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Modeling Delayed Mortality of Fire-Damaged Pines in Korea

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Abstract

This study aimed to develop and compare prognostic models (logistic regression, Cox proportional hazards, and random forest) to assess delayed mortality in pine (*Pinus densiflora*) following fires in Korea. Data from a 72-month monitoring of 734 trees across four fire areas were used, accounting for 19 variables: tree size, fire severity, multispectral indices, topography, and bioclimatic variables. Key predictors of mortality included diameter at breast height (DBH), bark scorch index (BSI), delta normalized burn ratio (dNBR), slope, topographic wetness index (TWI), precipitation of the warmest quarter, temperature seasonality and isothermality. The key results indicate that the random forest model was the most effective (AUC = 0.924; sensitivity = 0.892) in identifying trees at high risk of mortality. These results suggest that nonlinear approaches are effective for predicting delayed mortality in fire-damaged pines and can support rapid decision-making in post-fire forest management and restoration under increasing wildfire risk.

Keywords: wildfire; delayed mortality; modeling; random forest; logistic regression; Cox proportional hazards; *Pinus densiflora*; remote sensing

1. Introduction

Worldwide, climate change has increased the number of dry days and raised temperatures, leading to larger and more frequent wildfires [1–3]. In Korea, the annual average burnt area increased from 857 ha in the 2010s to 23,117 ha during the 2020s (2020–2025), and the number of large forest fires (≥100 ha) rose from 1.3 to 5.0 per year, indicating a substantial escalation of forest fire-related impacts, which culminated in a record-breaking event in March 2025 that burned 104,973 ha of forest area [4].

According to a survey conducted in 1956, three years after the armistice of the Korean War, 56% of Korea's forest area was degraded, and most of the current forests have been established through government-led restoration programs [5]. As a result, a substantial proportion of Korean forests consists of mature stands with abundant fuel and a uniform age structure, and pines (*Pinus densiflora* and *Pinus thunbergii*) account for 27% of the total forest area [6]. Approximately 64% of the total forest area is classified as natural forest [7]. In addition, even in planted forests, prescribed burning is not implemented, and only intensive thinning for fuel reduction is carried out on a limited basis [8]. Therefore, the increase in wildfire damage in Korea can be attributed to both climate change and forest structure. In Korea, *P. densiflora* is highly flammable due to its resin-rich tissues and high heat release, making it prone to ignition even at relatively low temperatures [9]. In addition, *P. densiflora* exhibits a mortality rate of 64% when surface fire causes stem charring to a

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height of 30%–60% of the total tree height, and shows a high mortality rate of 87% under intermediate levels of crown damage [10].

Wildfires are one of the most frequent and severe drivers of forest ecosystem change [11,12]. Wildfires can cause tree mortality not only through direct combustion of stems and crowns but also through indirect, secondary mechanisms associated with exposure to high temperatures. And the mortality of fire-damaged trees can influence forest carbon storage, biodiversity conservation, watershed functions, and other economic-social ecosystem services [13]. Because fire-induced tree mortality has diverse ecological and management implications, predicting post-fire mortality of fire-damaged trees is essential for risk assessment and conservation planning.

After a wildfire, tree mortality depends on multiple factors. Short-term predictors include fire characteristics such as type, duration, and intensity, as well as direct damage to crowns and stems caused by combustion, whereas long-term predictors include not only changes in soils and vegetation but also physiological stress induced by pests and diseases [14–18]. Extreme climatic conditions such as drought and heatwave stress also influence tree mortality [19–23], and topographic factors such as elevation, slope, and aspect further affect mortality patterns [24].

The application of diverse modeling approaches is crucial for understanding the mecha-nisms of post-fire tree mortality and for identifying management solutions appropriate to each fire-affected forest. Logistic regression, which estimates the probability of an event occurring, is the most basic model and has been used in more than one hundred studies on post-fire tree mortality [25]. The Cox proportional hazards model is a survival-analysis model originally developed in medical statistics to estimate the survival time until a spe-cific event, such as patient death. Although the Cox proportional hazards model is similar to logistic regression in estimating event probability, it also accounts for the time to event [26]. Random forest is a machine-learning ensemble method with excellent performance in classification problems [27].

Globally, studies on post-fire tree mortality are relatively common, but this is not the case in South Korea. Only a few studies have analyzed the characteristics of *P. densiflora* trees killed by wildfire in a single region using short-term survey data and statistical or modeling approaches [10,28–30]. Furthermore, these studies often lack long-term temporal monitoring beyond 1–2 years post-fire and do not adequately address the challenge of class imbalance in mortality datasets, which can substantially affect model performance and reliability. In addition, many of these studies have not fully accounted for variability in environmental conditions.

In this study, we used long-term monitoring data of fire-damaged *P. densiflora* stands, with observation periods ranging from 11 to 72 months, to identify key drivers of mortality, including climatic and topographic factors, and to evaluate three modeling approaches in order to identify the model best suited for predicting post-fire mortality.

2. Materials and Methods

2.1. Study Sites

This study was conducted in five Korean red pine (*P. densiflora*) stands located in four fire-damaged areas in Samcheok-si, Jeongseon-gun, and Gangneung-si in Gangwon-do Province, and Uljin-gun in Gyeongsangbuk-do Province, Korea. The study sites were selected from fire-damaged forests where *P. densiflora* was dominant and where individual trees remained alive after surface fires (Figure 1). Within each site, other tree species were either absent or present in very low numbers, and shrubs became abundant within 1–2 years after the wildfire. All selected stands were *P. densiflora* forests of age classes V–VI that were established after the late 1970s. The sites are characterized as temperate coniferous

forests, with mean annual temperatures ranging from 9.1 to 13.2 °C and mean annual precipitation ranging from 1112 to 1320 mm. Topographic conditions varied among regions, with slope aspects ranging from northwest (NW) to east (E) and elevations spanning from lowlands at 31.58 m to mountainous areas at 750.51 m. The mean slope ranged from 14.98° to 25.41°, reflecting the typical mountainous terrain of Korean forested landscapes (Table 1). No post-fire management interventions, including salvage logging or replanting, were conducted at any study sites during the monitoring period.

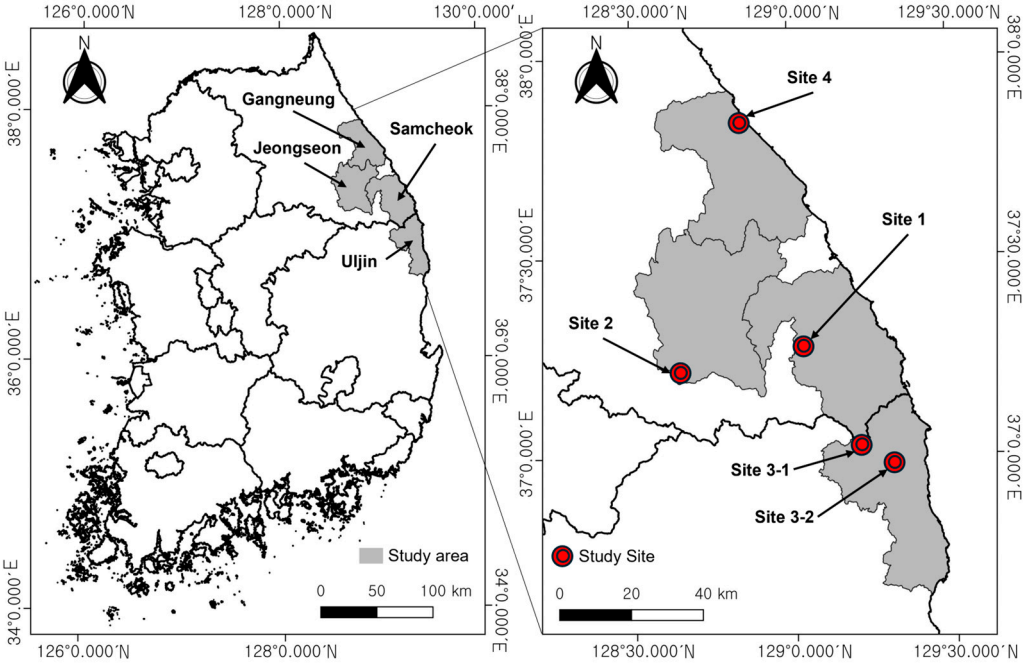


Figure 1. Location of Study Sites.

