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Development and Application of a Forest Fire Danger Rating System in South Korea

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Most of fires were human–caused fires in Korea, but meteorological factors are also big contributors to fire behaviors and its spread. Thus, meteorological factors as well as social factors were considered in the fire danger rating systems. This study aims to develop a Korean Forest Fire Danger Rating System (KFFDRS) to support forest fire prevention efforts in South Korea. The KFFDRS consists of three, 10–scale indices: daily weather index (DWI), fuel model index (FMI), and topography model index (TMI). DWI represents the meteorological characteristics, such as effective humidity, temperature and wind speed, and is adapted to local conditions through the use of one of eight logistic regression models. Among the weather variables, the effective humidity significantly ($p<0.01$) affected the probability of forest fire occurrence in the overall regions. Maximum temperature was also a significant indicator ($p<0.01$) in the Gangwon, Gyeonggi, Gyeongbuk, and Jeonbuk regions. However, mean wind speed was a significant indicator ($p<0.05$) only in the Gyeongbuk region, indicating that is had no significant effect on the probability of occurrence, except in one region. The results of predicting estimation showed that the probability of randomly selected fires ranges from 0.740 to 0.822, which represent a relatively high accuracy of the developed model. Both FMI and TMI were derived by analysing the forest types and ignition points of 126 forest fires from 1997 through 2001. These findings would be necessary for the policy makers in South Korea for the prevention of forest fires.

INTRODUCTION

A turning point in the history of Korean forest policy was achieved with the initiation of two successive, 10–year forest development plans in 1973. As a result, over the following two decades, 2 million ha, around 34% of the total forestry land in South Korea, was reforested. The 2005 forestry statistics show that South Korea has 6.39 million ha of forests covering about 64.2% of the total land area, of which nearly 42.3% (2.70 million ha) is coniferous forest. In South Korea, coniferous trees covers about 42% of forest lands and Japanese red pine (*Pinus densiflora* Sieb. et Zucc) covers about 58% of the coniferous forest (Korean Forest Service, 2006). Coniferous species in South Korea are considered to be vulnerable to fire (Lee *et al.*, 2006).

The broadleaved and mixed forests cover 25.9% (1.66 million ha) and 29.3% (1.87 million ha), respectively, with the remaining 2.5% (0.16 million ha) being classified as mixed types. The total growing stock is 506 million m^3 and the volume per ha is estimated at 79.2 m^3. However, nearly 60% of forest stands are aged less than 40 years (KFS, 2006).

Increasing in the forest age, woody fuel, ground litter and forest visitors, the forest fire risk has been significantly increasing. Therefore, Korean forestry is facing ever–increasing pressure to prevent and control forest fires. In April 2000, a catastrophic forest fire encompassing 23,794 ha erupted in a mountainous area on the East Sea, Gangwon–Do. This was the most disastrous forest fire since 1945, causing massive property damage. The seasonal westerly wind blowing from the continent in the spring and autumn creates dry conditions throughout the country. In addition, the sea wind and Föhn create hazardous forest fire conditions.

Although data are only available for recent years, forest fires have played a significant role in the change of Korean forest ecosystems. On average, from 1997 to 2001, 524 fires burned 6,231 ha of forest lands each year in South Korea. No fires were caused by natural phenomena according to the official statistics collected since 2000. All fires were brought about by man–made activity, especially burning by people in areas adjacent to rural forests. The main causes of forest fire include carelessness, weed burning, fireworks, and ceremonies honoring the dead (Fig. 1).

Prevention is one of the most important stages in management regimes for wildfire and other natural hazards (Vasilakos *et al.*, 2007). Fire danger rating systems have been adopted by many developed countries to deal

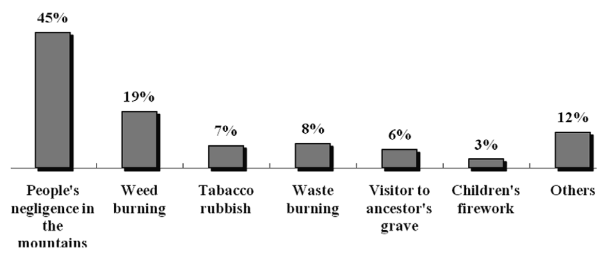

Fig. 1. Causes of forest fires in South Korea (1997~2001).

