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Predicting Post-Fire Tree Mortality in a Temperate Pine Forest, Korea

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Abstract: Warmer and drier conditions in temperate regions are increasing the length of the wildfire season. Given the greater fire frequency and extent of burned areas under climate warming, greater focus has been placed on predicting post-fire tree mortality as a crucial component of sustainable forest management. This study evaluates the potential of logistic regression models to predict post-fire tree mortality in Korean red pine (*Pinus densiflora*) stands, and we propose novel means of evaluating bark injury. In the Samcheok region of Korea, we measured topography (elevation, slope, and aspect), tree characteristics (tree/crown height and diameter at breast height (DBH)), and bark injuries (bark scorch height/proportion/index) at three sites subjected to a surface fire. We determined tree status (dead or live) over three years after the initial fire. The bark scorch index (BSI) produced the best univariate model, and by combining this index with the DBH produced the highest predictive capacity in multiple logistic regression models. A three-variable model (BSI, DBH, and slope) enhanced this predictive capacity to 87%. Our logistic regression analysis accurately predicted tree mortality three years post fire. Our three-variable model provides a useful and convenient decision-making tool for land managers to optimize salvage harvesting of post-fire stands.

Keywords: bark scorch index (BSI); forest ecosystems; natural disturbances; sustainable management; tree mortality; logistic regression; *Pinus densiflora*; wildfire

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1. Introduction

Agents of natural disturbance such as wind, fire, and insects affect forest dynamics and structure by altering ecosystem functioning, creating diversified habitats, and maintaining biodiversity [1–4]. Climate change will alter the natural disturbance regimes in forest ecosystems [1,5,6]. In recent decades, warmer and drier climates have increased the length of wildfire seasons and changed the patterns of wildfires [7–10]. Fire alters regeneration patterns and weakens plant defensive systems such as resistance to herbivores [11,12]. In addition, trees may be more vulnerable to fire-caused injury after climate-mediated drought stress and these consequences affect forest management planning [13,14].

Given these critical concerns, future post-fire landscape restoration will be challenging. This is particularly true in Korea, as Korean even-aged forests are characterized by a dense growing stock (approximately 154 m^3 ha^{-1}), leading to a high fuel accumulation. Thus, these forests are quite vulnerable to the expected increase in the frequency and severity of regional fire regimes [15]. Accordingly, predicting post-fire tree mortality for various tree species and forest types will be crucial for ensuring sustainable forest management in the face of climate change.

In the Republic of Korea, the majority of wildfires occur in the dry and windy spring. Between 1980 and 1999, 287 wildfires burned an average area of 1250 ha per year. More wildfires were observed over the last 20 years (2000–2019), where 481 wildfires burned an annual average area of 2650 ha [16], thereby demonstrating a marked increase in the occurrence and area burned because of more human activities in forests and climate change [17].

These wildfires have highlighted the need for reliable tools for predicting the post-fire mortality of Korean red pine (*Pinus densiflora* Sieb & Zucc.), a tree accounting for 28% of all trees in Korea [18]. Most previous studies have focused mainly on high intensity wildfires in productive forests [19] and the resulting substantial tree mortality [20]. This mortality can be immediate owing to the combustion of living tissue during the fire, or it can be delayed, with the tree slowly dying over a few years because of fire damage to the crown, trunk, and roots and, sometime later, arthropod attack [20]. Research on tree mortality following less intense fires, such as surface fires, remains less common, albeit a highly relevant subject for adapting forest management to climate change.

Surface fires alter the structure and function of forest ecosystems affecting the soil environment and causing the death of trees [21]. Tree mortality is a complex phenomenon influenced by multiple factors, including tree characteristics, climate, topography, and disturbance regimes [2]. Post-fire tree mortality is related to multiple direct and indirect fire effects [22]. Direct fire effects involve heat transfer and the resulting tissue necrosis, whereas indirect fire effects include altered physiology, insect damage, and pathogenic infection [23]. Despite their major economic and ecological consequences for forest ecosystems, these effects remain poorly understood and their consequences are difficult to predict.

The fire-induced cambium/phloem necrosis and xylem damage are the main causes of post-fire tree mortality [23]. Numerous methodologies have been applied to estimate cambial mortality, from the direct sampling of the cambial tissue to indirect measurements, such as the amount or height of crown/bark scorch or bark char severity [20,24,25]. Since measuring cambial activity directly is time-consuming, indirect alternatives have been developed. Bark injuries are commonly used as a substitute for direct cambium measurements because of the simpler approach of measuring bark injuries [20]; however, the correlation between bark injury and cambium status remains unreliable [20]. Therefore, it is necessary to develop accurate and cost-effective tools for predicting post-fire tree mortality.

This study describes tree mortality three years after a surface fire and identifies the main factors affecting within-stand mortality patterns. Simple and effective models are developed for predicting Korean red pine mortality after surface fires.

2. Materials and Methods

2.1. Study Area

Our study area (37°15′53″ N, 129°1′24″ E, 700–800 m asl) is located in the mountains around Samcheok, Korea, a region having stands dominated by Korean red pine (Figure 1). This region consists of pine forests in the crown layer, and *Quercus* sp. in the understory layer. Pine trees in our study stands originated from a plantation and were planted in 1972. In May 2017, the study area was affected by a 765 ha wildfire, which occurred in the minimally managed mountains around Dogye. Our study sites (1.4 ha) are in areas that experienced a surface fire.

