Multi-hazard mapping of droughts and forest fires using a multi-layer hazards approach with machine learning algorithms

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\section*{ABSTRACT}
The frequency of forest fires in Gangwon-do has increased in recent years due to advanced climate change and dry weather. The Gangwon-do area, the largest forest area in South Korea, has rich forest resources and ecological diversity, therefore there is an urgent need for more effective monitoring and prevention of forest fires. This study proposed a method to establish a multi-hazard probability map (MHPM) for two related hazards (forest fires and droughts) based on a multi-layer hazards approach and machine learning algorithms for monitoring forest fire susceptibility areas. First, extreme drought years were selected using the standardized precipitation index (SPI). An inventory drought map was constructed using the enhanced vegetation index (EVI) based on satellite image data. Then, 70\% of the inventory maps based on forest fires and droughts were used to construct hazard susceptibility maps and 30\% of these were used to validate three machine learning models: Classification and Regression Trees (CART), Random Forest (RF) and boosted Regression Trees (BRT). Eleven conditioning factors related to climate, topography, hydrology, and human activities were considered for the analysis. The results of the three models were then validated using the area under the receiver operating characteristic (ROC) curve (AUC), and the best performing model was selected (BRT; forest fire: 85\%, drought: 80\%). Finally, the susceptibility maps of forest fires and droughts were combined to construct the MHPM for the Gangwon Province, South Korea. The results show that the MHPM of forest fires and droughts constructed in this study is valid and reliable. This multi-hazard map can provide key information for planners and decision-makers to develop forest fire prevention and management plans and to more effectively prevent and reduce the frequency of forest fires.

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1. Introduction

The frequency and damage caused by natural disasters is increasing worldwide (Re 2011; Munich et al. 2014). Concurrently, the worsening trend of climate change greatly impacts the frequency and hazard level of natural disasters on a global scale (Kappes et al. 2012; Haque et al. 2019). Therefore, it is essential to predict, prevent, and establish management plans for natural disasters (Yousefi et al. 2020). One of the primary methods for predicting and managing natural hazards is the construction of hazard susceptibility mapping data (Yousefi et al. 2020). By generating geospatial information, susceptibility maps can provide important information for natural hazard prediction, prevention, and management.

However, much of the current research on natural hazards has focused on single hazards (Chen et al. 2019; Kaur and Sood 2019; Wang et al. 2019). Studies for such single hazards analyze risks as independent phenomena and do not consider the degree of susceptibility combined with interactions between hazards (Yousefi et al. 2020). Therefore, it is necessary to evaluate and analyze the interactions between hazards (Hillier et al. 2020). Multi-hazard studies can identify more concentrated damage and risk than single hazard studies. Such research requires a reanalysis of the spatial distribution of natural hazards on a per-region basis (Forzieri et al. 2016). This can reduce the probability of occurrence and the potential risk of hazards that may interact with each other (deforestation, casualties, economic loss, etc.) by mapping susceptibility across complex aspects of natural hazards.

Multi-hazard mapping is a method for considering multiple hazards at a given location. It allows an assessment of the interrelationships between multiple hazard events, including simultaneous or cumulative events and potential interactions between individual hazards (Kappes et al. 2012). Multi-hazard mapping usually includes multiple hazards that are all interrelated in different forms and affect a given space over a given period (Tilloy et al. 2019). Examples include increased risk of forest fires due to drought, increased risk of flooding due to forest fires, landslides and mudslides due to heavy rains, and tsunamis due to volcanic eruptions or earthquakes (Gill and Malamud 2014). There are two main problems in analyzing multi-hazard situations. First, direct comparisons are impossible because the damage process and the descriptive values of each disaster are different among multiple disasters (Tilloy et al. 2019). A classification of the damage intensity and a normalization of the continuum index are used to solve the first problem (Kappes et al. 2012). For the second problem, natural hazards are usually influenced by landscape data, so the description matrix is based on a qualitative approach that can be solved to some extent (Gill and Malamud 2014).

Forest fires and drought are the main natural hazards caused by increasing global climate change (Flannigan et al. 2000; Cheeseman 2016), and are the most common disasters in Gangwon Province, South Korea (Korea Forest Service 2017). Every year they cause severe ecological damage, human casualties, and economic losses in Gangwon Province. Moreover, these are unavoidable due to the abundant forest resources in this region of South Korea (Lee and Lee 2006). Three large-scale forest fires in Gangwon Province caused 1,196 hectares of damage in 2017, accounting for 81% of the total area lost in South Korea in that year (Korea Forest Service 2017).
Korea has experienced abnormally high temperatures every year since 2010, especially in spring and summer, with persistent high temperatures and a continuous lack of precipitation during the plant growing season from 2012 to 2017 (Korea Forest Service 2020). As a result, 29.7 hectares of pine forests in the Gangwon-do area died in May 2011, and the amount of combustible forest material increased, damaging the forest vegetation and making it fragile (Korea Forest Service 2020). Due to the dry weather, the occurrence and damage caused by forest fires is increasing in most parts of Korea, mainly from March to May. To date, there have been ten mega forest fires in South Korea, including seven in Gangwon Province. About 29,174 hectares of forest were destroyed in Gangwon Province due to the aforementioned forest fires, resulting in an economic loss of about $200 million (Korean: about 256.4 billion won, https://www.forest.go.kr). Overall, droughts and forest fires have created a threatening environment (high temperature and dry environment, ecological risk, increase in combustible forest materials, etc.) for forest hazards in Gangwon Province, South Korea.

