

Article

Environmental Drivers of Burn Severity Determined Using Linear and Nonlinear Relationships: A Case Study of the 2025 Uiseong Wildfire

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Abstract

This study investigated the linear and nonlinear effects of environmental drivers on burn severity during the 2025 Uiseong wildfire, the largest forest fire recorded in South Korea. Burn severity, quantified using the differenced Normalized Burn Ratio (dNBR), was analyzed with the Generalized Linear Model (GLM) and Generalized Additive Model (GAM). The results identified the Normalized Difference Vegetation Index (NDVI) as the dominant predictor, with approximately eightfold greater importance than any other variable. A clear threshold response showed that the probability of High-severity burns increased sharply when NDVI exceeded approximately 0.25–0.30. Coniferous forests were 3.65 times more likely to experience High-severity burns than broadleaf forests, whereas managed forests exhibited lower burn severity. Topographic and meteorological variables generally had weaker effects, although several showed nonlinear response patterns. Overall, fuel availability and continuity were the primary determinants of burn severity, while topographic and meteorological factors played secondary, modifying roles. However, the model showed limited ability to identify Low-severity areas. These findings provide a scientific basis for improving forest management and wildfire mitigation strategies.

Keywords: Uiseong wildfire; differenced normalized burn ratio; burn severity; generalized linear model; generalized additive model; normalized difference vegetation index

1. Introduction

In recent years, the frequency and impacts of large wildfires have increased, owing to intensified drying trends and more severe fire weather associated with climate change [1]. In Korea, drying conditions have become increasingly pronounced because of changes in temperature and precipitation regimes, with declining relative humidity identified as a key driver of wildfire occurrence. Reduced springtime humidity, in particular, has been recognized as a major factor increasing the likelihood of megafires [2,3]. A representative example is the wildfire that began in Uiseong County, Gyeongsangbuk-do, on 22 March 2025. Fueled by high temperatures, low humidity, and strong winds, the 2025 Uiseong wildfire became the largest wildfire in Korean history in terms of forest damage [4]. As large wildfires become more frequent and severe, quantitative assessment of their effects on forest ecosystems is increasingly important.

Burn severity describes the degree of organic matter consumption and the physical, chemical, and biological changes caused by wildfire [5]. It is a key indicator for evaluating



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post-fire ecosystem recovery and guiding restoration strategies [6,7]. The most widely used remote sensing metrics for burn severity are the Normalized Burn Ratio (NBR) and the differenced Normalized Burn Ratio (dNBR), which measures changes in NBR before and after wildfire [8]. By combining near-infrared and shortwave infrared bands, dNBR quantifies burn severity as a continuous variable and has been widely applied to large-scale wildfire assessments [9,10]. Sentinel-2 imagery has performed as well as or better than Landsat 8 for burn severity mapping [11] and has been increasingly used for dNBR-based assessments of recent wildfires [12].

Burn severity results from complex interactions among topographic, meteorological, vegetation, and anthropogenic factors. Previous studies have identified elevation, slope, wind speed, the Normalized Difference Vegetation Index (NDVI), and distance to forest roads as major determinants of burn severity [13,14]. More recently, machine learning techniques, particularly Random Forest, have been widely used to identify important predictors. However, because relationships between environmental variables and burn severity are often nonlinear, these methods provide limited insight into the underlying response functions despite effectively ranking variable importance [15]. Consequently, the generalized additive model (GAM), which flexibly captures nonlinear relationships while retaining interpretability, has emerged as a valuable alternative [16,17].

In Korea, studies related to the Uiseong wildfire have examined downslope windstorms in the lee of the Sobaek Mountains [18] and machine learning-based prediction of burn severity using stand structure and seasonal NDVI, highlighting NDVI as an important predictor [19]. However, most have focused on variable importance rather than the functional relationships between individual environmental factors and burn severity.

Consequently, it remains unclear (i) which environmental factors primarily determined burn severity under the extreme fire weather conditions of the 2025 Uiseong wildfire, (ii) whether their effects are adequately captured by linear terms. To address these questions, this study used burn severity classes derived from dNBR to examine the effects of topographic, meteorological, vegetation, and anthropogenic factors on burn severity during the 2025 Uiseong wildfire. Two models were applied for different purposes. An ordinal logistic regression model (GLM) was used to estimate the direction and magnitude of the effects of categorical site and stand attributes, including topographic position, slope, aspect, forest type, forest tending, and diameter class, expressed as odds ratios. A GAM was used to characterize the shapes of the response functions of continuous predictors, including potential thresholds and non-monotonic patterns. We hypothesized that fuel- and topography-related variables would exhibit predominantly linear relationships with burn severity, whereas meteorological and anthropogenic factors, including maximum wind speed, distance to forest roads, and forest management treatment status, would exhibit nonlinear responses with threshold effects. This approach provides a better understanding of the quantitative relationships between environmental drivers and burn severity under extreme wildfire conditions.

2. Materials and Methods

2.1. Study Area

The study area encompasses the region affected by the wildfire that ignited on 22 March 2025 [20], and subsequently spread to four adjacent municipalities, including Andong, Cheongsong, Yeongyang, and Yeongdeok (Figure 1). The region is located on the leeward side of the Sobaek Mountains, where strong localized westerly winds frequently occur during spring [18]. During the wildfire, the combination of strong winds and dry atmospheric conditions promoted rapid and widespread fire spread across the region [4].

