterranean climate, characterised by hot, dry summers and seasonal winter changes that promote the dense growth of diverse plant species, which are susceptible to drought during the summer.

Many areas within this Watershed have experienced wildfires in the past, with numerous damages recorded, particularly in the last decade. Additionally, the choice of this hydrological unit for this type of study aims to support ongoing research that focuses on the same study area from different perspectives.

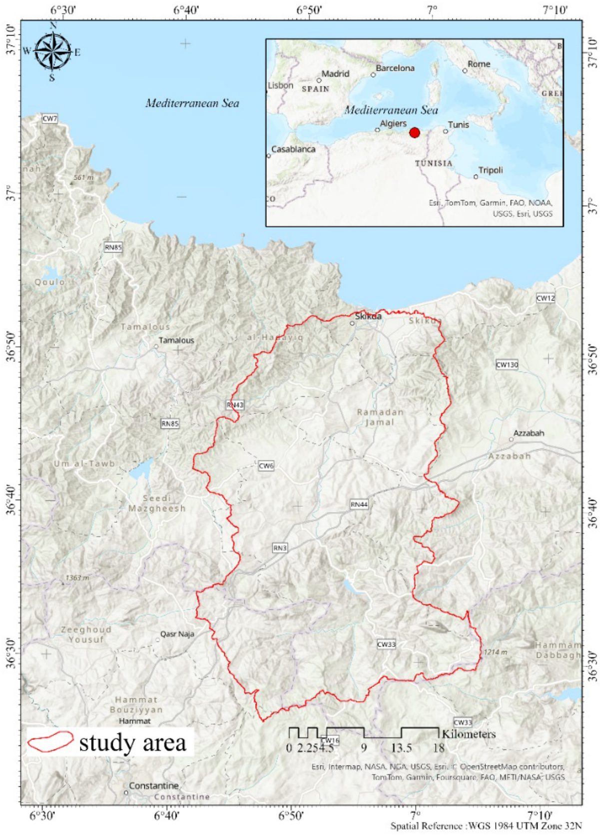

Figure 1: Geographic location of the study area

Methods

The study primarily relies on Geographic Information Systems (GIS) to understand the impact of slopes on the behaviour of forest fires in the study area. The diagram in Figure 2 illustrates the sequential steps typically followed in research. The research initially required the production of a map depicting areas previously affected by fires, categorised by severity. This was achieved using Google Earth Engine and ArcGIS, applying the dNBR (differenced Normalised Burn Ratio), a commonly used indicator (Zhao et al., 2023; Cai & Wang, 2022; Giddey et al., 2022; Guo et al., 2022; Jodhani et al., 2024). Generally, this index is utilised in satellite image analysis to assess the impact of fires on vegetation cover (Fassnacht et al., 2021).

The dNBR can be calculated using the following formula (Xu et al., 2024a):

dNBR = NBR_PreFire - NBR_PostFire

NBR is derived from Landsat 8 data using the formula:

NBR = Band 5 – Band 7/ Band 5 + Band 7

Where,

Band 5: Near Infrared (NIR)

Band 7: Shortwave Infrared (SWIR)

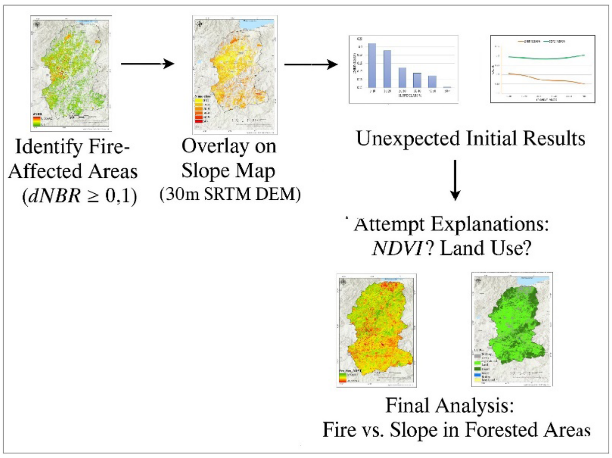

Figure 2: **Sequential steps followed in the research**

Landsat 8 Collection 2 Level 2 data were used for this study, with two observation periods: a pre-fire period (January 1, 2021 – February 28, 2021) and a post-fire period (October 15, 2021 – December 1, 2021). Figure 3 illustrates the areas affected by fires using the dNBR, with particular focus on highlighting areas with values greater than or equal to 0.1. These values represent regions that have been affected by fires according to the United States Geological Survey (USGS) (Sobrino et al., 2019). Values indicating areas that were not affected or that show improvements in vegetation cover were not considered.

