ADVANCES IN GEOMATICS

VOLUME 02 • ISSUE 01 • APRIL 2024
e-ISSN: 3023-4980

ORIGINAL ARTICLE

Submission: *29/01/2024*
Accepted: *24/02/2024*

ANALYSIS OF FIRE WEATHER INDEX IN SUMMER SEASON: A CASE STUDY OF AEGEAN AND MEDITERRANEAN REGION, TURKEY

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ABSTRACT

Forests are an indispensable part of the earth in terms of their biodiversity and contributions. Climate change stands as one of the most critical factors impacting forests, which cover approximately one-third of our planet's land area. In particular, the link between climate change triggered by human-induced atmospheric changes and high temperatures stands out as a very important dynamic with far-reaching implications for ecosystems. A striking example of this situation is the doubling of the number of forest fires caused by global warming since 1984. Monitoring of forest fires is extremely important in terms of disaster monitoring and prevention. Geographic Information Systems (GIS) and Remote Sensing (RS), which have been frequently used in the monitoring of fires in recent years, are prominent methods in terms of data collection, analysis and interpretation. In this study, it is aimed to perform fire risk analysis with the help of Fire Weather Index (FWI) values created with the help of meteorological parameters obtained from NOAA Geostationary Operational Environmental Satellite (GOES) remote sensing platform. The Aegean and Mediterranean regions of Turkey, which are exposed to more and more forest fires in the summer months every year, were selected as the study area. Accordingly, it was determined that the Aegean and Mediterranean regions are in the high and very high fire risk group for the summer months of July and August. However, it was determined that a decrease in fire risk values was observed in August 2022.

Keywords: Forest Fire, Fire Weather Index, Geographical Information Systems, Kriging.

Cited As:

Akyürek, Ö. (2024). Analysis of Fire Weather Index in Summer Season: a Case Study of Aegean and Mediterranean Region, Turkey, Advances in Geomatics, 2(1), 17-34. https://doi.org/10.5281/zenodo.11314022

INTRODUCTION

Forests are natural resources that provide several material and moral economic, ecological, and socio-cultural advantages, including food, fuel, shelter, clean air and water, medicine, income, employment, recreation, and beautification. Forests provide abundant biodiversity that benefits both economic and social life (Atasoy & Geçen, 2014). A vast 78 million hectares (ha) make up Turkey's environmentally diverse landscape. According to 2020 estimates, forest lands total 22.9 million ha. This forest area accounts for 29.4% of the country's total area (General Directorate of Foresty, 2021). Coniferous species account for 61 percent of Turkey's total forest assets (21678.134 ha). These species are widespread throughout the Mediterranean basin and have significant ecological and economic importance. Summertime and windy days increase the risk of forest fires in locations along this basin that are home to coniferous species. In the basin, high seasonal temperatures and winds have resulted in significant fires in a number of years from the past to the present (Elvan et al., 2021).

Climate change stands out as a paramount risk factor for the well-being of forests. Ongoing climate shifts manifest in prolonged summer droughts and heightened intensity of droughts during other seasons (Tatli & Türkeş, 2014). Fire, a natural occurrence on Earth, has been influencing terrestrial ecosystems for millions of years, contributing to the shaping of landscapes in various biomes (Jones et al., 2022). Fires rank among the leading causes of deforestation. Within the dynamic structure of the Earth, forest fires can arise from natural sources such as lightning, volcanic activities, and meteorites, as well as human-induced factors. Human activities, including campfires, fireworks, and discarded cigarette butts, result in the annual burning of extensive forested areas. Remarkably, the incidence of human-made fires globally surpasses that of natural fires by a considerable margin (Chen & Yang, 2018; Duran, 2014; Mansoor et al., 2022). Over the recent years, there has been a recurring occurrence of significant forest fires in Mediterranean countries. Surprisingly, over 95% of these fires can be attributed to human activities, encompassing instances of negligence and deliberate arson (de Rigo et al., 2017; Flannigan et al., 2006; Kalabokidis et al., 2014; Khabarov et al., 2016). Conversely, among European countries, Spain, Portugal, and Turkey are identified as the top three nations facing the highest risk of forest fires due to natural factors such as climate change (de Rigo et al., 2017). The Mediterranean basin is significantly affected by wildfires, witnessing more than 50,000 incidents each year, resulting in an estimated average burn of almost 900,000 ha. This encompasses an area roughly equivalent to 1.3–1.7% of the total Mediterranean forests (Tatli & Türkeş, 2014). Moreover, this number exhibits a gradual increase from year to year. Remarkably, the fire weather seasons have undergone a substantial lengthening, impacting 25% of the Earth's vegetated surface (Perry et al., 2022).

Weather conditions play a crucial role in influencing the probability and severity of fires. However, having appropriate meteorological conditions alone is insufficient to initiate a forest fire. The ignition of a fire occurs when oxygen, heat, and fuel (typically in the form of glucose known as a combustible substance) combine in the right proportions, forming what is commonly referred to as the fire triangle. Moreover, there is an increasing frequency of extreme weather events, such as extended periods of high temperatures, intense air dryness, strong winds, and sudden storms accompanied by heavy rainfall within a short time span (Johnson & Miyanishi, 2001).