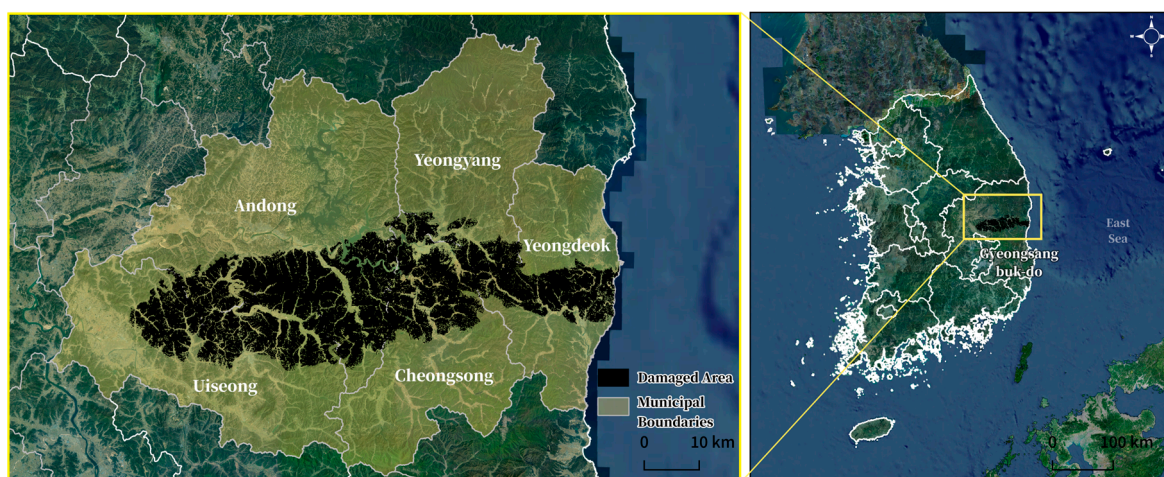


Figure 1. Study area of the 2025 Uiseong wildfire.

2.2. Burn Severity Assessment

Burn severity was assessed using Sentinel-2 Level-2A (L2A) imagery provided by the European Space Agency (ESA). The pre-fire image was acquired by Sentinel-2B on 14 March 2025 (11:06), and the post-fire image by Sentinel-2C on 29 March 2025 (11:07).

Wildfire impacts were quantified using the NBR, a widely used spectral index based on near-infrared (NIR) and shortwave infrared (SWIR) reflectance [8]. NBR was calculated separately for the pre- and post-fire images, and the dNBR was obtained from their difference.

$$\text{NBR} = (B8 - B12) / (B8 + B12), \text{dNBR} = \text{NBR}_{\text{pre}} - \text{NBR}_{\text{post}} \quad (1)$$

Sentinel-2 NIR (10 m) and SWIR (20 m) bands were used, with the SWIR band resampled to 10 m using bilinear resampling; cloud and cloud-shadow pixels were excluded using the Scene Classification Layer, and no additional topographic correction was applied. Visual inspection of the post-fire image indicated that residual smoke within the burned area was minimal. Based on the dNBR distribution (mean = 0.2762, SD = 0.2863), burn severity was classified into three classes using thresholds defined as the mean $\pm$ 0.5 standard deviations: Low ($0 < \text{dNBR} < 0.1331$), Moderate ($0.1331 \leq \text{dNBR} < 0.4194$), and High ($\text{dNBR} \geq 0.4194$). Pixels with dNBR values ≤ 0 were excluded from the burn severity classification. The continuous dNBR values were first classified into the three burn severity classes at a 10 m spatial resolution using these thresholds. The resulting 10 m burn severity map was then resampled to the 100 m analysis grid using the nearest-neighbor method. The resulting burn severity classes were checked by field verification at 12 sites.

2.3. Development of Environmental and Forest Management Variables

To identify the environmental drivers of burn severity, explanatory variables were developed in four categories: vegetation and fuel, topography, meteorology, and anthropogenic factors. All variables, including the burn severity classes, were resampled to a 100 m grid to match the resolution of the interpolated maximum wind speed surface, ensuring a consistent spatial resolution across the analysis. The coordinate system was standardized to the GRS80-based TM projection for the Central Belt of Korea (EPSG:5186) (Figure 2). Data sources and derivation methods are summarized in Table 1.

The NDVI, representing vegetation and fuel conditions, was derived from a low-cloud Sentinel-2 image acquired immediately before the wildfire (14 March 2025). The original data were aggregated to a 100 m grid using mean resampling, yielding an average NDVI of 0.507. NDVI was calculated as

$$NDVI = (B8 - B4) / (B8 + B4) \quad (2)$$

Because NDVI and NBR_{pre} share the NIR band of the same pre-fire image, NDVI and dNBR are not fully independent; the association between NDVI and burn severity was therefore interpreted as reflecting both fuel conditions and this spectral dependence. Forest type was reclassified into five categories based on forest stand codes: non-stocked land, coniferous forest, broadleaf forest, mixed forest, and bamboo forest.

For topographic variables, the topographic position index (TPI) was derived from a digital elevation model (DEM) provided by the National Geographic Information Institute. Aspect and slope were excluded from the final spatial regression model because preliminary analyses indicated substantial overlap with TPI and lower explanatory power. However, slope was retained in supplementary GLM analyses to further assess the influence of terrain steepness. For the GLM, TPI was classified into five slope-position classes using standard deviation-based thresholds [21,22].