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with wildfire prevention and pre–suppression planning, so that civil protection agencies are able to define areas with high probabilities of fire ignition and take the necessary action (Deeming *et al.*, 1977; Van Wagner 1987; Hoffmann *et al.*, 1999). The majority of the systems is mainly based on meteorological data that are collected by weather stations (Deeming *et al.*, 1977; Van Wagner 1987; Carrega 1991; Viegas *et al.*, 1999). Nevertheless, these systems adopt a different approach to spatial–temporal resolution for which they are applied, and they use various correlations of the input parameters. Few studies have assessed the relationship between fire danger indices and actual fire occurrences (Preisler *et al.*, 2004). Andrews and Bradshaw (1997) present programs for rating fire danger indices at a given location. They use logistic regression to estimate the linear relationship of each fire index to the logit of the probability of a fire–day, large fire–day, or multiple fire–days and generate probability curves relating each index to each of the three responses by linking daily fire activity at a given forest to index data from the closest weather station. Dayananda (1977), Poulin–Costello (1993), Mandallaz and Ye (1997) employ the Poisson model to assess the number of forest fires, while Anderson *et al.* (2000), Cunningham and Martell (1972), and Martell *et al.* (1987, 1989) use logistic regression to study the relationships between indices produced by CFFDRS (Van Wagner, 1987) and the probability of fire days. Chou *et al.* (1990, 1993) use logistic regression with weather and other explanatory variables, one of which is a modified Moran's coefficient, to take into account the spatial autocorrelation between nearby fires. Loftsgaarden and Andrews (1992) apply logistic regression to the danger rating system. Garcia *et al.* (1995) use logistic regression to predict the number of fire–days. Vasconcelos *et al.* (2001) also use logistic regression for spatial prediction of fire ignition. Markov chain models are used by Martell (1999).

Probabilistic risk assessment estimates the probabilities of hazardous events which take place within a specified time period and in a specified context (Brillinger *et al.*, 2003). It proceeded by reducing a complex situation to its simpler components, followed by the fitting and validation of stochastic models associated with the components. The probability framework is necessary to assess the utility of explanatory variables, such as weather condition at the ignition time. A non–parametric logistic regression with stratified data for each province was employed to model the probability of fire occurrence. Brillinger *et al.* (2003) state that fire occurrence depends on local conditions such as location, elevation, wind speed, precipitation, temperature, air humidity, topography, litter type, and level of suppression.

Geographic information systems (GIS) are widely used in order to collect, manage, analyze and present spatial data that are used in the identification of wildfire pattern occurrence (Chuvieco and Congalton, 1989; Chou 1992*a*, 1992*b*).

Forest fire danger rating constitutes the process of systematically evaluating and integrating numerous factors: the ease of a fire starting and spreading based on an assessment of ignition risk, the fire environment (i.e., fuels, weather, topography), and values–at–risk (Countryman, 1966). An FFDRS produces qualitative and/or numerical indices of fire potential that are used as a guide in a wide variety of fire management applications.

In 1968 the USDA Forest Service started work on the development of a fire danger rating system that would rely on science and engineering principles and on local observations. It incorporated basic laws of physics, thus making the system applicable nationwide. The result was the National Fire Danger Rating System (NFDRS). The first version of the NFDRS was released in 1972 (Deeming *et al.*, 1972). A modified, 1978 version included better recognition of drought and fire response after precipitation (Burgan, 1988). The Canadian FFDRS (CFFDRS), developed by the Canadian Forest Service (CFS), is the national system of fire danger rating used in Canada (Stocks *et al.*, 1989; Alexander *et al.*, 1996; Van Nest and Alexander, 1999). The CFFDRS comprises two primary subsystems: the Canadian Forest Fire Weather Index (FWI) System (CFS 1984; Van Wagner, 1987) and the Canadian Forest Fire Behavior Prediction (FBP) System (Forestry Canada Fire Danger Group, 1992; Taylor *et al.*, 1997). Chandler *et al.* (1983) defined the forest fire danger as an index based on fuel types, topography and weather conditions which affect the fire ignition, its spread and behaviors. The U.S. and Canadian models were also developed from the statistical analysis of large field data (Van Wagner, 1974; Lee *et al.*, 2002)). The statistical models applied in this study were also used optimistically in the NFDRS. The literature reviews of the forest fire danger rating showed that Canada and U.S. NFDRS can be a good example for developing NFDRS of South Korea (Wybo *et al.*, 1995). Conceptually, the KFFDRS deals with the prediction of fire occurrence from point–source weather measurements, such as from a single fire weather network station. The KFFDRS deals primarily with temporal weather variations, but can also account for diurnal variation in fire danger. The system accounts for spatial variation in weather elements between points of measurement. Models and other systems external to the KFFDRS must be capable of handling such interpolation. Spatial variation in fuels and terrain is a fire management information problem not easily handled by the KFFDRS or any FFDRS unless linked by computer technology to a GIS, which stores, updates and displays such land–based information in ways directly usable by forest fire managers.

