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MOLECULAR BIOLOGY

Gene Expression Programming For Forest Fire Risk Modeling In Western Himalayas

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ABSTRACT

Western Himalayas are mainly prone to chir pine forest fires, which are predominantly governed by climatic factors. Forest fire is one of the main reasons for forest degradation and has a hazardous impact on the environment, economy, and human health. Therefore, the present investigation aimed to develop forest fire risk models based on climatic parameters using gene expression programming (GEP) for Solan district of Himachal Pradesh. Climatic parameters *viz*., maximum temperature (T_x), minimum temperature (T_n), mean temperature (T_a), soil temperature (T_s), maximum relative humidity (RH_x), minimum relative humidity (RH_n), mean relative humidity (RH_a), rainfall (RF), sunshine hours (SS) and wind speed (WS), for the past fifteen years was randomly divided into a training set (75%) and validation set (25%). Training data was used to construct eight models, which had different combinations of ten weather parameters, and the models were validated using validation data. Several statistical criteria, *viz.*, coefficient of determination (R^2), Pearson's correlation coefficient (r), and statistical errors were used for the evaluation of the performance of Models. Model 2, Model 5, and Model 8 showed better performance in both the training and validation stage; however, among these models, Model 2 (R^2 = 1.00%; r = 1.00) was selected and described. Model 2 was generated using temperature, relative humidity, and rainfall as input data. This model can be exploited to predict and prevent forest fire hazards in the study area.

HIGHLIGHTS

- The study aimed to develop forest fire risk models using gene expression programming (GEP) for Solan district of Himachal Pradesh.
- Model 2, Model 5 and Model 8 were the best-performing models.
- Model 2 (R^2 = 1.00%; r = 1.00) was selected for further description, and Model 2 was generated using temperature, relative humidity and rainfall as input data.

Keywords*:* forest fire, gene expression programming, logistic regression, modeling

Fires are a serious feature of the forest ecosystem, primarily triggered by climate change (Alencar *et al*., 2015; Aragao *et al*., 2018; Brando *et al*., 2020). A warmer and drier climate leads to more intense and frequent forest fires (Pinol *et al*., 1998). Climate plays vital role in forest fire occurrences as it controls the

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severity of the weather. Recent increasing trend in the size and extent of forest fires across the world is a significant policy concern because of their potential negative impacts on ecological integrity (Bowman *et al*. 2009; Flannigan and Harrington 1988). Climatic parameters are critical forest fire risk factors. Cary *et al*. (2006), Prasad *et al.* (2008), Vadrevu *et al.* (2010), and Turkey *et al.* (2018) found that landscape fire models mainly were more sensitive to the difference in climate as compared to terrain and fuel patterns. Jolly *et al.* (2015) showed that fire weather seasons had lengthened by ~25%, resulting in a ~20% rise in wildfires.

Over the past decade, robust computing techniques, like Genetic programming (GP)were applied for modeling to model forest fire risk. Recently, GP was upgraded to gene expression programming (GEP). GEP uses fixed-length linear chromosomes and encodes a small program (Ferreira 2001). GEP gives a simple and reliable mathematical expression that can be applied practically. The method was used to solve problems including time series prediction, logistic regression, multi-agent strategies, symbolic regression, circuit design, evolutionary neural networks, *etc*. (Samadianfard 2012).

The coniferous forests in the Western Himalayan region are more prone to forest fires due to the presence of pine forests, which are characterized by the shedding of highly inflammable needles (Shah and Sharma 2015). Himachal Pradesh, which lies in western Himalayas, has a total forest area of 37,033 km^{2,} out of which 1,460 km^2 is sensitive to forest fires (Bahuguna and Singh, 2002). The average yearly loss due to forest fire incidences in Himachal Pradesh was estimated to be 1.13 crore (Anonymous 2016). Forest fires can damage vegetation cover, natural regeneration, wildlife habitat, micro-climate, carbon sink and biodiversity, invasion of weeds, adverse effect on people's livelihood, increase in greenhouse gases and air quality. In Himachal Pradesh, Solan district has been reported a large number of forest fires in recent years (Fig. 1). Hence, GEP-based forest fire risk modeling was planned for the prediction of probability forest fire occurrences in the study area.