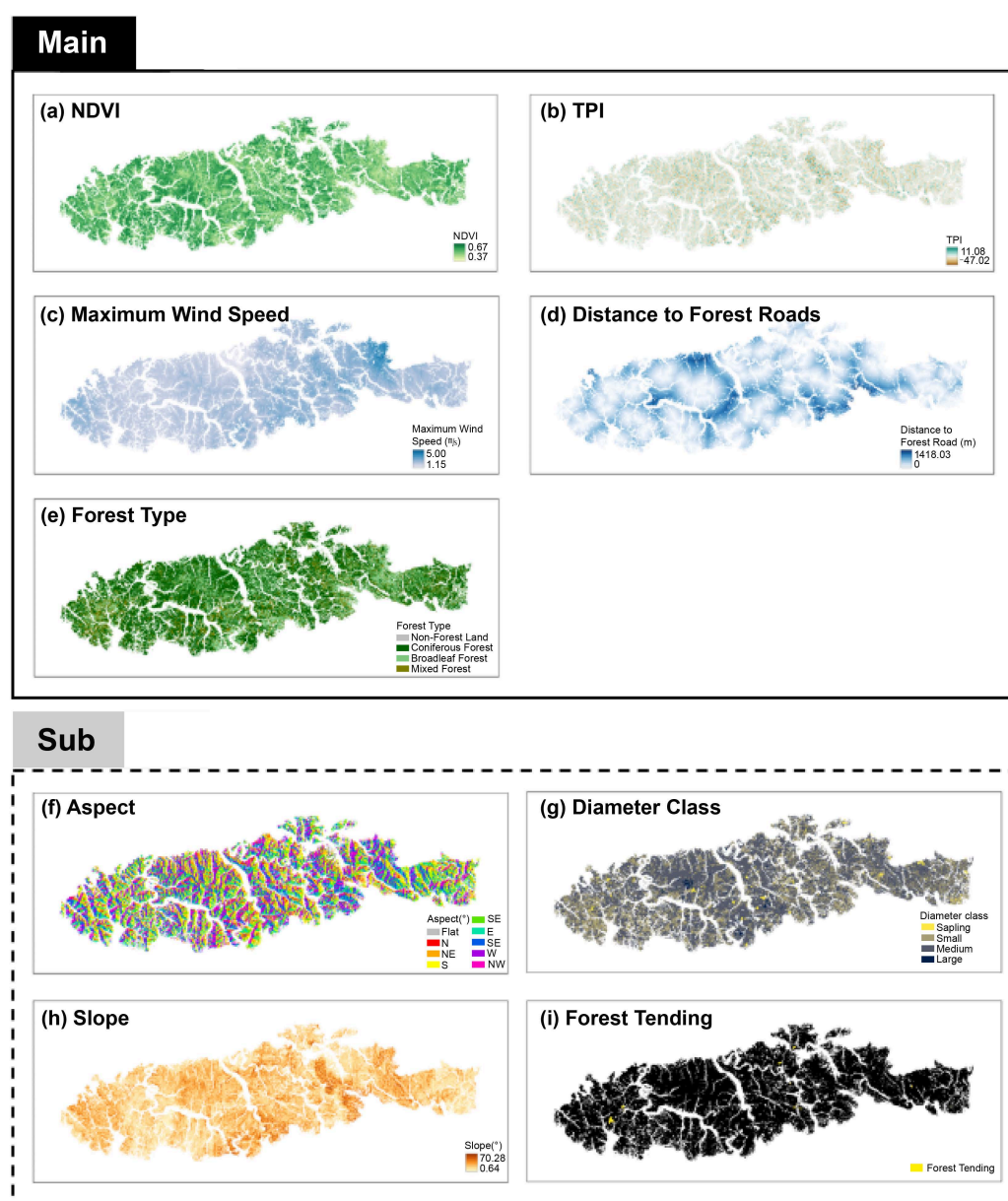


Figure 2. Variables used in the analysis.

Table 1. Source data and derivation methods for variables used in the analysis.

Category	Variable	Source Data	Derivation Method
Topography	Slope	Digital elevation model (DEM) (resampled to 100 m)	Geographic Information System (GIS) slope calculation using a 3×3 neighborhood window
	Aspect	DEM (resampled to 100 m)	Transformed into northness = $\cos(\text{aspect})$, eastness = $\sin(\text{aspect})$
	Topographic Position Index (TPI)	DEM (resampled to 100 m)	$TPI = z_0 - \text{mean elevation within a } 5 \times 5 \text{ cell (500 m} \times \text{500 m) window}$
Meteorology	Maximum Wind Speed	KMA ASOS and KFS AMOS observations	IDW interpolation after elevation-based residual correction
Vegetation	NDVI	Sentinel-2 Level-2A	$NDVI = (B8 - B4) / (B8 + B4)$
	Forest Type, diameter at breast height (DBH) Class	Korea Forest Service Forest Type Map (1:5000)	Classification based on attribute information
Forest Management Factors	Distance to Forest Roads	Korea Forest Service Forest Road Network (national and local forest roads)	Euclidean distance calculation
	Forest Tending	Korea Forest Service Forest Tending Project Areas (2022–2024)	Polygon boundaries of areas where forest tending was implemented

Maximum wind speed was selected as the meteorological variable, using hourly observations recorded during 21–28 March 2025, at 20 KMA ASOS and KFS AMOS stations. Due to the sparse distribution of weather stations and the elevation dependence of wind speed, a topographic residual inverse distance weighting (IDW) approach using a 10 m DEM was applied. First, an ordinary least squares (OLS) regression between observed wind speed and elevation estimated the topographic trend. Second, the residuals were interpolated to a 100 m grid using IDW. Finally, the trend component was added back to the interpolated residuals to generate the maximum wind speed surface. The mean maximum wind speed across the study area was 13.74 m/s.

