

Article

Exploring Forest Fire Dynamics: Fire Danger Mapping in Antalya Region, Türkiye

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Abstract: The Mediterranean region experiences the annual destruction of thousands of hectares due to climatic conditions. This study examines forest fires in Türkiye's Antalya region, a Mediterranean high-risk area, from 2000 to 2023, analyzing 26 fires that each damaged over 50 hectares. Fire danger maps created from fire weather indexes (FWI) indicated that 85.7% of the analyzed fire areas were categorized within the high to very extreme danger categories. The study evaluated fire danger maps from EFFIS FWI and ERA5 FWI, both derived from meteorological satellite data, for 14 forest fires between 2019 and 2023. With its better spatial resolution, it was found that EFFIS FWI had a higher correlation (0.98) with in situ FWIs. Since FWIs are calculated from temperature and fire moisture subcomponents, the correlations of satellite-based temperature (MODIS Land Surface Temperature—LST) and soil moisture (SMAP) data with FWIs were investigated. The in situ FWI demonstrated a positive correlation of 0.96 with MODIS LST, 0.92 with EFFIS FWI, and 0.93 with ERA5 FWI. The negative correlation between all FWIs and SMAP soil moisture highlighted a strong relationship, with the highest observed in in situ FWI (−0.93) and −0.90 and −0.87 for EFFIS FWI and ERA5 FWI, respectively.

Keywords: FWI; fire danger classes; MODIS LST; SMAP soil moisture; ERA5; correlations; Antalya



Citation: Atalay, H.; Dervisoglu, A.; Sunar, A.F. Exploring Forest Fire Dynamics: Fire Danger Mapping in Antalya Region, Türkiye. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 74. <https://doi.org/10.3390/ijgi13030074>

Academic Editors: Wolfgang Kainz and Godwin Yeboah

Received: 18 January 2024

Revised: 23 February 2024

Accepted: 26 February 2024

Published: 28 February 2024



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1. Introduction

Globally, recent years have seen a significant increase in the incidence of forest fires, which are increasingly linked to the impact of climate change. Despite ongoing uncertainty about the full extent of the impact of climate change and the creation of various scenarios, rising temperatures and unpredictable shifts in weather conditions present a growing threat to our ecosystems and societies, highlighting the increased risk of forest fires [1]. In particular, the Mediterranean countries, namely Spain, Portugal, and Türkiye, are identified as the countries with the highest susceptibility to this increasing risk [2]. Looking at the issue more closely from Türkiye's perspective, as stated in the 2021 Climate Assessment report prepared by the Ministry of Environment, Urbanization and Climate Change, this risk is primarily due to temperature anomalies [3,4]. Türkiye experienced its fourth warmest year in 2021, with an average temperature of 14.9 °C, reflecting a substantial deviation of 1.4 °C above the 1981–2010 average. This continued a trend of positive temperature anomalies observed since 1998, excluding 2011. The warmest year during this period was 2010, with an impressive temperature anomaly of +2 °C. In the subsequent year, 2022, Türkiye maintained the pattern as the seventh warmest year, recording an average temperature of 14.5 °C, surpassing the 1991–2020 average by 0.6 °C. With respect to the 1991–2020 trend, the years with the highest to lowest temperature anomalies are 2010, 2021, 2018, 2020, 2019, 2014, and 2022, indicating a consistent fluctuation in temperatures during these specific years [3,4].

Different rating systems and indices have been developed and used to explain the relationship between forest fires and climatic conditions and to calculate weather-based fire

danger [5,6]. There are many different indices used worldwide, including the Angstrom Index [7], Baumgartner Index [8], Canadian Fire Weather Index System (FWI) [9–11], F Index [12,13], McArthur Forest Fire Danger Index [14,15], Fosberg Fire Weather Index [16], Grassland Fire Danger Index [14,17], Haines Index [18], Keetch Byram Drought Index (KBDI) [19–21], US National Fire Danger Rating System [22–24], and Nesterov Index [25].

The Canadian FWI, part of the Canadian Forest Fire Weather Index System (CFFWIS), is the most popular of these indices, and is used in many countries [5]. For example, the UK's National Weather Service has developed the Fire Danger Rating System (FDRS) and the Met Office Fire Severity Index (MOFSI) based on the Canadian FWI [26]. Although the USA employs its own National Fire Danger Rating System (NFDRS) [22,27], Alaska, Florida and the northern and eastern states use the Canadian FWI in conjunction with the KBDI [5]. The European Forest Fire Information System (EFFIS) also utilizes the Canadian FWI as a basis and provides wildfire danger maps to more than 30 countries through web mapping services [28]. Derived from the ECMWF Reanalysis 5 dataset and released in early 2019, ERA5 FWI is another product used to assess fire weather conditions and understand global changes [29]. On the other hand, countries like Russia, Slovakia, and Germany utilize alternative indexes, including the Nesterov Index and others, to assess fire danger and related conditions [5,8]. The system used in Türkiye, the National Meteorological Early Warning System for Forest Fires (MEUS), utilizes 72 h forecast data from the 4.5 km resolution 00 GMT Alaro numerical weather prediction model. This dataset includes 2 m maximum temperature, 2 m average humidity, and 10 m wind vector components, producing hourly forest fire danger maps within the MEUS [30].

Numerous studies have demonstrated a significant correlation between forest fires, particularly large-scale ones, and FWI. In a study conducted across 11 different regions in Portugal between 1980 and 2004, FWI system components were calculated for daily, monthly, and seasonal periods (1 May to 31 October) using noon local standard time values. A significant correlation (61–80% for the variability in area burned and 48–77% for the variability in fire occurrences) was found between FWI and forest fires [31]. In France, a study examining the temporal and spatial patterns of the FWI system and its subcomponents from 1973 to 2009 revealed significant cross-correlations (correlation coefficients from a modified Mann–Kendall trend test ranging from 0.41 to 0.84) between fluctuations in fire activity across different years and the Canadian FWI [32]. In a study conducted in a region covering approximately 7000 hectares with sparse coniferous forest and evergreen shrublands in Northwestern Crete, Greece, fire occurrence was found to be highly correlated with the FWI subcomponents (Duff Moisture Code (DMC) (89%), Drought Code (DC) (78%), and Built Up Index (BUI) (90%)), while the correlation with FWI was 59% [33]. In the Muğla, Çanakkale, and İzmir regions of Türkiye, where forest fires are known to occur frequently, correlations between the size of burned areas and the Seasonal Severity Rating (SSR) and Daily Severity Rating (DSR) values obtained from the Canadian FWI were 60%, 50%, and 38%, respectively, revealing regional differences [34]. In another study, changes in FWI values between 1970 and 2018 in the Ayvalık, Bodrum, Çanakkale, Fethiye, Kuşadası, and Marmaris regions in Türkiye were used as an effective tool to assess whether there were shifts in the length and severity of the wildfire season compared to historical records [35]. In the study conducted in Rize, Türkiye, it was observed that FWI values were consistent with the fire that occurred in March 2014 and FWI values reached the highest level on the day the fire started [36]. A study conducted in Çanakkale, Türkiye, examined the relationship between large periodic fires (larger than 100 hectares) and climate data, focusing on the eight most severe fire seasons between 1969 and 2008. The investigation revealed a correlation (ranging from 57% to 88%) between the occurrence of fires and days with high DSR values obtained from the FWI. Notably, the year 2008 was identified as having the highest fire danger since 1969 [37]. Another study conducted in Çanakkale [38] analyzed the fires that occurred in 2008 and 2009 using the Canadian FWI and emphasized the consistency of the FWI with the fire data of those years and its effectiveness in predicting fire risk [38]. As evident from the aforementioned studies, FWI, which has proven to be highly effective in

predicting fire events and assessing potential fire-related conditions [2,35], has become an important global tool for identifying hazardous conditions that can lead to extensive fire events [39].

