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RESEARCH PAPER

Modelling the Effect of Temperature Increments on Wildfires

Amir Hossein Sadat Razavi, Majid Shafiepour Motlagh*, Alireza Noorpoor and Amir Houshang Ehsani

Department of Environmental Engineering, School of Environment, College of Engineering, University of Tehran, P.O.Box 14155-6135, Tehran, Iran

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ABSTRACT
Global fire cases in recent years and their vast damages are vivid reasons to study the wildfires more deeply. A 25-year period natural wildfire database and a wide array of environmental variables are used in this study to develop an artificial neural network model with the aim of predicting potential fire spots. This study focuses on non-human reasons of wildfires (natural) to compute global warming effects on wildfires. Among the environmental variables, this study shows the significance of temperature for predicting wildfire cases while other parameters are presented in a next study. The study area of this study includes all natural forest fire cases in United States from 1992 to 2015. The data of eight days including the day fire occurred and 7 previous days are used as input to the model to forecast fire occurrence probability of that day. The climatic inputs are extracted from ECMWF. The inputs of the model are temperature at 2 meter above surface, relative humidity, total pressure, evaporation, volumetric soil water layer, snow melt, Keetch–Byram drought index, total precipitation, wind speed, and NDVI. The results show there is a transient temperature span for each forest type which acts like a threshold to predict fire occurrence. In temperate forests, a 0.1-degree Celsius increase in temperature relative to 7-day average temperature before a fire occurrence results in prediction model output of greater than 0.8 for 4.75% of fire forest cases. In Boreal forests, the model output for temperature increase of less than 1 degree relative to past 7-day average temperature represents no chance of wildfire. But the non-zero fire forest starts at 2 degrees increase of temperature which ends to 2.62% of fire forest cases with model output of larger than 0.8. It is concluded that other variables except temperature are more determinant to predict wildfires in temperate forests rather than in boreal forests.
keywords: Wildfires, Climate change, Temperature, Modeling

INTRODUCTION

Neither all forest ecosystems have the functioning, compositions and structure of ecosystems

* Corresponding author Emails: shafiepour@ut.ac.ir, shafiepourm@yahoo.com

modulated by fire (Vilà-Vilardell et al., 2020). One of the most serious natural disasters that threaten the ecosystem is forest fires (Hamadeh et al., 2017). Forest fires have come to attention globally since they can cause great ecological, economic and humanitarian losses (Dey & Schweitzer, 2018; Spessa et al., 2015; Vilar et al., 2019). The more wildfires happen worldwide, the more losses to human lives and natural resources happen (Davis et al., 2017; Dennison et al., 2014; Hamadeh et al., 2017; Jahdi et al., 2016; Littell et al., 2009; Pérez-Sánchez et al., 2017; Srivas et al., 2017; Stavros et al., 2014). The recent fire cases in US have caused severe damage to urban and natural land uses; the volume of the damage is studied by scholars which reveal every detail of the losses.

Policy makers need to examine climate change and its effect for fire management (North et al., 2015). Accurate monitor of wildfire risk condition is one of the most common prerequisites to conservatively preserve forest wildfires (Flannigan et al., 2013; Vilar et al., 2019). The first step for fire monitoring is to develop a prediction model to provide information for resources allocation to fuel treatments (Jaafari et al., 2017; Nami et al., 2018; Parisien et al., 2016). The application of prediction models is based on an assumption that similar local conditions are more likely to result in future similar ignitions (Catry et al., 2009; Jaafari, Zenner, et al., 2019).

Fire activity is predicated to increase globally in wildland due to climate change (Flannigan et al., 2009; Seidl et al., 2017). One of the most important natural disasters in Australia is wildfire. Devastating wildfires occurred across eastern Australia from late winter of 2019 to summer of 2020 (Shi et al., 2021).