Therefore, there is an increasing need to develop an efficient forest fire danger rating system (FFDRS) to protect against large fire. The systems described in this paper have been developed to provide a systematic approach to the assessment of forest fire danger rating in South Korea. These systems have been successfully adopted by the KFS to help manage the impacts of fire both regionally and nationally.

MATERIALS AND METHODS

Fire and weather data

The forest fire occurrence dataset used the regional forest fire inventory for five years from 1997 to 2001. In this period, Gyeonggi, including Seoul and Incheon, had the most forest fires, at 331 (17.3%), followed by Gyeongbuk, including Daegu, with 297 fires (15.5%), and Chungnam, including Daejeon, with 271 fires (14.1%). The forest fire occurrence probability models were estimated using only the forest fire inventory from spring (February to May), which is the most dangerous dry season for forest fires (Fig. 2).

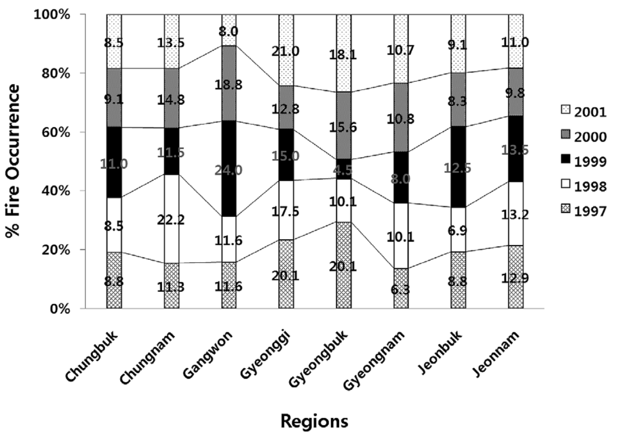

Fig. 2. Regional forest fires used in the forest fire occurrence probability model (1997–2001, for Feb.–May).

Forest fire occurrence depends on local weather conditions such as temperature, humidity, and wind speed (Brillinger *et al.*, 2003). To develop regional forest fire occurrence probability models we adopted regional daily weather variables related with fire ignition such as maximum temperature, maximum and mean wind speed, and relative and effective humidity. Effective humidity is the average humidity, weighted to the relative humidity of a particular day and the previous four days. The degree of dryness of wood can be estimated by the effective humidity (Korea Meteorological Administration (KMA) 2006). KMA currently calculates the effective humidity by Equation (1).

Hong (1987) describes that the coefficient value of the effective humidity is affected by the wood thickness. According to his statistical data, an effective humidity coefficient (r) approaching zero or one corresponds to a very fine or very thick wood thickness, respectively. A wood moisture content of 7 cm diameter corresponds to an effective humidity of r=0.7 (Hong, 1987). Sagae (2006) examined statistically and numerically the relationship between forest fire occurrence and the effective humidity. As a result, an effective humidity of 60% and daily minimum humidity of 40% provide boundary values for forest occurrence to become dangerous.

The effective humidity is calculated by Equation (1):

$$H_e = (1-r)(H_0+r(H_1)+r^2(H_2)+r^3(H_3)+r^4(H_4)) \quad (1)$$

where H_e is the effective humidity, H_0 the relative humidity of the day, H_n the relative humidity of n previous days, and r the coefficient of effective humidity. In this study, r was fixed at 0.7 (KMA, 2006).

This study incorporated important factors in the three categories that influence forest fire occurrence: weather, fuel type and topography (Fig. 3). The methods for developing forest fire occurrence probability models to calculate fire danger rating are illustrated in Fig. 3.

First, a daily weather index (DWI) for eight regions (Fig. 4) was developed using humidity, temperature, and wind speed information related to forest fire occurrence. The DWI was estimated using a logistic regression model with forest fire occurrence by region as the dependent variable and meteorological factors as independent variables. Secondly, a fuel model index (FMI) was developed according to forest type such as conifer, non–conifer and mixed forest. Lastly, a topography model index (TMI) was computed using geographical features, such as location and aspect of ignition point. The FMI and TMI were developed as relative ratios, using the maximum frequency as the highest index value. The DWI accounts for temporal factors, whereas the FMI and TMI account for

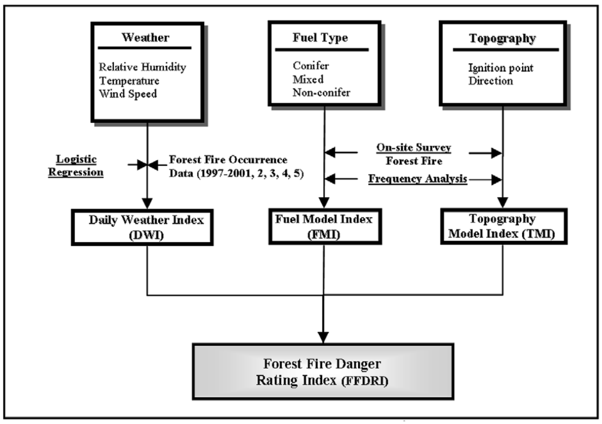

Fig. 3. Process for developing forest fire occurrence probability models to calculate the fire danger rating (Lee *et al.*, 2002; Lee *et al.*, 2005).