Existing studies indicate an interaction between droughts and forest fires (Cochrane 2003). A multi-hazard assessment in Europe showed that the interaction was primarily related with increased droughts, forest fires, and heat waves (Forzieri et al. 2016). An analysis of the correlation between droughts and forest fires in the United States showed that the size, magnitude, and frequency of forest fires are influenced by multiple interactions between forest fires and droughts (Littell et al. 2016). In tropical rainforests in Ghana, the frequency and scale of forest fires were found to be greater the more severe the deforestation during droughts (Dwomoh et al. 2019). In addition, researchers found that tree mortality increased due to damage to vegetation vasculature due to droughts (Anderegg et al. 2015). This indirectly implies that the amount of combustible material leading to forest fires increases due to drought-induced vegetation mortality, resulting in increased fire rates (Brando et al. 2019; Barlow et al. 2020). Furthermore, by confirming the interrelations between the damage and frequency of large-scale forest fires in Florida and hydrological droughts, it was found that droughts increased the magnitude of vegetation degradation and forest fire damage (Taufik et al. 2017).

Recently, multi-hazard studies have been conducted using various methods. Pourghasemi et al. assessed and mapped three multi-hazards: landslides, floods, and earthquakes, using the SWARA-ANFIS-Gray wolf metaheuristic (Pourghasemi et al. 2019). Yousefi et al. used three machine learning algorithms: support vector machines (SVM), boosted Regression Trees (BRT) and generalized linear models to map the complex hazard vulnerability of five natural hazards: snow avalanches, landslides, wildfires, land subsidence, and floods (Yousefi et al. 2020). Pourghasemi et al. used Random Forest (RF) machine learning algorithms for multi-hazard susceptibility mapping and assessed three natural hazards: forest fires, floods, and landslides (Pourghasemi et al. 2020). Nachappa et al. performed a multi-hazard susceptibility assessment and mapping of floods and landslides using two machine learning algorithms: SVM and RF, and compared model performance (Nachappa et al. 2020). Based on the existing research, it can be confirmed that machine learning algorithms have faster analysis speed and better accuracy in multi-hazard assessment and
mapping. In this study, multi-hazard susceptibility mapping and assessment of forest fires considering drought was performed using machine learning algorithms.

Although research on drought susceptibility mapping (Roodposhti et al. 2017; Dayal et al. 2018; Khan et al. 2020; Rahmati et al. 2020) and forest fire susceptibility mapping (Jaafari et al. 2018; Bui et al. 2019; Moayedi et al. 2020; Pham et al. 2020; Pourghasemi et al. 2020) is actively underway, to our knowledge, this study is the first from a multi-hazard conceptual perspective to use machine learning to map and assess multi-hazard susceptibility to forest fires and drought. In this study, a method is proposed to establish a multi-hazard probability map (MHPM) of forest fires and droughts using a multi-layer hazard approach and a machine learning algorithm to provide information on the highly susceptible areas for forest fire occurrence in Gangwon Province. The Gangwon-do area in South Korea is susceptible to natural hazards (drought, forest fires). Therefore, spatial data are required for effective prediction, prevention, and management planning. Although intensified efforts to suppress forest fires, such as standby areas for forest firefighting helicopters, are underway in various regions of Korea, the incidence of forest fires is increasing, and people in many areas are in danger (Korea Forest Service 2017). In this study, fire susceptibility was mapped considering drought, while detailed information on spatial units and highly susceptible areas were identified through the detection of drought-affected forest fire high susceptibility areas. The findings allow planners and managers to develop more effective and detailed plans for forest fire prevention and management. In this study, a MHPM for drought and forest fires in Gangwon-do, South Korea, was constructed using three machine learning algorithms (CART, RF, and BRT), and spatially susceptible areas for forest fire occurrence were monitored and evaluated.

2. Study area

Gangwon Province is located in northeastern Korea, bordered by the East Sea to the east, Gyeonggi Province to the west, Chungcheongbuk Province and Gyeongsangbuk Province to the south, and North Korea to the north. Gangwon Province, as the number one forest province in Korea, is approximately 81% comprised of forests, which accounts for approximately 21% of the total forest area in Korea. The large, forested area of Gangwon Province is affected by the climate zone and is prone to natural disasters such as forest fires and droughts. Korea suffered from nationwide droughts in 1994 and 1995 (Park and Schubert 1997). Droughts in 2001 and from 2008 to 2009 also caused severe damage to Korea, especially in Gangwon Province (Rhee and Im 2017). The drought period in Gangwon Province started in 2013 and lasted until 2017, with 2017 being the most severe drought period (www.drought.go.kr). In addition, seven of the ten mega forest fires in Korea to date have occurred in Gangwon Province (https://www.forest.go.kr).

Figure 1 shows precipitation and temperature data from nine ASOS weather stations in Gangwon Province: Sokcho, Cheorwon, Daegwanryeong, Chuncheon, Gangneung, Wonju, Inje, Hongcheon, Taebaek. The nine meteorological stations used in this study started observation in Gangwon Province before the 1990s, and
have meteorological data from the 1990s to the present. Additionally, this study used rainfall data from 1990 to 2019 from nine ASOS weather stations for the SPI analysis.