Fire regimes have been dominated by weather events which are uncontrolled due to changes in fire suppression and land-use, and climate warming (Duane et al., 2019; Jolly et al., 2015; San-Miguel-Ayanz et al., 2013). CO2 emission due to forest wildfire and climate change area exacerbated by each other in a positive feedback loop (Hamadeh et al., 2017; Ramanathan & Carmichael, 2008). Researchers believe climate change act as one of the main drivers in forecasting ecosystem change for the next decades (Abatzoglou & Kolden, 2013; Abatzoglou & Williams, 2016; Aponte et al., 2016; Moritz et al., 2012). Climatic changes along with socioeconomic changes can alter the composition, loading and connectivity of fuel types, which will in turn affect fire regimes (Hessl, 2011). These data depict a dramatic picture in spite of steady support of the EC (European Commission) and the numerous efforts of national and regional governments to help fire management policies get better (Elia et al., 2020).

In this study, the effect of climatic changes on wildfire hazard is identified based on use updated fire observations during a 23-year period and a wide array of environmental variables to develop an artificial neural network model with the aim of predicting potential fire spots.

This study focuses on non-human reasons of wildfires (natural) to compute global warming effects on wildfires. In this study, we aim to model the effect of temperature increments on wildfires. In other words, we want to show what happens to wildfires while temperature is increased by each step.

MATERIAL & METHODS

The study area includes all forest fire cases in United States from 1992 to 2015. As shown in Fig 1, the fire spots spread almost all over the United States (Short, 2017).

The fire cases in this study were acquired from a research data archive supplied by U.S. Department of Agriculture (USDA) as shown in Fig 1. The data were retrieved from the database which was published with the title of "Spatial wildfire occurrence data for the United States" and it contains spatial data of wildfires occurred in the United States from 1992 to 2015 and it is a part of the national Fire Program Analysis (FPA) system (Short, 2017). The data is acquired by reporting systems of federal, state, and local fire organizations.

For this project, we chose to acquire fire records from 1992 to 2015 only. Besides, only those fires records with burnt area of greater than 1 km^2 area examined to be able to focus on wildfires that are more destructive. One of the precious attributes of the database is the cause of each fire records which shows whether the fire was initiated by a natural or man-made reason. Due to the objective of this study, the fire records with man-made origin were excluded.

Based on the aforementioned explanation, 18204 fire records were extracted from the database.

Logistic regression is a common tool in some studies (e.g. Catry et al., 2009; Jaafari, Mafi-Gholami, et al., 2019). There are also other common methods like support vector machine (SVM), random forest, and neural network in this regard (Jaafari et al., 2018).

In this study, an artificial neural network is used to predict probable wildfire hotspot using weather condition parameters of a specific day and of a few days before that. We take data of eight days including the day that fire started and 7 previous days to forecast fire occurrence probability of that day.

The dataset used for model development includes wildfires occurred in USA during 1992 to 2015 and climatic parameters extracted from ECMWF, the European Centre for Medium-Range Weather Forecasts.

Due to lack of sufficiency and unavailability of directly measured weather data from synoptic stations in most of the forest in the world, we used the weather parameters computed by weather models and presented by ECMWF. This study also introduces a model that can check the power and reliability of these data for wildfire prediction that is presented in a next study.

Using the data of ECMWF, we take the “ERA5 from 1979 to present” database for the input of the model development (Hersbach, H. et al., 2020).

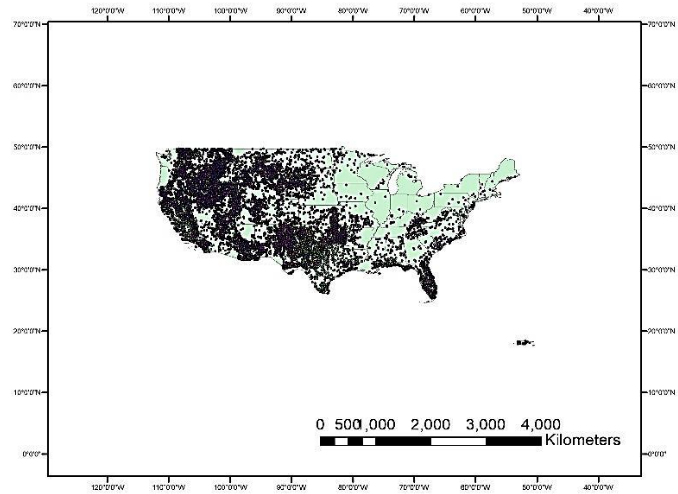
According to the document of this database, “ERA5 is the fifth generation ECMWF atmospheric reanalysis of the global climate (Hersbach, H. et al., 2020). Reanalysis combines model data with observations from across the world into a globally complete and consistent dataset using the laws of physics (ECMWF).” It provides the relevant data computed daily at 12 PM GMT.