Although remotely sensed observations of fire activity have been available for decades, forecasting fire events using satellite data has limitations due to the human origin of fires, often through negligence or arson. Therefore, fire danger models based on remote sensing focus on predicting meteorological conditions, such as accumulated precipitation, relative humidity, temperature, and wind speed, that are conducive to uncontrolled flames rather than pinpointing ignition locations [40]. One well-known model addressing these challenges is the EFFIS FWI implemented at the European Union level, aiming to uniformly assess fire hazards across Europe by undergoing rigorous testing for reliability and robustness [41]. Numerous studies, including [42], have explored the effectiveness of EFFIS FWI in predicting and managing forest fires. Integration with remote sensing technologies has notably improved its spatial resolution and predictive capabilities [43]. Another notable model, ERA5 FWI, is also utilized for evaluating fire weather conditions and exploring global changes in the literature. Recent studies affirm ERA5 FWI's accuracy in capturing essential meteorological variables for fire danger assessment [40,44]. A global evaluation of climate models using FWI components [29] reveals alignment with ERA5 data, emphasizing regional variations that underscore the importance of considering local nuances in fire dynamics.

In estimating thermal energy before the occurrences of fires, land surface temperature (LST), influenced by solar radiation, vegetation, and moisture, is a key parameter that reflects Earth's radiative temperature [45]. Satellite-retrieved LST is used to identify high-temperature areas as high-wildfire-risk zones [46]. Anomalies in LST, such as deviations from normal temperature patterns, serve as vital indicators for fire-prone areas [47,48]. A study emphasized LST's critical role in assessing burn severity in large-scale Mediterranean forest fires [49].

Another parameter affecting forest fire progression is soil moisture levels, which impact fuel flammability [50]. Satellite data, like SMOS and SMAP, aid in assessing wildfire risk globally [51–54]. Using L-band emissions, these satellites derive a comprehensive soil moisture product. In a study of Siberian Forest fires, based on 2002–2009 satellite data analysis, moisture levels from the previous summer were found to be a more reliable predictor of burned areas in larch forests than precipitation anomalies or fire weather indices [55]. An improvement to the FWI methodology has been proposed by incorporating the soil moisture deficit factor to formulate a comprehensive fire danger index [56]. In this context, Sentinel-1 radar satellite data were used to calculate soil moisture in order to evaluate the degree of water saturation in the soil surface layer. Additionally, to determine the moisture deficit of the upper layer, geospatial data, particularly the physical and hydrological characteristics of soils obtained from the European 3D Soil Hydraulic Database, are integrated into the calculation process. The validation of the proposed method demonstrates an improvement in both the accuracy and relevance of fire danger predictions.

In this study, forest fires occurring in Antalya region between 2000 and 2023 were analyzed using the Canadian FWI. The analysis focused on 26 forest fires that damaged more than 50 km² of forest area using local meteorological data. Fire danger maps were generated using FWI values obtained from local meteorological stations and satellite-based FWI data at various spatial resolutions. Subsequently, fire danger categories for the burned areas were determined from the produced danger maps based on different FWI datasets, and a comparative analysis was conducted. In the final step, correlation analysis was performed using SMAP soil moisture and MODIS LST data to examine the relationship between FWI and soil moisture and land surface temperature.

2. Materials and Methods

2.1. Study Area

The Mediterranean Basin, a region where forest fires are frequently observed, is classified under the Köppen–Geiger climate classification as Cs, characterized by generally mild and rainy winters followed by hot and dry summers [57]. This climate pattern is common in various European countries, including France, Italy, Greece, and Türkiye [38]. In Türkiye, forest fires are widespread, especially along the Marmara, Aegean, and Central Mediterranean coastlines, where the dominant climate mirrors the Mediterranean pattern [58].

Antalya, located in southwestern Türkiye and bordering the Mediterranean Sea (Figure 1a), is a region prone to forest fires, particularly in the summer months, owing to high temperatures and low humidity. The land use and land cover (LULC) data of Antalya, as depicted in the ESA WorldCover data for 2021 (Figure 1b), reveal a diverse range of forest types and vegetation within the region.



Figure 1. Study area. (a) Map of the Antalya region and (b) ESA WorldCover LULC map of Antalya.

As in many regions, increasing aridity levels in Antalya contribute to naturally occurring fires, while others are attributed to human-caused factors such as negligence or intentional actions. Given Antalya's significance as a tourism destination, the intentional burning of forests for construction purposes, known as arson, is a notable contributing factor. Figure 2 illustrates the potential causes of forest fires in the Antalya region between 2013 and 2022, based on data from the General Directorate of Forestry [59].

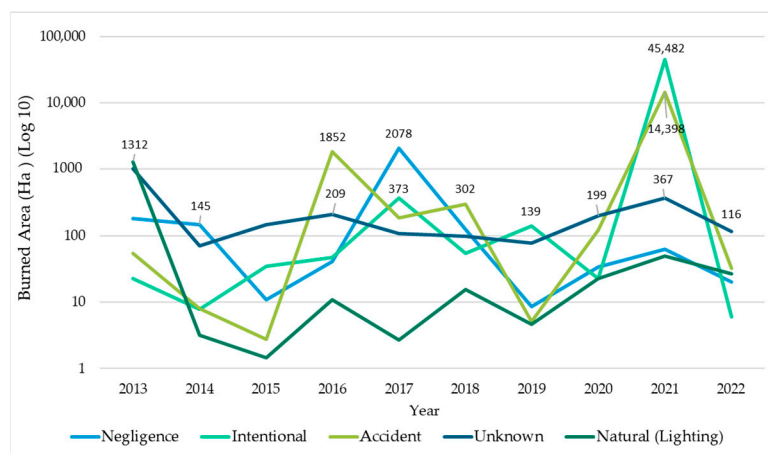


Figure 2. Causes and sizes of burned areas in forest fires, Antalya region.

In Figure 2, the largest area loss in 2021 (45,482 ha) was reported as intentional, while 14,398 ha burned due to accidents. The third largest loss occurred in 2017 (2078 ha) due to negligence, followed by 2016 with 1852 ha lost to accidental fires. Although the number of naturally occurring fires is relatively small, the largest fire reported in this context occurred in 2013 with an area of 1312 ha and was reported to be natural and of unknown cause.

Regardless of the cause—intentional, accidental, or due to negligence—the main factor influencing forest fires is ‘fuel,’ including dead and live vegetation. As is known, combustion requires oxygen and heat, and in well-oxygenated environments, fires spread rapidly. Ignition intensifies the heat, fueling the fire’s expansion. Seasonal conditions are also critical; in dry seasons with low humidity and high temperatures, the risk of fires increases due to reduced moisture and heightened potential for dry fuel [60].

2000–2023 Forest Fires, Antalya Region

Between 2000 and 2023, a total of seventy-two forest fires, varying in size, occurred in the Antalya region. To focus our study, fires exceeding 50 hectares were initially selected for analysis, resulting in the consideration of 36 fires. The selection of a 50-hectare threshold for forest fire size is based on EFFIS’s adoption for assessing the severity of forest fires in Europe [61]. However, due to the unavailability of in situ meteorological data for all 36 fires from the Antalya Regional Directorate of Forestry and EFFIS, the study narrowed its scope to 26 forest fires. In Figure 3, the locations and sizes of the analyzed forest fires are shown in pink color.