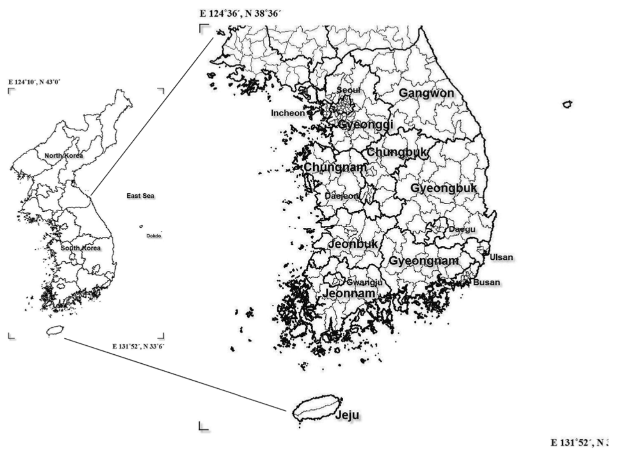

Fig. 4. Eight regions in South Korea for analysing the forest fire danger rating index (FFDRI).

spatial factors involved in predicting forest fire danger rating. To integrate the indices into the Forest Fire Danger Rating Index (FFDRI), we conducted a survey, comprised of Delphi questions, to eighty–four forest fire experts and then estimated the importance of the three indices i.e., DWI, FMI and TMI related to forest fire occurrence and quantified the relative weight using this importance rating.

Estimating for forest fire occurrence probability

Forest fire occurrence probability models were divided into eight regions considering geographical and administrative characteristics. The weather data used for estimating the regional probability models were collected from 8 representative weather stations. The forest fire occurrence probability of a specific day was developed, using a time series of the weather data and a dummy–variable for forest fire occurrence (Equation 2).

$$Pr_j = \ln\left(\frac{y_j}{1-y_j}\right) = \beta_0 + \beta_1 X_{1j} + \beta_2 X_{2j} + \beta_3 X_{3j} + \beta_4 X_{4j} + \beta_5 X_{5j} + \varepsilon_j ; \quad j=1,2,\ldots,n \tag{2}$$

Where $Pr_j = 0$ (when a forest fire does not occur) or 1 (when a forest fire occurs).
y_j is not a dummy variable, but a discrete variable.
X_k = weather factors in relation to forest fire occurrence.
X_k. $k = 1, 2, \ldots, 5$ denotes the five independent variables. X_1 = maximum temperature, X_2 = effective humidity, X_3 = minimum humidity, X_4 = maximum wind speed, X_5 = mean wind speed.

After the model is fitted on the data set and parameters $\beta_0, \beta_1, \ldots, \beta_5$ are estimated, the model can be used for probability prediction (Equation 3).

$$Pr(y_j=1) = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5)}{1+\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5)} \tag{3}$$

When the independent variable has an X_k value, the response function, $E(Pr_j)$, is expressed as the probability where the dependent variable, $Pr_j = 1$. In that case, the dependent variable is expressed as an indicator variable and logit and probit models are widely used to express probability relationships between dependent and independent variables.

Fuel and topographical conditions of forest fire points

To examine the effect of forest type on forest fire occurrence, on–site surveys were conducted at 126 points where forest fires had occurred over the last five years (Fig. 5). Various forest type factors were carefully examined to understand the compositional effects of tree types on ignition and the forests were reclassified into three types: conifer, non–conifer, and mixed forest. Frequency analysis of the three forest types was then performed to estimate an FMI from 1 to 10.