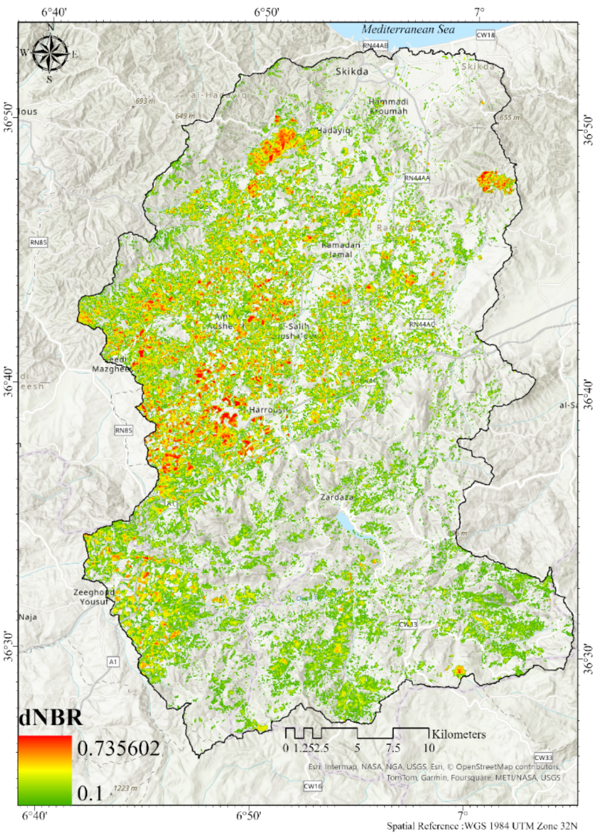

Figure 3: Burned areas identified based on dNBR values

The main reason for relying on this index is the difficulty of conducting field investigations (Oseghae et al., 2024), especially over the entire Watershed area and inventorying the affected regions. However, we attempted to verify this using satellite images, as shown in Figure 4, which was later compared with the slope map featuring multiple categories to explore the relationship between them.

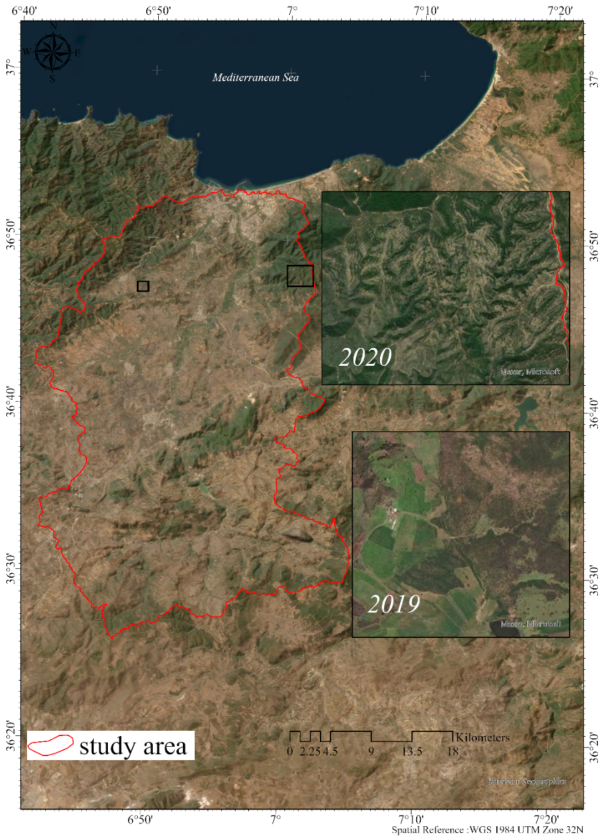

Figure 4: Some areas that were affected by fires in previous years

To produce the slope map, the 30-meter resolution Shuttle Radar Topography Mission SRTM digital elevation model was used, which is reliable for studies of this nature (Makumbura et al., 2024). To facilitate understanding the impact of slopes on forest fire behaviour, the categories represented in Figure 5 were used. This map only represents the slope categories in the area identified as having been affected by fires, according to the dNBR.

Results

Table 1 shows the data related to dNBR values. The results were obtained using the Zonal Statistics tool within the ArcGIS software suite to calculate various statistical values representing dNBR for each slope category. MIN and MAX represent the minimum and maximum dNBR values, respectively, for each