The data set of the detected wildfires that includes about 1.8 million records, is generated by USDA (United States Department of Agriculture) through which the data from 1992 to 2015 was extracted (https://www.fs.usda.gov/rds/archive/catalog/RDS-2013-0009.4)

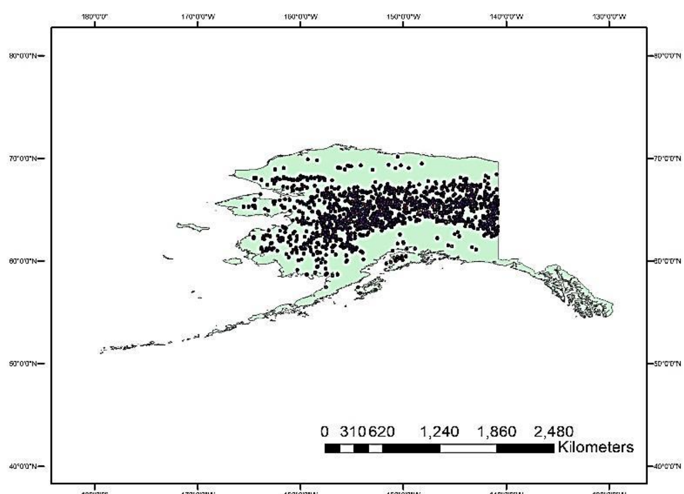
About one third of the land surfaces of the world are covered by forests. They are categorized based on their distance from the equator. There are different types of forests, but some share common traits based on the local climate. There are four categories into which forests can fit: tropical, subtropical, temperate, and boreal.

We focused on the United States of America forest due to complete and accessibility of this data over the years from 1992 to 2015.

The wildfires occurred in tropical forests were out of the scope and hence were excluded from the data, while the fires occurred in Alaska are taken to happen in boreal forest and the others in other states to happen in temperate forest. Therefore, about 18204 wildfires happened in temperate and boreal forests. In order to introduce the non-fire cases, the weather condition of 30 days before each fire case is assumed as non-fire case.



(a) Wildfires in all states of U.S (except Alaska)



(b) Wildfires in Alaska

Fig 1. The map of USA and wildfire location from 1992 to 2015

We take temperature at 2 meters above surface, relative humidity, total pressure, evaporation, volumetric soil water layer 1, snow melt, Keetch–Byram drought index (described in **Table 1**), total precipitation, wind speed (along U and V direction), and NDVI (described in **Table 1**) as 11 effective independent variables. The variables are described in Table 1.

Table 1: Meteorological variables used in this study

Parameter name	Unit	Description
Relative Humidity	%	At saturation point, water vapor has equilibrium vapor pressure. Relative humidity shows the ration of actual vapor pressure over equilibrium vapor pressure at a given temperature.
Keetch-Byram drought index	Dimensionless	The Keetch-Byram drought index (KBDI) is a number representing the net effect of evapotranspiration and precipitation in producing cumulative moisture deficiency in deep duff and upper soil layers. It is a continuous index, relating to the flammability of organic material in the ground. It is a closed system ranging from 0 to 200 units and represents a moisture regime from 0 to 20 cm of water through the soil layer. At 20 cm of water, the Keetch-Byram drought index assumes saturation. Zero is the point of no moisture deficiency and 200 is the maximum drought that is possible. At any point along the scale, the index number indicates the amount of net rainfall that is required to reduce the index to zero, or saturation (Hersbach, H. et al., 2020). There is a direct correlation between upper soil moisture deficiency and wildfire risk and The Keetch-Byram drought index (KBDI) was introduced this purpose.
Wind speed	$m/_{s}$	Wind speed in both directions are examined in this study. The U and V parameters show wind speed in eastward direction and northward direction respectively. A negative value means the direction of wind in the opposite direction stated in the definition.
2m temperature	K	Temperature at 2 meters above surface
Evaporation	m of water equivalent	The amount of evaporated water from the Earth's surface is accumulated in the parameter. It also includes transpiration.
NDVI (Normalized Difference Vegetation Index)	Dimensionless	NDVI is a measure of plant health and density. The index is computed using remote sensing images. the range of NDVI is between -1 to +1. Values close to +1 shows healthy and dense vegetation.
Total pressure	Pa	Atmospheric pressure of air at a specific elevation which is also known as barometric pressure.
Volumetric soil water layer 1	$m^3/_{m^3}$	Based on ECMWF Integrated Forecasting System model, layer 1 of soil includes top 7 cm layer from surface. The volumetric soil water shows the volume of water in the soil layer
Snowmelt	m of water equivalent	It shows how much water the snowpack contains. It is also known as Snow Water Equivalent (SWE). In other words, the water acquired from melting entire snowpack equals SWE.
Total Precipitation	m	This parameter shows total amount of water either as rain or snow falling on the surface