MATERIALS AND METHODS

Study area

Forest fire risk modeling using GEP was carried out in Solan district of Himachal Pradesh, which primarily falls under the Western Himalayan zone. The district occupies one-tenth area of the state and lies between 30.75°N to 31.37°N and 76.59°E to 77.24°E (Fig. 1). The elevation of the study area varies from 278m in the plain areas to 2154m in the hilly areas. The study area has sub-tropical climate with an average of 18.3°C mean temperature, 50.6% relative humidity, and 1030.8 mm annual rainfall. The area is mainly covered by forests, cultivated lands, urban lands, and barren lands. The forest areas are comprised of pure and mixed stands of *Pinus roxburghii*, which are reported with frequent forest fire incidences.

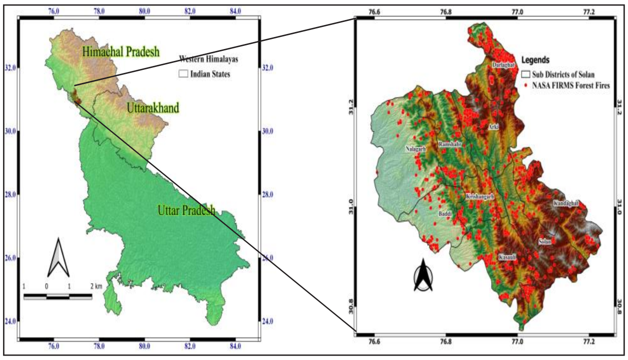

Fig. 1: Map showing study area and NASA FIRMS forest fires (2007-2021)

Climatic data

The summer season data of weather parameters *viz.*, maximum temperature (T_x), minimum temperature (T_n), mean temperature (T_a), soil temperature (T_s), maximum relative humidity (RH_x), minimum relative humidity (RH_n), mean relative humidity (RH_a), rainfall (RF), sunshine hours (SS) and wind speed (WS), of past fifteen years (2007-2021), were collected from Agro-meteorological Observatory of Department of Environmental Science, Dr. YS Parmar University of Horticulture and Forestry, Nauni, Solan.

Forest fire data

Forest fire records were collected from Solan Forest Range for the study period. During the past fifteen years, there were 45 fire incidences during the summer season. For GEP modeling, forest fire data were used as a binary variable (0 or 1), where zero (0) represented no fire, and one (1) indicated fire occurrence during the particular day (Garcia *et al*. 1995).

Gene expression programming (GEP)

GEP is a computer technique developed by Ferreira (2001). There are two main factors in GEP *viz.*, chromosomes and expression trees, the first one is composed of more than one gene of equal length and the second one are expressions of the genetic information encoded in chromosomes. GEP computer programs are all encoded in linear chromosomes, which are later expressed in expression trees.

Initially, the training set was selected from the whole data, and the rest of the data was used as a testing set. Parameters of GEP models were set according to Table 2.

The function set (+, -, /, *, exp, ln, sqrt, X2) used in the GEP models was simple in order to develop less complicated mathematical equations and avoid trigonometric functions. The parameters used in the training phase are given in Table 1. The algorithm was run until significant improvement in the performance of the models was achieved. GeneXpro Tools was used in the formulation of GEP models.

Table 1: Climatic parameter combinations for GEP models

Models	Climatic parameters									
	Temperature (°C)				Relative humidity (%)			Rainfall (mm/day)	Sunshine hours (hr/day)	Wind speed (m/sec)
	T_x	T_n	T_a	T_s	RH_x	RH_n	RH_a	RF	SS	WS
Model 1	√	√	√	√						
Model 2	√	√	√	√	√	√	√	√		
Model 3	√	√	√	√					√	
Model 4	√	√	√	√						√
Model 5	√	√	√	√	√	√	√	√	√	
Model 6	√	√	√	√	√	√	√	√		√
Model 7	√	√	√	√					√	√
Model 8	√	√	√	√	√	√	√	√	√	√

Note: subscript x = maximum, n = minimum, a = mean.