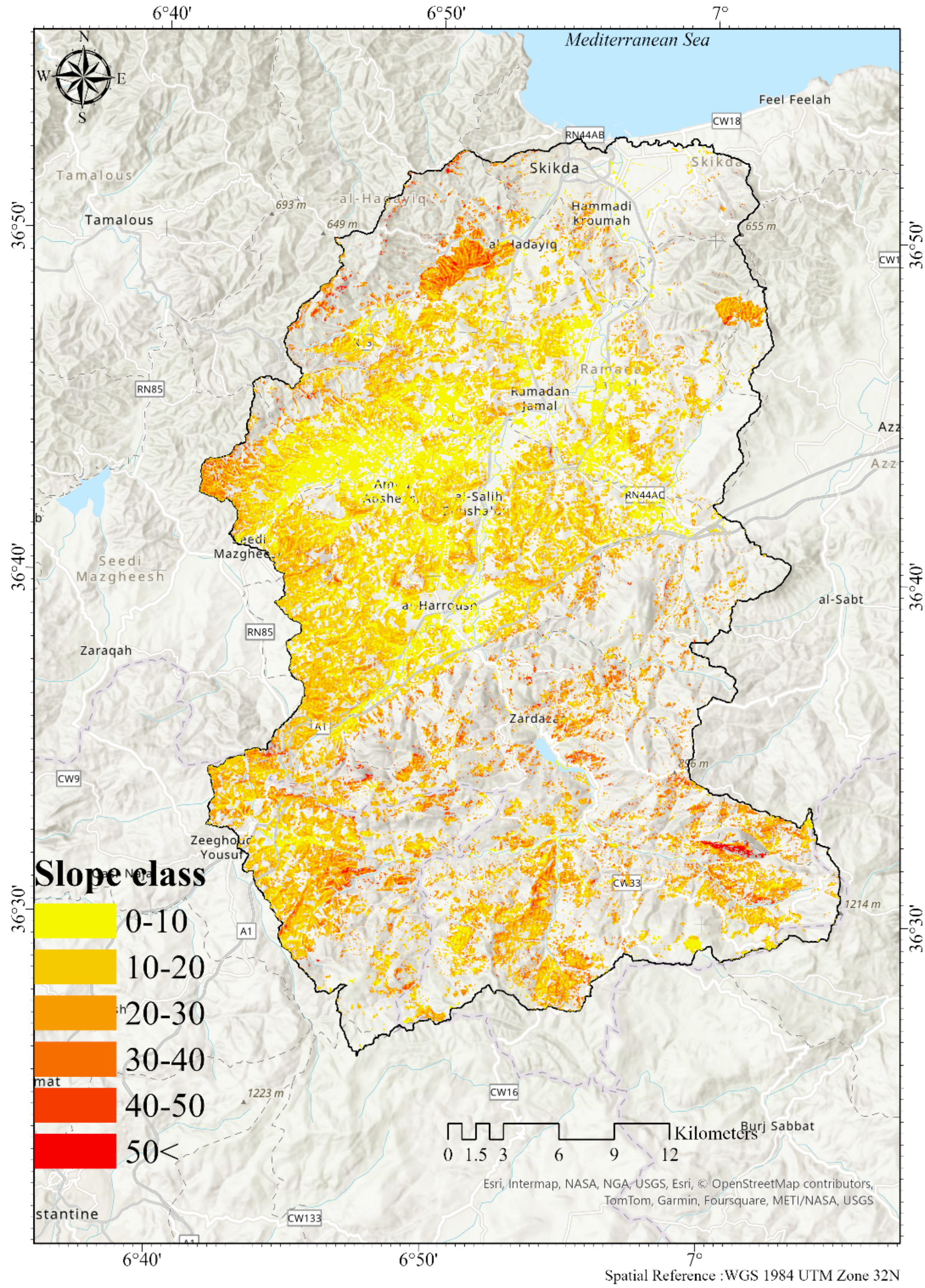

Figure 5: Classification of slope categories in the study area

category, while RANGE is the difference between the minimum and maximum values. MEAN and STD represent the average and standard deviation of the dNBR values for each category.

In general, the table illustrates how dNBR values change with varying slope categories. For example, in the first category, which includes areas with a mild slope between 0% and 10%, the dNBR value ranges from 0.1 to 0.735, with an average of 0.205 and a standard deviation of 0.081. This indicates a moderate variation in dNBR values.

Table 1: The changes in dNBR values across different slope categories

dNBR	AREA	MIN	MAX	RANGE	(MEAN)	STD
0-10	116.03	0.1	0.735	0.635	0.204	0.080
10-20	175.45	0.1	0.578	0.478	0.195	0.078
20-30	80.73	0.1	0.539	0.439	0.174	0.068
30-40	24.34	0.1	0.521	0.421	0.167	0.069
40-50	5.32	0.1	0.497	0.397	0.164	0.068
50<	1.94	0.1	0.468	0.368	0.150	0.058

The bar charts in Figure 6 illustrate the variation in the area of regions affected by fires according to the slope categories. The 10–20% and 0–10% slope categories account for the most significant areas affected by fires.

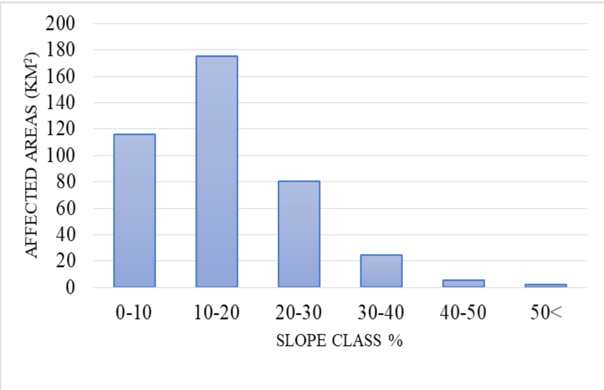

Figure 6: Variation in the area affected by fires according to the slope categories

The bar charts in Figure 7 also illustrate how the average dNBR values change with slope variations, where we observe that areas with steep slopes are less affected, indicating a limited impact of fires in high-slope regions.