3. Methodology and material

In this study, we proposed a method to establish a MHPM for forest fires and droughts using a multi-layer hazards approach and a machine learning algorithm to detect drought-affected forest fire high susceptibility areas in the study area. As shown in Figure 2, single-hazard modeling and susceptibility mapping of forest fires and droughts was performed using three machine learning algorithms: Classification and Regression Trees (CART), Random Forest (RF), Boosted Regression Trees (BRT), and inventory maps for each hazard. The best performing model among the three machine learning algorithms and the MHPM for droughts and forest fires in Gangwon Province were selected by accuracy validation using the area under the ROC curve (AUC). Furthermore, the selected best models of forest fires and droughts
were joined by a multi-layer hazards approach for detecting drought-affected forest fire high susceptibility areas.

### 3.1. Forest fire inventory map

In general, understanding and mapping the spatial distribution of natural hazards is important for studying the spatial relationships between the locations of hazards and their causes (Pourghasemi et al. 2019). In addition, hazard occurrence data are important for assessing and predicting susceptibility (Moayedi et al. 2020). Based on previous research, forest fire data was provided by the Korea Forest Service (https://www.forest.go.kr), and 270 sampling points for forest fire occurrence sites were constructed (Piao et al. 2022). Out of a total of 270 forest fire points, 70% were used to train the model for forest fire susceptibility mapping, and 30% were used to test the model (Piao et al. 2022).

Our analysis of the duration of forest fires revealed that most forest fires occurred in April (18.28%), May (18.28%), and March (16.79%). This result is consistent with Korea’s high occurrence of forest fires in the spring months of March–May due to the characteristics of the climatic zone, and droughts also occur mainly in the spring months of March–May (Shin and Lee 2004; Lim et al. 2019). Korea is situated in a warm climate zone with four distinct seasons: spring, summer, autumn, and winter. This leads to a variety of circumstances that can cause droughts. For example, snow slowly melts in the spring, which can be used as a moisture supply, but in the winter when snowfall is low or rapidly melts due to high temperatures in unusual weather, this can lead to severe droughts in the spring. In addition, a dry season can result in an increase in the number of dry days and a significant decrease in the amount and number of days of precipitation. For example, in 2017 the number of dry days increased by about 40% compared to the previous year, and the amount of precipitation decreased significantly. Due to the dry weather and drought, there has been an increase in the occurrence of forest fires and an increase in the area of damage in spring in Gangwon Province. Figure 3 shows the results of the detailed statistical analysis of forest fires by month.

### 3.2. Drought inventory map

Drought data on vegetation susceptibility in the lowest and the extreme drought years (Roodposhti et al. 2017) were constructed by specifying a climate drought index (DI) and satellite DI and selecting extreme drought years and years with the lowest number of droughts, with vegetation susceptibility as the medium of drought intensity. In this study, the Standardized Precipitation Index (SPI) was used as the climate DI and the EVI index was used as the satellite DI. A total of 175 drought-susceptible samples for extreme drought years and 175 non-drought-susceptible samples for lowest drought years were constructed through the analysis of extreme drought years and lowest drought years (Roodposhti et al. 2017).
3.2.1. Construction of the drought inventory map
This study used the sensitivity of vegetation to drought to evaluate and analyze drought, focusing on vegetation stress and soil moisture in the monthly SPI index (Roodposhti et al. 2017). Previous studies have shown that meteorologically induced droughts are related to hydrological droughts through secondary effects on soils (Taufik et al. 2017). Thus, vegetation susceptibility as the medium of drought intensity was used to respond to the effects of drought on the soil. The SPI is an effective and simple indicator to identify the occurrence of meteorological drought, and monthly SPI reflects soil moisture and vegetation stress (McKee et al. 1993; Belal et al. 2014; Lee et al. 2017; Nam et al. 2015). The minimum time scale for the analysis of SPI is 30 years.

3.2.2. Selection of extreme drought years
The SPI drought index was analyzed on a 1-month time scale using rainfall data from nine ASOS meteorological stations in Gangwon Province. Figure 4 shows the SPI indices for each ASOS weather station from 1990 to 2019. Considering the time series of satellite image data, we used 2003 as the lowest drought year as the maximum SPI value and 2017 as the extreme drought year as the minimum SPI value. This strategy was confirmed to be generally consistent with the information on drought years in Gangwon Province in the available literature (Rhee and Im 2017).

3.2.3. Drought sampling
Drought was measured using the SPI in Climate DI and rainfall data from the Korea Meteorological Administration. Daily rainfall data was measured from nine ASOS in the study area from January 1990 to December 2019. To construct drought sample
points, the Enhance Vegetation Index (EVI) was selected as the DI in the satellite image index. The EVI is a satellite vegetation index designed to enhance the vegetation signal and can be used to identify drought-related stresses in various environments (Huete et al. 2002). The EVI indices used in this study are: (1) (Venkatappa et al. 2019). We selected the lowest drought year, 2003, and extreme drought year 2017, by one-month scale SPI analysis. 