Table 2: Parameters used for the GEP models

Gep parameters	Values
Chromosomes	30
Genes	3 (Model 1,2,3,4,7), 4 (Model 5,6,8)
Head Size	8 (Model 1,2,3,4,7), 10 (Model 5,6,8)
Function Set	Addition (+) Subtraction (-) Multiplication (*) Division (/) Square root (sqrt) Exponential (exp) Natural logarithm (ln) x to the power of 2 (X2)
Linking Function	Addition
Fittness Function	Positive correlation
Mutation	0.00138
Inversion	0.00546
One-Point Recombination	0.00277
Two-Point Recombination	0.00277
Gene Recombination	0.00277
Gene Transposition	0.00277

In this study, the general formulation of the GEP models was used:

Probability (forest fire risk) =

$$\left(\frac{1}{1+\exp\left(-\left(\text{slope}*\text{y}\right)-\text{intercept}\right)}\right) \quad \ldots(1)$$

where, $y = \sum_{i=1}^{n} gene_i$, n = number of genes ...(2)

Performance criteria of the GEP models

Several criteria were used for evaluation as described in the following section.

Coefficient of determination (R^2)

R^2 is scaled between 0 and 1, and higher value indicates a better prediction ability of the model.

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Xi-X)(Yi-Y)\right]^2}{\sum_{i=1}^{n}(Xi-X)^2 \sum_{i=1}^{n}(Yi-Y)^2} \quad \ldots(3)$$

Pearson's correlation coefficient (r)

It is a normalized measurement of the covariance, such that the result always has a value between −1 and 1.

Pearson's correlation coefficient ($r_{X,Y}$) =

$$\frac{COV(Xi-Yi)}{\sigma_x \sigma_y} \quad \ldots(4)$$

Where;

COV(X,Y) = Covariance of X_i and Y_i

σ_x = Standard deviation of X

σ_y = Standard deviation of Y

Mean square error (MSE)

MSE of a model measures the average of the squares of the model. It is defined as follows:

$$\text{MSE} = \frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{n} \quad \ldots(5)$$

Root mean square error (RMSE)

Root mean square error (RMSE) measures the error of the model. If the predicted responses are very close to the correct responses, the RMSE will be small. It is defined as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{n}} \quad \ldots(6)$$

Relative absolute error (RAE)

It is expressed as a ratio of mean error to errors produced by naive model. A good model will produce RAE close to zero, while a poor model will produce a ratio greater than one.

$$\text{RAE} = \frac{\sum_{i=1}^{n}|X_i-Y_i|}{\sum_{i=1}^{n}|Y_i-Y|} \quad \ldots(7)$$

Mean absolute error (MAE)

The mean absolute error of a model is the mean of the absolute values of the individual prediction errors overall instances in the test set.

$$\text{MAE} = \frac{\sum_{i=1}^{n}|X_i-Y_i|}{n} \quad \ldots(8)$$

Relative squared error (RSE)

Relative squared error takes the total squared error and normalizes it by dividing it by the total squared error of the simple predictor. It can be used to compare models whose errors are measured in the different units.

$$\text{RSE} = \frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{\sum_{i=1}^{n}(Y_i-Y)^2} \quad \ldots(9)$$

Root relative squared error (RRSE)

The root relative squared error takes the square root value of the relative squared error, given as follows:

$$\text{RRSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{\sum_{i=1}^{n}(Y_i-Y)^2}} \quad \ldots(10)$$

RESULTS AND DISCUSSION

Table 3 depicts the performance of eight models for the training and testing stage, and it clearly illustrates the good agreement between the training and testing GEP models. The performance of