In the first step, data was normalized by the "standard score" method.

The architecture of proposed Artificial neural networks (ANN) includes one hidden layer and one output layer. 60% of data is used for training, 20% for validation and 20% for testing. You can find the schematic diagram of ANN in **Fig 2**. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons, can fit multi-dimensional mapping problems arbitrarily well. The network is trained with Levenberg-Marquardt backpropagation algorithm, in which case scaled conjugate gradient backpropagation is used.

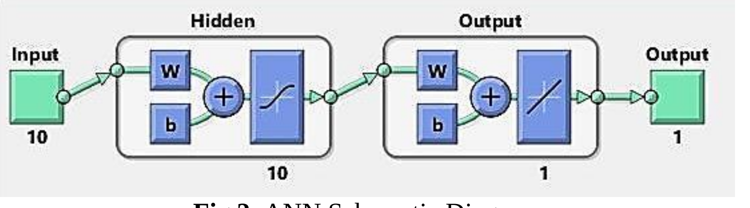


Fig 2. ANN Schematic Diagram

The model was developed to predict wildfire cases based on temperature variation. The dataset used for train, validation, and test of the model was provided by the history record of wildfires in US from 1992 to 2015 (Karen C., 2017). The large, destructive, uncontrolled, quick (rapid spread), self-Induced, unplanned, and unwanted wildfire cases were selected which include 18204 cases. The same number of non-fire cases were also extracted; it is assumed no fire has occurred one month before each 18204 records extracted as the wildfire cases at the same location. Both 18204 wildfire cases and 18204 non-fire cases were imported to the ANN. All cases were categorized based on their forest type (whether temperate or boreal) and processed separately.

The predictive variables including temperature (at 2 meters above surface), relative humidity, absolute pressure, evaporation, soil moisture, snow storage, Keetch–Byram drought index, precipitation, wind speed, and NDVI were taken from ECMWF (European Centre for Medium-Range Weather Forecasts); the full data is available online. The difference between each parameter and the past 7-day average before fire start was computed; except for NDVI. Due to small variation of NDVI during 7 days, its 7-day average was directly used in the model. Each parameter was normalized using the following formula:

$$\frac{data-average}{max-min} \tag{1}$$

The same process was performed for parameters of non-fire cases.

The ANN model was independently trained for each forest type (temperate or boreal).

The model should predict fire spots based on weather data to supply basic information decisive for relevant organizations to take necessary actions required for fire management.

The model output is a decimal number which can be interpreted as the potential of fire occurrence. The values greater than or equal to 1 states absolute fire while the values less than or equal to 0 states there is definitely no fire. The range between 0 and 1 is divided to three parts:

a. For values greater than or equal to 0.8, a warning attention should be sent to responsible organizations.
b. No attention is necessary for values less than 0.5.
c. The points with values between 0.5 and 0.8 should be monitored during the next few days.

RESULTS AND DISCUSSION

Among the different algorithms in ANN, Levenberg-Marquartdt had the best performance with regression factor of 9.8e-1 and MSE of 1.01e-2. Half of the data set related to temperate forests were used for network training; 25 percent of the data set were used in validation and the rest were used for testing step. Fig 3 represents regression in each step.