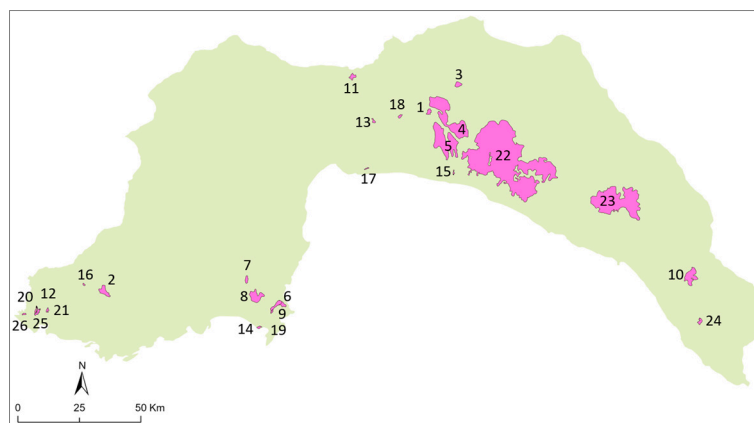


Figure 3. Locations and sizes of the 26 analyzed forest fires, sourced from EFFIS data.

To assess the distribution of each LULC class in the burned areas of the 26 fires, LULC data from ESA WorldCover were integrated into the study, as illustrated in Figure 4. As

shown, the most affected areas are forests, followed by shrublands and croplands. Notably, it has been observed that vegetation in wetlands, submerged or flooded for most of the year, is susceptible to fires during specific periods (e.g., 14 October 2017, 17 February 2021, and 11 August 2021). Although fires impact agricultural and residential areas, it is essential to emphasize that their extent in these regions is relatively low compared to forests. The significant damage in forested areas highlights the vulnerability of these ecosystems to such disasters, emphasizing the crucial need for comprehensive disaster management and prevention strategies.

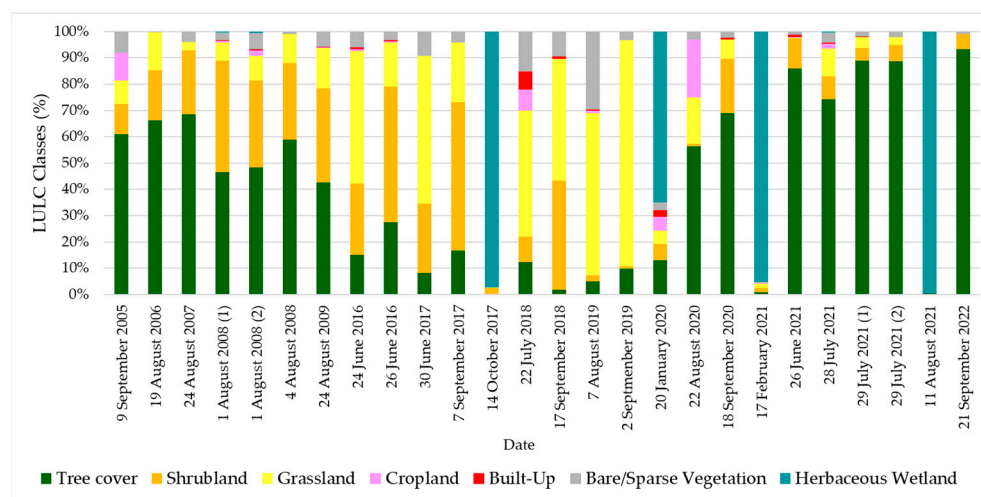


Figure 4. Distribution of LULC classes as a percentage of burned areas.

2.2. Materials

For this study, the following data sources were utilized:

- Meteorological station (in situ) data: Hourly temperature ($^{\circ}\text{C}$), humidity (%), wind speed (m/s), and precipitation ($\text{mm} = \text{kg/m}^2$) were obtained from the General Directorate of Meteorology for the years 2000–2023. There are 62 meteorological stations in the Antalya region. Due to a lack of data (wind and/or precipitation) in 18 stations, the data of the remaining 44 stations were used in the analysis (Figure 5). Due to the absence of precipitation data, FWI calculations were not possible for the years 2000–2005 and 2012–2013.
- EFFIS FWI data: As an integral component of the Emergency Management Services within the EU Copernicus program, EFFIS provides FWI data derived from two deterministic models (ECMWF at 8 km and MeteoFrance at 10 km spatial resolution) and one probabilistic model (ECMWF Probabilistic model at 18 km spatial resolution). In this study, FWI values calculated by the ECMWF model at 8 km were obtained from the EFFIS data center together with the burn area boundaries [62].
- ERA5 Reanalysis-based FWI: This dataset is generated by the ECMWF, serving as the computational hub for fire danger forecasting within the Copernicus Emergency Management Service (CEMS). The fire danger indices in this dataset are computed using weather forecasts derived from historical simulations obtained through the ECMWF ERA5 reanalysis [63]. The data are made available through the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) in NetCDF format at a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ (approximately 28 km grid cell size).
- MODIS Daily Land Surface Temperature (LST): Terra’s MOD11A1 dataset [64], which has a spatial resolution of 1 km and provides daily daytime LST information, was used in the study. Temperature calculations were performed in Google Earth Engine (GEE) using a generalized split-window algorithm [65].
- Soil moisture data: The NASA–USDA Enhanced Soil Moisture Active Passive (SMAP) Global dataset, obtained through GEE for the period from 2 April 2015 to 2 August

2022 [66], provides global soil moisture information at a 10 km spatial resolution. Measuring radiation in the L-band microwave wavelength (30–15 cm range, frequency of 1–2 GHz), SMAP quantifies water content in the uppermost soil layer (5 cm) globally, excluding water-covered or freezing regions [67]. This dataset is generated by assimilating soil moisture observations from the SMAP Level 3 satellite into a modified two-layer Palmer model using a one-dimensional Ensemble Kalman Filter (EnKF) technique [68].

- **ESA WorldCover data:** It provides the first global land cover products developed and validated in near-real time based on Sentinel-1 and Sentinel-2 data at 10 m spatial resolution for 2020 and 2021. This dataset was downloaded via GEE [69].

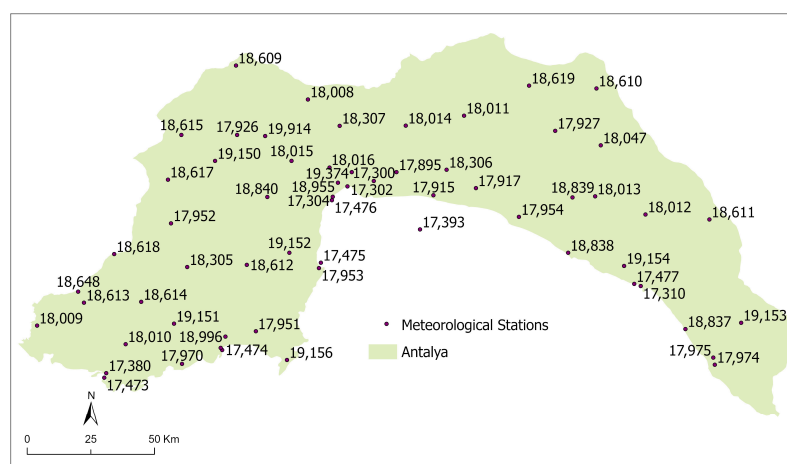


Figure 5. Locations of all meteorological stations in the Antalya region.

2.3. Methodology

The flowchart of the methodology used is shown in Figure 6. In situ FWI values were computed for each of the 44 stations using meteorological station parameters at noon. The calculation of in situ FWI involves six distinct subcomponents (three codes and three indexes), as explained further in Section 2.3.1. The three codes employed are the Fine Fuel Moisture Code (FFMC), DMC, and DC, while the two indexes are the Initial Spread Index (ISI) and BUI. First, FFMC was computed from air temperature, relative humidity, wind, precipitation; DMC was computed from air temperature, relative humidity, and precipitation; and DC was computed from air temperature and precipitation data. ISI was calculated using wind data, and BUI was derived from DMC and DC. FWI values were then computed from these subcomponents, and FWI danger maps were generated using the Kriging interpolation method based on the calculated values at each station for twenty-six forest fires.