The EVI was determined as follows:

\[
EVI = G \cdot \left( \frac{\text{NIR} - \text{RED}}{\text{NIR} + C1 \cdot \text{RED} - C2 \cdot \text{BLUE} + L} \right)
\]  

(1)

The NIR, RED, and BLUE are bands, L value to canopy background adjustment, “C” values as coefficients for atmospheric resistance, and G means the gain factor. The values of EVI constructed in this study are \( L = 1, C1 = 6, C2 = 7.5, \) and \( G = 2.5 \) (Huete et al. 2002). All EVI data are built on the Google Earth Engine (GEE) platform. The GEE platform is an efficient, free, cloud-based platform for processing and analyzing satellite image data (Gorelick et al. 2017). The GEE platform also runs efficiently based on data import and programming without the problems of insufficient manpower or computer configurations (Piao et al. 2022). We constructed satellite image data with EVI values for the lowest drought year (2003) and extreme drought year (2017) using the satellite image MODIS13Q1 product. We then processed the samples on the ArcGIS 10.8 platform.

3.2.4. Construction and interpretation of conditioning factors

In general, hazards occur under the influence and interrelationship of various conditioning factors (Van Westen et al. 2003; Verde and Zèzere 2010). In this study, 11 conditioning factors were selected for multi-hazard susceptibility mapping: elevation (m), slope (°), aspect, distance to river (m), distance to road (m), distance to urban area (m), rainfall (mm), annual mean temperature (°C), Normalized Difference Vegetation Index (NDVI), and the standard deviation of NDVI (SD-NDVI). These factors were chosen to reflect the spatial and temporal variations in the study area and to provide a comprehensive understanding of the interplay between these factors and the susceptibility to hazards.
Vegetation Index (NDVI), Topographic Wetness Index (TWI), and drainage density. Figure 5 shows the selection and data construction of 11 conditioning factors related to drought and forest fires. Based on the previous study of forest fire susceptibility in Gangwon Province (Piao et al. 2022), the conditioning factors for forest fire were selected and the conditioning factors for drought were considered based on the characteristics of the study site. Table 1 shows the details of the data sources for the 11 conditioning factors.

3.2.5. Elevation
Elevation can indirectly affect forest fire vulnerability by influencing precipitation, temperature, and humidity in the area (Camp et al. 1997; Verde and Zêzere 2010). This study used the digital elevation model product Shuttle Radar Topography Mission V3 product (SRTM3) to construct elevation data with a resolution of 30 m (Farr et al. 2007).

3.2.6. Slope
Many researchers have found that the rate of forest fire spread increases with an increasing slope (Kushla and Ripple 1997; Weise and Biging 1997; Lentile et al. 2006; Farr et al. 2007). This is one of the important factors in the occurrence of hill fires. Slope factors were prepared using SRTM, elevation data, and the slope tool on the ArcGIS 10.8 platform.
3.2.7. Aspect

Researchers have found that aspect orientation affects soil moisture and wind speed (Schmidt et al. 2008). This is an important influence that can indirectly affect forest fires and droughts. In addition, in the northern hemisphere, to which the study site belongs, solar energy reception is greater toward the south, and vegetation facing south is generally drier and less dense than features facing north (Prasad et al. 2008). In addition, depending on the sun’s path, eastern regions receive more UV and direct sunlight than western regions and therefore dry faster (Adab et al. 2013). In fact, the Gangwon Province area of Korea, the target of this study, was found to be drier and received more direct sunlight than other areas, depending on the location of different geospatial information in the 2000 large-scale forest fires (Shin and Lee 2004). In this study, aspect was produced using elevation data by using the aspect tool in the ArcGIS 10.8 platform.

3.2.8. Proximity factors

Human, animal, and vehicle interactions increase fire risk and increase the likelihood of forest fires (Jaiswal et al. 2002). It is now well known that the occurrence of forest fires is heavily influenced by human behavior (Mollicone et al. 2006). Distances to rivers, distances to roads, and distances to cities were constructed using the Euclid tool on the ArcGIS 10.8 platform. Distance to road data was obtained through the Korean National Spatial Data Infrastructure portal (http://www.nsdi.go.kr), and distance data to rivers with a resolution of 30 m was constructed from land cover data from the Ministry of Environment Environmental Geospatial Information Service (egis.me.go.kr).

3.2.9. Drainage density

Drainage density is a measure of how well a watershed is drained by a river, which impacts humidity (Montgomery and Dietrich 1989). In other words, based on the

### Table 1. Data sources for the multi-hazard probability mapping process.

| Data type         | Data Source                                                                 | Resolution |
|-------------------|----------------------------------------------------------------------------|------------|
| Satellite image   | https://code.earthengine.google.com/                                       | 30 m       |
| Geological data   | Korea Ministry of Environment (http://water.nier.go.kr/)                   | Line data  |
| Geological data   | Korea National Spatial Data Infrastructure Portal (http://www.nsdi.go.kr/)  | Polygon data |
| Geological data   | Korea Meteorological Administration (https://data.kma.go.kr/)              | Point data |
| Geological data   | Korea Ministry of the Interior and Safety (https://www.safekorea.go.kr/)   | Point data |
| Geological data   | Korea Ministry of Environment (https://egis.me.go.kr/)                     | Polygon data |
| Geological data   | https://code.earthengine.google.com/                                       | 30 m       |
| Geological data   | https://code.earthengine.google.com/                                       | 250 m      |
| Geological data   | Land Use Land Cover map (Urban Land Cover)                                |            |
| Geological data   | Forest Fire list                                                           |            |
| Geological data   | https://code.earthengine.google.com/                                       |            |
| Geological data   | https://code.earthengine.google.com/                                       |            |
| Geological data   | https://code.earthengine.google.com/                                       |            |
| Geological data   | https://code.earthengine.google.com/                                       |            |

2658 Y. PIAO ET AL.
magnitude of drainage density, it is possible to check the soil moisture and water retention in the area, which is one of the factors that affect drought and forest fires. The drainage density is measured by the total length of all streams divided by basin area.