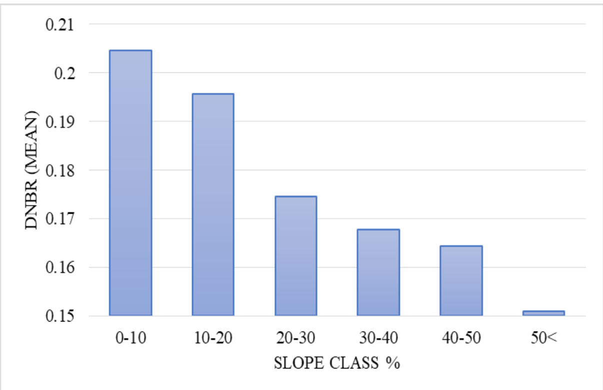

Figure 7: Change in dNBR values with slope variations

Figure 8 illustrates the vegetation cover distribution index across areas that were affected by fires. The pre-fire NDVI was calculated using Landsat-8 imagery from January 1, 2021, to February 28, 2021.

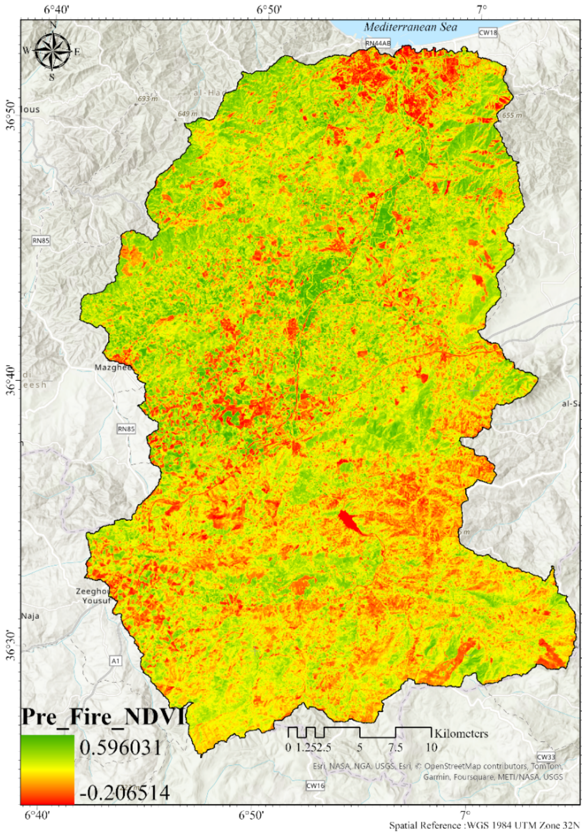

Figure 8: NDVI for the study area

To gain a clear understanding of how vegetation is distributed across slope classes, we conducted a distribution analysis using the same Zonal Statistics tool to obtain various statistical values representing the NDVI for each slope class. The curves in Figure 9 illustrate the mean values for both dNBR and NDVI, where we observe a gradual decrease in dNBR values as slope values increase, accompanied by a relatively stable NDVI or possibly a slight increase in the class greater than 50%.

The land use map obtained through supervised classification in Google Earth Engine is shown in Figure 10. It reveals a significant distribution of agricultural lands compared to other land uses, including forests.