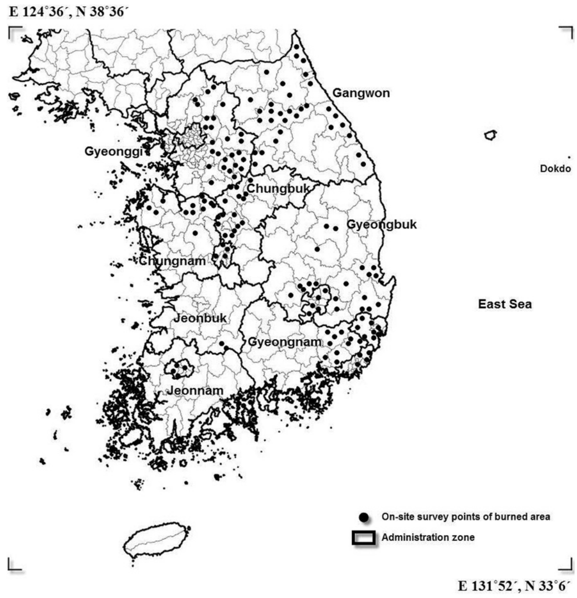

Fig. 5. On–site survey points of forest fire areas.

Topographical factors affecting forest fire occurrence were considered, using data obtained from the on–site surveys of the 126 points described above. We investigated the location (e.g., a flat, foothill, hillside, ridge), slope and aspect (E, W, S, N, NE, SE, NW, SW) of the ignition points. Using on–site survey data, TMI values ranging from 1 through 10 were then assigned to each region on the basis of fire occurrence number by topographical conditions of forest fire points.

Constructing of forest fire danger rating systems (FFDRS)

The FFDRS use a Windows 2000 NT Server as the platform with ArcGIS 9.1 and ArcSDE as the analysis tools and ArcIMS as the internet map server. ArcSDE and ORACLE RDMS were used as the data management system to store and manage the spatial data from the GIS, as well as outputs of forest fire danger rating. Visual Basic. NET and Avenue were used for programming. The base map was constructed using GIS spatial data with 100m cell size and attribute data of the three indices, i.e., DWI, FWI, and TMI.

RESULTS AND DISCUSSION

Forest fire occurrence probability models by weather conditions

Weather variables influencing forest fire occurrence were examined to estimate forest fire occurrence probability models for the eight regions of South Korea. A logistic regression model was used with fire occurrence by region as the dependent variable, and weather factors were assigned as independent variables. The estimated forest fire occurrence probability models are shown in

Table 1. Estimated results of forest fire occurrence probability model using logistic regression analysis. Where Tmax (°C×10) is the maximum temperature, EF (%×10) the effective humidity, and Wmean (m/s×10) the mean wind speed. The unit of weather variables used in the model was derived from the actual observed data at the weather stations

Regions	Model (Pr)	(%) predict value
Chungbuk	$[1+\{\exp(7.256-(0.015\times EF))\}^{-1}]^{-1}$	79.6
Chungnam	$[1+\{\exp(7.405-(0.015\times EF))\}^{-1}]^{-1}$	77.5
Gangwon	$[1+\{\exp(2.494+(0.004\times Tmax)-(0.008\times EF))\}^{-1}]^{-1}$	74.0
Gyeonggi	$[1+\{\exp(6.732+(0.007\times Tmax)-(0.014\times EF))\}^{-1}]^{-1}$	74.7
Gyeongbuk	$[1+\{\exp(5.396+(0.004\times Tmax)-(0.014\times EF)+(0.027\times Wmean))\}^{-1}]^{-1}$	75.9
Gyeongnam	$[1+\{\exp(2.216-(0.006\times EF))\}^{-1}]^{-1}$	74.3
Jeonbuk	$[1+\{\exp(5.556+(0.005\times Tmax)-(0.013\times EF))\}^{-1}]^{-1}$	82.2
Jeonnam	$[1+\{\exp(7.384-(0.014\times EF))\}^{-1}]^{-1}$	75.9

Table 2. Results of posterior analysis obtained from the regional forest fire occurrence probability models

Regions	Day	N	Mean	95% confidence interval	SD	t–value
Chungbuk	Fire	173	0.4581	[.2935 – .2173]	0.2311	14.873**
	No fire	493	0.2027	[.2891 – .2217]	0.1796	
Chungnam	Fire	271	0.6314	[.4261 – .3518]	0.2585	21.278**
	No fire	458	0.2424	[.4249 – .3531]	0.2259	
Gangwon	Fire	270	0.5197	[.3079 – .2401]	0.2365	16.530**
	No fire	445	0.2456	[.3066 – .2415]	0.2006	
Gyeonggi	Fire	331	0.6544	[.4059 – .3367]	0.2455	21.178**
	No fire	435	0.283	[.4057 – .3369]	0.2363	
Gyeongbuk	Fire	297	0.5871	[.3904 – .3196]	0.2545	20.324**
	No fire	458	0.2321	[.3893 – .3207]	0.2205	
Gyeongnam	Fire	183	0.3582	[.1497 – .0960]	0.1605	9.508**
	No fire	479	0.2351	[.1484 – .0980]	0.1442	
Jeonbuk	Fire	171	0.4399	[.3263 – .2415]	0.2657	16.798**
	No fire	494	0.1559	[.3171 – .2507]	0.1563	
Jeonnam	Fire	220	0.5394	[.3180 – .2483]	0.2189	16.126**
	No fire	469	0.2562	[.3176 – .2487]	0.2129	