Correlations between in situ FWI values derived from meteorological stations and two other FWI datasets (EFFIS FWI and ERA5 FWI) obtained from satellites with varying spatial resolutions were investigated. Given the availability of NASA–USDA Enhanced SMAP Global Soil Moisture Data from 2 April 2015 to 2 August 2022, additional correlations were explored within this period. As a final step, the relationships between soil moisture, temperature, and FWI were examined using two additional datasets: SMAP soil moisture and MODIS LST data.

2.3.1. Canadian Forest Fire Weather Index (FWI)

The pioneering research initiated by J.G. Wright in the 1930s aimed to understand and predict wildfire hazards in Canada, with a particular focus on red and white pine forests, which led to the development of the now widely used Canadian FWI system, a major milestone in the advancement of wildfire forecasting science [70]. The FWI index, which dates back to 1970, was formulated by combining earlier wildfire risk indices, the

ISI and BUI. The BUI and ISI are related to fire behavior, specifically addressing factors such as rate of spread and intensity [2]. The FWI has been further developed to provide a more comprehensive assessment of potential wildfires by considering both fuel moisture levels and prevailing weather conditions. This development takes into account moisture fluctuations in various soil layers on the forest floor.

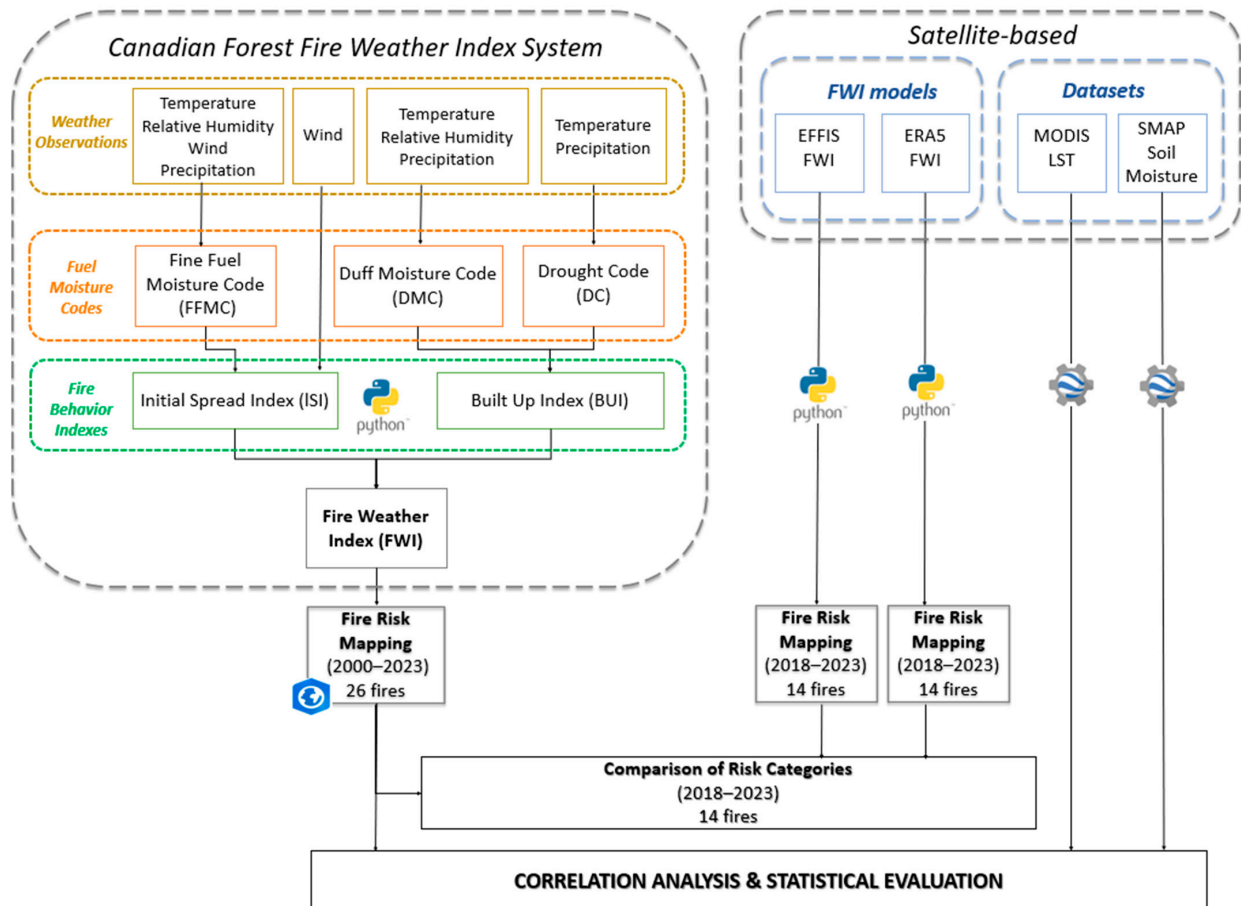


Figure 6. Flowchart of the study.

The FWI system consists of six distinct subcomponents, with three of them (FFMC, DMC, and DC) specifically associated with fuel moisture codes, while the remaining three (ISI, BUI, and the general index FWI) function as fire behavior indexes [56]. The FFMC measures moisture content in combustible materials such as branches, leaves, dry grasses, bark, and other substances located at a depth of 0–2 cm on the forest surface, providing crucial insights into moisture levels within this thin layer of deceased organic cover, including debris and residues. The DMC assesses moisture content in decomposing organic materials located 5–10 cm beneath the layer of organic surface residues and debris, playing a crucial role in evaluating moisture conditions within this specific layer of organic material. DC measures the organic moisture content at a depth of 10–20 cm in the forest floor [38,71]. These three subcomponents collectively describe fuel conditions, ranging from the surface to deeper soil layers, encompassing litter and organic layers [2]. Some research studies noted that the combination of FFMCs with a high ISI was more effective in predicting fire occurrences for specific fuel sources compared to the overall FWI [26,72,73]. Since fuel moisture codes integrate the previous day's values, initial values need to be determined; these specific values—85 for FFMC, 6 for DMC and 15 for DC—are documented in the literature [71,74]. It is noted that these calculations may vary under different conditions. For example, in regions where snow cover is not predominant, it is recommended to start the calculations on the third consecutive day when the midday temperature reaches 12 degrees

Celsius or above [75]. Regarding other parameters, the FWI System takes into account the previous 24-hour's cumulative precipitation as well as temperature, relative humidity, and wind speed measured at noon local standard time [76].

The first two fire behavior indexes, ISI and BUI, indicate fire spread rate and available fuel, respectively. ISI, a numerical indicator, predicts fire spread when surface-level fuel is dry. The ISI, which is influenced by wind speed and FFMFC, does not take fuel type into account like the other FWI components. BUI is also a numerical indicator, combining DMC and DC to represent the total fuel available for combustion. The last index, FWI, combining ISI and BUI, serves as a numeric indicator of fire intensity, with low values indicating low fire danger and higher values suggesting increased fire danger conditions [56].

The FWI system standardizes fire danger assessment using a reference fuel type, specifically a mature pine stand, without accounting for the diversity of other fuel types [2]. This limitation is problematic as fuel comprises both living and dead vegetation, including trees, shrubs, grasses, leaves, branches, as well as flammable materials on the forest floor like dry organic matter, fallen logs, and structures. Neglecting the diversity in fuel types is a drawback as the type and arrangement of fuel significantly influences the behavior and intensity of wildfires [76].

2.3.2. EFFIS FWI

EFFIS, under the governance of the European Commission's Joint Research Centre, relies on the Global ECMWF Fire Forecasting Model (GEFF) for assessing and forecasting global fire risk conditions through Numerical Weather Prediction (NWP) outputs [77–79]. The fire danger maps, routinely updated, provide valuable information on fire weather conditions and risk levels across diverse regions.

Predictive accuracy varies geographically, with regions abundant in vegetation fuel, like boreal forests, the Mediterranean, South America, and Central Africa, showing higher predictability due to fires primarily being triggered by drought conditions. Conversely, in temperate zones with limited vegetation fuel, such as the mountainous areas of Central Europe, wildfires can be influenced by fluctuating conditions like the temporary drying of organic matter on the ground, leading to lower predictive accuracy [78].