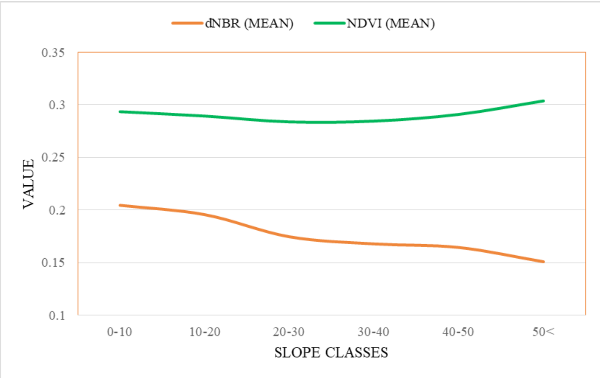

Figure 9: Mean values of both dNBR and NDVI across different slope classes

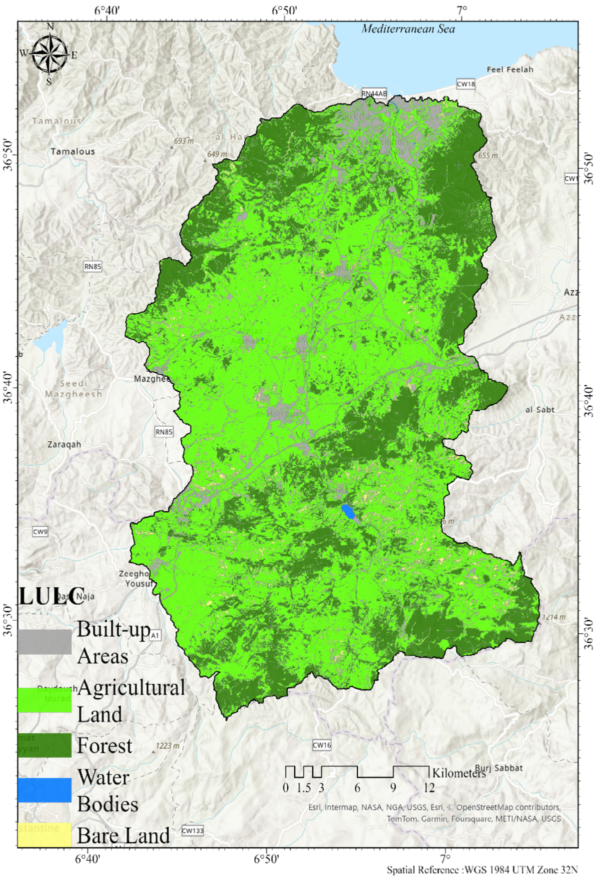

Figure 10: LULC for the study area

The large area of agricultural lands affected by fires, with an estimated area of 349 km² out of a total burned area of 404 km² (Figure 11). This means that 86% of the burned land is agricultural land.

The graph in Figure 12 illustrates the changes in mean values of both dNBR and NDVI over the area of forest affected by fire. The curve illustrates the change in average dNBR values, showing an increasing slope, with the highest value of 0.2 recorded in the 30-40% slope class.

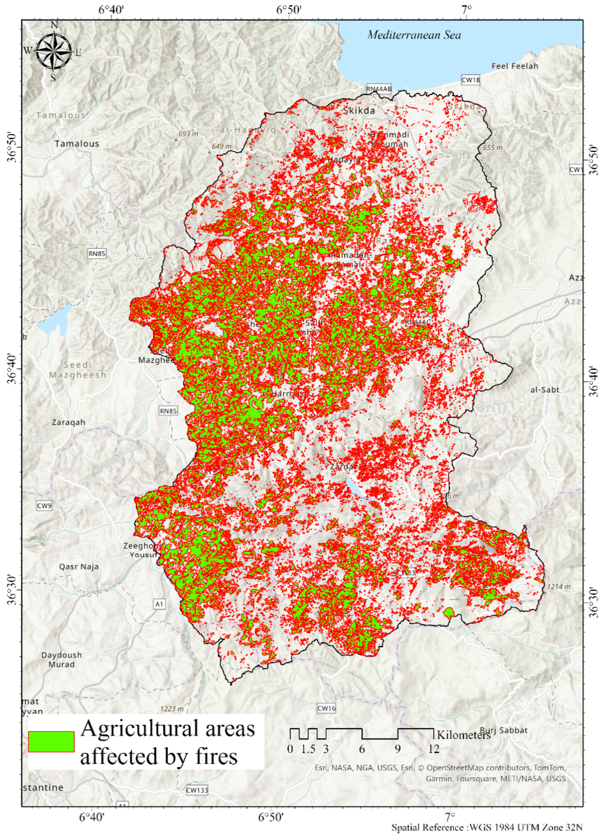

Figure 11: Agricultural areas affected by fires

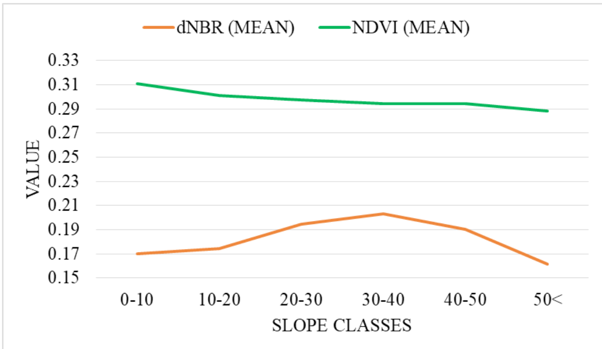

Figure 12: Changes in mean dNBR and NDVI values across the forest area affected by fire

Discussion

These results do not explicitly align with the commonly known fact that areas most prone to fires are those with steeper slopes. Instead, they may lead to a contrary understanding, challenging the prevailing trend. From this perspective, the question shifts from "How do slopes contribute to fire spread?" to "Why did fires not spread in steep slopes?" This is a different question that requires further analysis and broader research to find an answer.