As an anthropogenic variable, Euclidean distance to forest roads was calculated from the Korea Forest Service forest road network, with a mean distance of 1533 m. Forest management treatment history and diameter at breast height (DBH) class were excluded from the final spatial regression model because of limited spatial continuity and missing values in some categories. Nevertheless, both variables were included in supplementary GLM analyses to evaluate their potential effects.

2.4. Statistical Analysis and Model Development

Burn severity was classified into three categories (Low, Moderate, and High) based on dNBR thresholds described in Section 2.2. Since using all grid cells could introduce non-independence due to spatial autocorrelation [23], leading to inflated effective sample sizes, stratified random sampling by burn severity class was applied. The dataset was divided into training and validation subsets at an 8:2 ratio. Of the 100,081 valid grid cells (21,547 Low, 46,326 Moderate, and 32,208 High), 20,017 were assigned to the validation dataset, including 4310 Low-, 9265 Moderate-, and 6442 High-severity cells. The 100,081 valid cells (100,081 ha) are fewer than the satellite-derived burned area (103,376 ha) because boundary cells and cells with missing explanatory variables were excluded during aggregation to the 100 m grid.

Candidate predictors were first screened using random forest (RF) permutation importance. Multicollinearity was assessed using the Generalized Variance Inflation Factor (GVIF) and $GVIF^{1/(2 Df)}$, which account for the degrees of freedom associated with categorical variables [24]. Among the 14 candidate variables, NDMI (GVIF = 14.55) and NDVI (13.98) exhibited substantial collinearity. Likewise, maximum wind speed (5.36) and mean wind speed (4.86) were strongly correlated. NDVI was retained because of its stronger relevance to dNBR, while maximum wind speed was selected because it better represents the effects of extreme wind conditions on fire spread and burn severity. The final model included five explanatory variables: NDVI, TPI, maximum wind speed, distance to forest roads, and forest type. All variables satisfied the criterion $GVIF^{1/(2 Df)} < \sqrt{5}$, equivalent to the conservative threshold of Variance Inflation Factor (VIF) < 5 [24], indicating negligible multicollinearity.

To capture nonlinear responses, a GAM with smoothing functions, $s(\cdot)$, was fitted [17]. The degree of smoothing was selected automatically using generalized cross-validation (GCV) and penalized likelihood optimization. Separate one-vs-rest (OvR) models were developed for the Low, Moderate, and High burn severity classes, and class-specific partial dependence relationships were derived. Model performance was evaluated using the validation dataset based on classification accuracy, McFadden's pseudo- R^2 , the Akaike information criterion (AIC), and five-fold cross-validation [25]. Spatial autocorrelation was assessed using global Moran's I for the response variable, explanatory variables, and model residuals [26]. Variable importance was quantified using permutation-based decreases in prediction accuracy. All analyses were conducted in Python 3.14.3 (Python Software Foundation, Wilmington, DE, USA) using pyGAM 0.12.0 and scikit-learn 1.8.0.

3. Results

3.1. Spatial Distribution of Burn Severity

dNBR analysis of the 2025 Uiseong wildfire revealed that High-severity burns covered 32,588 ha, representing approximately 32% of the total burned area. Moderate- and Low-severity burns covered 48,028 ha (46%) and 22,760 ha (22%), respectively (Figure 3). The total burned area estimated from satellite imagery was 103,376 ha, approximately 4087 ha larger than the official estimate reported by the Korea Forest Service. This discrepancy falls within the uncertainty commonly reported for satellite-based burn assessments and may reflect sensor spectral characteristics, terrain shadow effects in complex mountainous terrain, and limitations in detecting Low-severity burns [8,27,28].

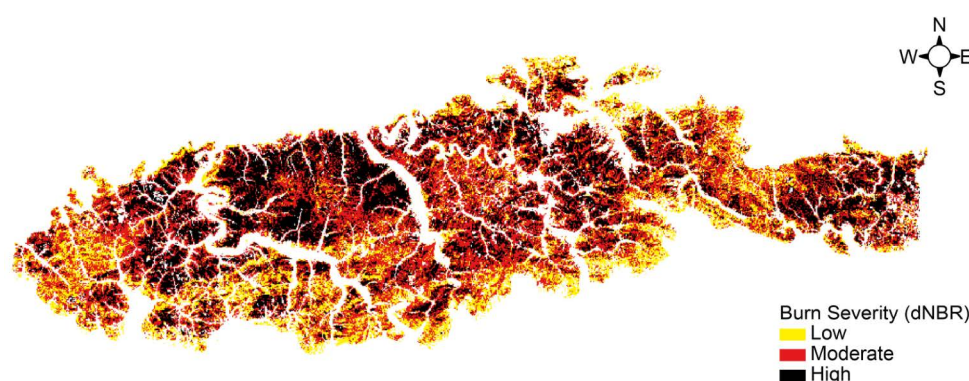


Figure 3. Spatial distribution of burn severity for the 2025 Uiseong wildfire derived from the differenced Normalized Burn Ratio (dNBR).