A single day marked by high temperatures, low humidity, and strong winds can be adequate to set in motion the processes leading to the ignition and spread of an abandoned forest fire, causing damage to thousands of hectares of forest. Wildfires are typically prevalent during periods of elevated temperatures and drought. The availability of fire fuel, including both live and dead vegetation, is greater in spring and summer compared to autumn and winter. During spring, a significant portion of ground vegetation dries up or deceased, and becoming a source of fuel for fires (Perry et al., 2022).

Fire Weather Indices serve as meteorological indicators specifically designed to provide information about the characteristics and impact of a fire event within an ecosystem. These indices have been developed for the purpose of integrating meteorological and fuel-related information into a singular value. This value can then be employed for issuing warnings in various regions. Among the widely adopted indices globally, the Canadian Forest Fire Weather Index (CFFWI) System holds prominence (Dimitrakopoulos et al., 2011; Van Wagner, 1987; Van Wagner & Pickett, 1985). Other commonly used indices include the US National Fire Danger Ratings System (NFDRS) (Deeming et al., 1977), Keetch-Byram Drought Index (KBDI) (Keetch & Byram, 1968), McArthur Forest Fire Danger Index (FFDI) (McArthur, 1967), and the Haines Index (Haines, 1988). A widely adopted method for globally ranking weather-related forest fire risk is the Canadian Forest Fire Weather Index System (CFFWIS) (Ertuğrul & Varol, 2016).

CFFWIS, stemming from extensive research conducted in Canada, was initially introduced by Van Wagner in 1968. Subsequent advancements were made by Van Wagner in 1970, with updates regarding the index's structure in 1974 and further developments in 1987 (Van Wagner, 1970, 1974, 1987). Over time, the CFFWIS has undergone continuous refinement for optimal functionality. It was officially implemented in Canada in 1971 and has been adopted by several other countries, including Portugal (Viegas et al., 2000), South-Eastern Asia (De Groot et al., 2005), and New Zealand (Dudfield, 2004; Ertuğrul & Varol, 2016). The Fire Weather Index (FWI) offered by CFFWIS quantifies the favorability of conditions for the spread and intensification of grass or forest fires, assuming one has been initiated. Six variables are included in the model to monitor the fuel moisture content, fire intensity, and the rate at which the fire spreads. The daily observations of the air temperature, relative humidity, wind speed, and 24-hour rainfall, all obtained at midday, serve as the basis for the calculations. The obtained indices show the peak fire danger in the mid-afternoon (Perry et al., 2022).

There are many studies in the literature where FWI values are used. Viegas et al., (2000) reported that FWI is useful for fire risk rating in countries with Mediterranean climates such as Greece and Italy. Vucetic & Vucetic, (2008) have been conducting fire risk analyses with the help of CFFWIS in coastal areas of Croatia, which has a Mediterranean coast since 1981, and calculating daily FWI values from June to September with the data obtained from 20 meteorological stations. Good et al., (2008) conducted a fire risk analysis for Tuscany, Italy and Thessaloniki, Athens and Heraklion regions of Greece by using FWI values obtained from meteorological stations. They also used the obtained FWI values to create a fire risk model. Dimitrakopoulos et al., (2011) monitored the Greek island of Crete with FWI during two fire seasons. They investigated the correlation of FWI components with fire occurrence. They also emphasized that FWI produces useful results as a meteorological fire danger rating index in the Mediterranean basin. Tatli & Türkeş, (2014) determined a climatic model of the entire Mediterranean basin environment by creating the Haines forest fire weather index from hourly meteorological data between 1980-2010. They identified the regions with medium and high fire risk within the Mediterranean basin. Ertuğrul & Varol, (2016) analyzed the coasts of the Aegean Region, which has a high risk of forest fires in Turkey, with the help of CFFWIS. They analyzed the relationship between the calculated index values and the number of fires and burnt areas. Satir et al., (2016) modelled Turkey's long-term forest fire risk for the current (1990 - 2010) and future (2061 - 2080) periods by using a fire weather index called F index derived from FWI. According to their results, they emphasized that the fire risk in Turkey will increase by 21.1% in 2070. Semenova & Sumak, (2022) analyzed the spatio-temporal distribution of fire conditions in mixed woodlands during the fire seasons between 1990 and 2020 using monthly average FWI values for each administrative area within the borders of Belarus and Ukraine. Ntinopoulos et al., (2022) analyzed the spatiotemporal patterns of fire risk using FWI values for regions within the borders of Greece using meteorological parameters obtained from NASA's National Centers for Environmental Protection (NCEP) programme. According to their results, the southeast of the country was identified as the region with the highest fire risk. Perry et al., (2022) analyzed the past and future trends in the frequency of high hazard fire weather conditions in the UK using FWI values. According to their results, they concluded that the southern regions of the country are more dangerous in terms of fire risk.

The aim of this study is to spatially and temporally investigate the FWI values generated by analyzing the meteorological parameters of the Aegean and Mediterranean regions, where the most fires occur in Türkiye during the summer months (June to August). The FWI values obtained after the analyses were compared with the fire points detected by Terra and Aqua satellites of MODIS remote sensing platform.