Table 1. Overview of Study Sites.

Site No.	Samcheok	Jeongseon	Uljin		Gangneung
	Site 1	Site 2	Site 3-1	Site 3-2	Site 4
Elevation (m)	750 ± 43	511 ± 11	282 ± 3	566 ± 5	31 ± 3
Aspect	NW	SW	SW	S	E
Slope (°)	22.48 ± 8.95	25.41 ± 6.65	14.22 ± 5.95	20.67 ± 6.43	14.98 ± 4.21
Dominant species	*P. densiflora*	*P. densiflora*	*P. densiflora*	*P. densiflora*	*P. densiflora*
Tree height (m)	17.7 ± 3.16	11.09 ± 2.20	16.05 ± 3.38	14.97 ± 3.60	15.53 ± 1.20
Crown height (m)	9.74 ± 3.21	5.59 ± 2.25	11.15 ± 4.95	6.13 ± 2.24	8.21 ± 2.68
DBH (cm)	33.55 ± 7.45	24.49 ± 6.16	30.47 ± 10.46	25.96 ± 7.32	36.47 ± 4.27
Age class (age range)	VI (50–60)	V (40–50)	V (40–50)	V (40–50)	V (40–50)
Wildfire occurrence date	9 May 2017	29 October 2020	4 March 2022		11 April 2023
Monitoring period	72 months	35 months	23 months		11 months
Monitored trees	351	182	65	106	30
Annual temperature *	9.1 °C	10.2 °C	11.4 °C	12.2 °C	13.2 °C
Maximum average temperature *	13.8 °C	16.6 °C	18.0 °C	17.6 °C	17.8 °C
Minimum average temperature *	5.5 °C	4.9 °C	5.2 °C	7.4 °C	8.9 °C
Precipitation *	1301 mm	1112 mm	1320 mm	1316 mm	1217 mm

* 2011–2020 average.

2.2. Sampling and Mortality Monitoring

Target trees were selected as those with no direct crown combustion and retained green needles. These trees showed visible bark charring, indicating forest fire damage. Each tree was assigned a unique identification number, and mortality was monitored at least once per year throughout the study period. The monitoring duration ranged from 11 to 72 months depending on the site. A total of 734 *P. densiflora* trees were surveyed across five sites: 351 at Site 1 (Samcheok), 182 at Site 2 (Jeongseon), 65 at Site 3-1 (Uljin), 106 at Site 3-2 (Uljin), and 30 at Site 4 (Gangneung). Mortality was recorded when the entire crown had senesced, with green foliage turning completely brown, or when no foliage remained on the crown. Trees that had been cut at the stem or uprooted to the extent that survival was deemed impossible were also classified as dead.

2.3. Variable Construction for Fire-Damaged Pine Mortality Data

The field survey methods, like the selection of field plots, measurement of sample trees, and monitoring procedures, were based on Kwon et al. (2021) [31]. In the present study, we further extended this approach by incorporating multispectral indices derived from remote sensing, topographic variables obtained using GIS, and bioclimatic variables calculated from meteorological data collected at an automatic weather station.

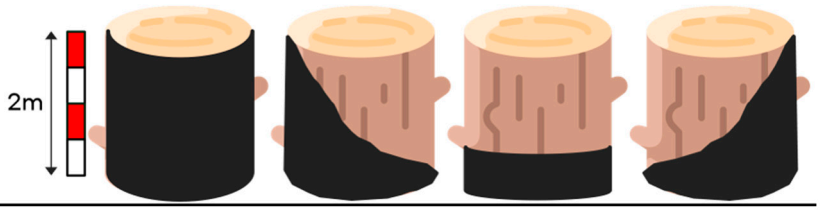
2.3.1. Fire-Damaged Tree Variables

Fire-damaged tree variables were composed of in situ measurements taken after fire events and remotely sensed indices that capture pre-fire and post-fire conditions. In the field, we measured tree size parameters including diameter at breast height (DBH), tree height, and crown height. Crown height was defined as the vertical distance from the forest floor to the lowest live foliage. Variables related to fire severity were derived by measuring the height and extent of bark scorch on the trunk. At all sites, all variables used for model training were collected through field surveys conducted within one year after the wildfire.

For each tree, the height of the highest visible bark scorch was measured from the ground in four directions. A rectangular area was defined on the bark surface at this height. The proportion of this area that was filled by scorch was recorded. From these measurements, Bark Scorch Height (BSH) and Bark Scorch Index (BSI) were calculated as illustrated in Figure 2.

To capture status changes in *P. densiflora* before and after fires, we analyzed multispectral indices derived from Sentinel-2 imagery. The indices used were the Normalized Difference Vegetation Index (NDVI), a widely used indicator of vegetation vigor; the Normalized Burn Ratio (NBR), commonly used to detect burn severity; and the Moisture Stress Index (MSI), which is sensitive to canopy moisture stress [32–35].

Wildfires in South Korea predominantly occur in March and April, prior to the onset of the rainy season. To minimize the influence of rainfall on multispectral indices, satellite images acquired within one month before and after each fire event were used. Using GPS coordinates, we extracted the pixel values corresponding to the location of each tree from the processed multispectral index images and incorporated them as predictor variables in the mortality models. For each index, the difference between the pre-fire and post-fire values was calculated and used as a predictor variable: dNDVI, dNBR, and dMSI (Table 2).



	N	E	S	W
H	2.00 m	2.00 m	0.50 m	2.00 m
R	100 %	50 %	100 %	50 %

$$BSH = \frac{H_N + H_E + H_S + H_W}{4} = \frac{2.00 + 2.00 + 0.50 + 2.00}{4} = 1.625$$

$$BSI = \frac{H_N R_N + H_E R_N + H_S R_N + H_W R_N}{4}$$

$$= \frac{(2.00 \times 1.00) + (2.00 \times 0.50) + (0.50 \times 1.00) + (2.00 \times 0.50)}{4} = 4.50$$

H: Maximum scorch height on the pine tree's stem,
R: Ratio of burned area to scorch height on one side,
N: North side of fire-damaged tree, E: East side of fire-damaged tree,
S: South side of fire-damaged tree, W: West side of fire-damaged tree

Figure 2. Calculation of Bark Scorch Height (BSH) and Bark Scorch Index (BSI).

Table 2. Sentinel-2 Satellite Image Information for Multispectral Indices.

	Image * Capture Date			
Site	**Site 1**	**Site 2**	**Site 3**	**Site 4**
Pre-fire	30 April 2017	26 October 2020	23 February 2022	7 April 2022
Post-fire	20 May 2017	31 October 2020	15 March 2022	12 April 2022

* Source: Sentinel-2 https://apps.sentinel-hub.com/eo-browser/ (accessed on 17 May 2025).

2.3.2. Topography Variables

Topography variables included elevation, slope, aspect, and the topographic wetness index (TWI) for each tree. TWI quantifies the relative potential of a location to accumulate water during rainfall and was used here as a proxy for topographically driven moisture stress in forest fire-damaged stands. Topographic variables were extracted for the location of each tree using GPS coordinates and incorporated as predictors in the mortality models.