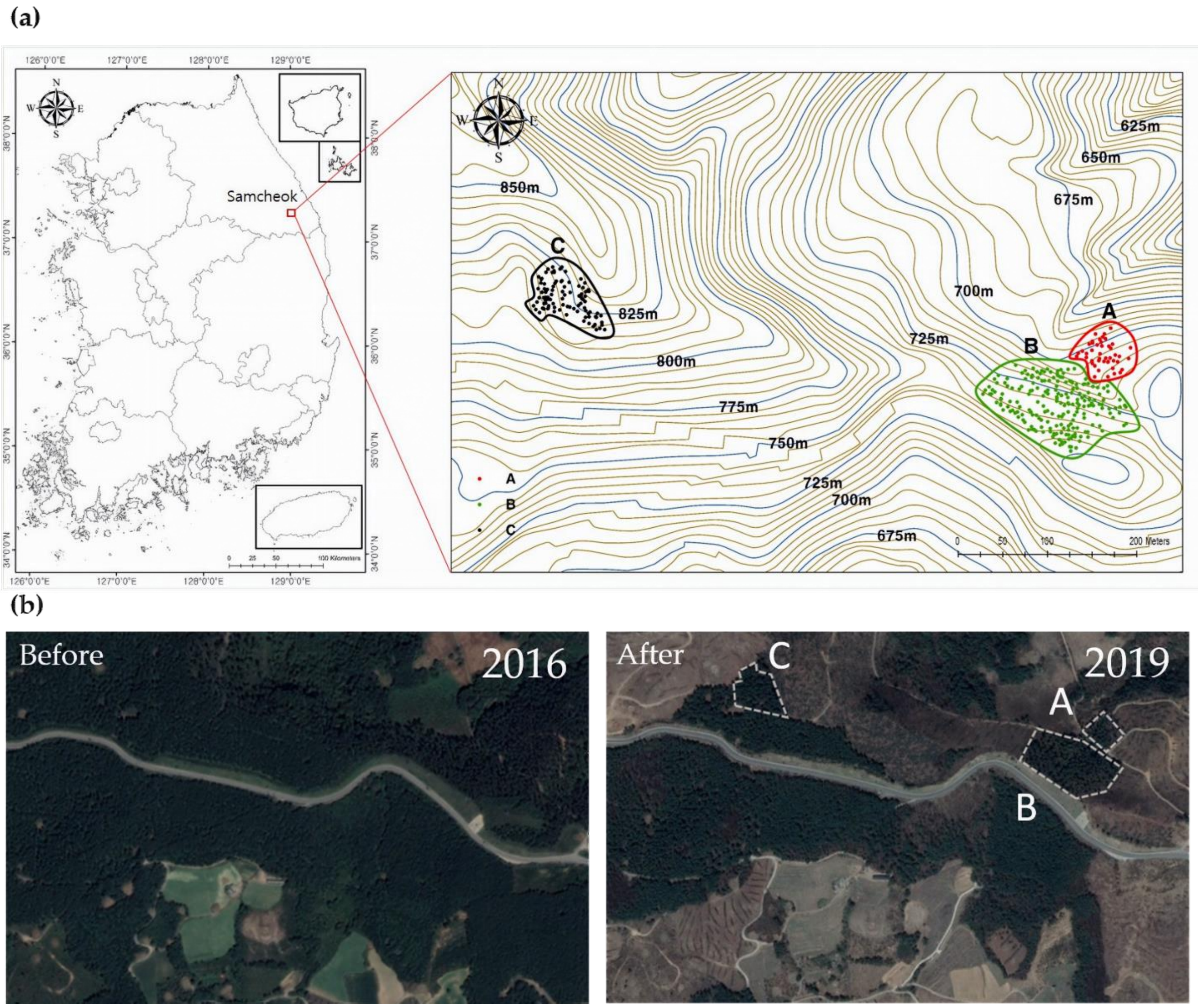

Figure 1. (**a**) Location (37°15′53″ N, 129°1′24″ E, 700–800 m asl) and topographical map of the study area near Samcheok, the Republic of Korea. Each point represents a tagged tree that was scorched by a surface wildfire in May 2017; (**b**) A pair of satellite photos showing the study area before and after the May 2017 Samcheok wildfire.

The regional climate is temperate with warm and humid summers and cold, dry winters owing to the influence from the Siberian High. The mean annual temperature is 12.6 °C, and mean total annual precipitation is 1280 mm (Mountain Meteorology Observation System, Korea Forest Service 2019). The general wind direction in the study sites during the wildfire came from the south-western direction with a mean speed of 14 m/s (Figures S1 and S2). Soils are silt loam (SiL) and silt clay loam (SiCL).

2.2. Experimental Design and Sampling

We established three study sites after the May 2017 wildfires to monitor post-fire tree mortality. We selected sites subjected to a lower fire intensity and only 5% to 8% of the burned area was affected by surface fire. We measured all Korean red pine trees within each study site, although not those in the 10 m buffer zones surrounding each study site. The measured trees were all standing trees having intact crowns and were at least 8 m tall with a diameter at breast height (DBH) of >15 cm. A total of 413 trees were numerically tagged and surveyed four times over three years (11 July 2018, 19 October 2018, 20 September 2019, and 8 July 2020). We categorized trees as either dead or living based on crown state (intact, browning, or absence) for delayed mortality one year after the wildfire. All the studied trees had an intact crown at the beginning of this investigation. One year post the fire (2018), we assessed site topography (elevation, slope, and aspect), tree characteristics (DBH, tree height, crown height), and bark injury (bark scorch height and proportion). We selected these eight variables to calculate rates of post-fire tree mortality using simple-to-use nondestructive methods. For each tree, we measured DBH at 1.2 m above the ground on the uphill side of the tree. We recorded tree and crown height. We also measured slope and aspect using a digital hypsometer (Haglof Vertex III and Transponder T3, Sweden) and transformed them to eight cardinal directions for aspect with raster calculator. Elevation was measured with GPS (GPS Status & Toolbox, MobiWIA-EclipSim). We collected all topographical measurements on a tree's uphill side perpendicular to the slope at a sufficient distance to obtain an accurate value. We divided each sampled tree trunk into quadrants (centered on N, S, W, E, respectively), and for each quadrant, we measured bark scorch height (BSH) and proportion of scorched wood (BSP, Figure 2a). Then, we defined the bark scorch index (BSI) as the sum of BSH multiplied by BSP for each quadrant (Figure 2b). In Figure 2a, the left photo study tree has a BSH of 1.9 and BSP of 0.8, whereas the study tree on the right photo has a BSH of 1.3 and a BSP of 0.6. BSI was developed to determine whether the tree would be dead or living after a surface fire. We expected that combining BSH with BSP would predict post-fire tree mortality more accurately.

Figure 2. Calculations of the bark scorch index (BSI). (**a**) Photos showing measurements of two fire-scarred trunks. The left photo study tree has a bark scorch height (BSH) of 1.9 and a bark scorch proportion (BSP) of 0.8. These values for the trunk on the right photo are 1.3 and 0.6, respectively; (**b**) Bark scorch index (BSI) for a trunk is calculated by multiplying BSP and BSH for each quadrant, and then the four obtained values are summed. For this example, the BSI is (2.0 × 0.8) + (1.5 × 0.45) + (1.2 × 0.65) + (0.7 × 0.5) = 3.405.