** at the significance within 1%

Table 1. As a result, among the weather variables, the effective humidity significantly ($p<0.01$) affected the probability of forest fire occurrence in the overall regions. Maximum temperature was also a significant indicator ($p<0.01$) in the Gangwon, Gyeonggi, Gyeongbuk, and Jeonbuk regions. However, mean wind speed was a significant indicator ($p<0.05$) only in the Gyeongbuk region, indicating that is had no significant effect on the probability of occurrence, except in one region. This does not mean that wind is not an important factor for predicting fire risk, but rather that wind speeds measured at weather stations do not appear to be good indicators of risk at surrounding locations (Preisler *et al.*, 2004).

Validation for probability models and daily weather index (DWI)

Reliability of the estimated probability model of 8 provinces nationwide was tested by the climate factors of eight regions between 1997 and 2001. The time–series data of the climate factors were divided into the day of forest fire or the day of no forest fire. The data were used as variables in the probability models of forest fire occurrence. A result of posterior test of the model is shown in table 2. In reality, it was verified that the probability of fire occurrence in the day of forest fire was statistically significant from the day of no forest fire under 1% level. It was confirmed that the estimated value of the probability of fire occurrence in the day of forest fire was higher than that of the day of no forest fire.

Forest fire occurrence probability models, using weather data by regional groups, have been demonstrated to effectively predict dangerous rates of forest fire occur-

Table 3. Daily weather index (DWI) by weather conditions

Ratio interval	DWI	Estimating Ratio interval
10%	1	[.0000~.0406]
20%	2	[.0407~.0818]
30%	3	[.0819~.1307]
40%	4	[.1308~.1917]
50%	5	[.1918~.2648]
60%	6	[.2649~.3615]
70%	7	[.3616~.4711]
80%	8	[.4712~.6004]
90%	9	[.6005~.7562]
100%	10	[.7563~1.000]

Table 4. Daily weather index validation of fire and non–fire days obtained from the regional forest fire occurrence probability models

Regions	Day	Daily weather Index (DWI)										
		1	2	3	4	5	6	7	8	9	10	Total
Chungbuk	Fire	2	3	6	16	18	26	13	40	24	25	173
	No Fire	87	80	62	62	62	44	44	30	19	3	493
Chungnam	Fire	2	2	6	9	8	21	34	29	50	110	271
	No Fire	94	61	42	51	42	47	42	33	33	13	458
Gangwon	Fire	1	8	9	16	17	21	36	47	62	53	270
	No Fire	50	71	56	50	49	49	44	45	24	7	445
Gyeonggi	Fire	2	4	6	8	10	22	26	41	63	149	331
	No Fire	62	44	48	45	46	50	45	34	43	18	435
Gyeongbuk	Fire	1	4	21	8	13	16	33	32	69	100	297
	No Fire	90	74	46	52	44	40	28	41	32	11	458
Gyeongnam	Fire	–	3	8	11	45	31	31	38	16	–	183
	No Fire	2	39	98	91	86	70	50	34	9	–	479
Jeonbuk	Fire	6	13	10	12	11	17	21	37	19	25	171
	No Fire	118	91	86	63	44	37	24	16	13	2	494
Jeonnam	Fire	–	2	2	10	54	56	50	37	57	35	220
	No Fire	52	62	59	60	15	18	44	31	32	13	469
Total	Fire	14	39	68	90	176	210	244	301	360	497	1,916
	No Fire	555	522	497	474	388	355	321	264	205	67	3,731

rence. Here we set up the DWI, using values of past regional forest fire probability, predicted by a posterior test through the regional forest fire occurrence probability model. The FFDRI was established using the probability obtained for each regional probability model, after which the weather values were converted to index values, as shown in Table 3. The DWI was calculated by setting up Table 3 to estimate the value of the regional past forest fire occurrence probability predicted by the posterior test. We classified past DWI into fire days and non–fire days in each region (Table 4). As shown in Table 4, the DWI value was high for the frequency of occurrence on fire days but remained low on non–fire days, thereby confirming its accuracy as a predictor of forest fire occurrence. At high DWI values, forest fires occurred at a much higher frequency in Gyeonggi, Gyeongbuk, and Gangwon than in Chungbuk, Jeonbuk, and Gyeongnam.