1. MATERIALS AND METHODS

1.1. Study Area

In this study, the Aegean and Mediterranean regions of Turkey, which are exposed to intense forest fires during summer periods, were selected as the study area. The Mediterranean region, which ranks second in terms of forest cover in Turkey with 19.6%, and the Aegean region, which ranks third with 15.9%, have a total forest cover of just over 8 million hectares (General Directorate of Foresty, 2021). The natural vegetation of the coastal zone consists of red pine, which has a high demand for heat and light and is resistant to drought, and evergreen maquis where these are destroyed. Maquis is a plant community consisting of hard-leaved, densely branched evergreen shrubs of 2 m or more in height, adapted to the climatic conditions and growing environment in the Mediterranean region. In high places, coniferous larch, cedar, and fir forests dominate (Akyürek, 2023; Şensoy et al., 2008).

The predominant climate in both regions of the study area is Mediterranean. This climate type is characterized by hot and dry summers and mild and rainy winters. In the coldest month of January, the average temperature is 6.4°C, while the hottest month of July sees an average temperature of 26.8°C. The annual average temperature is approximately 16.3°C. The average annual total precipitation is 725.9 mm, with the majority of precipitation occurring during the winter season. The share of summer precipitation in the annual total is 5.7%. Therefore, summer drought is dominant in the region. The average annual relative humidity is around 63.2%. In this climate type, evaporation is high throughout the year and especially in summer (Şensoy et al., 2008). Climate change is shown as the biggest reason for the increase in fires in recent years, especially in the countries around the Mediterranean. As a result of the increase in the frequency and intensity of heat waves due to climate change, the incidence of vegetation fires has also increased. Due to climate change, the amount of moisture in the vegetation, which is exposed to extremely arid conditions due to climate change, is reduced, resulting in it becoming more easily flammable (Sari, 2022; Tavşanoğlu, 2021; Tüfekçioğlu et al., 2022).

Figure 1 shows the study area and the sampling points of the derived meteorological data. In the study, meteorological parameters obtained from the analysis of climate data collected by NOAA GOES satellites by NASA's The Modern-Era Retrospective analysis for Research and Applications (MERRA-2) program were used. The spatial resolution of the climate data produced by the MERRA-2 program is 0.5° latitude x 0.625° longitude and covers the entire globe. The data produced are available to users from NASA POWER (Prediction of Worldwide Energy Resource) Data Access Viewer with 0.5° x 0.5° grids.

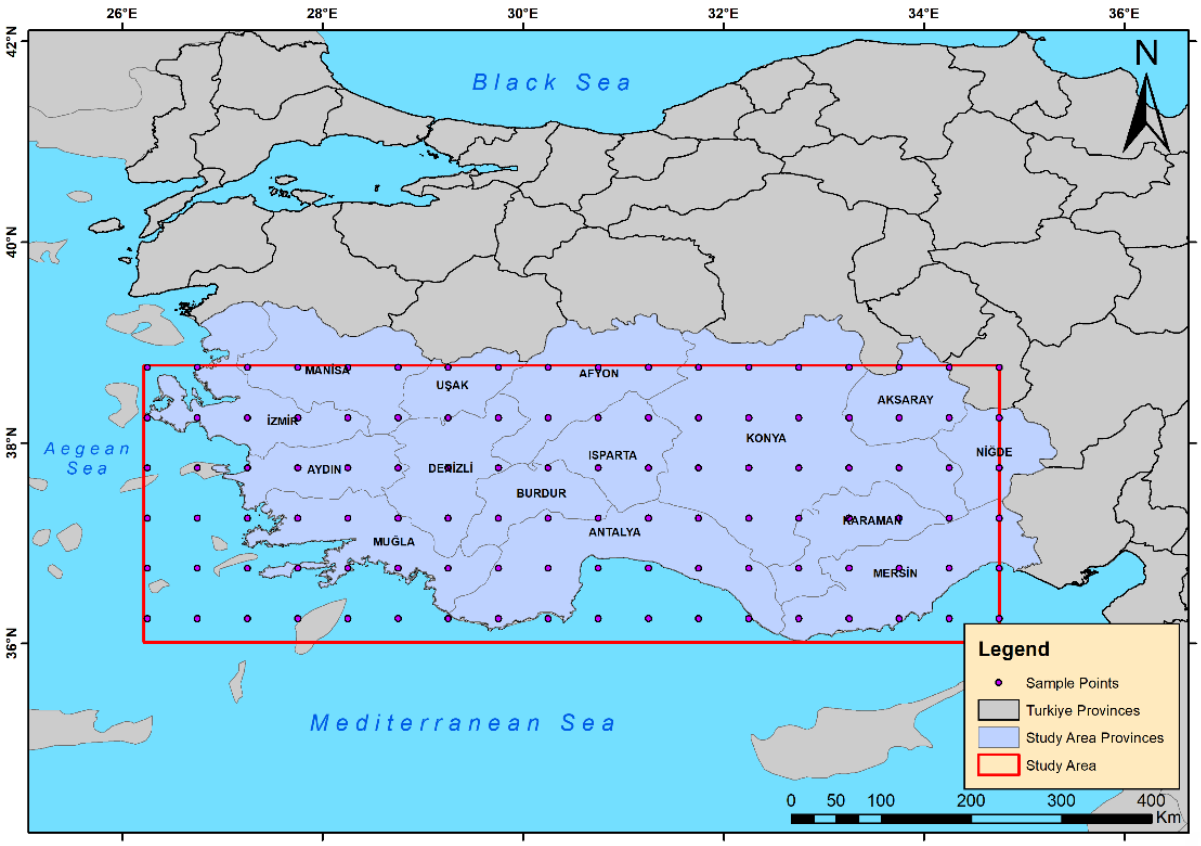

Figure 1. Study area.