To consider other potential variables influencing mortality patterns, we measured the following 11 soil chemical factors, one year after the fire: pH, total nitrogen (TN, %), available phosphorus (P, P_2O_5, ppm), organic matter 138 (OM, %); NaCl (%); electric conductivity (EC, dS·m^{-1}); exchangeable cations (K^+, Na^+, Ca^{2+}, Mg^{2+}); and 139 cation exchange capacity (CEC, cmol$^+$/kg) [26,27]. We also analyzed inter-tree competition based on DBH and inter-tree distance [28,29]. Competition data were taken one year after the wildfire in Korean red pine stands (n = 413). The distance ($Dist_{ij}$) and DBH of each neighboring tree ($_j$) within a 4 m radius of the subject tree ($_i$) were measured to calculate the Hegyi's competition index (CI_i) as:

$$CI_i = \sum_{j=1}^{n} \left(\frac{DBH_i}{DBH_j} \times \frac{1}{Dist_{ij}} \right) \tag{1}$$

2.3. Data Analysis

We applied logistic regression to develop models differentiating living trees from dead trees by applying a binary response variable (dead/living). Therefore, all sampled Korean red pines were coded as either 0 (living) or 1 (dead) based on their condition during the three years of sampling after fire. We considered p-values ≤ 0.05 to be statistically significant. To overcome the limited sample size, we performed a preselection to test all measured variables. We developed models using only one explanatory variable at a time and included in the logit model all variables having nonsignificant but relatively lower p-values ($p \leq 0.25$). Our models for Korean red pine included the eight above mentioned independent variables, i.e., elevation (m), slope (°), DBH (cm), tree height (m), crown height (m), BSP (%), BSH (m), and BSI except for aspect. We selected these variables as obtaining them was relatively quick, nondestructive, and provided accurate estimates. The logistic regression equation used to model mortality was the following:

$$P\text{m} = \frac{1}{1 + e^{-(\beta_1 + \beta_2 X_2 + \cdots + \beta_k X_k)}} \tag{2}$$

where P_m corresponds to the probability of mortality, X_2–X_k are independent fixed variables and β_1–β_k are regression coefficients estimated from the mortality data.

We added the explanatory factors one at a time, applying a statistical method to decrease the Akaike information criterion (AIC). The AIC ranges from 0 to ∞, and lower values represent a better data fit. We used the eight independent variables to obtain the best fitting model (two topographical, three tree characteristics, and three bark injury variables). After conducting several tests, we selected BSI as the variable producing the best fit. We calculated delta AICs (ΔAIC) for the logistic regression models and selected the best model with the smallest AIC value (same as ΔAIC = 0). We considered models to be comparable to the best model when their ΔAIC values were <2. We considered ΔAIC values of 3–9 as less significant and values of ≥10 as nonsignificant [30]. A Hosmer–Lemeshow test determined the goodness of fit for logistic regression and how well the data fit the model. We applied a log-likelihood function to compare the fit of different coefficients and to derive the maximum likelihood estimates of the model parameters. We calculated McFadden's pseudo-R^2 to examine the goodness of fit. McFadden's R^2 is comparable to the R^2 obtained from linear regression models. Moreover, we evaluated all the models' predictive performance by determining the area under the receiver operating characteristic curve (AUC). The receiver operating characteristic (ROC) indicates model accuracy when categorizing living and dead trees. A value of 0.5 is the same as chance, and 1.0 implies a perfect fit. Values between 0.7 and 0.8 represent acceptable discrimination, 0.8 to 0.9 indicate good discrimination, and values ≥0.9 reflect excellent discrimination [31]. Multicollinearity of the predictor variables was verified using variance inflation factors (VIF) [32]. A VIF > 4 indicates a multicollinearity [33]. Assessing model accuracy was simplified by providing the threshold value 0.5 to compare models, however, this value can vary depending on management goals [34]. To determine site heterogeneity, we used

Duncan's multiple range test (DMRT) by comparing the means of 9 variables in the three study sites. All the analyses were run using R software v. 3.5.0 [35].

Our three-year post-fire mortality model should be considered to be a preliminary estimate of mortality as additional mortality in the next years is expected. We produced various models based on our logistic regression analyses to provide forest managers with options for estimating mortality using both simple and complicated combinations of variables. To provide a practical example, we presented a two-year post-fire mortality model based on BSI and DBH.

3. Results

3.1. Tree Mortality

Among the 413 Korean red pine in our dataset, 65 (16%) died after three years. In the first year after the fire, tree mortality varied between 0% and 14% among the three sites (Figure 3). Tree mortality increased after three months post fire and continued to increase in a fairly constant manner over the three years at sites A and B. Site C did not have any mortality through to the final observation period. The increasing rate in delayed tree mortality for sites A and B was the greatest between October 2018 and September 2019. Then, the ratio of tree mortality decreased slightly from September 2019 to July 2020.

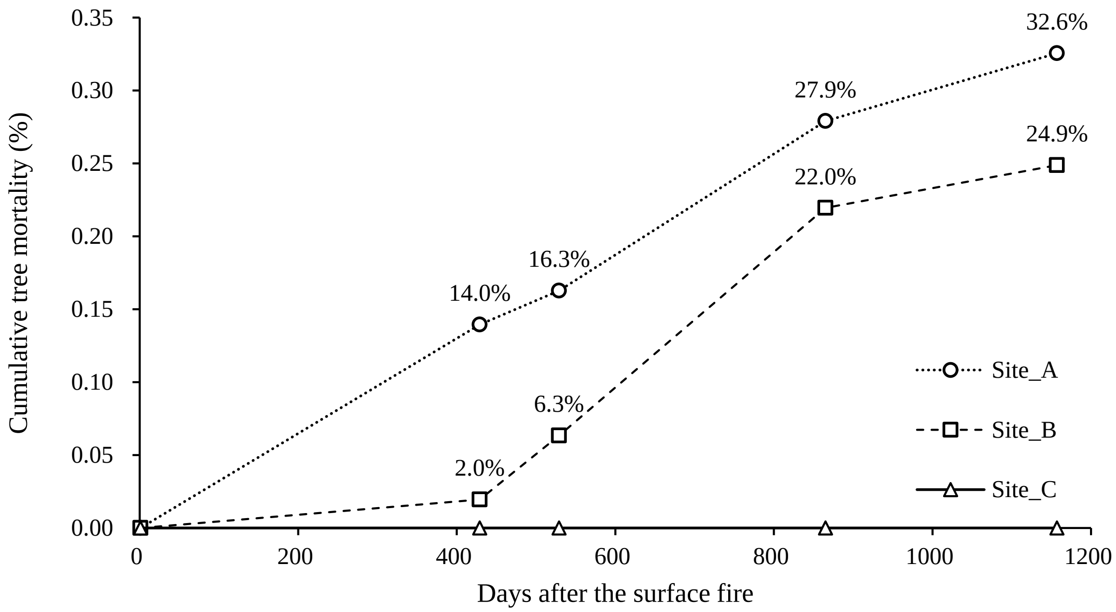

Figure 3. Three years of cumulative tree mortality after the May 2017 surface fire. Measurements took place on 11 July 2018, 19 October 2018, 20 September 2019, and 8 July 2020.