2.3.3. Weather Variables (Bioclimatic Variables)

To assess the effects of climatic conditions on delayed mortality, we used bioclimatic variables [36,37]. Meteorological data were obtained from the nearest Automatic Weather System station for each study site. For each monitoring time point, we extracted meteorological data from the one-year period preceding the observation and used these data to derive a set of 19 bioclimatic variables. To reduce multicollinearity among bioclimatic variables, Pearson correlation coefficients were computed (Figure 3). Variables with correlation coefficients ≥ 0.7 were excluded (Table 3). Seven bioclimatic variables were retained for model training: Bio 3 (isothermality), Bio 4 (temperature seasonality), Bio 10 (mean temperature of the warmest quarter), Bio 12 (annual precipitation), Bio 15 (precipitation seasonality), Bio 18 (precipitation of the warmest quarter), and Bio 19 (precipitation of the coldest quarter).

Table 3. Information on Bioclimatic Variables.

	Bioclimatic Variables	Model Inclusion
Bio 1 (°C)	Annual mean temperature	Excluded
Bio 2 (°C)	Mean diurnal range: mean of monthly (T_{max}–T_{min})	Excluded
Bio 3 (%)	Isothermality: 100 × (Bio 2/Bio 7)	Used
Bio 4 (%)	Temperature seasonality: T_{std} × 100	Excluded
Bio 5 (°C)	Max temperature of the warmest month	Excluded
Bio 6 (°C)	Min temperature of the coldest month	Excluded
Bio 7 (°C)	Temperature annual range: Bio 5–Bio 6	Excluded
Bio 8 (°C)	Mean temperature of the wettest quarter	Excluded
Bio 9 (°C)	Mean temperature of the driest quarter	Excluded
Bio 10 (°C)	Mean temperature of the warmest quarter	Used
Bio 11 (°C)	Mean temperature of the coldest quarter	Excluded
Bio 12 (mm)	Annual precipitation	Used
Bio 13 (mm)	Precipitation of the wettest month	Excluded
Bio 14 (mm)	Precipitation of the driest month	Excluded
Bio 15 (%)	Precipitation seasonality: P_{std} × 100	Used
Bio 16 (mm)	Precipitation of the wettest quarter	Excluded
Bio 17 (mm)	Precipitation of the driest quarter	Excluded
Bio 18 (mm)	Precipitation of the warmest quarter	Used
Bio 19 (mm)	Precipitation of the coldest quarter	Used

T_{max}: Monthly average high temperature, T_{std}: Standard deviation of monthly temperature, T_{min}: monthly average low temperature, P_{std}: Standard deviation of monthly precipitation.

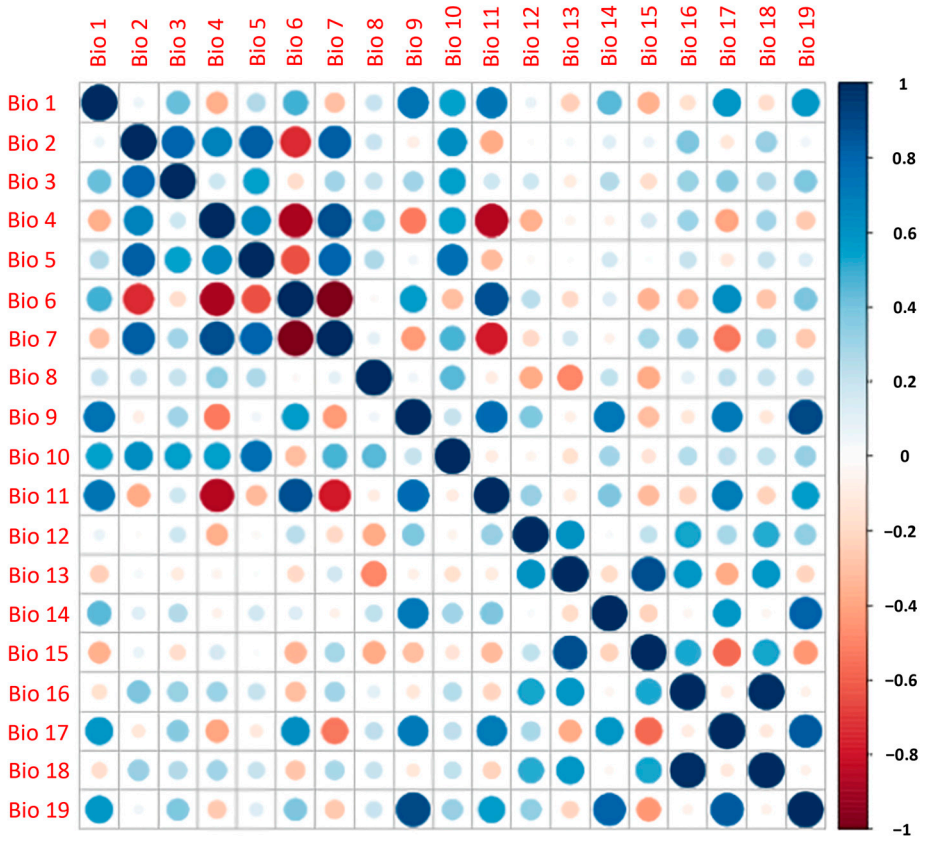


Figure 3. Correlation Analysis of Bioclimatic Variables. Circle size and color: Pearson correlation coefficient.

2.4. Models for Predicting Delayed Mortality of Forest Fire-Damaged Pines

2.4.1. Logistic Regression Model

The logistic regression model, a generalized linear model, uses a logit link function to estimate the relationship between a binary response variable and a set of predictor variables [38]. And the basic form of the model is expressed as follows:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k \quad (1)$$

where p is the predicted probability of post-fire tree mortality, X_k represents each predictor variable, and β_k is the corresponding regression coefficient.

To assess the linearity assumption of the logistic regression model, residual plots and smoothed residual curves were visually inspected for each predictor, evaluating whether the residuals were randomly distributed around zero. In addition, to statistically test whether the linearity assumption was valid, the Box–Tidwell test was performed using the following test form.

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_k X_k + \cdots + \gamma X_k \ln(X_k) \quad (2)$$

An interaction term of the form X_k was added to the model, and the significance of the interaction coefficient γ was evaluated to confirm the linearity of the logit with respect to each predictor.

2.4.2. Cox Proportional Hazards Model

The Cox proportional hazards model is a survival analysis model that is widely used in medical statistics to estimate survival time until the occurrence of a specific event, such as patient death [39]. In survival analysis, the hazard function $h(t)$, which represents the instantaneous event rate at time t, is expressed as:

$$h(t) = h_0(t) e^{(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)} \quad (3)$$

where $h_0(t)$ is the baseline hazard function, X_k denotes each predictor variable, and β_k is the corresponding regression coefficient.

To assess the linearity assumption, Martingale residuals were examined for each predictor [40]. The proportional hazards assumption was evaluated using Schoenfeld residuals [41]. Because the weather variables (bioclimatic variables) are time-dependent, the proportional hazards assumption was tested only for topography variables and fire-damaged tree variables.

In both the logistic regression and Cox proportional hazards models, we applied backward elimination based on the Akaike information criterion (AIC) to select variables that significantly influenced tree mortality [42].

2.4.3. Random Forest Model

The random forest model is an ensemble algorithm that combines multiple decision trees with bootstrap aggregating (bagging), known for its high predictive accuracy and robustness to overfitting [43]. Because model performance depends on parameter settings, we fixed the number of trees at 500 and the maximum depth at the package's default, and then optimized the node size and the number of variables tried at each split (Mtry). The node size was set between 1 and 57, and Mtry was set between 1 and 19, the total number of predictor variables. A total of 100 random forest models were trained using the training dataset, with different combinations of these parameters. And the parameter set

yielding the highest area under the ROC curve (AUC) was selected. Variable importance, provided by the random forest algorithm, was also used to assess the relative influence of each predictor on delayed mortality.

2.5. Model Performance Comparison and Evaluation Indices

For each monitoring time point, a dataset comprising 3571 observations of fire-damaged *P. densiflora* was compiled. At each site, the data were partitioned according to monitoring occasions (Site 1: 7 times, Site 2: 5 times, Site 3: 3 times, and Site 4: 3 times). The cumulative mortality rate at each monitoring time was calculated as the cumulative number of dead trees relative to the total number of trees at each site.