1.2. Dataset

In this study, temperature, relative humidity, wind speed and precipitation data, which are the parameters required to create FWI, were obtained from NASA's POWER Data Access Viewer site and used as a data set. The POWER solar data relies on satellite observations to derive surface insolation values. The meteorological parameters are obtained from the MERRA-2 assimilation model, which stands as the initial long-term global reanalysis incorporating space-based observations of aerosols. This model effectively captures the interactions of aerosols with other physical processes in the climate system. In the POWER dataset, data and parameters are presented on a global grid with spatial resolutions identical to the input data. Specifically, the resolution is 0.5° latitude x 0.625° longitude for the meteorological datasets. The grid reference system utilized is WGS84.

In addition, fire points detected with the help of Aqua and Terra satellites of NASA Fire Information for Resource Management System (FIRMS) MODIS remote sensing platform were used for fire data of the study area and period. MODIS is a remote sensing platform with spectral and radiometric characteristics and a spatial resolution of 1 km designed for fire observation. The MODIS platform performs detection using a contextual algorithm based on brightness temperatures obtained from fires using strong mid-infrared radiation (from 4 - 11 µm electromagnetic spectrum channels), which increases sensitivity to smaller and colder fires and reduces the occurrence of false alarms (Fornacca et al., 2017; Giglio et al., 2016, 2018; Iban & Sekertekin, 2022; Oom & Pereira, 2013). A two-stage filtering method was used to avoid misclassification of fire point data. Firstly, the fire data were filtered according to the default vegetation fire type (type=0) in the table information. Secondly, and most importantly, they were filtered according to their overlap with vegetation classes in CORINE 2018 land cover/use data. Thus, by eliminating the fire points that coincide with the outside of the wooded areas, only forest fires were provided.

1.3. Methods

1.3.1. Fire weather index

The FWI system depends solely on daily weather observations collected at noon local standard time, covering temperature, relative humidity, wind speed, and precipitation (if any) over the previous 24 hours. This system consists of six standard components, where the first three primarily involve fuel moisture codes that monitor daily variations in the moisture levels of three distinct classes of forest fuel, each exhibiting different drying rates. Among these components, the Fine Fuel Moisture Code (FFMC) signifies the moisture content of litter and other cured fine fuels within a forest stand, existing in a layer of dry weight approximately 0.25 kg/m^2. Another component, the Duff Moisture Code (DMC), portrays the moisture content of loosely compacted, decomposing organic matter, weighing approximately 5 kg/m^2 when dry. The Drought Code (DC), the ultimate moisture-related component, indicates the moisture content in a deep layer of compact organic matter, potentially weighing 25 kg/m^2 when dry. The remaining three components serve as fire behavior indexes, capturing the rate of spread, fuel weight consumed, and fire intensity. The Initial Spread Index (ISI) combines wind and FFMC, representing the rate of spread without the influence of variable fuel quantities. The Buildup Index (BUI) combines DMC and DC, indicating the overall fuel available to a spreading fire. Lastly, the Fire Weather Index (FWI) integrates ISI and BUI, reflecting the intensity of the spreading fire as the energy output rate per unit length of the fire front. Importantly, FWI provides a comprehensive representation of the overall fire weather conditions (Van Wagner, 1970, 1974, 1987). The methodological workflow implemented in the study to obtain the FWI values is shown in Figure 2.

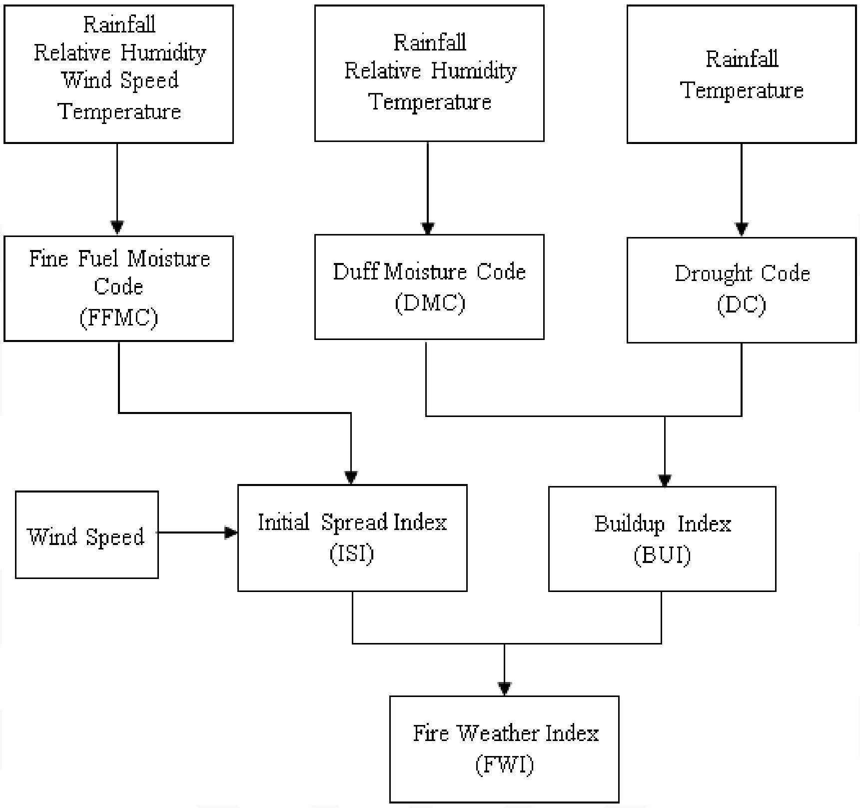

Figure 2. Fire Weather Index methodological workflow (Van Wagner, 1987).