Topography, tree characteristics, and bark injury showed significant mortality patterns between dead and living trees (student's t-test $p < 0.01$, Table 1). The three study sites differed significantly, in pairwise analyses, for six of the nine measured variables (Duncan's multiple range test (DMRT) $p < 0.05$, Table 1). The mean slope of the terrain around dead trees (26°) was greater than that for living trees (23°), and dead trees were found at a higher mean elevation (770 m) than living trees (734 m). Dead trees also tended to be located on sites having a northern aspect. Taller trees having a smaller diameter were most susceptible to mortality from the surface wildfire. The dead trees also had a higher BSP and BSH, thus a higher BSI. Site A trees experienced the highest mortality, whereas Site C had zero mortality. Site C trees presented the least bark injury with average BSH, BSP, and BSI scores of 0.7 m, 48.7%, and 1.7, respectively. DBH was greatest in Site C, although Site C was located at the highest elevations relative to the elevations of sites A and B ($p < 0.05$). the slope varied between 10.8° and 32.7° across all sites, and Sites A and C shared lower slope angles than those measured at Site B ($p < 0.05$). The aspect varied from northeast to northwest for all trees in the study sites A and B, while 94% of trees located in the site C faced from south to west. We did not obtain a significant role for competition or the soil factors in predicting mortality.

Table 1. Summary of variables for tree mortality following the May 2017 surface wildfire. Values are the mean and standard deviation, measured in July 2018.

Categories	Variables	Dead Trees	Live Trees	Site A	Site B	Site C
Topography	Elevation (m)	734.4 (±15.7) **	769.6 (±86.0) **	726.3 (±6.1) ^{b}	737.6 (±19) ^{b}	849.5 (±5.6) ^{a}
	Slope (°)	26.3 (±7.8) *	23.1 (±8.0) *	21.2 (±8.9) ^{b}	26.4 (±6.3) ^{a}	19.0 (±8.2) ^{b}
	Aspect	N	NE	N	NE	SW
Growth feature	DBH (cm)	30.6 (±6.7) **	34.3 (±7.5) **	33.5 (±7.7) ^{b}	32.1 (±6.8) ^{b}	36.9 (±7.6) ^{a}
	TH (m)	18.9 (±2.4) **	17.3 (±3.2) **	22.0 (±1.6) ^{a}	17.9 (±2.8) ^{b}	15.3 (±1.9) ^{c}
	CH (m)	11.5 (±2.4) **	9.5 (±5.3) **	13.7 (±2.3) ^{a}	10.72 (±5.6) ^{b}	6.7 (±1.5) ^{c}
Bark injury	BSH (m)	2.6 (±1.1) **	1.3 (±1.0) **	2.7 (±1.7) ^{a}	1.7 (±0.9) ^{b}	0.7 (±0.4) ^{c}
	BSP (%)	78.9 (±14.8) **	57.9 (±20.4) **	74.19 (±18.3) ^{a}	65.6 (±20.1) ^{b}	48.7 (±18.1) ^{c}
	BSI (ns)	8.6 (±3.9) **	3.6 (±3.2) **	8.8 (±6.0) ^{a}	5.0 (±3.0) ^{b}	1.7 (±1.3) ^{c}

Student's t-test, ** $p < 0.01$, * $p < 0.05$; Parameter values followed by the same letter are not significantly different (Duncan, $p < 0.05$). Duncan's multiple range test (DMRT) of the variables by sites. DBH, diameter at breast height; TH, tree height; CH, crown height; BSH, bark scorch height; BSP, bark scorch proportion; BSI, bark scorch index (BSH × BSP). Aspect is categorical for eight cardinal directions and was not tested for significant differences among dead and live trees, nor sites.

3.2. Factors Influencing the Probability of Mortality Following a Surface Fire

Univariate logistic regression produced models of post-fire mortality of Korean red pine on the basis of topography, tree characteristics, and bark injury (Table 2). The model results showed that DBH, tree height, and bark injuries (BSH, BSP, and BSI) were significant predictors of post-fire tree mortality. Bark scorch variables were crucial for predicting mortality after a surface fire, being a factor involved in all of the strongest logistic regression models. The best univariate models for Korean post-fire mortality contained bark injury variables. The ROC curve analysis showed that the three bark injury models discriminated between living and dead trees at a reliable level (AUC = 0.81–0.86, $p < 0.001$). BSH and BSP produced the models having the lowest AIC and highest AUC values among single-factor models. The best univariate model was produced when both of these single factors were combined, i.e., BSI (AIC = 255). DBH and tree height each showed intermediate levels of model fitness. Models that included a measure of crown height and topography (elevation and slope) did not discriminate well, owing to the near-zero Z-values and weaker p-values. However, the results of topographical factors were likely to indicate that locations on steeper slopes, at lower elevations, and with a northern aspect, increased tree mortality. The VIF values (VIF < 4) of the eight explanatory variables illustrated that multicollinearity issues were not an issue in the univariate models.

Table 2. The univariate logistic regression models in the selection of topographical, tree characteristic, and bark injury variables for Korean red pine mortality following surface wildfire.

Category	Variable	Estimate	Std. Error	Z	p	AIC	ΔAIC	AUC	VIF
Topography	Elevation	−0.005	0.002	−2.4	0.018	329.3	73.9	0.682	1.034
	Slope	0.051	0.019	2.8	0.005	330.1	74.7	0.597	1.249
Growth feature	DBH	−0.07	0.02	−3.5	<0.001	325.2	69.8	0.641	1.426
	TH	0.169	0.047	3.6	<0.001	324.3	68.9	0.652	2.449
	CH	0.085	0.041	2.1	0.039	331.2	75.8	0.712	2.16
Bark injury	BSH	1.086	0.155	7	<0.001	268.3	12.9	0.838	1.214
	BSP	21.263	2.997	7.1	<0.001	270.5	15.1	0.808	1.145
	BSI	4.075	1.285	3.2	<0.001	255.4	0	0.862	°

DBH, diameter at breast height; TH, tree height; CH, crown height; BSH, bark scorch height; BSP, bark scorch proportion; BSI, bark scorch index (BSH × BSP). The best models were determined according to Akaike model selection approach (ΔAIC < 2). VIF, variance inflation factors.