3.2.10. Normalized difference vegetation index
The NDVI uses satellite imagery to indicate the vigor of vegetation in a target area. It is currently the most commonly used index in vegetation vigor analysis studies (Tucker 1979). Therefore, the NDVI index can be used to determine the degree of influence on wildfire occurrence through the degree of vegetation vigor (Bui et al. 2017). For example, the monitoring of dense vegetation will affect the amount of combustion material accordingly (Anderegg et al. 2015; Barlow et al. 2019; Brando et al. 2019).

The NDVI was determined as follows:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$  \hspace{1cm} (2)

3.2.11. Topographic wetness index
The TWI was developed to quantify soil moisture in irregular mountainous areas to quantify hydrology-based topographic control (Moore et al. 1991). That is, the TWI index allows observation of high and low soil moisture levels and differences in forested areas. It can determine the extent of impact on drought and forest fires.

The TWI was determined as follows:

$$TWI = \ln \frac{a}{\tan b}$$  \hspace{1cm} (3)

where “a” is specific catchment, and “tanb” is the gradient.

3.2.12. Meteorological factors
Temperature changes affect the frequency and extent of wildfire damage (Gillett et al. 2004; Heimann and Reichstein 2008). Changes in rainfall can also affect soil moisture (Guttman 1998). Thus, rainfall variability can directly affect wildfire and drought susceptibility (Zaitchik et al. 2013).

4. Multi-hazard probability mapping
Machine learning techniques are currently being used in various fields and are frequently used for natural disaster prediction and assessment (Pham et al. 2020). Machine learning techniques offer a fast analysis speed with excellent accuracy in predicting natural hazards (Pourghasemi et al. 2020). In this study, three machine learning algorithms were used to construct the MHPM: CART, RF, BRT. Each machine learning model was run 500 times, which is a sufficient number to confirm the model’s accuracy (Abdullah et al. 2019). Among the three machine learning models, RF, BRT, and CART, the best performing models were selected for each hazard.
susceptibility map for drought and forest fires. The best models of forest fire and drought were jointed based on a multi-layer hazards approach to construct the MHPM for forest fires and drought, where each hazard susceptibility result map of forest fires and drought was classified into five risk levels: very low, low, moderate, high, and very high. The high and very high levels in the risk class of each hazard susceptibility result map were used as susceptible hazard areas. The MHPM was constructed based on the hazard susceptibility area of the best model for forest fires and droughts and the risk classes were classified into four types: non-hazards and minor hazards, forest fires, droughts, forest fire high susceptibility area. The forest fire high susceptibility area in the four types of MHPM results is the area with both forest fire and drought risk (that is, forest fire $+$ drought). According to previous multi-hazard studies, the relationship between droughts and forest fires is increasing probability, and the relationship is unidirectional from droughts to forest fires. Therefore, in the MHPM results, we defined the areas where forest fires and droughts exist together as areas with higher susceptibility to forest fires. This was used to improve the reference and application in actual forest fire management and prevention.

4.1. Classification and regression trees (CART)

CART is a nonparametric data mining technique, mainly used for regression or classification problems (Breiman et al. 1984). CART uses a nonparametric nonlinear technique called binary partitioning algorithm. Here, CART recursively partitions the data to predict the distribution of key target attributes and explores the relationship between the response and the predictor variables (Breiman et al. 1984).

4.2. Random Forest (RF)

The RF algorithm proposed by Breiman is an integrated tree-based machine learning technique developed from CART. It is one of the most widely used machine learning algorithms today (Breiman 2001). The RF algorithm is one of the integrated learning methods used for classification and regression analysis by constructing multiple decision trees during training (Park and Lee 2020). RF includes bootstrap aggregation (bagging) and random feature selection, combining multiple samples extracted by bagging training samples with a classification tree and making predictions through a voting process (Breiman 2001). RF is actively used for data prediction and is suitable for high-dimensional nonlinear modeling such as natural disasters (Gigović et al. 2019). RF is now widely used for multi-hazard analysis, with fast analysis speed and excellent performance (Pourghasemi et al. 2020).

4.3. Boosted regression trees (BRT)

Friedman’s proposed BRT model combines two powerful statistical techniques to make predictions, a boosting technique and a decision tree algorithm (Friedman 2001). BRT uses combinatorial methods to fit complex nonlinear relationships, construct regression trees to predict target variables, and apply augmentation techniques
to improve predictive power by minimizing the risk of overfitting. The boosting technique randomly selects a subset of data to iterate into a new tree model to minimize the loss function (Elith et al. 2008). Therefore, BRT is suitable for combining several simple models for spatial prediction.