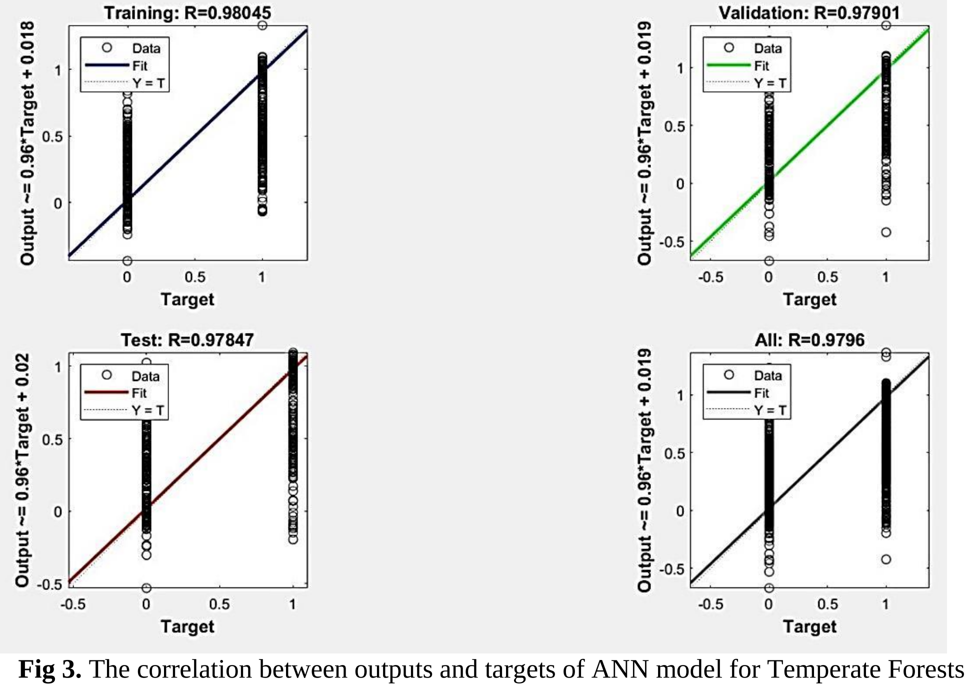


Fig 3. The correlation between outputs and targets of ANN model for Temperate Forests

The error status during model development is represented in Fig 4.

Fig 4. Error Status of ANN model for Temperate Forests

With regression factor of 9.55e-1 and MSE of 2.21e-2, Levenberg-Marquartdt algorithm had the best performance for prediction model development of boreal forests. Sixty percent of the data set related to boreal forests were used for network training; 20 percent of the data set were used in validation and the rest were used for testing step. Fig 5 represents regression in each step.

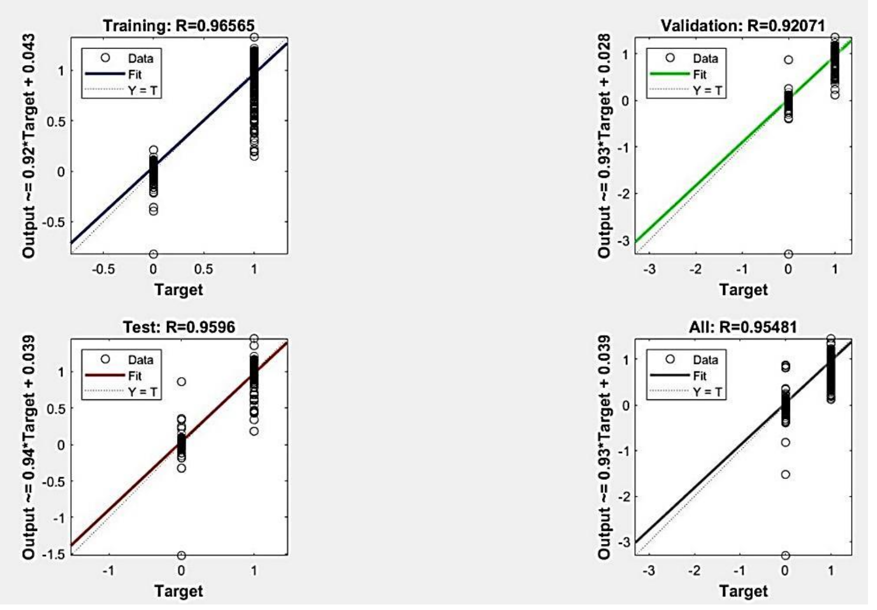


Fig 5. The correlation between outputs and targets of ANN model for Boreal Forests

The error status during model development is represented in Fig 6.