Post-fire tree mortality increased as slope increased (Figure 4). We observed that dead trees tended to be found on north-facing slopes, with all the dead trees occurring at northern aspects (N 66%, NE 29%, and NW 5%). DBH was a significant predictor having an inverse relationship with the probability of mortality. However, trees with a DBH of 45–50 cm showed an opposite trend, likely because of the low number (n = 15) of samples. Mortality also decreased with tree height for trees taller than 20 m. For trees less than 20 m in height, the percent mortality increased as tree height increased. Crown height followed the same pattern. Tree mortality was likely to increase as BSI increased. BSI values between 6 and 8 showed the largest increase in tree mortality, increasing from 17% to 47% over three years. The trees with BSI values ≤4 were more likely to survive, having only 3% tree mortality. However, trees with a BSI value between 8 and 10 did not follow the rising trend.

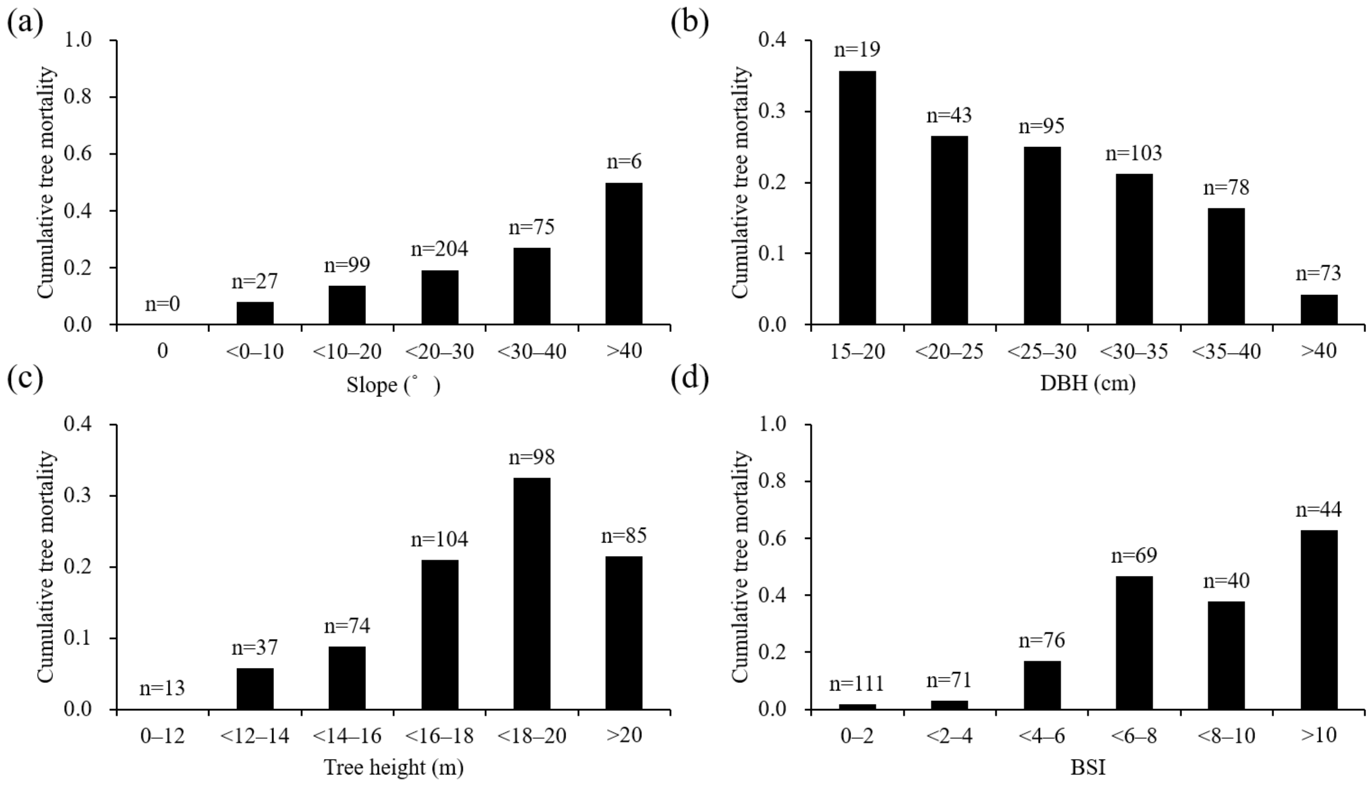

Figure 4. Bar charts showing the percentage of cumulative tree mortality by (**a**) slope; (**b**) diameter at breast height (DBH); (**c**) tree height; and (**d**) bark scorch index (BSI) value.

The multiple logistic regression analyses used seven predictors (elevation, slope, aspect, DBH, tree height, crown height, and BSI) together to produce the best model, as well as their coefficients (Tables 3 and 4). The results showed that the four formulas (all variables, tree characteristic variables with BSI, slope + DBH + BSI and DBH + BSI) successfully predicted post-fire tree mortality. When considering each formula of variables, the formulas that included DBH and BSI were all significant. Among the significant formulas, three variables (slope, DBH, and BSI) produced the best model for post-fire tree mortality. In particular, samples on steeper slopes (odds ratios (OR) = 1.07), with smaller tree diameters (OR = 0.91), and higher BSI values (OR = 1.45) were more likely to experience higher tree mortality (Figure 5). Although tree height was predictive of tree mortality in the univariate analysis, it was not an independent predictor in the logistic regression analysis. Conversely, slope was a significant predictor with DBH and BSI in the optimal logistic regression analysis model, although it was not predictive in the univariate analysis alone. The best multiple logistic regression model combined slope, DBH, and BSI to produce the model with the lowest AIC value and the highest AUC (Table 3).

Table 3. Multiple logistic regression analyses of independent predictors for Korean red pine mortality over three years following a surface wildfire.