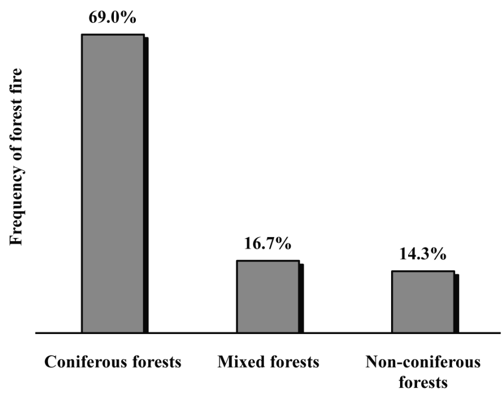

Fig. 6. Frequency of forest fire by forest type.

Fuel model index (FMI) by forest type

Forests were classified into conifer (at least 75% coniferous trees), non–conifer (at least 75% broad–leaf trees) and mixed forest types (other). Secondly, we conducted frequency analysis on the three forest types at 126 forest fire sites to calculate an FMI from 1 to 10. We used forest type instead of tree type because of the difficulty in classifying all of the forest sites in the whole country into tree types and the difficulty in measuring the distribution of tree types at each site. Of the 126 fire occurrence points, coniferous forests accounted for approximately 69% of the total burnt area (87 points) followed by mixed forests with 16.7% (21 points) and non–coniferous forests with 14.3% (18 points) (Fig. 6). Therefore, the frequency analysis results indicate that the forest fire danger rating of the coniferous forests was about four– and five–fold greater than that of the mixed

Table 5. Fuel model index (FMI)

Index	Danger rating	Fuel model index
1	Low	–
2		non–coniferous forest
3	↑	mixed forest
4		–
5	Moderate	–
6		–
7		–
8	↓	–
9		–
10	High	coniferous forest

forests and non–coniferous forests, respectively.

To develop a scale consistent with DWI and TMI, we established the FMI scale from one to ten. The FMI value of coniferous forests, where most forest fires occurred, was set at 10, mixed forests were estimated to be 3, and non–coniferous forests were assigned a value of 2 (Table 5).

Topography model index (TMI) by topographical characteristics

In developing the TMI, the location of forest fire occurrences was classified into groups, as shown in Table 6: bottom foothill (90 points, 71.4% of occurrences), upper foothill (20 points, 15.9%), bottom middle slope (13 points, 10.3%), upper middle slope (2 points, 1.6%), and bottom ridge (1 point, 0.8%). Fire occurrence appeared to be inversely related to elevation, possibly because of the accessibility of the bottom foothills and the consequently higher frequency of weed burning on them. The southwest aspect had the highest forest fire frequency with 22 points (17.5% of fires), followed by the northwest with 20 points (15.9%), the northeast with 19 points (15.1%), the southeast with 18 points (14.3%), and the south with 17 points (13.5%), as shown in Table 5. These results indicated that the fire ignition at the southern aspect had a slightly higher frequency of forest fire occurrence than the northern aspect (Table 7).

Using the frequency of the aspect and location of forest fire occurrence points, the danger rating of forest fire occurrence was indexed according to topographical characteristics. Namely, the southwest and bottom foothills, where fire occurrence frequency was the highest, were assigned index values of 5 (Table 8). We established the maximum value of 5 to make the combined aspect and ignition point values equal to a maximum index value of 10. For example, the TMI of the southwest and bottom foothill is 10, being the sum of an aspect value of 5 and an ignition point index of 5.

Table 6. Frequency of forest fire by location of ignition points

Division	N	%
Bottom foot hill	90	71.4
Upper foot hill	20	15.9
Bottom middle slope	13	10.3
Upper middle slope	2	1.6
Bottom ridge	1	.8
Total	126	100.0

Table 7. Frequency of forest fire by aspect of ignition points

Division	N	%
N	12	9.5
NE	19	15.1
E	6	4.8
SE	18	14.3
S	17	13.5
SW	22	17.5
W	12	9.5
NW	20	15.9
Total	126	100.0

CONCLUSIONS

Forest fire occurrence patterns were statistically investigated with the goal of developing the FFDRI, using past weather data sets collected from eight weather stations and data sets of 126 forest fires for a 5–year period from 1997 to 2001. The weather data provided various meteorological factors, such as temperature, humidity and wind speed, while the fuel type and topographic characteristics were surveyed at the 126 fire sites. Analysis of variance, correspondence analysis, and multidimensional scaling were used to determine the forest fire patterns of the study sites, and logistic regression analysis was used to determine the FFDRI, which was used to develop a web–based, danger rating system. The systems were designed to automatically generate FFRDI predictions.

The principal conclusions of this paper are as follows.