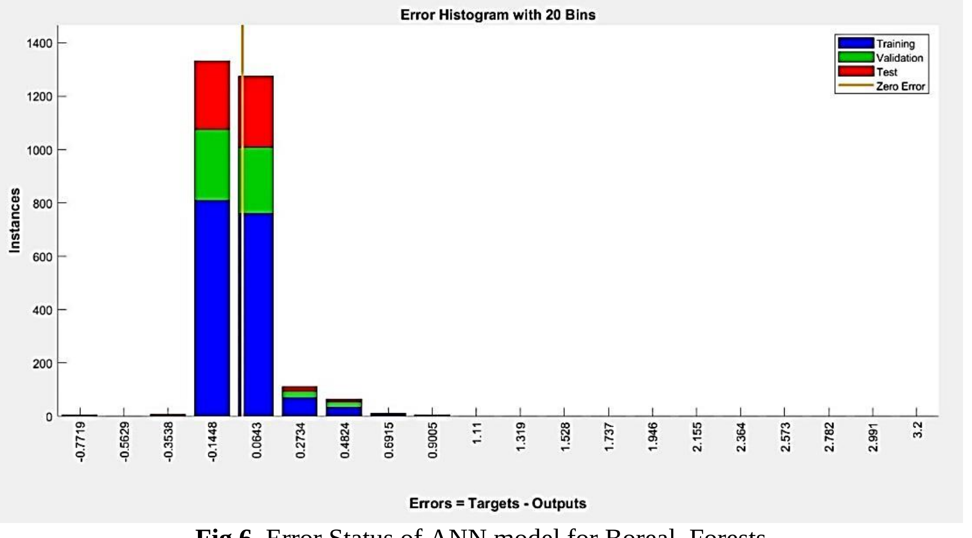


Fig 6. Error Status of ANN model for Boreal Forests

The sensitivity of the models to temperature variation was analyzed based on non-fire record data sets. For the sensitivity analysis, temperature was increased by 0.1 to 3 degrees of Celsius from past 7-day average value.

A 0.1-degree Celsius increase in temperature relative to 7-day average temperature before a fire occurrence results in prediction model output of greater than 0.8 for 4.75% of fire forest cases. The model output chart for each 0.1 degree Celsius increment is plotted in the Fig 7.