Model	X^2	Log-Likelihood	McFadden's Pseudo R^2	AIC	ΔAIC	AUC
M_1	5.32	−115.72	0.31	245.45	5.49	0.87
M_2	11.52	−159.82	0.04	325.64	85.7	0.673
M_3	12.7 **	−122.28	0.27	252.56	12.6	0.864
M_4	31.62 ***	−150.94	0.09	309.88	69.9	0.733
M_5	7.02	−119.78	0.28	249.56	9.6	0.867
M_6	7.27	−115.98	0.31	239.96	0	0.87
M_7	7.24	−119.84	0.28	245.68	5.7	0.867
M_8	16.16 **	−122.64	0.27	251.28	11.3	0.862

X^2, The Hosmer–Lemeshow test is a statistical test of goodness of fit for logistic regression models. Bold lettering refers to the best model based on the ΔAIC values. Model factors are in Table 4. *** $p < 0.001$ and ** $p < 0.01$.

Table 4. Coefficients in the multiple logistic regression models.

Variables	Model	Formula
All	M_1	−1.6278 + (−0.0014 × Elevation) + (0.0645 × Slope **) + (−0.0909 × DBH **) + (0.0201 × TH) + (−0.0010 × CH) + (0.3632 × BSI ***)
Topography	M_2	0.7224 + (−0.0043 × Elevation *) + (0.0645 × Slope *)
	M_3	−3.5282 * + (−0.0017 × Elevation) + (0.0536 × Slope *) + (0.3561 × BSI ***)
Growth features	M_4	−2.3565 * + (−0.0882 × DBH ***) + (0.2063 × TH ***) + (0.0001 × CH)
	M_5	−1.0877 + (−0.0861 × DBH **) + (0.0251 × TH) + (−0.0111 × CH) + (0.3546 × BSI ***)
Optimal models	M_6	−2.4525 * + (0.0649 × Slope **) + (−0.0892 × DBH ***) + (0.3733 × BSI ***)
	M_7	−0.9018 + (−0.0824 × DBH ***) + (0.3607 × BSI ***)
	M_8	−4.9233 *** + (0.0547 × Slope **) + (0.3621 × BSI ***)

DBH, diameter at breast height; BSI, bark scorch index; CH, crown height; TH, tree height. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$.

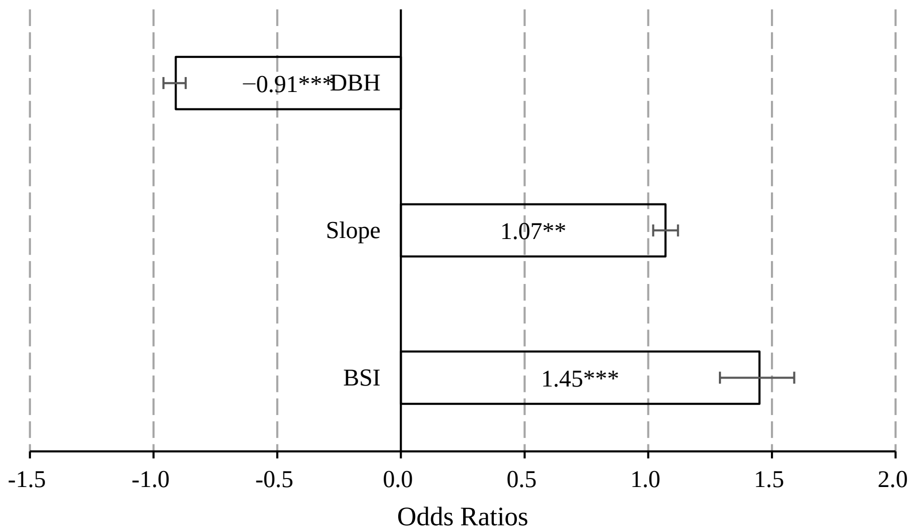

Figure 5. Odds ratio plot of the final model of Korean red pine mortality following a surface wildfire where DBH and BSI correspond to the diameter at breast height and bark scorch index, respectively. DBH, diameter at breast height. * Represents significant values according to *** $p < 0.001$ and ** $p < 0.01$.

The multiple logistic regression analyses revealed that the probability of Korean red pine mortality following surface wildfire was likely to increase with BSI, especially for trees having a low DBH (Figure 6a). According to the two-year post-fire tree mortality model, DBH and BSI were major drivers explaining delayed tree mortality after a surface wildfire. Standing trees having a 5 cm BSI and 50 cm DBH made up 4% of the mortality after fire. However, trees having a DBH = 10 cm represented 52% mortality after fire. A tree characterized by a DBH of 30 cm and a BSI of 10 experienced 56% mortality, whereas an identical DBH-valued tree with a BSI of 15 had a higher mortality (89%).

The probability table for Korean red pine mortality following a surface fire was produced, based on the two-year post-fire tree mortality. This scenario represents a practical example for forest managers on the basis of combining BSI and DBH (Figure S3). We excluded slope in the two-year post-fire tree mortality model because of the low deviance (8.2). The harvesting guideline that we established was a probability of mortality of $\geq$30%; a single tree had a probability of mortality of more than 30% if BSI $\geq$ 6 and DBH of 20 cm. However, trees having a DBH $\geq$ 48 cm and BSI < 13 had a probability of mortality of 1–27% mortality. This post-fire harvesting guideline, i.e., >30% is only an example and is not absolute (Figure S3); thus, it can be adjusted according to the user's needs or the particular region.

The predictive multiple logistic regression model for the three-year post-fire tree mortality was improved by adding slope after DBH and BSI (Figure 6b). The line indicates that the trends in post-fire tree mortality, when using DBH and BSI, moved markedly to the left, as the slope increased. Post-fire tree mortality was greatly influenced by slope when holding DBH and BSI constant. For instance, a tree with a DBH of 50 cm, BSI of 10, and slope of 0° had 6% probability of tree death, whereas the same tree on 20–30° slope experienced a 23% probability of death. A BSI $\geq$ 25 almost ensured tree mortality regardless of DBH and slope.