Table 3: Performance of the GEP models for the training and validation datasets

Models	R^2	r	MSE	RMSE	RAE	MAE	RSE	RRSE
Training								
Model 1	0.884	0.940	0.002	0.040	0.016	0.004	0.012	0.110
Model 2	1.000	1.000	0.000	0.000	0.001	0.000	0.000	0.001
Model 3	0.912	0.955	0.002	0.043	0.022	0.006	0.013	0.116
Model 4	0.898	0.947	0.001	0.038	0.016	0.004	0.011	0.103
Model 5	1.000	1.000	0.000	0.000	0.001	0.000	0.000	0.001
Model 6	0.956	0.978	0.000	0.007	0.005	0.001	0.000	0.018
Model 7	0.908	0.953	0.002	0.042	0.020	0.006	0.013	0.113
Model 8	1.000	1.000	0.000	0.000	0.001	0.000	0.000	0.001
Validation								
Model 1	0.908	0.953	0.000	0.008	0.009	0.002	0.000	0.022
Model 2	1.000	1.000	0.000	0.000	0.001	0.000	0.000	0.001
Model 3	0.889	0.943	0.000	0.011	0.013	0.004	0.001	0.030
Model 4	0.889	0.943	0.000	0.022	0.016	0.004	0.003	0.059
Model 5	1.000	1.000	0.000	0.000	0.001	0.000	0.000	0.001
Model 6	0.892	0.944	0.001	0.028	0.024	0.007	0.006	0.074
Model 7	0.911	0.955	0.000	0.009	0.009	0.002	0.001	0.023
Model 8	1.000	1.000	0.000	0.000	0.001	0.000	0.000	0.001

the models was compared based on statistical parameters shown in Table 3. The values of R^2, r, and errors for each GEP model during the training process were nearly identical to those of the testing process. Model 2, Model 5, and Model 8 showed the highest value for R^2 (1.00%) and r (1.00), while the value for all statistical errors was negligible. Hence, Model 2, Model 5, and Model 8 models performed better than the remaining models. Among these three models, Model 2 was selected for the study, because the model was constructed using less input parameters (Table 1) and still better performing as compared to the other two models.

Expression trees and mathematical equations of GEP Model 2

As shown in Fig. 2, GEP Model 2 contained three genes, and gene1 and gene3 had three and one number of constants, respectively. These coefficients and their magnitudes are shown in Table 4. From Fig. 2 the algebraic formulation for GEP Model 2 was attained by putting input variable ($d0 = T_x$; $d1 = T_n$; $d2 = T_a$; $d5 = RH_n$; $d6 = RH_a$ and $d7 = RF$) and constants.

$$\text{Gene1} = \frac{\dfrac{C_4}{C_2/C_7 + RF}}{C_2} + RH_n \qquad \ldots(11)$$

$$\text{Gene2} = RH_a \qquad \ldots(12)$$

$$\text{Gene3} = RH_a \times \left[\left(\frac{\sqrt{T_x}}{C_2 + RH_a}\right) \times \left(\frac{T_a}{T_n} - RF\right)\right] \qquad \ldots(13)$$