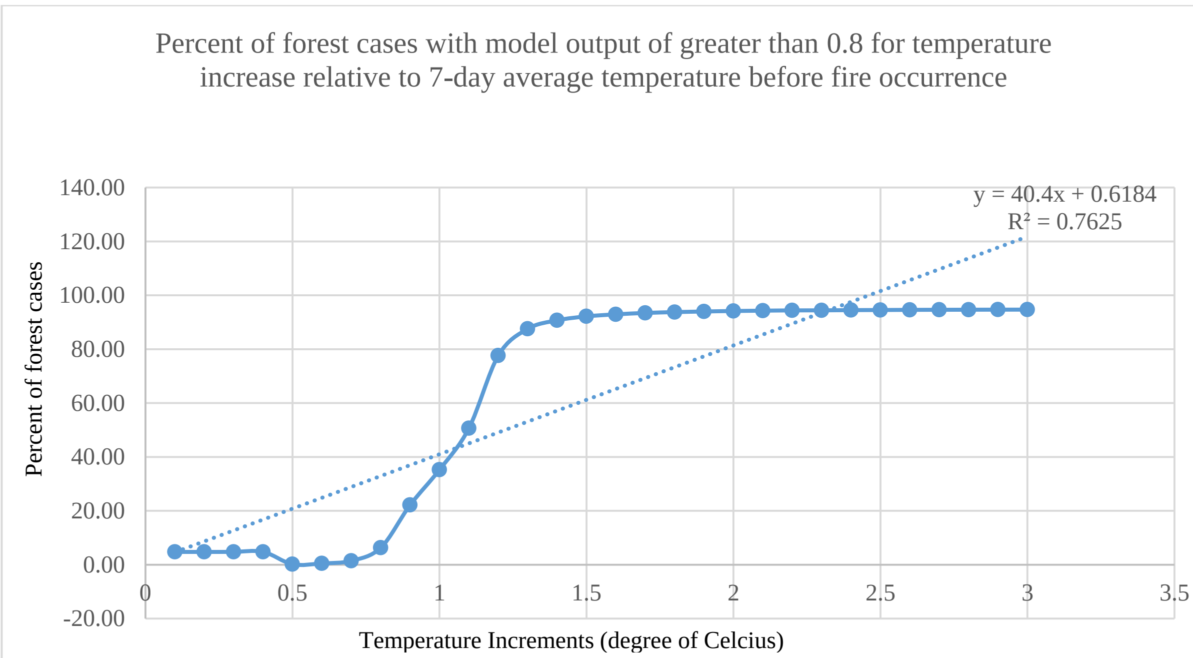


Fig 7. Model output for temperature increments in Temperate Forests

A linear regression was fit to the chart with regression factor of 0.76.

The average temperature during days with fire occurrence is 14.37 degree of Celsius and is 1.06 degree higher than the 7-day average temperature before fire occurrence which is equal to 13.31 degree of Celsius. Moreover, the Fig 7 shows a 1.1 degree increase in temperature relative to the past 7-day average results in 50% of wildfire occurrence.

The curve starts to grow on 0.5-degree increase, and it has the highest growth rate between 0.8 & 1.2 degree increase. Almost 90% of the fire cases have the prediction model output of greater than 0.8 that means serious fire threat if the temperature increase is higher than 1.3 degree.

The model output for temperature increase of less than 1 degree relative to past 7-day average temperature represents no chance of wildfire in boreal forests. But the non-zero fire forest starts at 2 degrees increase of temperature which ends to 2.62% of fire forest cases with model output of larger than 0.8. The model output chart for each 0.1 degree Celsius increment is plotted in the Fig 8.