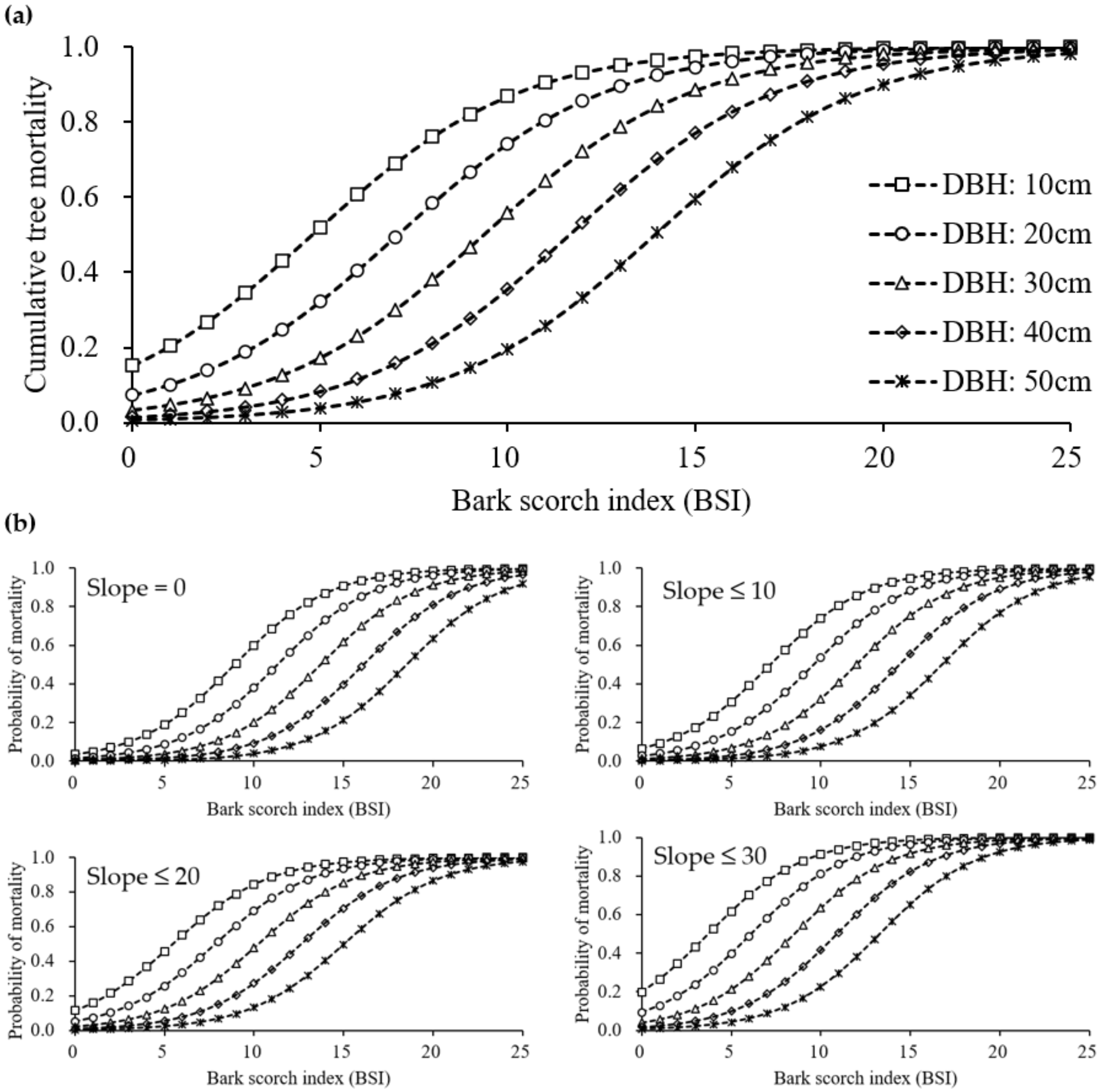

Figure 6. Multiple logistic regression models with a binary response variable, (**a**) For predicting the two-year post-fire tree mortality in relation to diameter at breast height (DBH) and the bark scorch index; (**b**) For predicting the three-year post-fire tree mortality in relation to the bark scorch index (BSI), DBH, and various slopes between 0° and 30°.

4. Discussion

Forest managers require reliable predictions of post-fire tree mortality under climate change scenario (warmer and drier) to adapt harvesting plans and meet commercial and conservation goals [24]. This study provided a dataset of Korean red pine trees monitored over three years following a surface fire. We focused on the pine plantation forests, which cover a large portion of Korea's temperate zone, and we combined topography with tree characteristics and fire-related bark injuries for our models. To the best of our knowledge, our study is the first to present a tool for fast decision making for land managers, applicable upon the first year following a surface fire in a Korean red pine forest. Our model presents a more powerful index than previous approaches and predicts post-fire tree mortality in a simpler and faster method for practitioners.

4.1. Post-Fire Korean Red Pine Mortality Modeling

Measures of bark injuries were the most important predictors of Korean red pine mortality following a surface fire. We measured the bark injuries as a surrogate for cambium status; it remains uncertain, however, how well the bark injuries reflect cambium status.

Previous studies used more complex codes or classification systems of bark or bole injuries to predict post-fire tree mortality [20,36]. Our novel index (BSI) combined BSH and BSP to better represent cambium status and predict post-fire tree mortality. We showed that BSI was the best univariate model among all measured variables.

Tree size is used extensively as a critical variable in evaluating tree resistance to fire damage [37]. However, DBH was the only significant variable in our models among the measured tree characteristic variables, because tree and crown height did not directly relate to trees affected by the surface fire. Our models predict mortality to decrease with increasing DBH, thereby confirming a pattern observed in previous studies [38,39]. The DBH is closely related to bark thickness and is used in many models instead of bark thickness to indicate resistance to basal heating [19,37,40]. However, some post-fire tree mortality models have reported that DBH was not a significant predictor of post-fire tree mortality [24]. DBH's failure as a predictor likely occurred because DBH could not represent bark thickness very well in the sampled conifer species in those studies. Therefore, tree diameter in Korean red pine may be a significant predictor of post-fire mortality because of its close correlation with bark thickness.

Topographical factors also influenced Korean red pine mortality following a surface fire. Dead trees are likely to be at lower elevations, on steeper slopes, and with a northern aspect. For instance, Site C, having only living trees, had opposite trends for topographical traits relative to the other sites (A and B). Lydersen and North (2012) [41] found that southwestern aspects (Northern Hemisphere) had significantly greater proportions of bark scorch, whereas differences between northeast- and southwest-facing slopes were generally small. Likewise, we expected a similar pattern that most dead trees had northwest to northeast aspects, due to the wind blowing from the south-western direction. However, this question was not confirmed in this study because the aspects between dead and living trees were not significantly different, probably due to high variation among sites and the low number of replications in this study (only three sites). Moreover, stands burned by low and moderate fires are found on less steep plots (slope <18%), probably owing to lower stand densities on these sites [42]. Topography can directly influence fire intensity [43], fire frequency [44], and forest vegetation by altering environmental factors, including soil moisture [45], soil thickness [46], and microclimate [47]. Previous studies [41] have also demonstrated the effect of topography on tree density [48] and species composition [44].