Trees confirmed as dead during previous monitoring occasions were excluded from subsequent data partitions, resulting in a dataset comprising 3571 fire-damaged *P. densiflora* trees. The dataset was split into 80% for model training and 20% for independent evaluation.

Model performance was compared using the receiver operating characteristic (ROC) curve and the area under the curve (AUC). For each model, the optimal threshold was defined as the value that maximized Youden's index. Youden's index is defined as

$$Youden's\ Index = Sensitivity + specificity - 1 \tag{4}$$

and we selected the point on the ROC curve at which this value was maximized. Using this cutoff, performance metrics (accuracy, sensitivity, specificity, precision, F1-score, Brier score) were calculated from the confusion matrix based on true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), and N is number of predictions, f_t is the predicted probability for the t-th event, and o_t is the actual outcome for the t-th event (0 or 1)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$precision = \frac{TP}{TP + FP} \tag{6}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{7}$$

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

$$F1\ score = 2 \times \frac{Sensitivity \times Precision}{Sensitivity + Precision} \tag{9}$$

$$Brier\ score = \frac{1}{N}\sum_{t=1}^{N}(f_t - o_t)^2 \tag{10}$$

2.6. Statistical Analysis and GIS Processing

We performed all data processing and statistical analyses in R (version 4.3.2; R Foundation for Statistical Computing, Vienna, Austria) using the following packages: tidyverse and dplyr for data manipulation, autoReg and rstatix for logistic regression, survival and rms for the Cox proportional hazard model, random forest, and vip for randomforest, and pROC for model performance assessment. Topographic analysis and the computation of multispectral indices from Sentinel-2 imagery were performed using QGIS (version 3.28.11; QGIS Development Team).

3. Results

3.1. Changes in Cumulative Mortality and Variable Importance

Over the 72-month monitoring period following a forest fire occurrence, 191 of 734 monitored *P. densiflora* trees died, resulting in a cumulative mortality rate of 26.0% (Figure 4). Short-term mortality within two years after fire varied widely among sites, ranging from 5.4% to 42.1%. In contrast, at Site 1, which was monitored for the longest period, cumulative mortality continued to increase for approximately five years after the fire, with little additional mortality observed after six years.

To identify the variables that strongly influenced mortality, we examined variable importance from the random forest model. Among the fire-damaged tree variables, DBH, BSI, BSH, and dNBR showed high importance. In particular, DBH, BSI, and BSH were the most influential predictors in the model (Figure 5). Among the topography variables, slope and TWI at the tree location showed high importance. For the weather variables, Bio 18 (precipitation of the warmest quarter), Bio 4 (temperature seasonality), and Bio 3 (isothermality) were identified as the most important predictors.

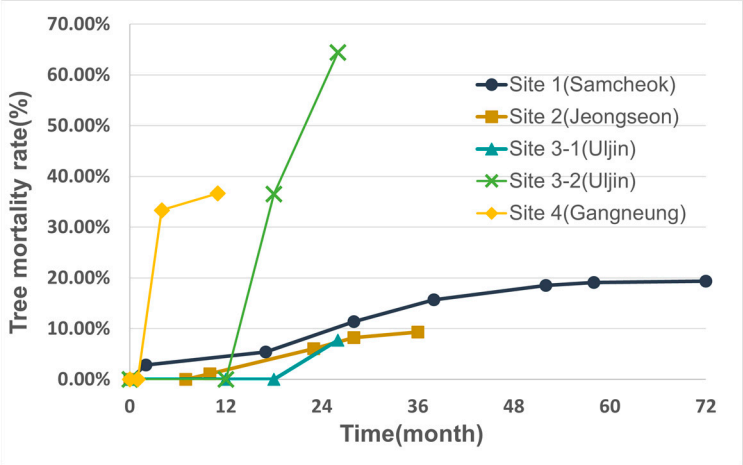


Figure 4. Survival Curves by Study Site.

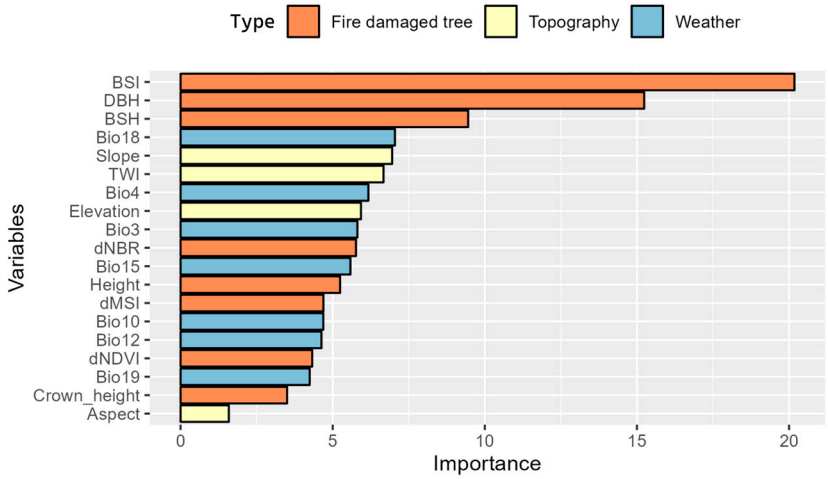


Figure 5. Variable Importance in the Random Forest Model.

3.2. Verification of Basic Model Assumptions and Parameter Optimization

3.2.1. Linearity Assumption in the Logistic Model

To verify the linearity assumption of the logistic regression model, residual plots and smoothed residual curves were visually inspected (Figure 6). The scatter of residuals

around zero showed no clear systematic pattern across all variables, indicating that the linearity assumption was satisfied for all variables included in the model. In most plots, the smoothed residual curve (blue line) remained close to the horizontal line at zero, lying nearly parallel or coincident with the ideal line y = 0 (red line). Minor deviations or slight curvatures in the smoothed curves for DBH and BSI did not lead to large deviations from zero, and thus were judged to be consistent with linearity assumption. These results indicate that the model's predictions reflect a stable relationship between fire-damaged tree mortality and the predictors. These results also indicate that the model does not systematically under- or over-predict mortality across the range of any predictor variable.

The linearity assumption was further statistically tested using the Box–Tidwell test (Table 4). All interaction terms constructed for the test showed *p*-values greater than 0.05, supporting that the linearity assumption was not violated at the 5% significance level. However, the *p*-values for BSI and DBH were 0.0522 and 0.0654, respectively, which are very close to the 0.05 threshold. The slight curvature observed in the residual scatter plots, together with the Box–Tidwell test results, suggests that the linearity assumption for DBH and BSI may weaken at extreme values.

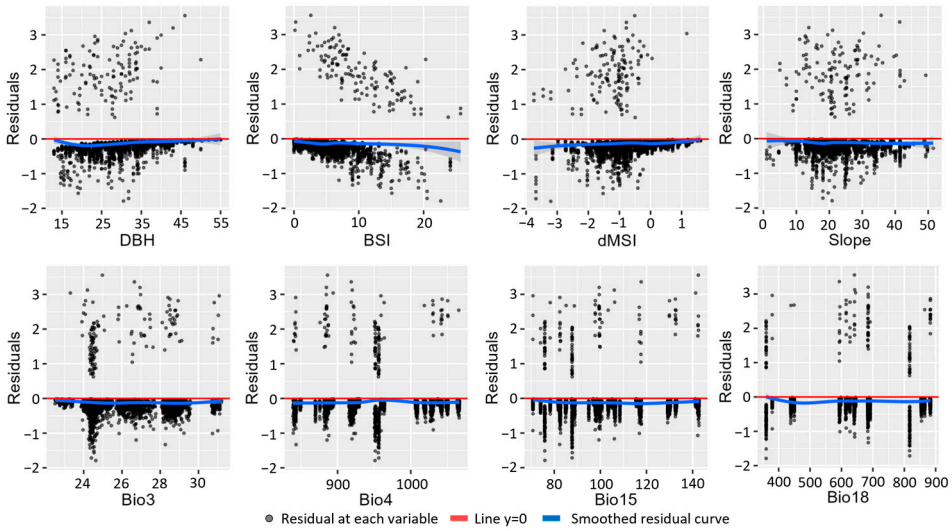


Figure 6. Residual Scatter Plot for Testing Linearity of Variables.