2.3.3. ERA5 FWI

ERA5, the fifth-generation atmospheric reanalysis dataset developed by ECMWF, offers detailed information on historical weather and climate spanning from 1940 to the present, with a horizontal resolution of approximately 31 km [80]. This dataset assimilates observational data from satellites, ground-based observations, and various sources into a numerical weather prediction model, resulting in a consistent and coherent representation of atmospheric conditions.

In the study region, three distinct FWI datasets were compared with the monthly average in situ FWI, EFFIS FWI, and ERA5 FWI data (Figure 7). As is evident, the monthly FWI values obtained from the three different models exhibit consistency, with a higher correlation observed between in situ FWI and EFFIS, as opposed to ERA5 FWI. McElhinny et al. (2020) found a negative bias in ERA5-calculated FWI values in Canada, especially Alberta, with a mean bias error of -3.67 , reaching -10 to -15 in the Alberta region, possibly associated with wind speed or precipitation forecasting [81]. In our present study, a high correlation (86%) and a positive bias ($\approx +20$) were observed between FWI and ERA5 reanalysis data and in situ FWI.

2.3.4. FWI Danger Maps

FWI risk maps were created for each fire using the Kriging interpolation method with the FWI values calculated at each meteorological station. Kriging, a geostatistical interpolation method used in spatial analysis and geostatistics, estimates the value of a variable at unobserved locations based on observed values at nearby locations [82]. This

approach is well suited for mapping a variable of interest or generating continuous surfaces, proving particularly effective with fewer spatial sample points.

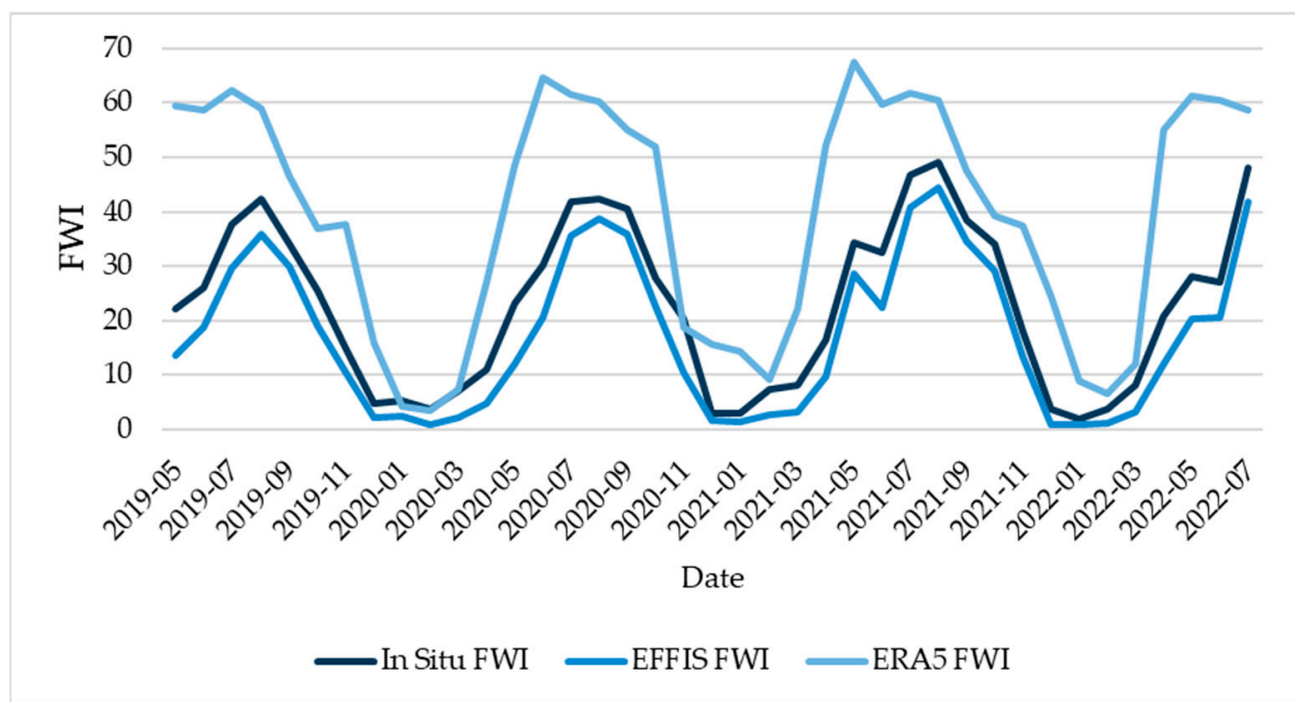


Figure 7. Monthly average comparison of FWI data from in situ, EFFIS, and ERA5.

The FWI fire danger classes, derived from EFFIS and detailed in Table 1, form the basis for the danger maps generated in this study, ensuring a consistent spatial representation of fire danger levels across Europe, the Middle East, and North Africa. The inclusion of the “Very Extreme” class was prompted by the Mediterranean region fires in June 2021 [77]. Table 1 presents the class ranges for fire danger as defined by EFFIS.

Table 1. EFFIS FWI fire danger classes.

Fire Danger Classes	EFFIS FWI
Low	<11.2
Moderate	11.2–21.3
High	21.3–38.0
Very High	38.0–50.0
Extreme	50.0–70.0
Very Extreme	≥70.0

The application of EFFIS’s FWI thresholds is constrained by the potential for the overestimation or underestimation of fire danger, attributed to climate variability influenced by the diverse geography of the Mediterranean region. These limitations restrict the generalizability of the thresholds to the specific conditions of countries in the region, as highlighted in studies by refs. [83,84].

2.3.5. Correlation Analysis

Pearson correlation analysis quantifies the linear relationship between two continuous variables using the Pearson correlation coefficient (r), ranging from -1 to 1 . An r close to 1 signifies a strong positive correlation, while an r near -1 indicates a strong negative correlation; an r close to 0 suggests no correlation [85]. To evaluate the influence of fire weather conditions, as indicated by the FWI, on the extent and intensity of burned areas,

correlation analyses were performed. This involved three distinct FWI values from different input sources and their correlation with SMAP soil moisture and MODIS LST data.

3. Results

Rising air temperatures have a significant impact on the FWI as they accelerate vegetation burning. Higher temperatures expedite the evaporation of moisture from plant material, reducing fuel moisture content and facilitating easier ignition and sustained flame spread. Therefore, as shown in Figure 8, air temperatures for a 3-month period (June, July, and August) in the summer season by year from 2015 to 2023 for station 17917 were analyzed and it was shown that the hottest days occur in the second half of June and August. The blue lines in the figure represent this 3-month summer period. The reason for choosing this station as a sample station is that it is the closest station to the site of the largest forest fire in the region and in Türkiye (28 July 2021).