1.3.2 Kriging

Similar to the weighted average method, the Kriging method uses a weighting model that provides more influence from nearby points. The main problem in Kriging interpolation method is to determine these weights. In order to find the most appropriate weights, it is necessary to know the spatial dependencies between the sampling points. This spatial dependence can be defined either by using a covariance function or a semivariogram function. In the Kriging method, the weights are direct functions of the semivariogram models. These Kriging weights play a crucial role in determining the interpolation value. In this context, it is essential for the weights to be unbiased to ensure the accuracy and reliability of the interpolation value. The advantage of the kriging technique over traditional interpolation methods is that the spatial structure is estimated with semivariogram diagrams instead of a predetermined standard weighting process. Another important advantage is that the kriging technique specifies both the estimation and the error arising from this estimation (İnal & Yiğit, 2003).

Geostatistical approaches, such as kriging, are under another category of interpolation techniques. These techniques rely on statistical models that include autocorrelation, capturing the statistical correlations among the observed points. This distinctive characteristic of geostatistical approaches allows them not only to generate a prediction surface but also to offer a measure of the accuracy or certainty associated with the predictions.

Kriging works under the presumption that the directions or distances between sample points can be used to determine the spatial correlation that accounts for surface variance. To establish the output value for each location, the Kriging tool fits a mathematical function to a specified number of points or to all points within a predetermined radius. This approach consists of multiple steps: surface generation, variogram modeling, exploratory statistical analysis of the data, and, optionally, variance surface investigation. When there is a known directional bias or spatially correlated distance in the data, kriging is very appropriate (Oliver, 1990; Royle et al., 1981).

Kriging is comparable to Inverse Distance Weighting (IDW) in that it uses weights assigned to the measured values in the immediate vicinity to forecast values at unmeasured regions. A weighted sum of the available data points is the generic formula for both interpolators:

$$Z(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \tag{1}$$

Here:

- $Z(s_i)$ represents the measured value at the i-th location.
- λ_i denotes the unknown weight assigned to the measured value at the i-th location.
- s_0 is the prediction location.
- N is the total number of measured values (Mitchell, 2005).

This formula encapsulates the concept of weighting the measured values based on their distances or other spatial relationships to estimate the value at the prediction location. The weights (λ_i) are determined through the interpolation method being used, whether it's Kriging, IDW, or another similar technique.

In IDW, the weight (λ_i) is exclusively determined by the distance to the prediction location. On the other hand, the kriging method assigns weights based not only on the distance between measured points and the prediction location but also on the broader spatial arrangement of these points. To incorporate spatial arrangement into the weights, it is necessary to quantify spatial autocorrelation. In ordinary kriging, the weight (λ_i) is influenced by a fitted model to the measured points, taking into account the distance to the prediction location and the spatial relationships among the measured values in the vicinity of the prediction location (Mitchell, 2005; Oliver, 1990; Royle et al., 1981).

In this study, temperature, relative humidity, wind speed and precipitation data were obtained from the sample points shown in Figure 1 and FWI values of each sample point were calculated with the help of codes written in Python programming language according to the workflow shown in Figure

2. Afterwards, FWI values in the whole study area were calculated by Kriging method and the regions with high fire risk were identified and compared with the fire data.

2. RESULTS

In this study, it is aimed to determine the areas with high fire risk by analyzing the FWI values generated by using meteorological parameters and to compare them with the fires that have occurred. For this reason, firstly, the meteorological parameters of the Aegean and Mediterranean regions selected as the study region were obtained through the POWER system under the control of NASA. The meteorological parameters of the summer period (June-July-August) within the 5-year period between 2018-2022, which is the study period, were obtained daily and used to create FWI values. FWI values were obtained by transferring the methods developed by the Canadian Forestry Service to python open source software environment. Then, the point-based FWI values were spread over the entire study area with the help of kriging method. The obtained values are shown in Figure 3.

FWI values are categorized into 5 classes by the Canadian Forestry Service. The classes of FWI values and the limit values of these classes are shown in Table 1.

Table 1. FWI fire danger classes and limit values.

Class Name	Limit values
Very low danger	FWI < 5.2
Low danger	5.2 ≤ FWI < 11.2
Moderate danger	11.2 ≤ FWI < 21.3
High danger	21.3 ≤ FWI < 38
Very high danger	38 ≤ FWI < 50
Extreme danger	50 ≤ FWI

When Figure 3 is analyzed, it is seen that the lowest values are generally obtained in June. However, when a year-based analysis is carried out, a significant increase is observed in the last two years (2021-2022), especially in the regions of Aydın and Mugla provinces that have a coast to the Aegean Sea. The highest values in all years were determined in July. Especially in July 2022, FWI values in Izmir, Aydın and Mugla provinces are the highest values in the whole study period. There are two points where FWI values are clustered as high in July. The first one is the Aegean Sea coasts where Aydın, Mugla and İzmir provinces are located, and the other one is the region where Mersin and Karaman provinces are located. When the FWI values for August are examined, it was determined that the highest values were reached in 2019, 2020 and 2021. Especially in 2020, the highest values were determined within the borders of Mersin and Karaman provinces. One of the noteworthy points is that FWI values, which show a continuous increase in June and July according to years, show a downward trend in August. When the 2021 and 2022 August values are examined, this situation is clearly seen. When Figure 3 is analyzed according to the class values in Table 1, it is seen that the dominant fire class value for June is low and medium fire risk class. Only in 2021 and 2022, this fire risk class rises to a high level for Aydın and Mugla provinces. When the values for July are analyzed, it is seen that there is a high and very high fire risk for all years. It is possible to say the same for August. Except for 2022, the fire risk in August is at high and very high levels for all years. However, in 2022, the fire risk value decreased/decreased from very high level to high and medium level in other regions of the study area except the eastern regions.