4.4. Model accuracy validation

Validation is an important step in assessing the accuracy of each model. To construct a machine learning model for MHPM, we compared forest fire and drought susceptibility maps derived from CART, RF, and BRT using forest fire and drought inventory data. In this study, the area under the ROC curve (AUC) was used to verify the accuracy of the forest fire and drought susceptibility maps generated using the CART, RF, and BRT models. ROC curves are a widely used model validation method (Shabani et al. 2021). The accuracy and performance of the prediction model is evaluated by comparing the false-positive rate (specificity) on the x axis of the sensitivity plot and the true positive rate (sensitivity) on the y axis by balancing these two rates (Fawcett 2006). AUC is a value that indicates the model’s accuracy and specifies the probability that more pixels are correctly marked than incorrectly marked (Nachappa et al. 2020). The AUC values range from 0.5 to 1.0. Higher AUC values indicate higher accuracy of the sensitivity map, while lower AUC values indicate lower accuracy. Generally speaking, the closer the AUC value is to 0.5, the worse the model prediction, the higher the AUC value is to 0.8, the better the model prediction, and the closer the AUC value is to 1, the better the model prediction (Nachappa et al. 2020).

5. Results

5.1. Susceptibility mapping validation results

Figure 6 shows the accuracy assessment of forest fire and drought susceptibility mapping. In the forest fire susceptibility mapping, the AUC of the CART model was 0.751 (accuracy ≈ 75%), the AUC of the RF model was 0.835 (accuracy ≈ 84%), and the AUC of the BRT model was 0.846 (accuracy ≈ 85%). In the drought sensitivity mapping, the AUC of the CART model was 0.723 (accuracy ≈ 72%), the AUC of the RF model was 0.788 (accuracy ≈ 79%), and the AUC of the BRT model was 0.795 (accuracy ≈ 80%). Among the three models, the forest fire and drought susceptibility mappings have the highest accuracy of the BRT model, and the AUC values are both ≥0.8 (forest fire: BRT ≈ 0.85, drought: BRT ≈ 0.8), which is an excellent performance. This result indicates that the BRT model has the highest prediction accuracy and was selected for the production of the forest fire and drought MHPM.

5.2. Forest fire and drought susceptibility mapping assessment

Figure 7 shows the results of the forest fire and drought susceptibility mapping using the three models. Susceptibility probability values range from 0 to 1, and the closer the value is to 1, the more susceptible the space is to attack. In this study, we used the natural breaks method, classified forest fire and drought susceptibility mapping
The BRT model has a higher predictive performance compared to CART and RF and allows the classification of a denser distribution of very high areas. This provides more detailed information in the spatial analysis and assessment of hazards. Table 2 shows the area ratios of the three model taxa for the forest fire and drought susceptibility mapping results. In combination with the spatial analysis, the CART model performs poorly, resulting in a very extreme classification of susceptible areas. For each hazard, forest fire (very low: 27.79%, low: 14.98%, moderate: 6.44%, high: 7.46%, very high: 43.33%), drought (very low: 28.6%, low: 16.34%, moderate: 6.44%, high: 7.46%, very high: 43.33%).

Figure 6. AUC value plot of classification and regression trees, random forest, and boosted regression trees models.

Figure 7. Forest fire and drought susceptibility mapping results of Classification and Regression Trees, Random Forest, and Boosted Regression Tree models. Susceptibility map risk levels: very low, low, moderate, high, and very high.
moderate: 8.53%, high: 21.81%, very high: 24.72%). The distribution of RF is predicted to be similar to BRT, but tends to be more concentrated on moderate areas compared to BRT. Furthermore, the taxa are not spatially concentrated and tend to be fragmented and dispersed, which are disadvantages in hazard monitoring. For each hazard, forest fire (very low: 15.14%, low: 22.7%, moderate: 25.88%, high: 20.73%, very high: 15.55%), drought (very low: 13.48%, low: 17.91%, moderate: 25.66%, high: 25.19%, very high: 17.76%). The BRT model has advantages in performance. Since the classification of vulnerable areas is aggregated, it can provide more detailed spatial information than the RF model. For each hazard, forest fire (very low: 19.86%, low: 18.79%, moderate: 18.7%, high: 19.55%, very high: 23.11%), drought (very low: 19.4%, low: 19.73%, moderate: 20.79%, high: 20.67%, very high: 19.41%).

### 5.3. Results of multi-hazard probability map

The combination of forest fire and drought susceptibility maps predicted by the best performance model (Forest Fire: BRT, Drought: BRT) generated a forest fire and drought MHPM. As shown in Figure 8, the generated MHPMs were classified into four types (non-hazard and minor hazard, forest fire, drought, and forest fire high susceptibility area) based on foreseeable conditions. Areas without hazards or with weak hazards are classified as non-hazards and minor hazards, areas susceptible to forest fire as forest fires, drought susceptible areas as droughts. Areas that are more susceptible to forest fires due to the effects of droughts (lack of water resources, destruction of forest vegetation, increase in combustible materials, etc.) were classified as forest fire high susceptibility areas. It has been shown that forest fires in the study area are mainly caused by human activities and disturbances and that fires are very likely to occur around cities and on gentle slopes (≤17°) where humans are active (Piao et al. 2022). Related to this, when examining the MHPM of forest fires and droughts it can be clearly confirmed that forest fire high susceptibility areas have a more susceptible distribution spatially near cities. This indicates that information can be provided while focusing on monitoring spatial areas that require the highest priority for the prediction, prevention, and development of forest fire management plans.