The NDVI is involved in many studies that focus on identifying and predicting fire-prone areas (Tonbul et al., 2016; Ji et al., 2024), and it is used to understand the distribution of vegetation across the landscape. One hypothesis that could explain these results is that there is a proportional distribution between areas affected by fires, represented by dNBR, and areas with dense vegetation across slope classes (Klimas et al., 2025). In other words, higher slope classes have less vegetation cover, which is why they were not significantly affected by these fires.

The study indicates that the reduced fire-induced vegetation damage in steeper slope classes is not due to a lack of vegetation cover, thereby challenging the earlier assumption. The curve representing the variation in NDVI values shows that vegetation density remains relatively stable with increasing elevation. This suggests that the conditions for fire spread due to this factor exist on the slopes, but these areas were not affected, or there are factors preventing fire spread to these slopes, such as the absence of suitable vegetation cover. This necessitates the exploration of land use patterns and vegetation types (Eker et al., 2024) as an attempt to explain the previously obtained results. These results may not reflect the true behaviour of fires on slopes.

Based on the previous map (Figure 10), it can be hypothesized that the areas most prone to fires may be agricultural lands, which could explain the results obtained earlier. Large areas of agricultural land are affected by fires (Figure 11). These results indicate that most areas with significant fire damage were not located on steep slopes but rather consisted of agricultural lands, predominantly used for wheat and barley cultivation. These findings align with what is known about fire spread in agricultural areas (Samphutthanont, 2024), particularly in fields that have been harvested, such as wheat and barley, due to the availability of dry material after harvest. This provides a plausible explanation for the large area identified as having been affected by fires.

Additionally, the index not only identifies areas affected by fires during the study year (2020) but can also detect areas that were affected by fires in previous years, making it highly likely that the index reflects the actual events.

Another assumption is that the wildfires affecting agricultural lands are intentional and initiated by farmers seeking insurance compensation or financial assistance from the government for those affected by the wildfires. Farmers may resort to this behavior when their agricultural yields are unsatisfactory or economically unviable.

On the other hand, there is another possibility that the results indicating areas affected by fires may not be accurate. This is not only due to the data resolution of 30 meters, meaning each pixel represents an area of approximately 900 square meters, but also because of potential errors that can arise from considering agricultural lands in general as areas affected by fires (Samphutthanont, 2024). The spectral properties of agricultural land change depending on the season, whether during planting, harvest, irrigation, or drying. These seasonal changes can lead to an increase or decrease in reflectance in the bands used to calculate dNBR, potentially resulting in false signals (Chen et al., 2020). For example, after harvesting, the soil becomes exposed, which reduces the reflectance of vegetation spectra, making it resemble areas that have been affected by fires.

Forest cover, on the other hand, represents a more stable domain compared to agricultural lands, as it undergoes less significant seasonal changes, especially since the plant species present are almost evergreen, meaning their spectral properties do not change drastically. Therefore, focusing the study on forest areas affected by fires could yield more realistic results.

The change in the average dNBR values, with an increasing slope (Figure 12), suggests that the increase in slope in forest areas contributes to greater fire damage. On the other hand, the decrease in dNBR values on slopes greater than 40% can be attributed to changes in vegetation density, weather conditions, and the soil type present on these steep slopes.

Therefore, there is a significant priority for preventive and emergency interventions in sloped forest areas to prevent the spread of fires, such as creating buffer zones between these areas and flatlands, including roads and other areas. Additionally, a specific afforestation method could be implemented in the future for sloped areas.

On the other hand, this research highlights the need to verify the results of both indices, dNBR and NDVI, and to use them with caution due to the spectral variations that affect the study areas, especially those associated with seasonal variations, in order to avoid errors in classification.

This research also emphasizes the importance of incorporating multi-criteria analysis in studies that aim to predict areas likely to experience wildfires. These studies often rely heavily on the NDVI index without giving equal weight to, or even considering, the type of vegetation cover. This approach can lead to results that are not sufficiently reliable.

This study focused on the impact of slopes on vegetation damage caused by fires, using remote sensing techniques to assess the damage after the fires occurred. It highlights the importance of linking fire spread to the type and density of vegetation present. Our study has shown that this is one of the key factors that should be considered to gain a broader understanding of the expected behaviour of future fires in the region.

However, accurately assessing the impact of slopes on vegetation damage from fires will require examining this effect alongside other influencing factors such as temperature, wind, and humidity (Eker et al., 2024). Therefore, it is also important to explore new methods of monitoring fire behaviour during its occurrence to refine our understanding in this regard.