Analysis by forest type indicated that coniferous forests had the highest proportion of High-severity burns (46.6%) (Table 2). In contrast, Moderate-severity burns predominated in mixed (50.4%) and broadleaf forests (63.0%). The substantially higher proportion of

High-severity burns in coniferous forests is likely attributable to their greater canopy fuel loads and more continuous fuel structure, which promote crown fire development and increase fire severity [29–31].

Table 2. Distribution of burn severity by forest type.

Class	Burned Area (ha)			Percentage (%)		
	B + C + M	C + M	C	B + C + M	C + M	C
High	32,588	29,320	25,689	31.5	41.8	46.6
Moderate	48,028	27,061	19,503	46.5	38.6	35.4
Low	22,760	13,716	9917	22.0	19.6	18.0
Total	103,376	70,097	55,109	100.0	100.0	100.0

Note: B = Broadleaf forest, C = Coniferous forest, M = Mixed forest.

3.2. Analysis of Burn Severity Drivers Using the GLM

Ordinal logistic regression analysis indicated that topographic position, aspect, forest type, and forest structural characteristics were significantly associated with burn severity. Among topographic positions, ridge sites had the highest odds ratio (OR = 2.34) relative to valley locations. Among slope aspects, southeast-facing slopes showed the highest OR (2.05), followed by south-facing (OR = 1.87) and east-facing slopes (OR = 1.82), all relative to north-facing slopes. Coniferous forests had the highest odds ratio among forest types (OR = 3.65). In contrast, forest management treatment (OR = 0.38) and stands dominated by large-diameter trees (OR = 0.67) were associated with a lower likelihood of High burn severity (Table 3).

Table 3. Results of the burn severity factor analysis.

Variable	Class	Coefficient (β)	OR
TPI	Valley (Ref)	-	-
	Lower slope	0.19	1.21
	Mid slope	0.47	1.6
	Upper slope	0.71	2.04
	Ridge	0.85	2.34
Slope	$0^\circ \leq \text{Slope} < 5^\circ$ (Ref)	-	-
	$5^\circ \leq \text{Slope} < 15^\circ$	0.07	1.07
	$15^\circ \leq \text{Slope} < 25^\circ$	0.02	1.02
	$25^\circ \leq \text{Slope} < 35^\circ$	−0.37	0.69
	$\geq 35^\circ$	−0.46	0.63
Aspect	North (Ref)	-	-
	East	0.6	1.82
	Southeast	0.72	2.05
	South	0.62	1.87
Forest Type	Broadleaf forest (Ref)	-	-
	Coniferous forest	1.29	3.65
	Mixed forest	0.51	1.67
	Non-forest	−0.46	0.63

Table 3. Cont.

Variable	Class	Coefficient (β)	OR
Forest Tending	Non-treated (Ref)	-	-
	Treated	−0.964	0.38
Diameter Class	Sapling (DBH < 6 cm) (Ref)	-	-
	Small (6 cm $\leq$ DBH < 18 cm)	−0.62	0.54
	Middle (18 cm $\leq$ DBH < 30 cm)	−0.65	0.52
	Large (DBH $\geq$ 30 cm)	−0.40	0.67

Note: Ref = reference category ($\beta = 0$, OR = 1.00).

3.3. Nonlinear Response Characteristics Identified by GAM

The total effective degrees of freedom (EDF) for the smooth terms ranged from approximately 41 to 58 across burn severity classes, indicating significant nonlinear responses that departed substantially from linear assumptions. Variable-specific partial dependence curves identified NDVI as the dominant predictor, with a substantially greater influence than all other variables. Permutation-based variable importance analysis assigned NDVI an importance score of 0.103, approximately eight times higher than that of the second most important variable, forest type (0.013). Maximum wind speed (0.004), TPI (0.004), and distance to forest roads (0.004) contributed comparatively little to model performance (Figure 4).

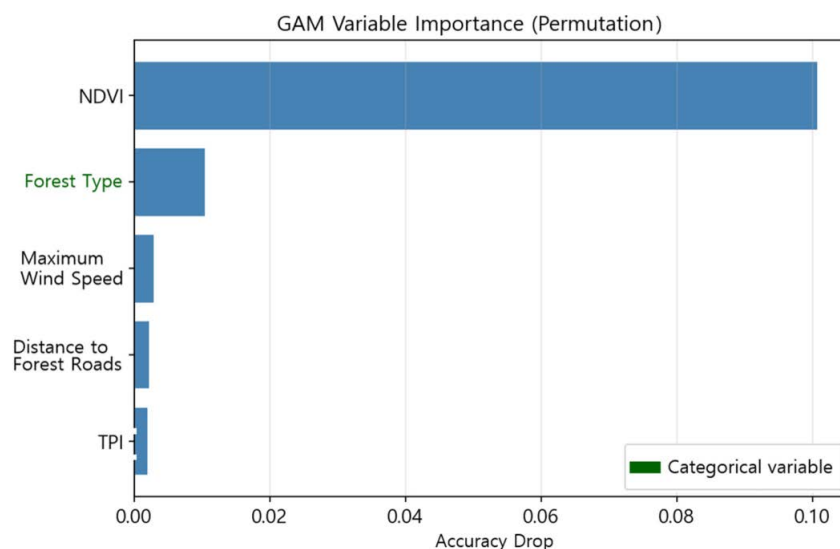


Figure 4. Permutation-based variable importance in the Generalized Additive Model (GAM).