Table 4. Results of the Box-Tidwell Test.

Predictors	Logistic Regression Linearity	
	Odds Ratios	*p*
DBH	1.23	0.0522
BSI	0.89	0.0654
dMSI	0.27	0.1616
Slope	1.03	0.5106
Bio 3	1.18	0.9549
Bio 4	1.02	0.8159
Bio 15	1.13	0.2762
Bio 18	1.01	0.4741

3.2.2. Linearity and Proportional Hazards Assumptions in the Cox Model

Linearity of the predictors in the Cox model was assessed using Martingale residuals (Figure 7). For all variables, residuals were randomly distributed around zero, and the smoothed residual curves (blue lines) closely followed the horizontal line y = 0. This indicates that the model does not systematically over- or under-predict survival time at

any particular value of the predictors, and that the hazard ratio remained approximately constant across the range of each predictor.

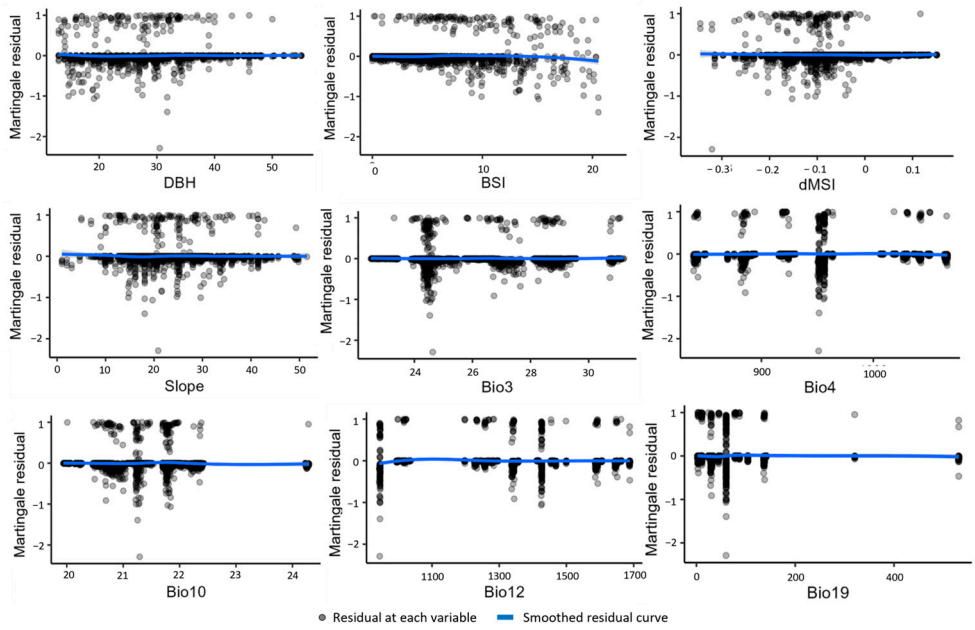


Figure 7. Martingale Residual Scatter Plot for Testing Linearity of Variables.

The proportional hazards assumption was evaluated using scaled Schoenfeld residuals (Figure 8). Visually, the residuals for each variable showed no clear trend over time, and the smoothed residual curves (blue lines) remained close to zero without pronounced bends. Consistent with this visual assessment, the Schoenfeld tests indicated no statistically significant violation of the proportional hazards assumption for any variables (DBH: $p = 0.117$; BSI: $p = 0.483$; dMSI: $p = 0.610$; slope: $p = 0.314$). Because all p-values were greater than 0.05, the proportional hazards assumption was considered satisfied for all variables in the Cox proportional hazards model. These results support the suitability of the Cox proportional hazards model for modeling post-fire mortality of *P. densiflora* in this study.

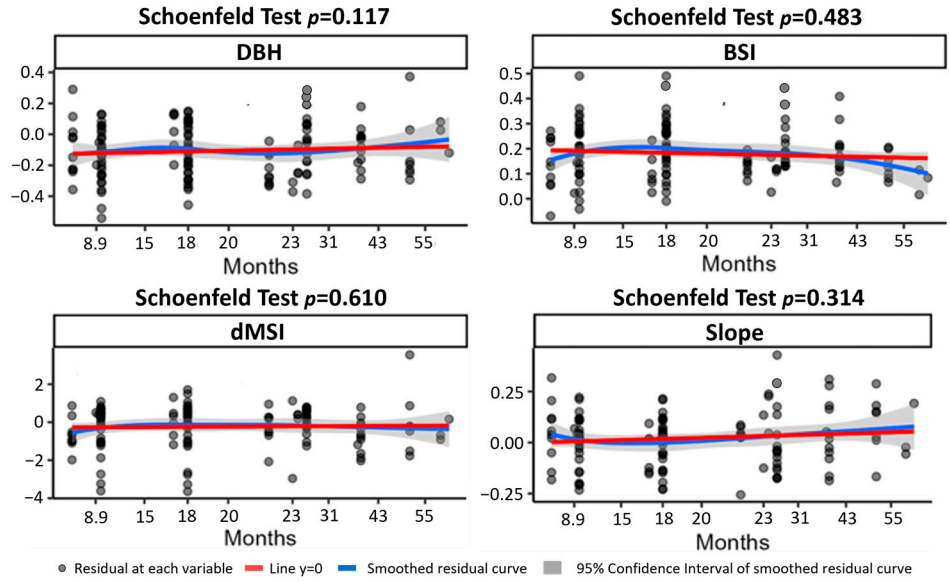


Figure 8. Schoenfeld Residual Scatter Plot for Testing Proportional Hazards Assumption.

3.2.3. Parameter Optimization for the Random Forest Model

The performance of the random forest model was evaluated across a range of node sizes and numbers of variables tried at each split (Mtry) (Figure 9). Smaller node sizes tended to yield higher performance. However, both very small and very large values of Mtry were associated with lower AUCs. The highest AUC was achieved when the node size was 1, and the Mtry was 15. This result is consistent with previous studies that applied random forest models to post-fire tree mortality and similar ecological applications [44–46].

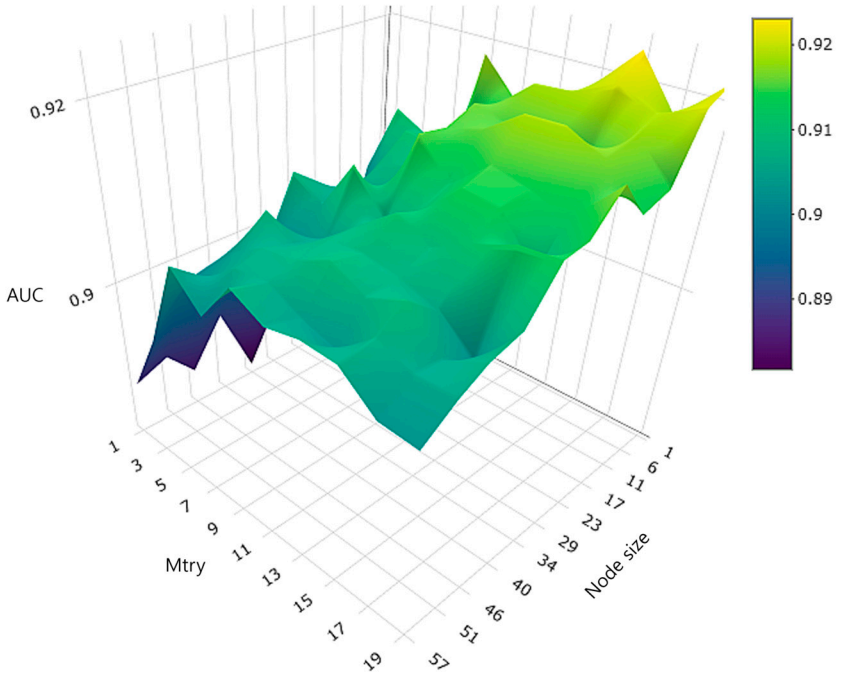


Figure 9. AUC Results for Different Parameters of the Random Forest Model.