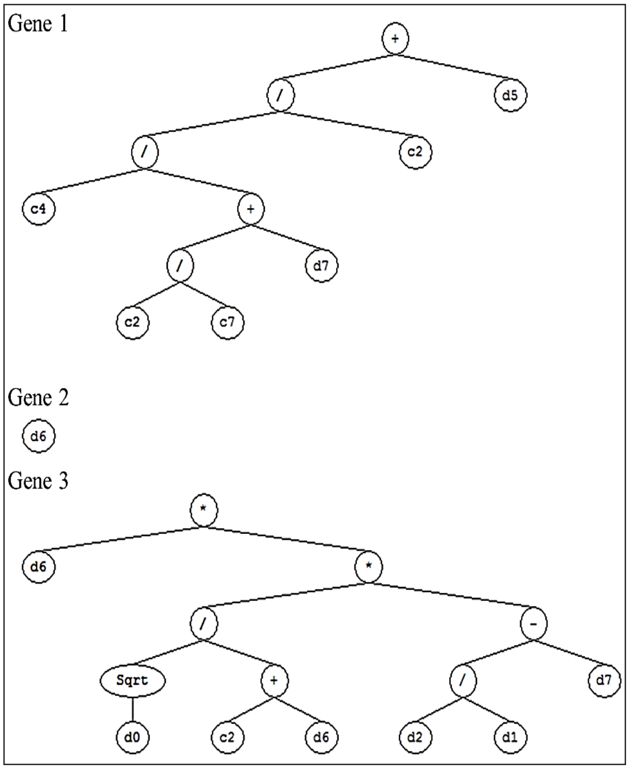

Fig. 2: Expression tree for GEP Model 2

Recalling equation (2), the mathematical equations GEP model can be expressed as follows.

$$y = \frac{\frac{C_4}{(C_2/C_7)+RF}}{C_2} + RH_n + RH_a\left[RH_a \times \left\{\left(\frac{\sqrt{T_x}}{C_2+RH_a}\right)\times\left(\frac{T_a}{T_n}-RF\right)\right\}\right] \quad \ldots(14)$$

Table 4: Constants for GEP Model 2 formulations

Constants	Value
Gene1 C_2	0.024
Gene1 C_4	-10.783
Gene1 C_7	-589159.825
Gene3 C_2	2.713
Slope	$1.47 * 10^{-9}$
Intercept	-8.070

By replacing the values of all the constants in Table 4, equation (14) took the following form: 1

$$y = \frac{\frac{-10.78}{(0.024/-589159.825)+RF}}{0.024} + RH_n + RH_a + \left[RH_a \times \left\{\left(\frac{\sqrt{T_x}}{2.71+RH_a}\right)\times\left(\frac{T_a}{T_n}-RF\right)\right\}\right] \quad \ldots(15)$$

Putting this value slope and intercept in equation (1) in order to calculate forest fire risk, as follows:

Forest fire risk (probability) =

$$\left(\frac{1}{1+\exp\left(-\left(1.47*10^{-9}*y\right)-\left(-8.07\right)\right)}\right) \quad \ldots(16)$$

Where;

T_x	=	Maximum temperature (°C)	RH_x	=	Maximum relative humidity (%)
T_n	=	Maximum temperature (°C)	RH_n	=	Minimum relative humidity (%)
T_a	=	Mean temperature (°C)	RH_a	=	Mean relative humidity (%)
T_s	=	Soil temperature (°C)	RF	=	Rainfall (mm/day)
SS	=	Sunshine hours (hr/day)	WS	=	Wind speed (m s^{-1})

Equation (16), which includes temperature, relative humidity, and rainfall parameters, was the best function obtained using GEP to estimate the probability of fire occurrence. Results from regional climate models (Beniston 2004; Schar *et al*. 2004; Founda and Giannakopoulos 2009), indicated an increase in forest fire risk due to more frequent heat waves and high maximum daily temperatures. Ying *et al.* (2021) found that the threshold of the relative humidity in Yunnan region of Southwest China was 37.48% ± 15.60% for the 50% ignition probability and relative humidity dominated ignition during the period of 2003-2015. Arpaci *et al.* (2013) found that mean daily temperature was a good estimator for forest fire prediction in Austria during the summer. In Germany, Holsten *et al.* (2013) found relative humidity to be a good indicator of fire danger. In the case of the Djerdap National Park, the best model for forest fires was obtained by a combination of temperature, precipitation, and relative humidity (Zivanovic and Tosic 2020).

CONCLUSION

The present study intended to develop forest fire risk models based on climatic parameters using gene expression programming (GEP) for Solan district of Himachal Pradesh. Climatic parameters were randomly divided into a training set (75%) and a validation set (25%). Training data was used to construct eight models, which had different combinations of ten weather parameters, and the models were validated using validation data. Model 2, Model 5, and Model 8 showed better performance in both the training and validation stage; however, among these models, Model 2 (R^2 = 1.00%; r = 1.00) was selected and described. Model 2 was generated using temperature, relative humidity, and rainfall as input data. In future this model can be exploited for the prevention of forest fire hazards in the study area.

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