The partial dependence curve for NDVI revealed a distinct threshold response for High burn severity. The log-odds reached a minimum of approximately −3.7 at NDVI values of 0.25–0.30, then increased sharply with increasing NDVI, reaching approximately +3 at NDVI $\approx$ 0.7. In contrast, Low burn severity was most probable at low NDVI values, whereas Moderate burn severity peaked at approximately NDVI = 0.4 (Figure 5a). For TPI, High burn severity showed strongly negative contributions in valleys (negative TPI; log-odds $\approx$ −1.7), followed by a gradual increase toward positive contributions on ridges and upper slopes (positive TPI; log-odds $\approx$ +1.2), producing an overall increasing response (Figure 5b). The partial dependence curve for maximum wind speed exhibited a U-shaped, non-monotonic pattern for High burn severity. Positive contributions occurred at wind speeds below approximately 12 m s^{−1}, became negative between 13 and 19 m s^{−1}, and

increased sharply again above approximately 20 m s^{-1} (Figure 5c). However, observations above this value were sparse and the uncertainty increased, so this pattern should be interpreted with caution. For distance to forest roads, High- and Moderate-severity burns showed weak positive contributions within approximately 0–4000 m, followed by a sharp decline beyond this distance (Figure 5d).

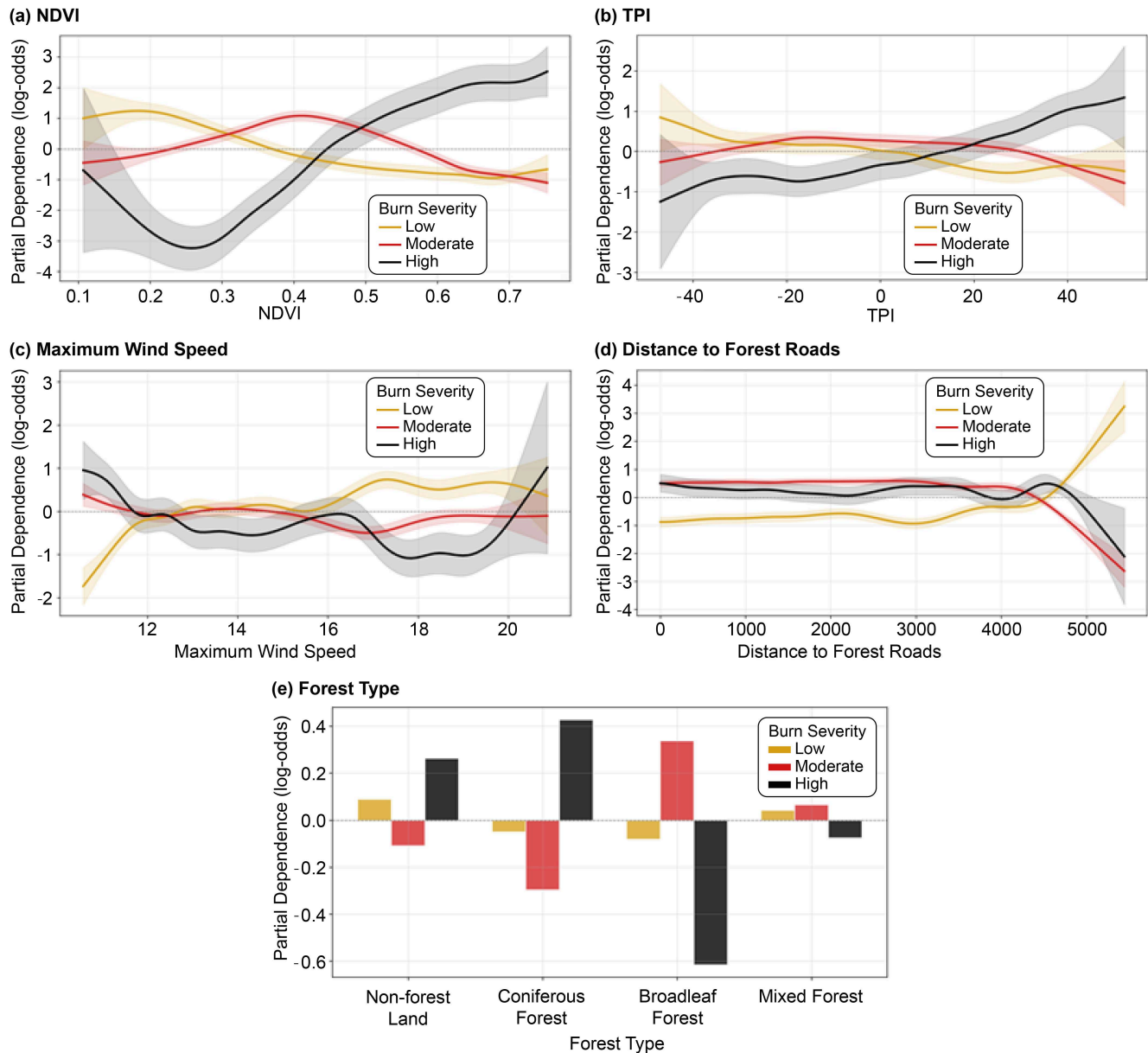


Figure 5. Partial dependence plots of environmental variables from the Generalized Additive Model (GAM). Partial dependence curves illustrate the effects of (a) Normalized Difference Vegetation Index (NDVI), (b) Topographic Position Index (TPI), (c) maximum wind speed, (d) distance to forest roads, and (e) forest type on the log-odds of Low, Moderate, and High burn severity classes.