3.3. Model Performance Comparison and Evaluation

3.3.1. ROC Curve Analysis

ROC curves were generated using the trained models and the test dataset, and the AUC was calculated to compare model performance (Figure 10). The logistic regression model yielded an AUC of 0.890 (95% CI: 0.843–0.937), indicating high predictive ability, although it was the lowest among the three models. The optimal cutoff value was 0.27, classifying trees with predicted post-fire mortality probabilities above this threshold level as dead to balance sensitivity and specificity on the ROC curve. This result is broadly consistent with the 0.30 threshold suggested in previous logistic regression studies predicting delayed mortality of fire-damaged pines [31].

The Cox proportional hazards model achieved an AUC of 0.892 (95% CI: 0.834–0.951), comparable to that of the logistic model despite being a survival model rather than a simple binary classifier. The optimal cutoff value was 0.96, classifying only trees with very high hazard ratios as dead, thereby minimizing misclassification of surviving trees and yielding high specificity at the expense of sensitivity.

The random forest model achieved the highest AUC among the three models, with a value of 0.924 (95% CI: 0.886–0.963). The optimal cutoff value was 0.04, which is very low. In contrast to the Cox model, the random forest model prioritizes identifying dead trees, resulting in high sensitivity but relatively lower specificity.

AUC is a prevalence-independent metric that is particularly useful for evaluating model performance on imbalanced datasets, such as fire-damaged tree mortality data [47]. Given that the random forest model achieved the highest AUC, it was considered the

best-performing model among the three approaches. This indicates that it most accurately reflects the underlying mortality probability structure of fire-damaged *P. densiflora*.

Differences in optimal cutoff values across models reflect the fact that each model uses a different algorithm to estimate delayed mortality, and thus, the point on the ROC curve where the joint value of sensitivity and specificity is maximized differs among models. Among the three models, the random forest model, with a cutoff value of 0.04 and high sensitivity, best meets the objective of this study: accurate prediction of post-fire tree mortality of fire-damaged pines.

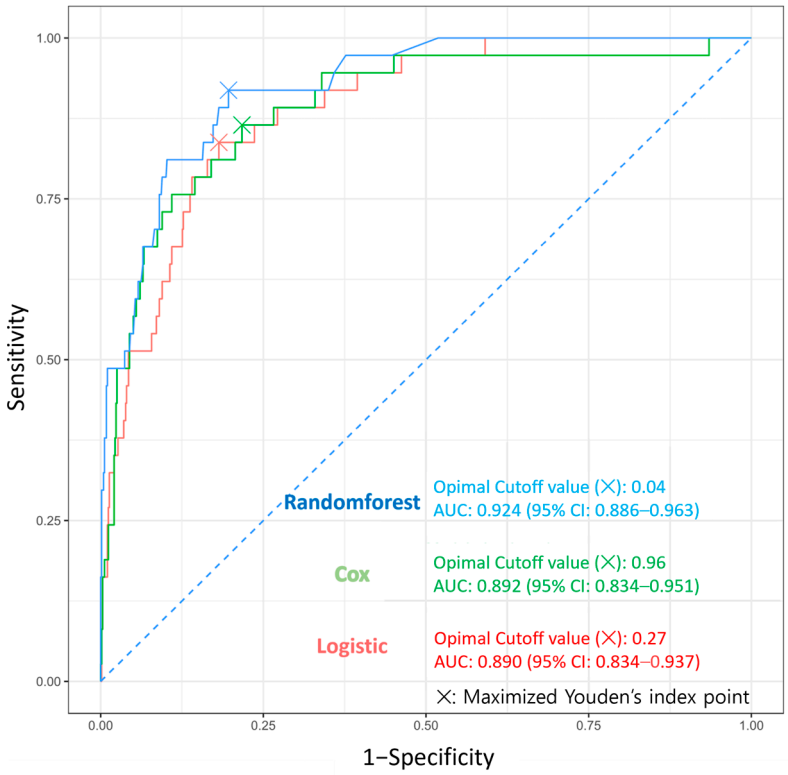


Figure 10. ROC Curve Plot for three Models.

3.3.2. Confusion Matrix, F1-Score and Brier Score Comparison

Confusion matrices were calculated for each model using the test dataset (Table 5). For survivor prediction, the logistic regression model achieved a specificity of 0.8183, which was very similar to the random forest model's specificity of 0.8035. The Cox proportional hazards model showed a lower specificity of 0.7829, indicating relatively poorer performance in correctly identifying surviving trees.

For mortality prediction, the random forest model reached a sensitivity of 0.8919, higher than the logistic regression model (0.8378) and the Cox proportional hazards model (0.8649). This indicates that the random forest model predicts fire-damaged tree mortality better than the other two models. In addition, the random forest model showed superior performance in metrics that account for class imbalance in the training data, namely the F1-score and the Brier score. The F1-score was 0.3251, the highest among the three models, indicating the most balanced predictive performance, and the Brier score was 0.331, the closest to 0, suggesting that the predicted probabilities showed the best agreement with the observed mortality outcomes.

Table 5. Comparison of Model Performance Using a Confusion Matrix.

		Model predicted		
		0 (=Alive)	1 (=Dead)	
Actual status	0 (=Alive)	554	123	Specificity 0.8183
	1 (=Dead)	6	31	Sensitivity 0.8378
F1-score 0.3246		Accuracy 0.8193	Precision 0.2013	Brier score 0.0400
Logistic regression model				
		Model predicted		
		0 (=Alive)	1 (=Dead)	
Actual status	0 (=Alive)	530	147	Specificity 0.7829
	1 (=Dead)	5	32	Sensitivity 0.8649
F1-score 0.2963		Accuracy 0.7871	Precision 0.1788	Brier score 0.8954
Cox proportional hazard model				
		Model predicted		
		0 (=Alive)	1 (=Dead)	
Actual status	0 (=Alive)	544	133	Specificity 0.8035
	1 (=Dead)	4	33	Sensitivity 0.8919
F1-score 0.3251		Accuracy 0.8081	Precision 0.1988	Brier score 0.0331
Random forest model				

4. Discussion

4.1. Variables Influencing the Mortality of Fire-Damaged Pines

Among the fire-damaged tree variables, BSI and dNBR showed the highest variable importance. In particular, BSI showed much higher variable importance than the other predictors. This is likely because the mean BSI values at the high-mortality sites, Site 3-2 and Site 4, were 12.22 and 10.04, respectively, which are far above the overall mean BSI of 5.79 for all trees in the dataset. Indices of bark charring are widely used in fire-damaged tree mortality studies as indicators of fire-damage intensity. Their high importance in this study is consistent with the large influence of stem charring on post-fire mortality reported in previous studies [48–50]. The dNBR, a widely used multispectral index for quantifying burn severity, has also been reported as a key predictor in remote sensing-based assessments of fire-damaged forest mortality, and the present results are consistent with these findings [51–53].