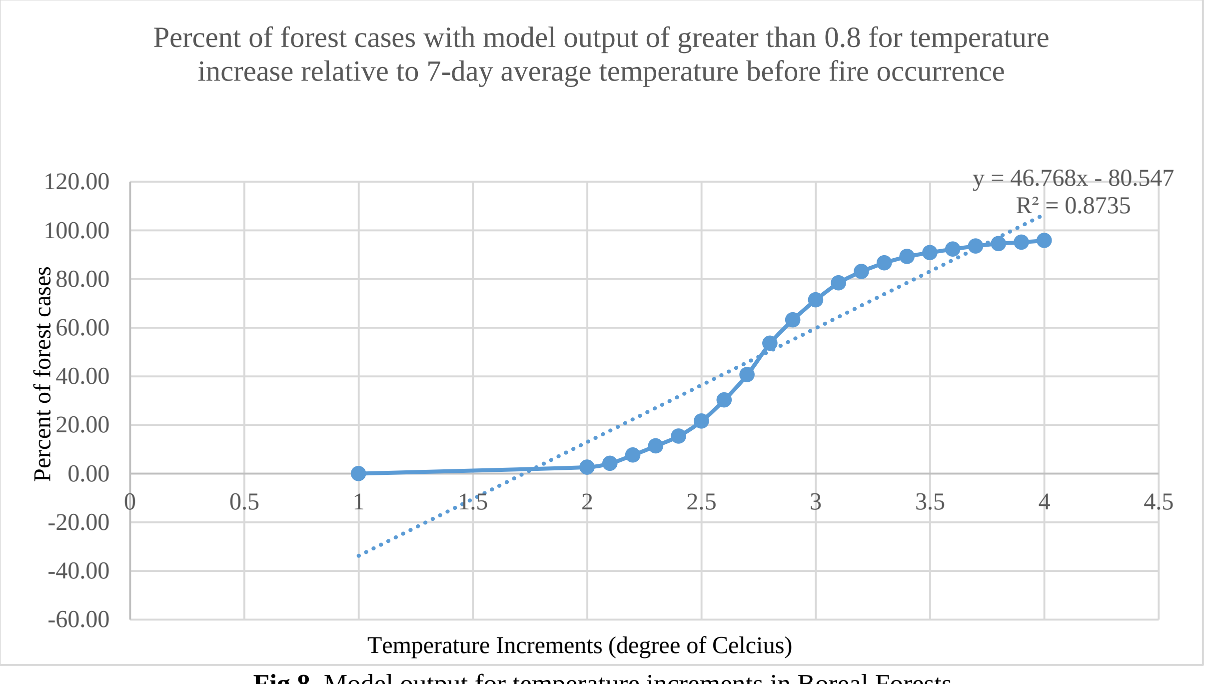


Fig 8. Model output for temperature increments in Boreal Forests

A linear regression was fit to the chart with regression factor of 0.87.

The average temperature during days with fire occurrence is 13.78 degree of Celsius and is 0.98 degree higher than the 7-day average temperature before fire occurrence which is equal to 12.79 degree of Celsius. Moreover, the Fig 8 shows a 2.8 degree increase of temperature relative to the past 7-day average results in 50% of wildfire occurrence.

The curve starts to grow on 1 to 2 degrees increase, and it has the highest growth rate between 2.5 and 2.8 degrees increase. Almost 90% of the fire cases have the prediction model output of greater than 0.8 which means serious fire threat if the temperature increase is higher than 3.5 degree.

These data can be compared with recent studies. In a 2021 study in Victoria, Australia fifteen factors including temperature were selected as input to 3 models in order to produce daily maps of the probability of a wildfire over the next 7 days (Bergado et al., 2021).

Their models showed higher accuracy for predicting wildfires for the next 7 days than previous studies done in Australia. They also suggest development of similar methods to encode information on the probability that a location would experience an ignition. Future works on incorporating temporal information, accepting as inputs and producing as outputs sequences, would be relevant (Bergado et al., 2021).

In another study, different neural networks were used for wildfire susceptibility. They concluded that explanatory variables such as maximum temperature, soil temperature, normalized difference vegetation index (NDVI) and accumulated precipitation have a large impact on the model (Zhang et al, 2021).

A study were done to investigate the burned area interannual variability (IAV) and its climatic sensitivity globally and across nine biomes from 1997 to 2018. We found that tropical savannas, tropical forests, and semi-arid grasslands near deserts were primary contributors to the global burned area IAV, collectively accounting for 71.7%-99.7% of the global wildfire IAV estimated by satellite observations. They also found that precipitation was a major fire suppressing factor and dominated the global and regional burned area IAVs, and temperature and shortwave solar radiation were mostly positively related with burned area IAVs (Tang et al., 2021).

It is suggested that by developing neural networks models, we can help the world to predict wildfires as early enough as wildfires can be managed and controlled better.

CONCLUSION

Based on model outputs and fire percentage occurrence in charts of Fig 7 and Fig 8, a temperature interval can be introduced as “transient temperature span” for each forest type. There is high fire occurrence probability if the temperature increase is larger than the transient temperature span during a period of less than 7 days.

In other words, weather forecast in a region is useful to detect fire hazard for the next 7 days. The detection of fire hazard is crucial for responsible organizations to get prepared and manage the resources. The input variables to the model include temperature, absolute pressure, relative humidity, wind speed, evaporation, Keetch-Byram Drought Index, NDVI, soil surface moisture, snow storage, and precipitation.

The transient temperature span is about 0.8 to 1.2 degrees for temperate forests and about 2.5 to 2.8 degrees for boreal forests.

The similarity of the two curves in Fig 7 and Fig 8 suggests that temperature increase is one of the most important causes of wildfires. Moreover, with low values of temperature increase, other input variables have a lot more contributory role in fire prediction rather than temperature. Their roles and their magnitude are suggested in future study.

It is concluded that other variables except temperature are more determinant to predict wildfires in temperate forests rather than in boreal forests. On the contrary, with temperature increase greater than transient temperature span, the wildfire is mostly dependent on temperature while other variables may have less important effect on the model output. Like before, with low temperature increase, it is suggested to focus study on variables other than temperature in boreal forests.

So, there is a positive linear relationship between wildfire occurrence and temperature increase. Using weather parameters, it is possible to model the relationship and predict fire cases affected by global warming.

GRANT SUPPORT DETAILS

The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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