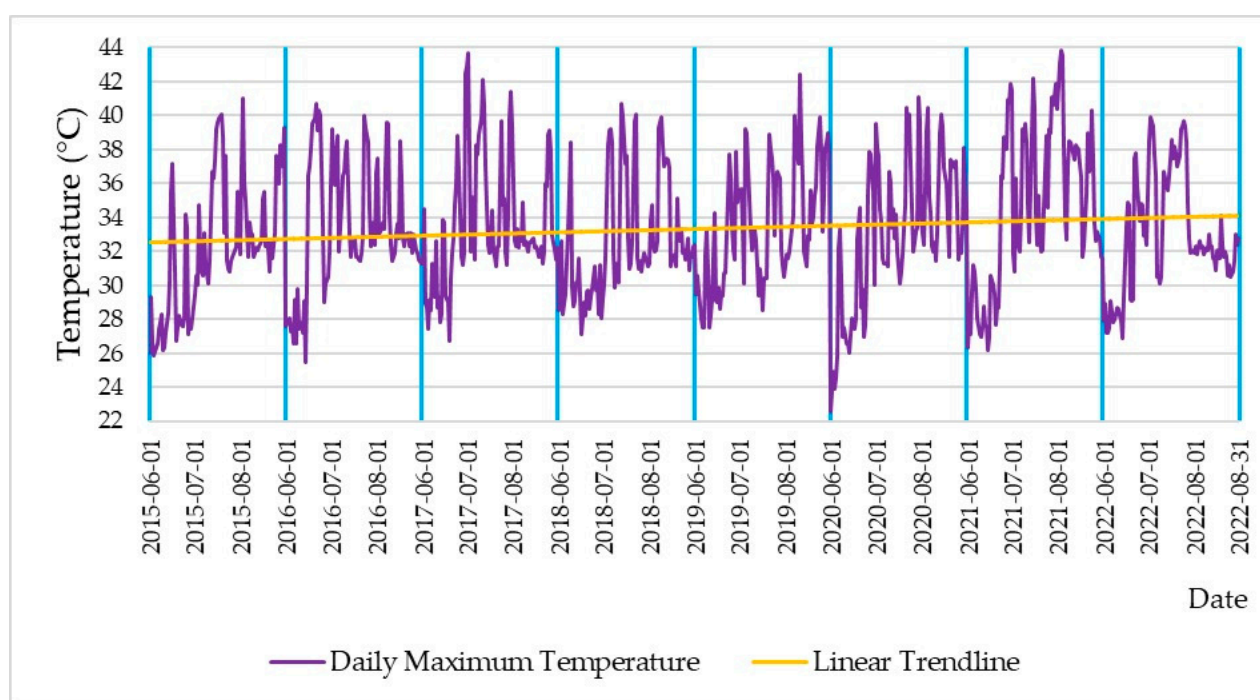


Figure 8. Daily maximum temperatures from June to August at station 17917 (2015–2022).

In 2021, the year marked by the devastating Mediterranean fires, average temperatures in July and August surpassed those of other years. Specifically, the maximum temperature in 2021 rose by nearly 2–3 degrees compared to 2015. While a one-degree temperature increase may appear modest, its conjunction with other factors establishes favorable conditions for the occurrence of large-scale forest fires.

In this study, for each forest fire event, in situ FWI was calculated at each meteorological station, and FWI values obtained from satellite-based models at various spatial resolutions were utilized. As shown in Figure 9, depicting the average monthly FWI values from 2015 to 2023 at station 17917 as an example, it is evident that the highest FWI values consistently occur during the summer months, namely June, July, and August, every year. Notably, the graph highlights a peak FWI value of 62.09 in July 2021, aligning with Türkiye's largest forest fire in Manavgat on 28 July 2021, which resulted in the burning of an extensive area (54,769 hectares). The graph further underscores the heightened risk of forest fires in the Antalya region between June and August, characteristic of its Mediterranean climate zone.

In fire risk studies, seven consecutive days with high FWI values and total number of days with high FWI values are considered as important parameters in the literature. These metrics provide valuable information for assessing and understanding fire dynamics and related consequences. In this context, the relationship between the measured temperature values (red) and FWI values (blue), calculated using meteorological parameters and taking into account the danger classes at the sample station (ID: 17917), is given in Figure 10 for the years 2015–2023. As can be seen, the number of FWI >70 days in 2021 is higher than in other years when destructive fires occur.

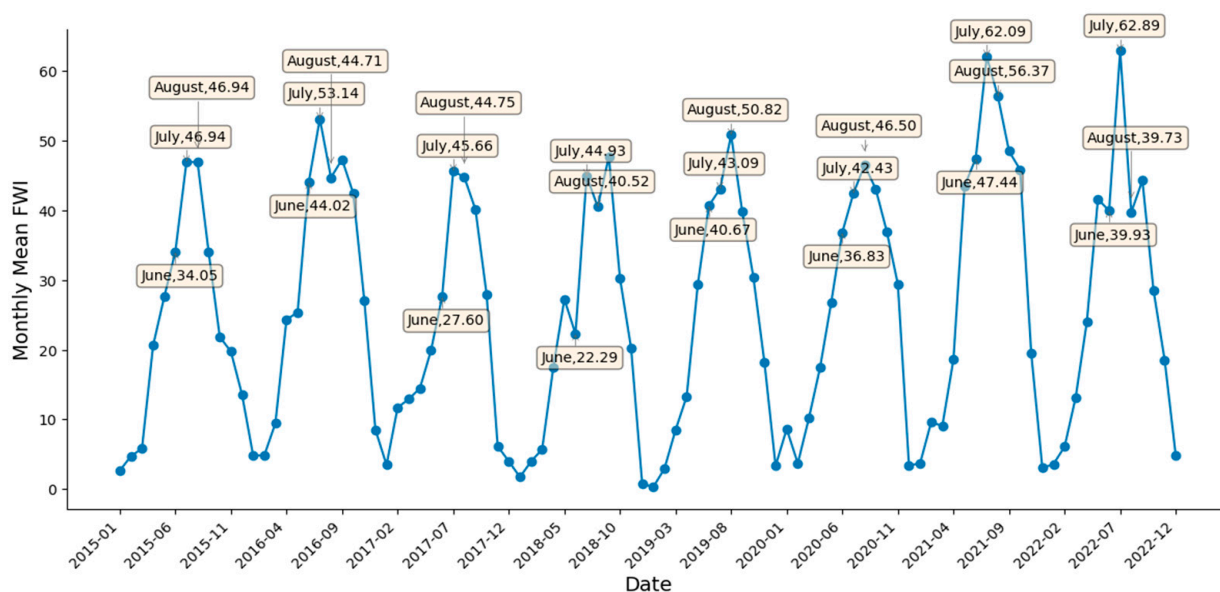


Figure 9. Example of monthly mean FWI values at station 17917.

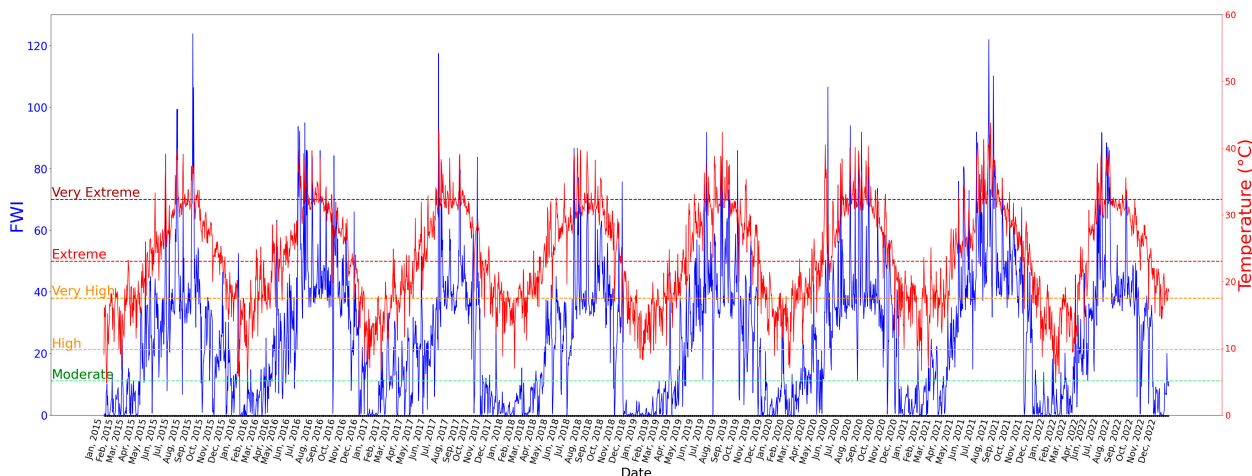


Figure 10. Measured noon temperatures and calculated FWIs for the period 2015–2023 at station 17917.