Furthermore, the area ratios of the four MHPM class types and the occurrence of forest fires in the area correspond to class type. A sample of 270 forest fire occurrences from the forest fire inventory map was used for forest fire occurrence. Among the four types of MHPM, non-hazards and minor hazards accounted for 36.1% of the total study area, while forest fire occurrence had 30 forest fires with a low risk of 11.11%. The forest fire type accounted for 23.84% of the total study area, and 126
forest fires occurred, accounting for 46.67% of forest fire occurrences, which is a high risk. By contrast, the drought type, although accounting for 21.24% of the total study area and similar to the forest fire type, had 14 forest fire occurrences with a very low risk of 5.19%. Finally, the forest fire high susceptibility area type had the smallest area, accounting for 18.82% of the total study area, but had a high risk with 37.04% of 100 forest fires. Overall, the MHPM is generally consistent with the actual forest fire susceptibility in the current study area, and it can clearly be confirmed that the forest fire high susceptibility area type has a high susceptibility to forest fires. In other words, forest fire risk can be effectively and centrally reduced by developing forest fire high susceptibility area management plans.

6. Discussion

6.1. The significance of methodological research

More than 90% of forest fires in Gangwon Province are caused by human activities and disturbances (Korea Forest Service 2004, https://www.forest.go.kr). Studies have
shown that anthropogenic fires can lead to more extreme fire behavior and increase the frequency and extent of forest fire damage in areas where anthropogenic activities and disturbances account for the highest incidence of forest fires (Hantson et al. 2022). In addition, increased drought can lead to reduced living biomass and increased combustible ash, which may increase the incidence of forest fires (Brando et al. 2019; Barlow et al. 2020). In future, increasingly severe droughts and forest fires will cause more ecological damage in areas subject to human activities and disturbances, resulting in more human casualties and economic losses (Lindenmayer et al. 2022). In general, as forest fires and droughts intensify increasing the frequency of forest fires and ecological damage, effective forest fire management programs need to be developed by considering forest fires and droughts in an integrated manner.

6.2. Multi-hazard concept of droughts and forest fires

The results of this study were generated by considering forest fires and droughts separately, and the results of forest fires and droughts were joined using the multi-layer hazards approach to monitor forest fire high susceptibility areas.

In multi-hazard studies, there are three possibilities of relationship between hazards: 1. Triggering 2. Increased probability 3. Triggering and increased probability. According to a previous study (Gill and Malamud 2014), the relationship that exists between droughts and forest fires is the second point: increasing probability, and is unidirectional from droughts to forest fires. That is, drought leads to the increased probability of forest fires, but the occurrence of forest fires does not affect drought

As mentioned in 6.1, more than 90% of forest fires are caused by human activities and disturbances in this study area. i.e., the main cause of forest fires is not drought but human activities and disturbances. Since drought mainly increases the probability of forest fire occurrences such as an increase in combustible material and soil moisture deficits, all may indirectly increase the probability of forest fire occurrence (Brando et al. 2019; Barlow et al. 2020).

In the study area, forest fire occurrence events are mainly concentrated in March–May. Furthermore, according to the climatic zone in which the study area is located and the literature (Park and Schubert 1997; Rhee and Im 2017, drought likewise occurs mainly in spring. Although forest fires occur mainly due to anthropogenic activities and disturbances, the main drought season (March–May) accounts for the majority of forest fire events (53.35%). This is one of the reasons why we mainly considered drought and forest fires in our multi-hazard study.

6.3. Forest fire prevention policy recommendations

This study constructed a MHPM for forest fires and droughts through multi-hazard mapping using single-hazard analysis and model selection. The classification of forest fire high-susceptibility area types through MHPM allows for more spatially focused and effective designation of directions and locations for forest fire prevention and control planning preparation than existing forest fire susceptibility areas. Previous studies revealed that the most important factor for forest fires in Gangwon Province
is slope, suggesting that areas with slopes \( \leq 17^\circ \) are most susceptible (Piao et al. 2022). In other words, in an area where the majority of wildfires occur due to human intervention and activities, the slope of a site does not necessarily affect the probability of forest fires, but significantly impacts the behavior of the forest fires. This finding is also consistent with previous research that human-caused fires can induce more extreme fire behavior (Hantson et al. 2022).

Between March 2022 and May 2022, two major forest fires occurred in Gangwon Province, Korea. Figure 9 shows the two large forest fire locations, and the occupied type in MHPM. In zooming in to view the study area region of MHPM, we find that it further narrows and concentrates the highly susceptible areas for forest fire occurrence. Both hill fires in Gangwon-do, Gangneung-si, on March 4, 2022, and in Gangwon-do, Yangyang-gun, on April 22, 2022, caused significant forest cover damage and economic loss (https://www.forest.go.kr). It can be confirmed that both of the recent major forest fires occurred in the forest fire high susceptibility area of the MHPM. This indicates that the MHPM constructed in this study effectively reduces the spatial extent of forest fires through the combination of drought and forest fires and the effective monitoring of forest fires at the study sites. In other words, the MHPM constructed in this study delineates forest fire high incidence areas and narrows the existing large forest fire-prone areas, which can effectively prioritize the detection needed to develop forest fire prevention plans and take prompt measures accordingly. Even though previous forest fire susceptibility mapping studies (Piao et al. 2022) were monitored according to the classification of susceptibility (e.g., very low, low, moderate, high, very high), high forest fire susceptibility areas are too large and difficult for practical forest fire management and prevention. However, considering droughts and forest fires from a multi-hazard perspective, it is possible to monitor a more susceptible area (forest fire high susceptibility area, forest fire + drought) for forest fires in the study area. That is, the areas more susceptible to forest fires are monitored based on the highly susceptible areas of forest fires in the previous study. This, in turn, largely reduces the size of the areas that are more in need of priority