Among the topography variables, slope and the Topographic Wetness Index (TWI) at the tree location showed high variable importance. Steep slopes can limit groundwater availability and increase moisture stress in trees, which may partially explain the relatively high importance of slope in this study [54]. Trees growing on slopes often develop asymmetric crowns, a trait that can increase the risk of wind- or fire-induced tree falling [55]. In fire-damaged trees, structural weakening can reduce strength by up to 24%, potentially increasing the risk of stem breakage or the tree falling at the burned site in the trunk compared with non-damaged trees [56,57]. The TWI indirectly reflects soil moisture conditions by capturing the tendency of water to accumulate at a given location. Low TWI values indicate

locations where available water may decline sharply after fire under drought conditions. This increases the risk of delayed mortality due to severe moisture stress [58–63].

Among the weather variables, Bio 18 (precipitation of the warmest quarter) showed the highest variable importance. In Korea, the warmest quarter largely coincides with the summer East Asian monsoon, when a substantial proportion of annual precipitation is concentrated. For *P. densiflora* stands typically affected by spring fires, this monsoon period coincides with a key phenological phase of intense cambial activity and tissue regeneration [63,64]. When summer rainfall is reduced during this time (low Bio 18), trees experience both high atmospheric evaporative demand and insufficient soil water supply, greatly constraining hydraulic recovery and increasing the likelihood of hydraulic failure or carbon starvation [65,66]. Thus, the strong importance of Bio 18 suggests that the survival of fire-damaged *P. densiflora* depends on whether sufficient summer monsoon rainfall is available during the growing seasons after fire.

Taken together, the high importance of BSI, dNBR, slope, TWI, and Bio 18 suggests that post-fire mortality of *P. densiflora* is governed not by simple linear effects of individual predictors, but by nonlinear and interacting responses to the combined influences of fire damage, topography-driven water availability, and climatic stress.

Due to these nonlinear and interactive responses, the predictive performance of the random forest model was likely superior to that of the logistic regression and Cox models, which rely on linearity assumptions.

4.2. Mortality–Predictor Relationships Based on Model Assumption

4.2.1. Potential Non-Linear Responses of BSI and DBH to Mortality Probability

In the linearity checks of the logistic regression model, BSI and DBH satisfied the statistical test of linearity, but their residual curves showed slight curvature at extreme values. This pattern is consistent with, but does not by itself prove, the possibility that when BSI exceeds a certain range indicating severe bark scorch, mortality probability may increase more steeply than would be expected under a strictly linear response. We therefore consider a threshold-like effect of high bark scorch on mortality as a working hypothesis that requires more detailed analysis in future studies rather than as a firmly established relationship.

DBH also showed a complex pattern: small trees generally exhibited higher mortality probability, but very small trees may deviate from a simple linear increase, suggesting that a saturating or threshold-like response could be present. One plausible physiological explanation is that non-linear changes in bark thickness with increasing stem size may alter the thermal protection of the cambium, given that the critical temperature at which bark can no longer protect cambial tissue is related to bark thickness [67,68]. However, since both DBH and BSI satisfy the linearity assumption in this study, this interpretation should be considered a hypothesis requiring specific verification. This must be verified through internal diagnosis of damaged trees, such as using Electrical Resistivity Tomography (ERT) [69].

4.2.2. Temporal Influence of Mortality-Related Variables

In the Cox proportional hazards model, all variables met both the linearity and proportional hazards assumptions. This indicates that the fire-damaged tree variables included in the model (DBH, BSI, and dMSI) and the topography variable (slope) exerted consistent effects on post-fire mortality throughout the survival period. In addition, by treating trees that survived until the end of their site-specific follow-up as right-censored, the model explicitly accounts for differences in monitoring duration among sites, so that unequal observation lengths are incorporated into the time-to-event framework rather than ignored.

The present Cox model thus appears capable of capturing not only short-term (1–2 years) mortality but also longer-term (3–5 years) delayed mortality trends [70].

In the cumulative mortality patterns, sites with high BSI, such as Site 3-2 (Uljin) and Site 4 (Gangneung), exhibited a sharp increase in mortality within 1–2 years after the fire. In contrast, sites with large DBH and low slope, such as Site 1 (Samcheok), Site 2 (Jeongseon), and Site 3-1 (Uljin), showed delayed mortality over several years, extending from 3 to 5 years after fire occurrence. Together, the assumption checks and the temporal patterns of cumulative mortality suggest that the probability of post-fire mortality responds approximately linearly to these predictors, but the timing of death varies among trees. Within this time, the relative influence of each predictor remains stable, despite differences in follow-up length across sites. This indicates that modeling based on initial post-fire inventory data can be a key tool for medium- to long-term prediction of mortality and for guiding post-fire forest management and restoration planning.

4.3. Modeling and Evaluation for Predicting Post-Fire Mortality

4.3.1. Importance of Parameter Optimization for Random Forest Models

In general, a smaller node size produces finer and more diverse decision trees, which tends to maximize AUC improvement in random forest models, and this pattern was also observed in the present study [71]. The fact that a smaller node size consistently improved model performance in the parameter-tuning results further suggests that the improvement was likely driven by the class imbalance in the training data [72]. In this study, dead trees were fewer than surviving trees, so a smaller node size probably allowed minority-class (dead) characteristics to be represented more sensitively, thereby improving the sensitivity used to calculate AUC.

In contrast, the number of variables sampled at each split (Mtry) decreased AUC when set too low or too high, and showed a highly non-linear pattern with the highest AUC at 15 Mtry. When Mtry is too small, the information available to each decision tree is limited; when it is too large, the diversity among trees decreases. The fact that 15 Mtry yielded the highest AUC among the values tested suggests that the predictors in this study interacted in a complementary way to influence post-fire mortality.

4.3.2. Evaluation of Post-Fire Mortality Prediction Models

The logistic regression model showed performance comparable to the random forest model in all metrics except sensitivity, which was the lowest among the three models. This indicates that the predictors used in the model are approximately linearly related to mortality probability, thus allowing relatively stable survival prediction. The particularly low sensitivity of the logistic regression model likely arose from the class imbalance in the training data. As a result, the model learned the characteristics of surviving trees well, but insufficiently captured the features of the minority class (dead trees), leading to lower sensitivity. Some variables such as DBH and BSI, may exhibit non-linear relationships with mortality at extreme values, which could have further reduced the mortality-prediction performance of the logistic regression model that relies on a linear relationship assumption.

The Cox proportional hazards model showed the lowest performance in all metrics except sensitivity. In this model, trees with small DBH, high BSI, and steep slopes were predicted to have post-fire mortality probabilities above the cutoff value from the very beginning of the survival period. Consequently, many trees that were actually still alive early in the follow-up period were classified as dead, which reduced the overall model performance. The Cox model showed a lower F1 score compared with the other two models. This suggests that it is not primarily optimized for direct binary mortality prediction using

a cutoff value. Instead, the model may be better suited for estimating the temporal trend of mortality risk over time [73].

The random forest model exhibited notably higher sensitivity and F1 score than the other two models. This is likely because random forest, as an ensemble of many decision trees, is inherently robust to outliers and noise [74]. In addition, random forest better captures the characteristics of minority classes and effectively represents complex non-linear relationships and interactions among predictors [75,76]. These properties enabled the model to more accurately predict relatively rare mortality events, making it the best-performing model.

The finding that the models exhibited high sensitivity and low specificity due to class imbalance, and that the random forest model outperformed the other models in prediction accuracy, has also been reported in previous studies [77]. Moreover, the performance metrics (sensitivity, specificity, and AUC) of the three models used in this study were similar to or, in some cases, higher than those reported in earlier studies [31,77,78]. However, these results alone do not justify an absolute conclusion that the variables and models used in this study are universally optimal for predicting mortality, as the observed performance may partly reflect the ecological characteristics of the target species. Therefore, performance comparisons with other studies should be interpreted not as an absolute standard, but rather as a reference for the typical range of predictive performance in mortality modeling. Considering these points, the models in this study can be regarded as having achieved a level of predictive performance that is meaningful from a research perspective.