Figure 10 shows that, overall, as air temperature rises, FWI also increases; however, the relationship between air temperature and FWI is complex and non-linear. This complexity arises from variations in the rate of FWI increase influenced by factors such as humidity, wind speed, and fuel type. In dry and windy conditions, even a slight temperature increase can exert a notable impact on FWI.

3.1. Fire Danger Mapping with In Situ FWI

Since 2000, the Antalya region has experienced thirty-six forest fires, each exceeding 50 hectares. For the twenty-six fires with available data, FWI fire danger maps calculated using meteorological data are shown in Figure 11, with the burned areas marked according to EFFIS records. Due to their low spatial resolution and compatibility issues, EFFIS and ERA 5 FWI danger maps are not presented with in situ FWI danger maps.

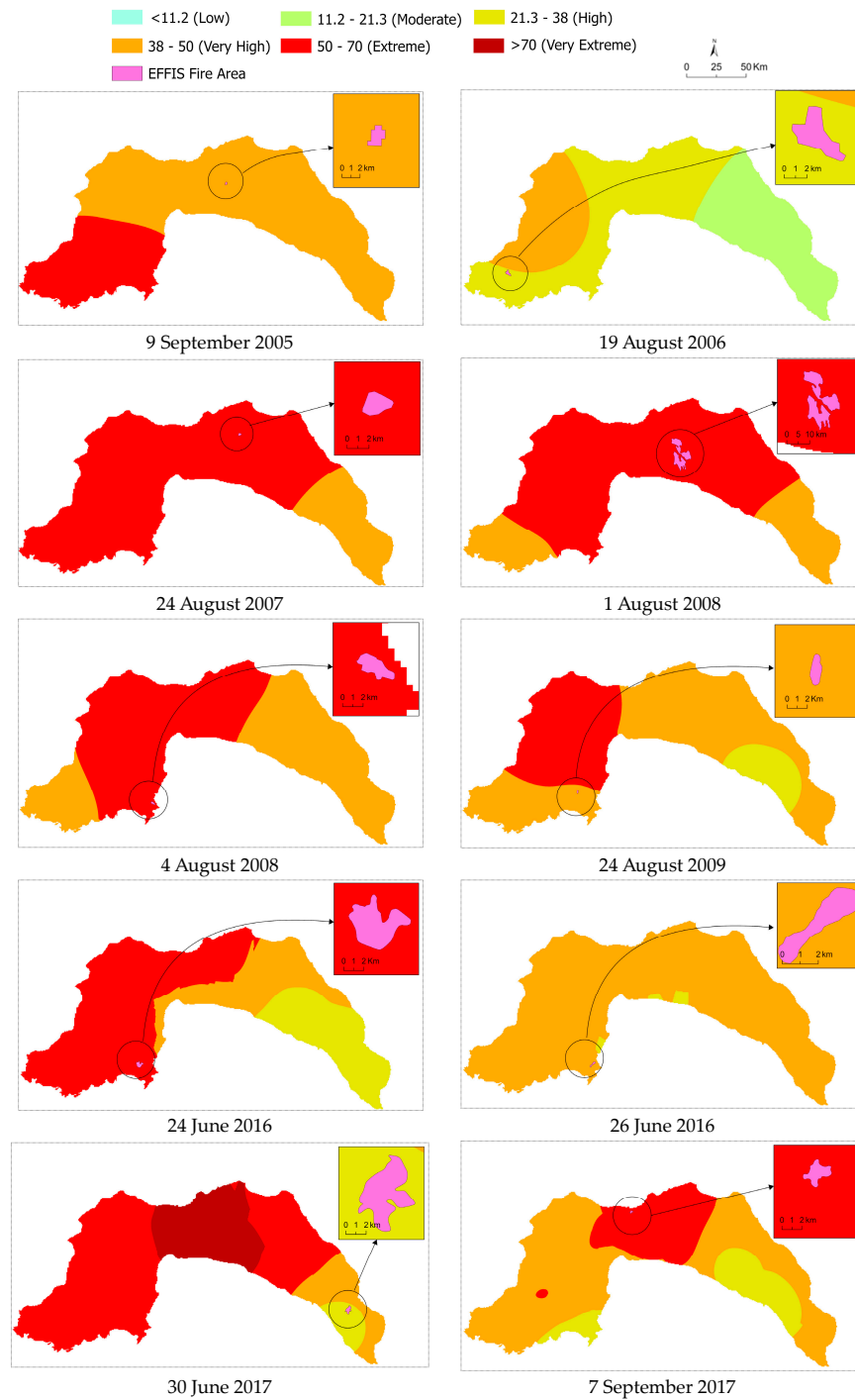


Figure 11. Cont.

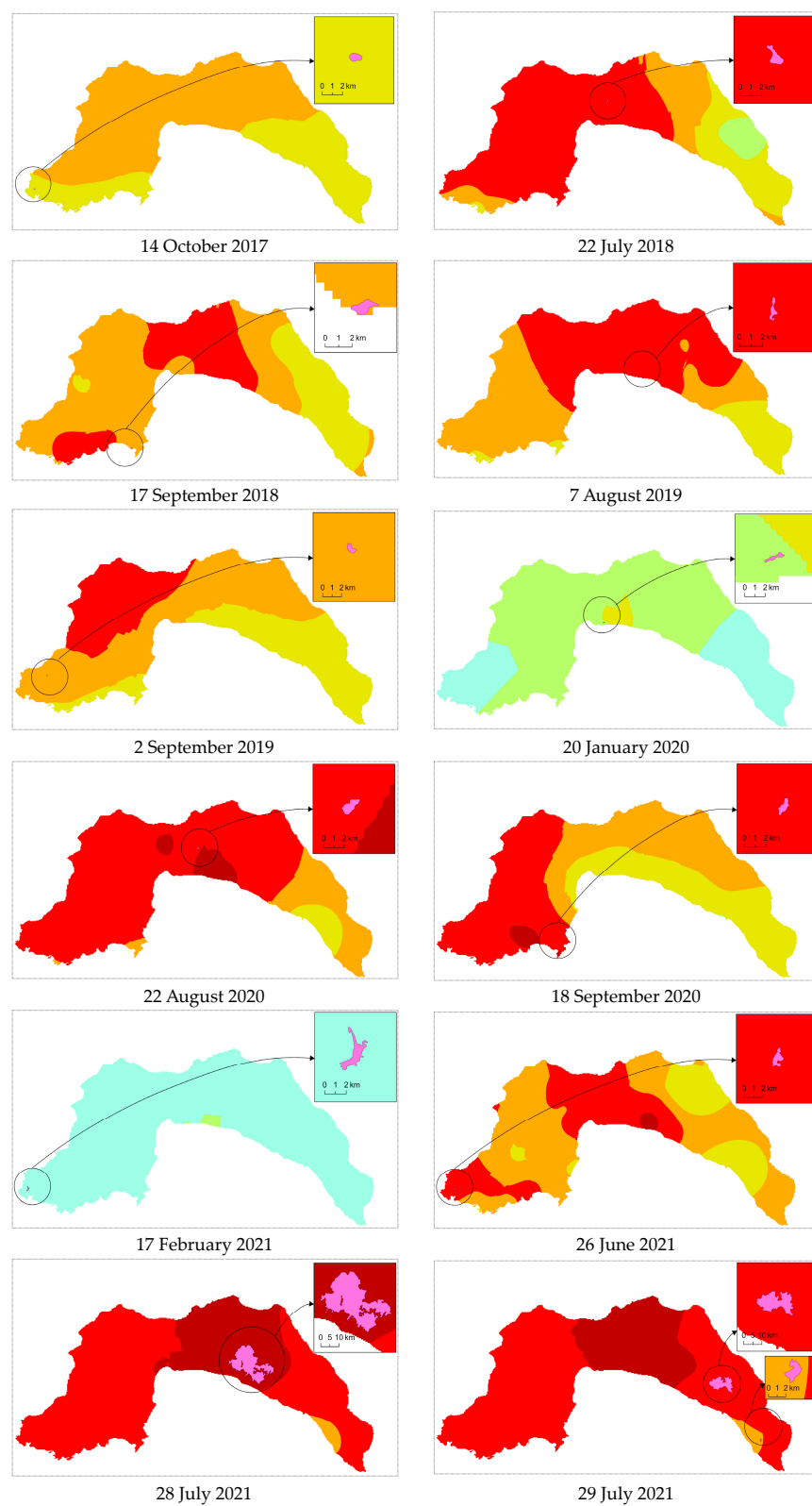


Figure 11. Cont.