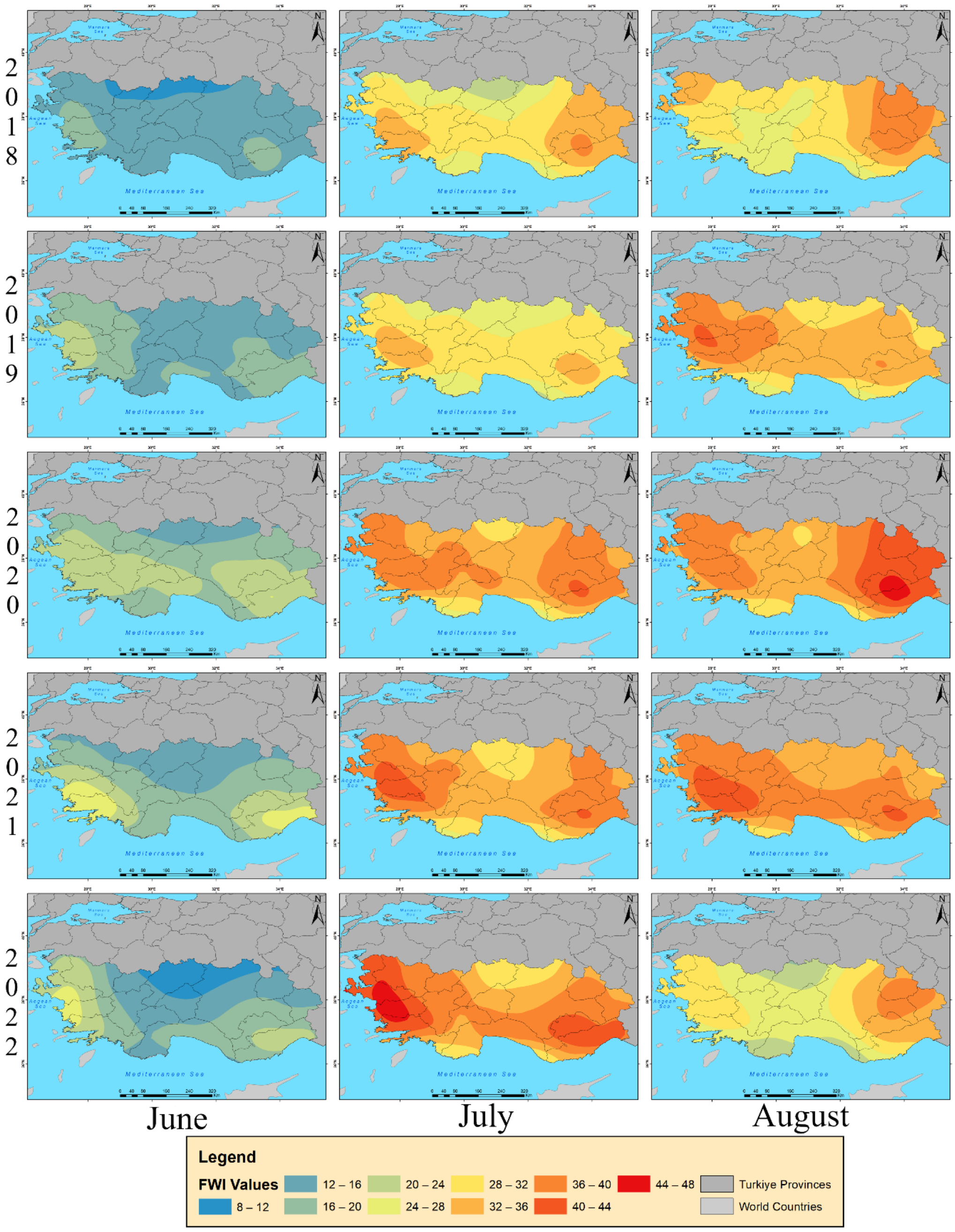

Figure 3. FWI index values in summer season.

The graph shown in Figure 4 shows the monthly minimum, maximum and average values of the FWI values corresponding to the FWI limit values given in Table 1 and the fire points. When the average values shown in grey in Figure 4 are examined, it is seen that the fires that occurred in June for all years generally occurred in moderate risk group areas and had the lowest values in all years. When the months of July and August for all years were analyzed, it was found that all values were within the high and very high risk groups. The highest FWI average value was determined as 39.39 in August 2021.