Conclusions

Several factors influence fires affecting vegetation. In this study, which focused on understanding the impact of slopes on these fires, the dNBR and slope maps were used as key methods to address the research question, and some interesting findings were revealed. A significant impact on vegetation was observed in lower slope classes. The research required further validation of the results using the NDVI and LULC map, where an attempt was made to interpret these results and clarify some of the reasons that led to the increased affected area in these slope categories. Among the factors identified were spectral changes in agricultural areas, which led to them being considered as fire-affected areas. Subsequently, forest areas, which have lower seasonal changes, were considered. A positive relationship was observed between increased slopes and the degree of fire damage, especially in slopes below 40%, reinforcing the priority for preventive and emergency interventions in sloped forest areas to prevent the spread of fires. On the other hand, this study highlights some limitations in the use of both dNBR and NDVI, emphasizing the need for cautious application. It also underscores the importance of considering land use maps, particularly in multi-criteria analysis, to achieve more accurate predictive results.

Acknowledgement

We thank the Territory Planning Research Center for its technical assistance.

Author contribution

FT: conceived and supervised the study, designed the methodology, and conducted the literature review. **NR:** contributed to the analysis and interpretation of results and assisted in map preparation. **YB** and **HD** were involved in preparing maps, verifying results, and monitoring the research progress. **ZZ:** contributed to the translation and finalizing the manuscript. **AZ:** and **MB:** contributed to data processing, validation, and interpretation of spatial analyses. **SK:** assisted with the literature review, editing, and manuscript preparation. All authors contributed to the discussion of results and approved the final version of the manuscript.

Conflicts of interest

The authors reported no potential conflicts of interest.

References

An, S. H., Lee, S. Y., Park, G. S., & Ohga, S. (2009). Development of forest fire spread simulation on up and down slope. *Journal of the Faculty of Agriculture, Kyushu University*, *54*(1), 85–89. https://doi.org/10.5109/14042

Butler, B. W., Anderson, W. R., & Catchpole, E. A. (2007). Influence of slope on fire spread rate. *USDA Forest Service Proceedings*, 75–82.

Cai, L., & Wang, M. (2022). Is the RdNBR a better estimator of wildfire burn severity than the dNBR? A discussion and case study in southeast China. *Geocarto International*, *37*(3), 758–772. https://doi.org/10.1080/10106049.2020.1737973

Chen, D., Loboda, T. V., & Hall, J. V. (2020). A systematic evaluation of influence of image selection process on remote sensing-based burn severity indices in North American boreal forest and tundra ecosystems. *ISPRS Journal of Photogrammetry and Remote Sensing*, *159*(August 2019), 63–77. https://doi.org/10.1016/j.isprsjprs.2019.11.011

Eker, R., Çýnar, T., Baysal, Ý., & Aydýn, A. (2024). Remote sensing and GIS-based inventory and analysis of the unprecedented 2021 forest fires in Türkiye's history. *Natural Hazards*, 10687–10707. https://doi.org/10.1007/s11069-024-06622-0

Fassnacht, F. E., Schmidt-Riese, E., Kattenborn, T., & Hernández, J. (2021). Explaining Sentinel 2-based dNBR and RdNBR variability with reference data from the bird's eye (UAS) perspective. *International Journal of Applied Earth Observation and Geoinformation*, *95*(October 2020). https://doi.org/10.1016/j.jag.2020.102262

Giddey, B. L., Baard, J. A., & Kraaij, T. (2022). Verification of the differenced Normalised Burn Ratio (dNBR) as an index of fire severity in Afrotemperate Forest. *South African Journal of Botany*, *146*, 348–353. https://doi.org/10.1016/j.sajb.2021.11.005

Guo, L., Li, S., Wu, Z., Parsons, R. A., Lin, S., Wu, B., & Sun, L. (2022). Assessing spatial patterns and drivers of burn severity in subtropical forests in southern China based on Landsat 8. *Forest Ecology and Management*, *524*(September). https://doi.org/10.1016/j.foreco.2022.120515

Ji, C., Yang, H., Li, X., Pei, X., Li, M., Yuan, H., Cao, Y., Chen, B., Qu, S., Zhang, N., Chun, L., Shi, L., & Sun, F. (2024). Forest wildfire risk assessment of Anning River Valley in Sichuan Province based on driving factors with multi-source data. *Forests*, *15*(9), 1523. https://doi.org/10.3390/f15091523

Jodhani, K. H., Patel, H., Soni, U., Patel, R., Valodara, B., Gupta, N., Patel, A., & Omar, P. J. (2024). Assessment of forest fire severity and land surface temperature using Google Earth Engine: A case study of Gujarat State, India. Fire Ecology, 20(1), 23.