Our results from the logit models confirmed that both tree diameter and bark injury are important predictors of conifer mortality following a fire. These findings confirm previous studies [20,25,36]. Our models showed that BSI and DBH were both robust individual predictors of post-fire tree mortality and performed nearly as well as the best model. The best set of predictive variables for our logit models included slope, BSI, and DBH; however, excluding slope from the model would depend on the practitioner's preferences when it is a gentle slope. Although we applied our accuracy assessment with a 0.5 cutoff to simply model comparisons, practitioners can customize the post-fire tree mortality guidelines by selecting different or more applicable cutoff levels and by examining ecological elements.

4.2. Potential Factors Influencing Post-Fire Tree Mortality

The delayed mortality of bark-scorched trees could also be potentially influenced by root injury, inter- and intraspecific competition, insects, and pathogens. As fires can markedly decrease fine-root biomass, which would reduce water uptake [49], indirect tree mortality can also occur through hydraulic limitation caused by root injuries [23]. Competition with neighboring trees can also influence post-fire tree mortality by limiting essential soil resources, because slower-growing trees are more likely to die than faster-growing trees for trees having similar levels of fire-induced injury [50]. Insects and pathogens can also alter delayed tree mortality by reducing growth and impairing conductivity [23,51,52]. In this study, we also analyzed the inter-tree competition and soil properties. However, we did not obtain a significant result in predicting mortality, likely because of the relatively low fire intensity.

Prediction of post-fire tree mortality can also be influenced by tree species. The previous models predicting Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) and ponderosa pine (*Pinus ponderosa*) mortality following wildfire were optimal when they included variables of crown volume, cambium kill rating, and the presence of beetles [53]. The best model for predicting sugar pine (*Pinus lambertiana*) mortality included percent crown length, cambium kill rating, and beetle attacks, whereas the best white fir model also included DBH [24]. Predicting post-fire tree mortality has also relied on fire intensity, bole scorch height, bark thickness, and tree height [54,55]. Thus, it is important to identify those variables that are optimal for a given tree species.

Estimating a cambium kill rating is laborious, and therefore multiple post-fire tree mortality models lack this measurement [56]. Models without a cambium kill rating are indeed less accurate and have lower discriminatory power, thereby demonstrating the trade-off between cost/labor and reliability [53]. Nonetheless, field workers may prefer using simpler measurements for cost-efficiency purposes to have broader applicability of these models. For instance, the Ryan and Reinhardt model has been extensively applied in fire management settings despite lacking a cambium kill rating component [57]. Although our model did not produce the highest accuracy relative to similar models, our use of DBH and BSI to represent cambium status provided an acceptable average discriminatory ability of 87%. Further studies with our model should include a cambium kill rating and many replicates to improve our post-fire tree mortality predictions.

4.3. Issues Related to Our Experimental Design

Most post-fire tree mortality occurs within the first two years after a fire, and, in North American forests, patterns of fire-related tree death stabilize by the third year [20,24,55]. We also found a similar tree mortality pattern in Korean red pine dominated forests, i.e., an intensive pulse of mortality in the first two years after the surface fire and a reduced mortality rate over the third year. We expect tree mortality to continue rising, although at a lower rate over the following years. However, a longer-term study of tree mortality is necessary, as we did not observe a flattened mortality curve (rate at zero) by the end of our study, and patterns of tree survival can be predicted at least ten years after a fire [58].

The major determinants of fire behavior and burn severity were not estimated in the burned stands because we confined our study to surface fires, and Korean land managers consider crown-damaged trees as trees to be harvested. Thus, we focused on trees with intact crowns after a surface wildfire to provide practical knowledge to Korean forest managers. Moreover, constraining models to certain types of fire can heighten the accuracy of post-fire tree mortality predictions.

The regional characteristics may also indirectly influence site effects on post-fire tree mortality. Our data is specific to the Samcheok region, located near the East Sea, and is an area where the summer climate is hot and humid [59] with very cold winters, relative to comparable temperate regions, because of the strong influence of the Siberian High [60]. Measurements of microclimate variables, such as wind, temperature, relative humidity, and local fire fuel, i.e., accumulated deadwood, can enhance model predictability and can clarify the complicated interactions among topography, microclimate, fuels, and fire impacts [42]. Furthermore, similar studies of other tree species and sites are needed to determine the general importance of slope, BSI, and DBH as predictors of mortality after a surface fire.

5. Conclusions

The increasing number of large wildfires in Korean red pine forests has focused attention on predicting post-fire tree mortality. The development of tree mortality models using physiological factors such as cambial status is recommended [61]; however, such measurements are costly and have not yet produced reliable models. This study provides simple and effective models using easy-to-measure bark injuries as a proxy of direct cambium sampling. This new tool can help forest managers to establish criteria for selecting those trees available for salvage post-fire. Our univariate models for Korean red pine relied on the use of the novel BSI index to produce the best univariate models of post-fire tree mortality. A logit model combining slope, DBH, and BSI offered the best predictions. The simple nature of the three selected variables demonstrated that practitioners could easily and reliably estimate the three-year tree mortality after a surface fire. Further studies should test whether slope, DBH, and BSI are the three best predictors of Korean red pine mortality in other regions, regardless of differences in fire intensity and fire timing. Our models will help forest managers to reduce the number of trees salvaged after a fire, and therefore help forest ecosystems remain resilient following more frequent and severe fire disturbances expected under a warmer and drier climate change scenario.

Supplementary Materials: The following are available online at https://www.mdpi.com/2071-1050/13/2/569/s1, Figure S1: The wind rose chart during the Samcheok wildfire in 2017. Figure S2: Meteorological data observed during the Samcheok wildfire in 2017. The figure represents wind speed and relative humidity. Figure S3: A Korean practical example of harvesting criterion: 30% based on the multiple logistic regression model with a binary response variable for predicting the two-year post-fire tree mortality in relation to the diameter at breast height (DBH) and the bark scorch index (BSI). The green area represents trees to retain while brown is for harvesting.

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