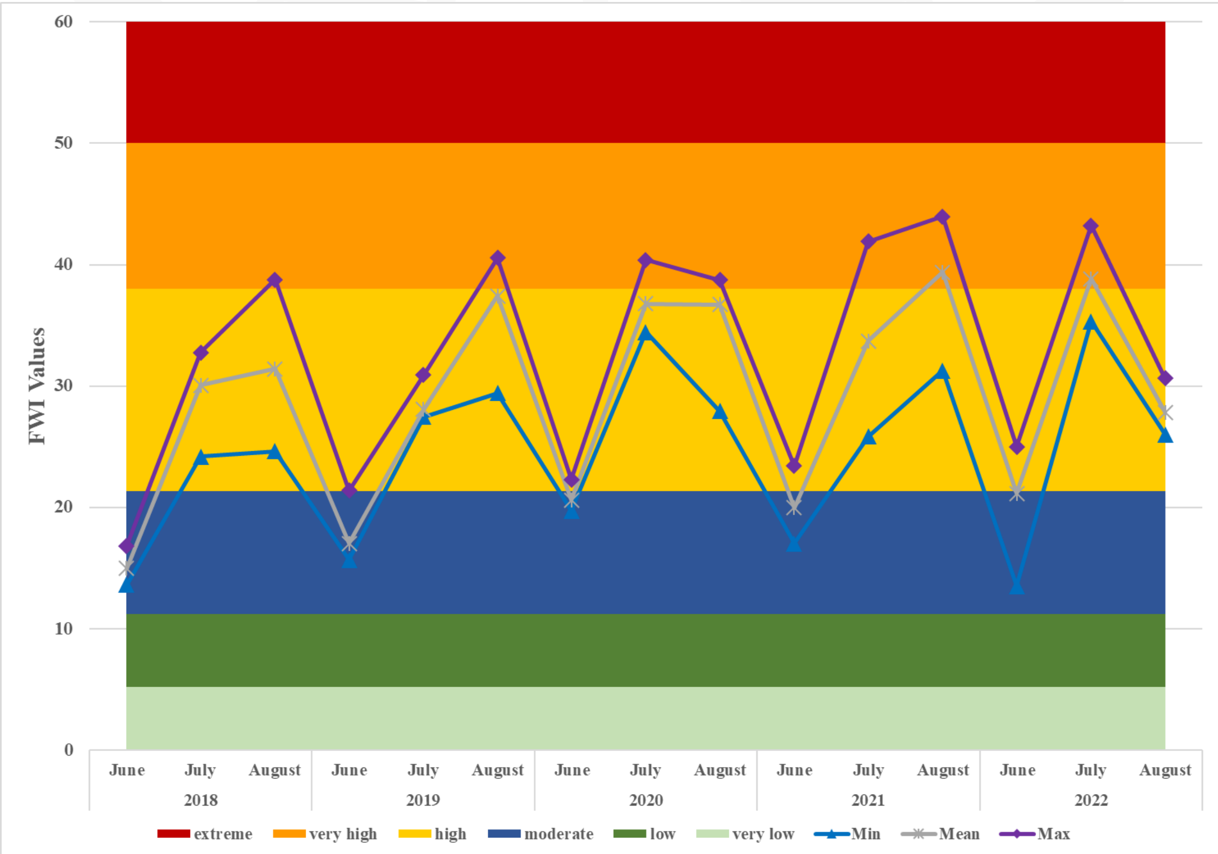

Figure 4. Fire FWI values and risk zones.

In July and August 2021, many forest fires occurred in the Aegean and Mediterranean regions with devastating consequences. Especially the fires in Antalya–Manavgat and Mugla–Marmamis caused the destruction of hectares of forests. Figure 5 shows the FWI values for August 2021 and the forest fires that occurred in the study area during this year. The values of the fire points are the fire points detected by the Aqua and Terra satellites of the MODIS remote sensing platform from FIRMS. It was mentioned in section 2.2 that forest fire point data were obtained by overlapping forested and wooded areas in CORINE land cover data. Accordingly, when Figure 5 is analyzed, İzmir, Manisa, Usak, Aydın, Denizli, Mugla, Burdur, Antalya, Mersin and Karaman provinces are classified in high and very high fire risk group according to FWI values.

In addition, the fire points that occurred in August 2021, shown in Figure 5, also confirm this situation. In particular, the fires that occurred in Mugla and Antalya provinces (regions where intense fire points are shown as clustered) occurred within the FWI very high fire risk zones.