1) The major meteorological factors influencing forest fire occurrence are maximum temperature and effective humidity. In addition, the probability of forest fire

Table 8. Topography model index (TMI)

Index	Danger rating	TMI	
		Aspect	Ignition point
0.5	Low	–	Bottom ridge/Upper middle slope
1.0		–	Bottom middle slope
1.5	↑	E	Upper foot hill
2.0		–	–
2.5	Moderate	N / W	–
3.0		–	–
3.5		–	–
4.0	↓	SE / S	–
4.5		NW / NE	–
5.0	High	SW	Bottom foot hill

occurrence in the Gyeongbuk region was also strongly correlated with mean wind speed.

2) The FFDRI ranges from 1.0 to 10.0, and was developed as a function of DWI, FMI, and TMI. DWI is expressed as the function of maximum temperature, effective humidity, and mean wind speed. FMI and TMI are expressed as functions of the frequency of fire occurrence by fuel type, slope aspect and the location of forest fire ignition points.

3) An interface was developed to automatically generate the FFDRI and provide the results of FFDRI analysis on the internet to all interested parties.

We developed the FFDRI by integrating the DWI from meteorological factors, the FMI with forest type, and the TMI with topographical features. The FFDRI considers not only the spatial distribution of potential forest fire areas, involving such factors as forest type and topography, but also temporal distribution, involving daily weather factors (Fig. 7). The web–based KFFDRS was constructed using GIS spatial data with 100 m cell size, three indices (DWI, FWI, and TMI), and three different maps: topography, forest type, and weather stations information map.

The KFFDRS developed in this study will enable the generation of a comprehensive fire management plan. Each local forest fire manager will be able to devise fire prevention and suppression plans, using constructed thematic maps and FFDRI statistics. The KFFDRS receives real–time meteorological data through an exclusive network, connecting KFS and KMA. These meteorological data are automatically input into the FFDRI model, and the occurrence danger index is calculated and expressed in the prediction map. The calculated data are saved on the database server. Finally, this prediction map is provided to common users and local forest fire managers through the internet.

The web–based KFFDRS currently provides information about the FFDRI at http://forestfire.kfri.go.kr/ffdri_current_eng.asp (Fig. 8). This system provides information according to four dangerous levels: red–colored “Extreme” is an FFDRI value above 86, orange–colored “High” is from 66 to 85, yellow–colored “Moderate” is from 51 to 65, and blue–colored “Low” is below 51.

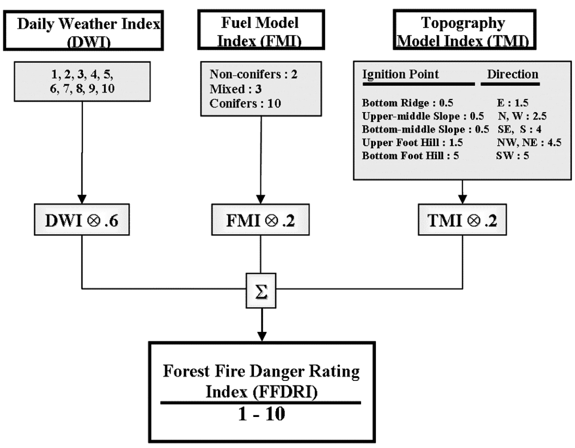

Fig. 7. Diagram of the forest fire occurrence danger index model.

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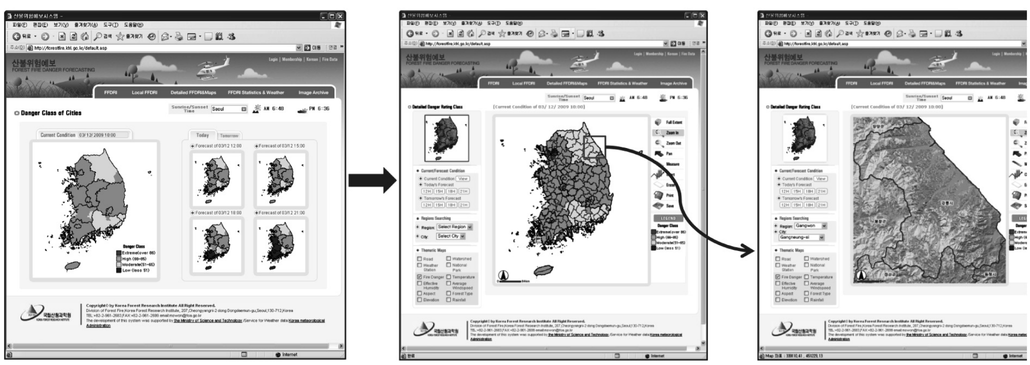

Fig. 8. Forest fire hazard maps generated by the forest fire danger rating systems.

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