4.3.3. Appropriate Performance Metrics for Data and Model Characteristics

The mortality rate of fire-damaged trees in this study was 26.0%, meaning that the dataset is imbalanced, with fewer dead than living trees. In such cases, evaluating models solely by accuracy may overestimate models that perform well for predicting survival but poorly for predicting mortality [79]. It is therefore necessary to consider not only accuracy and specificity (survival prediction) but also sensitivity and F1 score, which better reflect the ability to predict mortality [80,81].

When these metrics are considered, the random forest model showed higher performance than the Cox proportional hazards model across all indicators and showed performance similar to the logistic regression model. In particular, its sensitivity and F1 score—the metrics that best capture mortality prediction—were the highest among the three models, making it the most suitable for the present study's objective of predicting post-fire mortality of pine trees. This suggests that mortality prediction of fire-damaged trees involves complex physiological and ecological mechanisms. Non-linear ensemble models such as random forest may therefore provide more reliable and reproducible support for this task.

4.4. Application of Models in Post-Fire Management and Restoration

In this study, the cutoff value was set at the threshold where the sum of specificity and sensitivity was maximized for each model. In general, fire-damaged trees tend to have reduced resistance to pests and diseases and may attract insects [82–85]. In South Korea, the impact of pine-wood nematodes is particularly severe, and *P. densiflora* killed by fire can serve as oviposition sites for the Monochamus beetles, the vector of the pine-wood nematode, thereby increasing the risk of infection to nearby surviving trees [86]. Therefore, in this study, we focused on the model performance for predicting dead trees and evaluated the models primarily in terms of sensitivity rather than precision.

However, when applying these models in real post-fire management settings, the cutoff value can be adjusted according to management objectives, allowing sensitivity and

precision to be tuned to achieve the desired level of performance. By applying a lower cutoff value in the model, forest managers can adopt a proactive strategy that targets trees at high risk of death and associated pest problems before they arise. In contrast, in areas where the burned forest has high genetic or conservation value, a higher cutoff can be used to retain as many potential seed trees as possible and remove only those trees whose mortality is almost certain, thereby supporting a more conservative, preservation-oriented management approach. As mentioned in the Introduction, in Korea, the proportion of mature forests is steadily increasing, while forest management for fuel reduction is still implemented only to a limited extent. In areas where surface fires have occurred and the risk of fire recurrence is high, forest managers could use the model-predicted probability of tree mortality to identify priority trees for thinning to prevent crown fires.

However, because the models developed in this study were calibrated under specific regional and climatic conditions in Korea and for a single species, *P. densiflora*, forest managers should exercise caution when applying them directly to burned areas in practice. To ensure prediction reliability, the models may need recalibration using additional data, adjusted critical thresholds, and additional variables such as stand density and other aspects of forest structure.

4.5. Limitations

In this study, we predicted post-fire tree mortality based on tree size, fire-damage intensity, topography, and weather, and we interpreted the importance of these predictors in an ecological context. However, we did not explicitly analyze nonlinear response interactions among predictors, nor did we account for post-fire ecological processes that can affect tree mortality, such as pest and disease outbreaks, wildfire behavior, weather events (e.g., typhoon), competition among trees, or pre-fire tree condition [87–89]. Incorporating these factors into future models could enhance their applicability for post-fire forest management decisions, including pest control and thinning.

Mortality prediction indexes based on the soot or scorch severity of fire-damaged trees, such as the bark scorch index (BSI), have been validated in multiple studies as powerful tools [28,90–93]. However, because such indices must be collected through field surveys, they require considerable time and labor and are limited in their applicability to large-area fire-damaged forests. In addition, the R (ratio of burned area to scorch height on one side) used to calculate the BSI may be subject to observer bias. In contrast, remote sensing-based indexes such as the difference normalized burn ratio (dNBR) can be rapidly applied over large forest areas. In addition to the indices used in this study, various spectral indices exist, so future studies should explore remote sensing indices that are more suitable for predicting mortality.

Moreover, sample size differed among sites, so the models—especially the random forest model—may be more influenced by conditions at Site 1 than at data-poor sites. Future studies should consider site-level weighting or stratified modeling to better balance the influence of locations with highly uneven sample sizes. The dataset used to train the models in this study exhibited class imbalance between dead and surviving trees. As a result, the models may not have fully learned the characteristics of dead trees. This issue is particularly important given that the focus of this study was delayed mortality, and therefore there is a need to apply resampling techniques in future work to address the class imbalance in the data. Differences in the monitoring period across sites could have further exacerbated this problem. At Site 1, which had the longest monitoring period, no additional mortality was observed after approximately six years. In contrast, the other sites were monitored for up to 36 months only, so additional mortality may have occurred after that time. Although the Cox model result partly mitigates the impact of unequal monitoring

durations across sites, this issue is not completely resolved. Only Site 1 was monitored until mortality stabilized, whereas the other sites were followed for a shorter period, so some late mortality may have been missed. Future research should apply consistent long-term monitoring to all sites, comparable to Site 1, until post-fire mortality stabilizes.

The monitoring interval may also have affected model performance. Because tree mortality is recorded at the time of each survey, when the monitoring interval is one year, it is difficult to accurately determine the actual timing of death. For example, it is hard to distinguish whether a tree died during a hot summer with extreme heat or during a dry winter with low precipitation. Given the nature of the Cox proportional hazards model, which explicitly accounts for time, such uncertainty in the timing of events may lead to reduced prediction performance. Compared with logistic regression, the Cox proportional hazards model shows higher prediction performance when predicting the same event if the observation period is longer, the monitoring interval is shorter, and the mortality rate is higher [94]. Therefore, future studies should consider not only direct confirmation of mortality through field surveys but also methods for accurately detecting the timing of death using remote sensing.

5. Conclusions

In this study, we used monitoring data on fire-damaged trees for up to 72 months to compare and evaluate three mortality prediction models and to identify the most suitable model. The main predictors of mortality included DBH, BSI, dNBR, slope, TWI, precipitation in the warmest quarter, temperature seasonality, and isothermality. Taken together, these variables indicate that post-fire tree mortality is influenced not only by tree size and fire-damage intensity but also by external factors such as topography and climate.

The three models showed different strengths depending on management objectives and the nature of predictor–response relationships. The random forest model most effectively captured the minority (mortality) class and nonlinear patterns, yielding high sensitivity and F1 scores and making it suitable when the primary goal is to identify high-risk trees or stands and to minimize missed mortality cases. The logistic regression model provided stable estimates when relationships between predictors and mortality were approximately linear, and its simple functional form was useful where interpretability is prioritized. The Cox proportional hazards model was valuable for assessing how mortality risk changes over time and for evaluating the timing of delayed mortality, which is informative for planning, monitoring, and interventions, although it tended to overestimate mortality probability for trees with extreme characteristics.

In future studies, it will be necessary to compare models based on field survey indices such as the BSI with models based on remote-sensing indices such as the dNBR, so that the mortality prediction approach developed here can be extended from labor-intensive plot surveys to large-area assessments of fire-damaged forests. In addition, long-term and more frequent monitoring of fire-damaged trees across sites will be needed to capture late mortality and to reduce uncertainties related to class imbalance, unequal follow-up durations, and the exact timing of death. Such monitoring, combined with explicit analysis of nonlinear responses, interactions among predictors, and post-fire biotic processes (e.g., pest and disease outbreaks and competition), would allow future models to more fully describe the ecological mechanisms of delayed mortality and to provide stronger support for operational decisions in post-fire forest management and restoration.

The results of this study provide a basis for a new, model-based approach to post-fire assessment and restoration planning, enabling more rapid and efficient strategies for prioritizing restoration actions under increasing fire-related mortality driven by climate change.

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Conflicts of Interest: The authors declare no commercial or financial conflicts of interest. Early post-fire data from the Samcheok site were partially reported in Kwon et al. (2021) [31]; the current study extends that dataset with longer monitoring and additional sites and applies new modeling approaches.

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