Figure 9. The location and the occurred occupied type of the recent large forest fires in a multi-hazard probability map; light pink x: occurred in a forest fire high susceptibility area on 2022-04-22; light blue x: occurred in a forest fire high susceptibility area on 2022-03-04.
management and prevention. That is, it can be used as a reference for planning in practical management and prevention applications.

6.4. Research limitations and future directions

At present, multi-hazard research is a relatively new field with no clear definition of multi-hazards, and presents different results depending on the research methods (Tilloy et al. 2019). There are many limitations and uncertainties in the field of multi-hazard research (Gill and Malamud 2014). This study used a multi-layer hazards approach to superimpose forest fires and drought hazards in one area using a machine learning model, therefore the physical occurrence between the two hazards (forest fires and droughts) and hazard interrelations was not considered in the current study (Tilloy et al. 2019). That is, a probabilistic statistical analysis of the extent of forest fire occurrence and drought was performed. This approach does not allow for observing physical interrelations, such as cascade effects. However, it is undeniable that the MHPM constructed with the multi-layer hazards approach was effective in this study area (Pourghasemi et al. 2019). We confirmed this based on the accuracy of the constructed machine learning model and the prediction of recent actual forest fire events by the MHPM results and agreed that this approach and the resultant maps are effective for forest fire prevention and reduction in the study area. However, further in-depth studies that consider the interrelations between forest fires and droughts in a multi-hazard framework need to be continued, and this is the main research question to be addressed in our future studies.

When using machine learning models, the constructed data is the core of the calibration and validation of the model. There is no clear answer to the question of which model is more accurate, therefore other uncertainties generally derive from assumptions and simplifications inherent in the model (Tilloy et al. 2019). The ROC curve (AUC value) is used to validate the model in this study, and is influenced by the selection of factors and the randomness of the inventory chart, which does not clearly indicate the actual effect of the model (Fawcett 2006). To reduce uncertainty, we performed additional reliability verification on the share of events that occur.

In this study, drought was analyzed as a single hazard with the aim of mapping and assessing multi-hazards. Drought susceptibility maps (DSM) were constructed by selecting extreme drought years and lowest drought years using the SPI and by selecting vegetation vulnerability as a mediator affected by drought through the EVI. Although the uncertainty of mapping was reduced by selecting extreme drought years and non-drought years, the exact drought period and drought type (flash drought, etc.) could not be considered for DSM mapping because the vulnerability of vegetation cover was used as a mediator. Therefore, it does not provide a consistent interpretation of the actual drought. This is one of the limitations that need to be addressed in our future research. In addition, in terms of space, the study area is adjacent to the DMZ, a special political region between South Korea and North Korea, therefore there is a limit to the construction of some influencing factors (soil properties, drainage grade, etc.) (Piao et al. 2022).
7. Conclusion

In terms of ecosystem damage, forest fires are one of the most devastating natural hazards, causing large-scale forest cover and ecological damage every year. Therefore, the monitoring and prevention of forest fires is crucial. The MHPM of forest fires and droughts constructed in this study monitors the forest fire high susceptibility area based on the characteristics of the Gangwon Province area. In other words, the range of forest fire susceptibility was narrowed, while the range of forest fire high susceptibility areas was expanded. As the previous forest fire susceptibility mapping study (Piao et al. 2022) had a wide range of very high-risk areas, spatial areas selected for forest fire prevention and management plans could not be effectively developed.

In this study, susceptibility maps for forest fire and drought were constructed based on a multi-layer hazard approach using three machine learning models (CART, RF, BRT) and 11 selected conditioning factors based on the characteristics of the Gangwon Province region. The best performing BRT model was selected based on the accuracy of AUC value verification, and a reliable and more effective MHPM was constructed for the Gangwon-do region of Korea by combining the susceptibility maps of forest fire and drought. The results of this study can be summarized as follows:

1. We proposed a method to predict forest fire high susceptibility areas using a multi-layer hazards approach with machine learning algorithms, which we applied to the Gangwon-do area in South Korea.
2. A multi-hazard probability map of related hazards forest fires and droughts was developed.
3. The map provides key information for forest fire prevention and management plans.

In summary, this multi-hazard map can provide planners and decision-makers with critical information to develop forest fire prevention and management plans, and to prevent and reduce the frequency of forest fires more effectively. However, multi-hazard research is a relatively new field, and there are no clear definitions of multi-hazards. Furthermore, different research methods have produced different results. Our results were completed using only a preliminary multi-layer hazards approach, and further studies are required, including hazard interactions in the multi-hazards framework.

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