Conversely, Low burn severity increased markedly with greater distance from forest roads. Partial dependence analysis of forest type indicated that coniferous forests contributed positively to High burn severity (log-odds $\approx +0.42$). Broadleaf forests contributed positively to Moderate burn severity ($+0.30$) and negatively to High burn severity (-0.60) (Figure 5e). Mixed forests exhibited intermediate responses. Although bamboo forests showed large positive estimates, the sample size was extremely small ($n = 4$), resulting in wide confidence intervals and unstable estimates; therefore, they were excluded from further interpretation.

Overall, the GAM identified the strongest nonlinear responses for the threshold relationship of NDVI and the increasing response of TPI. Although maximum wind speed and distance to forest roads also exhibited nonlinear patterns, their low importance scores indicate that they played secondary roles compared with the dominant effects of NDVI and forest type.

3.4. Model Performance and Assessment of Spatial Autocorrelation

The GAM achieved a mean five-fold cross-validation accuracy of 0.593, indicating stable predictive performance (Table 4). McFadden's pseudo- R^2 varied among burn severity classes, with the highest value for High severity (0.254), followed by Moderate- (0.104) and Low (0.044) (Table 5). These results indicate that the model explained variation in High-severity burns more effectively than in Moderate- or Low-severity burns. Confusion matrix analysis likewise showed better classification performance for the Moderate- and High-severity classes. In contrast, the recall for Low burn severity was only 0.03, indicating that most Low-severity cells were classified as Moderate severity. This indicates that the model poorly identified Low-severity burns and tended to assign them to a higher severity class.

Table 4. Five-fold cross-validation accuracy.

Fold	Accuracy
1	0.5946
2	0.5892
3	0.5925
4	0.5936
5	0.5959
Average	0.5932

Table 5. Model performance of GAMs for each burn severity class (One-vs-Rest, OvR).

Class	AIC	Pseudo- R^2	EDF (Total)
Low	80,719.77	0.0442	44.56
Moderate	100,102.08	0.1036	41.09
High	75,710.71	0.2537	58.21

To evaluate the model's spatial performance, global Moran's I was calculated for the model residuals. The response variable (dnBR) exhibited strong positive spatial autocorrelation ($I = 0.377$, $p < 0.001$). After GAM fitting, Moran's I for the residuals decreased to 0.285, 0.069, and 0.221 for the Low-, Moderate-, and High-severity classes, respectively (all $p < 0.001$). Relative to the original spatial structure of the response variable, these reductions indicate that the GAM smoothing functions accounted for approximately 82% and 41% of the spatial autocorrelation in the Moderate- and High-severity classes, respectively.

4. Discussion

4.1. Major Drivers of Burn Severity in the Uiseong Wildfire

The results indicate that burn severity was associated with the combined effects of fuel, meteorological, and topographic conditions rather than with any single factor. Among the explanatory variables, NDVI exhibited substantially greater explanatory power, identifying vegetation condition as the dominant predictor of burn severity. This finding suggests that vegetation vigor remains a key predictor of burn severity even under extreme fire weather. Areas with low vegetation vigor are less likely to experience High-severity burns because

of limited fuel availability, whereas highly productive, densely vegetated stands provide greater fuel continuity and biomass accumulation, substantially increasing the likelihood of severe burns. The pronounced threshold response at NDVI values of approximately 0.25–0.30 further indicates the probability of High-severity burns increases sharply above this range, potentially reflecting differences in vegetation density and fuel continuity [13].

Burn severity also differed among forest types, reflecting variations in fuel characteristics. Coniferous forests were 3.65 times more likely to experience High-severity burns than broadleaf forests, consistent with their greater canopy fuel loads and more continuous fuel structure, which promote crown wildfire development [29,31]. Similar patterns were reported for previous large wildfires in Korea, where red pine forest area was the primary explanatory variable of burn severity [32] and coniferous forests burned approximately three times more severely than deciduous forests [33]. In contrast, stands dominated by large-diameter trees were less likely to experience severe burns than younger stands, likely because thicker bark and higher canopy base heights increase fire resistance [34,35]. Burn severity was also lower in areas that had undergone forest management treatments, supporting previous studies showing that reducing fuel loads and continuity mitigates wildfire intensity and impacts [29,36].

Maximum wind speed increased the probability of High-severity burns under extreme wind conditions but contributed relatively little to overall model performance. Although strong winds clearly accelerated wildfire spread during the Uiseong wildfire [18], the weak effect estimated here may reflect limitations of the interpolated wind dataset. As wind surfaces were generated by spatial interpolation, they may not adequately capture localized airflow in complex mountainous terrain. Unlike temperature, wind speed is strongly influenced by terrain-induced processes, including changes in wind direction, valley and slope winds, and turbulence [37]. Consequently, the topographic residual-IDW approach may have underestimated the spatial variability of wind speed. These findings suggest that wind speed may have played an important role in overall wildfire spread but contributed less to explaining local variation in burn severity. TPI exhibited an increasing response, with higher probabilities of High-severity burns on ridges and upper slopes. This pattern is consistent with the tendency of wildfires to spread more rapidly along ridge tops and upper slopes [38]. Similarly, higher burn severity on southeast-, south-, and east-facing slopes than on north-facing slopes is likely attributable to lower fuel moisture resulting from greater solar radiation [39,40]. However, because topographic factors had relatively low importance score, they appear to act less as independent drivers and more as secondary factors that modify burn severity.