Makumbura, R. K., Dissanayake, P., Gunathilake, M. B., Rathnayake, N., Kantamaneni, K., & Rathnayake, U. (2024). Spatial mapping and analysis of forest fire risk areas in Sri Lanka – Understanding environmental significance. *Case Studies in Chemical and Environmental Engineering*, *9*(March), 100680. https://doi.org/10.1016/j.cscee.2024.100680

Nájera De Ferrari, F., Duarte, E., Smith-Ramírez, C., Rendon-Funes, A., Sepúlveda Gonzalez, V., Sepúlveda Gonzalez, N., Levio, M. F., Rubilar, R., Stehr, A., Merino, C., Jofré, I., Rojas, C., Aburto, F., Kuzyakov, Y., Filimonenko, E., Dörner, J., Pereira, P., & Matus, F. (2024). Multi-temporal assessment of a wildfire chronosequence by remote sensing. *MethodsX*, *13*(September). https://doi.org/10.1016/j.mex.2024.103011

Oseghae, I., Bhaganagar, K., & Mestas-Nuñez, A. M. (2024). The Dolan Fire of central coastal California: Burn severity estimates from remote sensing and associations with environmental factors. *Remote Sensing*, *16*(10). https://doi.org/10.3390/rs16101693

Paudel, G., Pandey, K., Lamsal, P., Bhattarai, A., Bhattarai, A., & Tripathi, S. (2024). Geospatial forest fire risk assessment and zoning by integrating MaxEnt in Gorkha District, Nepal. *Heliyon*, *10*(11), e31305. https://doi.org/10.1016/j.heliyon.2024.e31305

Samphutthanont, R. (2024). Assessing Agricultural burned areas using dNBR Index from Sentinel-2 Satellite Data in Chiang Mai, Thailand. *Geographia Technica*, *19*, 46–56. https://doi.org/10.21163/gt_2024.192.04

Shan, Y., Gao, B., Yin, S., Shao, D., Cao, L., Yu, B., Cui, C., & Wang, M. (2024). Influence of terrain slope on sub-surface fire behavior in boreal forests of China. *Fire*, *7*(2), 1–14. https://doi.org/10.3390/fire7020055

Sobrino, J. A., Llorens, R., Fernández, C., Fernández-Alonso, J. M., & Vega, J. A. (2019). Relationship between forest fires severity measured in situ and through remotely sensed spectral indices. *Forests*, *10*(5), 1–13. https://doi.org/10.3390/f10050457

Soualah, L., Bouzekri, A., & Chenchouni, H. (2024). Hoping the best, expecting the worst: Forecasting forest fire risk in Algeria using fuzzy logic and GIS. *Trees, Forests and People*, *17*(June), 100614. https://doi.org/10.1016/j.tfp.2024.100614

Talukdar, N. R., Ahmad, F., Goparaju, L., Choudhury, P., Qayum, A., & Rizvi, J. (2024). Forest fire in Thailand: Spatio-temporal distribution and future risk assessment. *Natural Hazards Research*, *4*(1), 87–96. https://doi.org/10.1016/j.nhres.2023.09.002

Tonbul, H., Kavzoglu, T., & Kaya, S. (2016). Assessment of fire severity and post-fire regeneration based on topographical features using multitemporal Landsat imagery: A case study in Mersin, Turkey. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *41*(July), 763–769. https://doi.org/10.5194/isprsarchives-XLI-B8-763-2016

Tout, F. (2023). A model to predict the outbreak areas of forests arsons. *Geografická Revue*, *19*(1). https://doi.org/10.24040/GR.2023.19.1.62-75

Vergara, A. J., Valqui-Reina, V. S., Cieza-Tarrillo, D., Munoz-Astecker, L. D., Ocaña, C. L., Cubas, J., & Auquiñivin-Silva, E. A. (2024). Integration of the AHP method and GIS techniques for mapping areas susceptible to forest fires in the southern Amazon Region (Peru). *International Journal of Design and Nature and Ecodynamics*, *19*(3), 769–778. https://doi.org/10.18280/ijdne.190307

Vogiatzoglou, K., Papadimitriou, C., Ampountolas, K., Chatzimanolakis, M., Koumoutsakos, P., & Bontozoglou, V. (2024). An interpretable wildfire spreading model for real-time predictions. *Journal of Computational Science*, *83*(September), 102435. https://doi.org/10.1016/j.jocs.2024.102435

Xu, E., Wei, M., Li, T., Lei, V., Gao, J., Wang, N., & He, Y. (2024a). Assessing burn severity and vegetation restoration in Alberta's boreal forests following the 2016 Fort McMurray wildfire–a remote sensing time-series study. *Sustainable Environment*, *10*(1). https://doi.org/10.1080/27658511.2024.2361569

Xu, H., Chen, J., He, G., Lin, Z., Bai, Y., Ren, M., Zhang, H., Yin, H., & Liu, F. (2024b). Immediate assessment of forest fire using a novel vegetation index and machine learning based on multi-platform, high temporal resolution remote sensing images. *International Journal of Applied Earth Observation and Geoinformation*, *134*(September), 104210. https://doi.org/10.1016/j.jag.2024.104210

Zhao, Y., Huang, Y., Sun, X., Dong, G., Li, Y., & Ma, M. (2023). Forest fire mapping using multi-source remote sensing data: A case study in Chongqing. *Remote Sensing*, *15*(9). https://doi.org/10.3390/rs15092323.