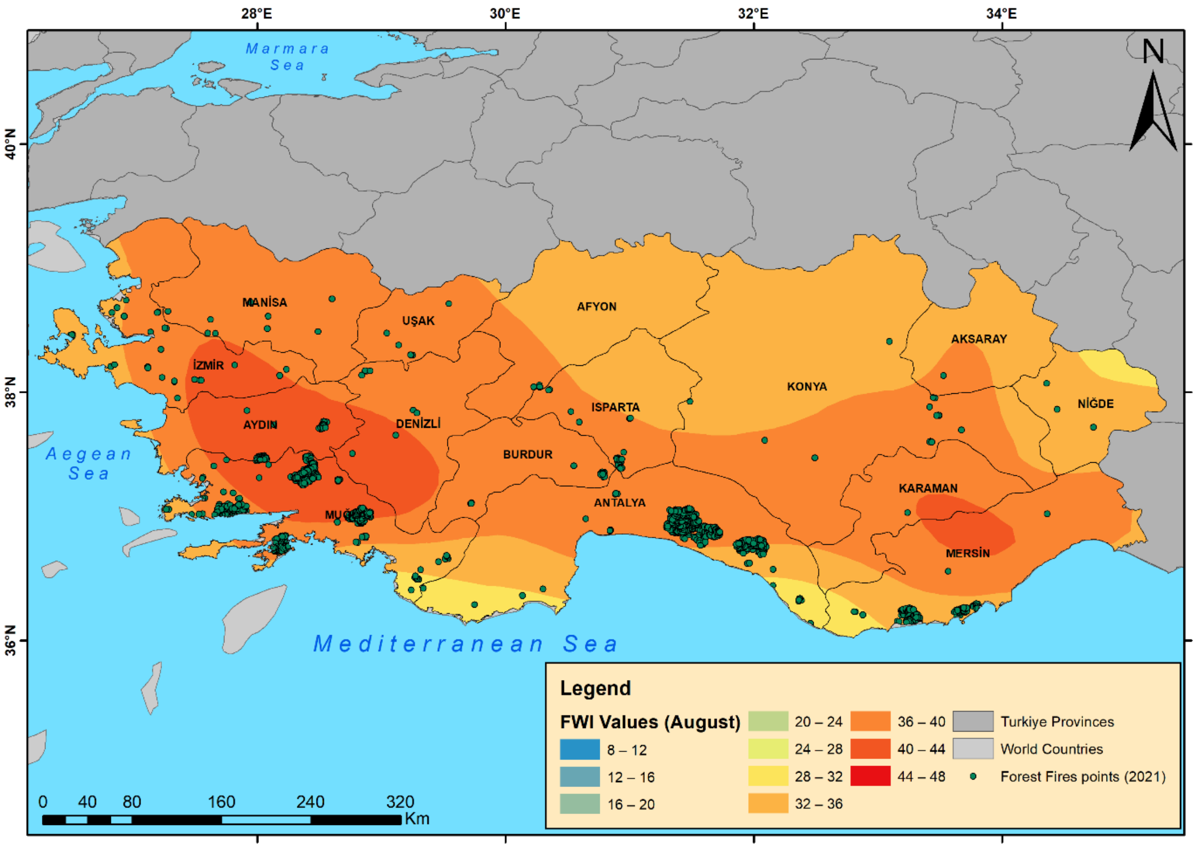

Figure 5. FWI values and forest fire points in 2021 August.

DISCUSSION AND CONCLUSION

In this study, the FWI values generated by the analysis of meteorological parameters of the Aegean and Mediterranean regions of Turkey, which are exposed to intense forest fires every year, were examined. The FWI values of the region were calculated by analyzing the meteorological parameters of the study region with the codes developed in the open source python programming language.

When the FWI values obtained for the three-month summer period are examined, it is concluded that the study area is under high or very high fire risk in July and August. In 2021, it was concluded that FWI values can detect the occurrence of fire or provide useful information about risky areas. With the data obtained in the study, it is possible to make an opinion about whether the fires occurred naturally or due to arson or other artificial causes. It can be concluded that artificial causes rather than natural causes should be investigated as the cause of forest fires occurring in regions with very low fire index.

This study obtained similar results with studies such as Viegas et al., (2000), Vucetic & Vucetic, (2008), Good et al., (2008), Tatli & Türkeş, (2014), Satir et al., (2016), Ntinopoulos et al., (2022), San-Miguel-Ayanz et al., (2012), and Perry et al., (2022) which used similar datasets and methods in the literature. In this study, as in the studies in the literature, it was revealed that it is possible to monitor the fire risks arising from drought and other factors caused by intense heat waves occurring in the Mediterranean basin with FWI. The analysis of FWI values is seen as an important source of information for the monitoring of high fire risk areas that have occurred and may occur. The most important feature that differentiates this study from the studies of Dimitrakopoulos et al., (2011), Ertuğrul & Varol, (2016), Semenova & Sumak, (2022) and Carvalho et al., (2008) in the literature is that by using the geostatistical analysis methods, the measurements made at certain points can be carried to the points where measurements have not been made. Thus, the information obtained can be spread over large study areas and it becomes possible to analyze and infer information.

In this study, Geographic Information Systems (GIS) serves as an essential tool for creating databases, processing, analyzing, querying, and consistently updating data gathered from diverse sources. Simultaneously, Remote Sensing (RS) systems frequently collaborate with GIS, functioning as a potent method for data collection and analysis. Information, recognized as a crucial asset, takes center stage in the realm of disaster management and response. This underscores the pivotal role played by GIS and RS as integral components within disaster management systems, employed for the generation and analysis of information. GIS, harnessing the capabilities of satellite imagery, offers advantages across every phase of disaster management, establishing itself as a preferred tool for mitigating the impact of disasters in numerous countries. The collective prowess of GIS and RS guides decision-makers toward precautionary measures that enhance civil protection. The synergy between GIS supported by RS data enables the swift creation of post-disaster scenarios. This integration provides extensive opportunities for decision-making institutions and organizations both before, during, and after a disaster event, as well as for those tasked with implementing these decisions. The amalgamation of these technologies not only reduces the time required for planning and decision-making but also brings forth robust simulation capabilities. This, in turn, enhances the precision of interventions in the field, leading to an increasing adoption of such systems with each passing day.

Simulations and forecast values to be created by monitoring FWI values can be used as a pioneer of a system that can prevent fires before they occur. As future work, it is considered to develop these methods and to share the useful information obtained with decision makers and those who produce policies to combat fires.

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