Distance to forest roads exhibited a pattern contrary to our initial expectation. Although greater distances would generally be expected to reduce firefighting accessibility and increase burn severity, the probability of High-severity burns declined in the most distant areas. However, even locations within the 0–4000 m distance range may have limited accessibility in mountainous forest environments, making it difficult to interpret them simply as being “close to forest roads.” Additionally, areas farther from forest roads may coincide with high-elevation sites, non-stocked land, or regions with lower fuel availability. Estimation uncertainty associated with the relatively small sample size at the greatest distances should also be considered. Moreover, the permutation importance score for distance to forest roads was only 0.004, indicating a negligible contribution to model performance. Therefore, the observed pattern likely reflects the combined influence of site characteristics and fuel conditions rather than a direct effect of road accessibility.

These results are broadly consistent with recent machine-learning studies, which identified fuel, pre-fire weather, and topography as key predictors of burn severity, with their relative importance varying among fires [41]. In a recent study of the 2021 Bootleg

Fire, fuel characteristics, including fuel treatments and fuel structure, played a central role in explaining burn severity under consistently severe weather conditions [42]. These findings support the importance of vegetation and fuel-related conditions in explaining spatial variation in burn severity in the present study. Recent machine-learning studies have also demonstrated the applicability of ensemble and gradient-boosting approaches to burn-severity prediction. For example, Das et al. [43] reported an overall accuracy of approximately 0.58 using random forest and gradient-boosting models for soil burn severity prediction.

4.2. Limitations and Future Research

Several limitations should be acknowledged. First, model performance was substantially stronger for High burn severity (pseudo- $R^2 = 0.254$) than for Low burn severity (pseudo- $R^2 = 0.044$), indicating differences in explanatory power among burn severity classes. The model also rarely identified Low-severity cells (recall = 0.03); because this study prioritized interpretable response functions over predictive accuracy, direct comparison of the final GAM/GLM framework with alternative predictive machine-learning models was beyond the scope of this study. Second, the wind speed variable may not have adequately represented actual local wind fields in complex terrain. Third, residual spatial autocorrelation remained significant in all classes (Moran's $I = 0.069$ – 0.285), and the random 8:2 split may therefore have overestimated predictive performance. Spatially blocked cross-validation and residual semivariogram analysis should be applied in future work. Fourth, resampling the 10 m burn-severity classes to a 100 m analysis grid using nearest-neighbor resampling may have reduced the representation of fine-scale spatial variation in burn severity and topographic conditions. Future research should incorporate high-resolution numerical weather prediction data to better quantify wind effects and refine burn severity classifications by expanding field validation using the Composite Burn Index (CBI). In addition, the external validity of these findings should be evaluated across multiple wildfire events and geographic regions.

5. Conclusions

Using burn severity classes derived from dNBR (Low, Moderate, and High) as the response variable and vegetation, topographic, and meteorological factors as explanatory variables, this study applied a GLM and a GAM to investigate the drivers of burn severity during the 2025 Uiseong wildfire. The results identified vegetation vigor (NDVI) as the most influential predictor of burn severity, exerting substantially greater influence than any other variable. Although wind speed and topographic variables contributed relatively little as independent predictors, they appear to have played secondary, modifying roles. A pronounced nonlinear threshold response was observed, with the probability of High-severity burns increasing sharply when NDVI exceeded approximately 0.25–0.30. This finding suggests that vegetation condition and fuel continuity are important factors associated with burn severity, even under strong winds and severe atmospheric dryness. Coniferous forests were 3.65 times more likely than broadleaf forests to experience High-severity burns, whereas forest tending was associated with lower burn severity. Model performance was highest for High burn severity and lowest for Low burn severity. Overall, the results indicate that vegetation-related conditions showed the strongest association with the spatial pattern of burn severity in large wildfire. By integrating satellite-based burn severity assessment with spatial statistical modeling, this study provides a quantitative evaluation of the drivers of burn severity in a large wildfire that can inform future forest management and wildfire mitigation strategies.

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Data Availability Statement: Sentinel-2 Level-2A imagery is publicly available from the Copernicus Data Space Ecosystem (<https://dataspace.copernicus.eu/>) (accessed on 10 June 2025)). The processed datasets generated in this study are held by the National Institute of Forest Science (NIFoS) and will be available following an embargo from the date of publication.

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Abbreviations

The following abbreviations are used in this manuscript:

AIC	Akaike Information Criterion
CBI	Composite Burn Index
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
dNBR	Differenced Normalized Burn Ratio
EDF	Effective Degrees of Freedom
ESA	European Space Agency
GAM	Generalized Additive Model
GCV	Generalized Cross-Validation
GLM	Generalized Linear Model
GRS80	Geodetic Reference System 1980
GVIF	Generalized Variance Inflation Factor
IDW	Inverse Distance Weighting
IPCC	Intergovernmental Panel on Climate Change
KMA	Korea Meteorological Administration
L2A	Level-2A
NBR	Normalized Burn Ratio
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
OR	Odds Ratio
OvR	One-vs-Rest
SWIR	Shortwave Infrared
TM	Transverse Mercator
TPI	Topographic Position Index
VIF	Variance Inflation Factor

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