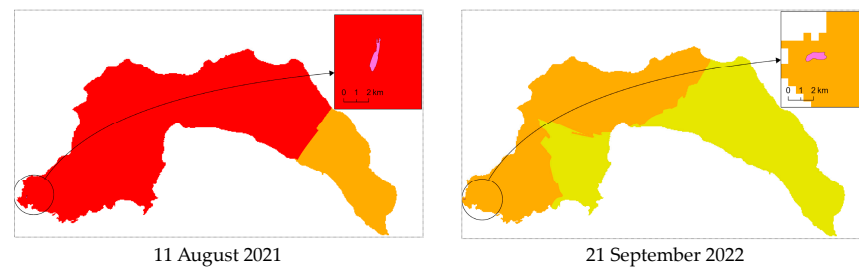


Figure 11. Twenty–six forest fires and associated fire danger maps.

Table 2 summarizes the comparison of fire danger classes obtained from three different FWI datasets for twenty-six fires. On 1 August 2008, two different fires (1 and 2) occurred. Fires occurring from 2018 onwards were considered, as the FWI danger maps generated by EFFIS using meteorological satellite data have been digitally accessible since 2018. ERA5 FWI, which has a low spatial resolution, is only considered after 2018 to be compatible with EFFIS FWI.

Table 2. Forest fire dates, burned area sizes, and associated fire danger classes calculated using three different FWIs.

#ID	Start (d/m/y)	Finish (d/m/y)	Burned Area (ha)	In-Situ FWI	EFFIS FWI	ERA5 FWI
				Fire Danger Class		
1	9 September 2005	11 September 2005	299	Very High	NA*	NC*
2	19 August 2006	25 August 2006	959	High	NA	NC
3	24 August 2007	24 August 2007	411	Extreme	NA	NC
4	1 August 2008 (1)	1 August 2008	8951	Extreme	NA	NC
5	1 August 2008 (2)	01 August 2008	7456	Extreme	NA	NC
6	4 August 2008	4 August 2008	510	Extreme	NA	NC
7	24 August 2009	24 August 2009	267	Very High	NA	NC
8	24 June 2016	26 June 2016	1722	Extreme	NA	NC
9	26 June 2016	27 June 2016	591	Very High	NA	NC
10	30 June 2017	1 July 2017	2085	High	NA	NC
11	7 September 2017	7 September 2017	375	Extreme	NA	NC
12	14 October 2017	14 October 2017	75	High	NA	NC
13	22 July 2018	22 July 2018	132	Extreme	Very Extreme	Extreme
14	17 September 2018	17 September 2018	114	Very High	Very High	Very High
15	7 August 2019	7 August 2019	63	Extreme	Extreme	Very High
16	2 September 2019	2 September 2019	56	Very High	Very High	Extreme
17	20 January 2020	20 January 2020	55	Moderate	Moderate	Low
18	22 August 2020	22 August 2020	142	Extreme	Extreme	Extreme
19	18 September 2020	18 September 2020	78	Extreme	High	Extreme
20	17 February 2021	17 February 2021	266	Low	Low	Low
21	26 June 2021	26 June 2021	121	Extreme	High	Extreme
22	28 July 2021	6 August 2021	54769	Very Extreme	Very Extreme	Extreme
23	29 July 2021 (1)	10 August 2021	15860	Extreme	Extreme	Very Extreme
24	29 July 2021 (2)	30 July 2021	266	Very High	Very High	Very Extreme
25	11 August 2021	11 August 2021	93	Extreme	Extreme	Extreme
26	21 September 2022	23 September 2022	79	Very High	Very High	Extreme

NA*: not available; NC*: not calculated.

When analyzing twenty-six forest fires larger than 50 hectares that occurred between 2000 and 2023, the distribution by month is as follows: eleven fires in August (42.31% of the total), eight in September (30.77% of the total), four in July (15.38% of the total), five in June (19.23% of the total), and one each in January, February, and October (3.85% of the total for each of these months). While the fire season in Türkiye varies across regions, typically extending from May to September, the examination of FWI values indicates that fires in January and February are frequently linked to negligence or intentional arson, occurring outside the recognized fire-prone period.

The fire danger assessment of burned areas in FWI danger maps, derived from meteorological station data, reveals a concerning distribution: one in the extreme category, thirteen in the very extreme category, seven in the very high category, three in the high category, one in the medium category, and one in the low category. The cumulative percentage of high to very extreme danger classes is 85.71%. The fire that occurred on 27 July 2021 in Türkiye led to the destruction of 54,769 hectares of area, categorizing it as a ‘very extreme danger’ according to the FWI danger classes. For the comparative analysis of the fire danger classes identified by the three FWIs, only 14 common fires were considered. The resulting distribution is summarized in Table 3, reflecting the proportions by total incidents recorded from 2018 to 2023.

Table 3. Proportional distribution of fire danger classes determined by three FWIs for 14 common fires (2018–2023).

FWI Danger Class	In Situ FWI	%	EFFIS FWI	%	ERA5 FWI	%
Low	1	7.14	1	7.14	2	14.28
Moderate	1	7.14	1	7.14	0	0
High	0	0	1	7.14	0	0
Very High	4	28.57	3	21.43	2	14.28
Extreme	7	50.00	6	42.86	8	57.14
Very Extreme	1	7.14	2	14.29	2	14.28
Σ	14	100	14	100	14	100

When evaluating the 14 forest fires presented in Table 3, it becomes evident that the majority of these fires fall within the “Extreme” class according to all three FWI values. It is also observed that the fire numbers exhibit consistency across all danger classes, typically differing by only 1–2 instances.

In addition, the analysis included a comparison of each danger class for the six subcomponents within the FWI system across the three FWI datasets. This examination was conducted for 14 common fires using the thresholds outlined in Table 4, and the results are presented in Figure 12. As expected, the danger classes of the subcomponents for the two fires that occurred during the winter season (specifically on 20 January 2020 and 17 February 2021) were consistent and notably lower than those of the other fires.

Table 4. Thresholds of the fire danger classes for subcomponents within the FWI system [86].

Fire Danger Classes	FWI	FFMC	DMC	DC	ISI	BUI
Low	<11.2	<82.7	<15.7	<256.1	<3.2	<24.2
Moderate	11.2–21.3	82.7–86.1	15.7–27.9	256.1–334.1	3.2–5.0	24.2–40.7
High	21.3–38.0	86.1–89.2	27.9–53.1	334.1–450.6	5.0–7.5	40.7–73.3
Very High	38.0–50.0	89.2–93.0	53.1–83.6	450.6–600.0	7.5–13.4	73.3–133.1
Extreme	50.0–70.0	93.0–96.0	83.6–160.7	600.0–749.4	13.4–26.8	133.1–193.1
Very Extreme	>70.0	>96.0	>160.7	>749.4	>26.8	>193.1

On a subcomponent basis, there is, in general, a consistency (with a maximum difference of 1–2 levels) among the danger classes for the three FWI subcomponents. Moreover, concerning the general index FWI, it is evident that the EFFIS FWI subcomponent exhibits greater consistency with the in situ FWI subcomponent compared to the ERA5 FWI, which incorporates data from a lower spatial resolution meteorological satellite.

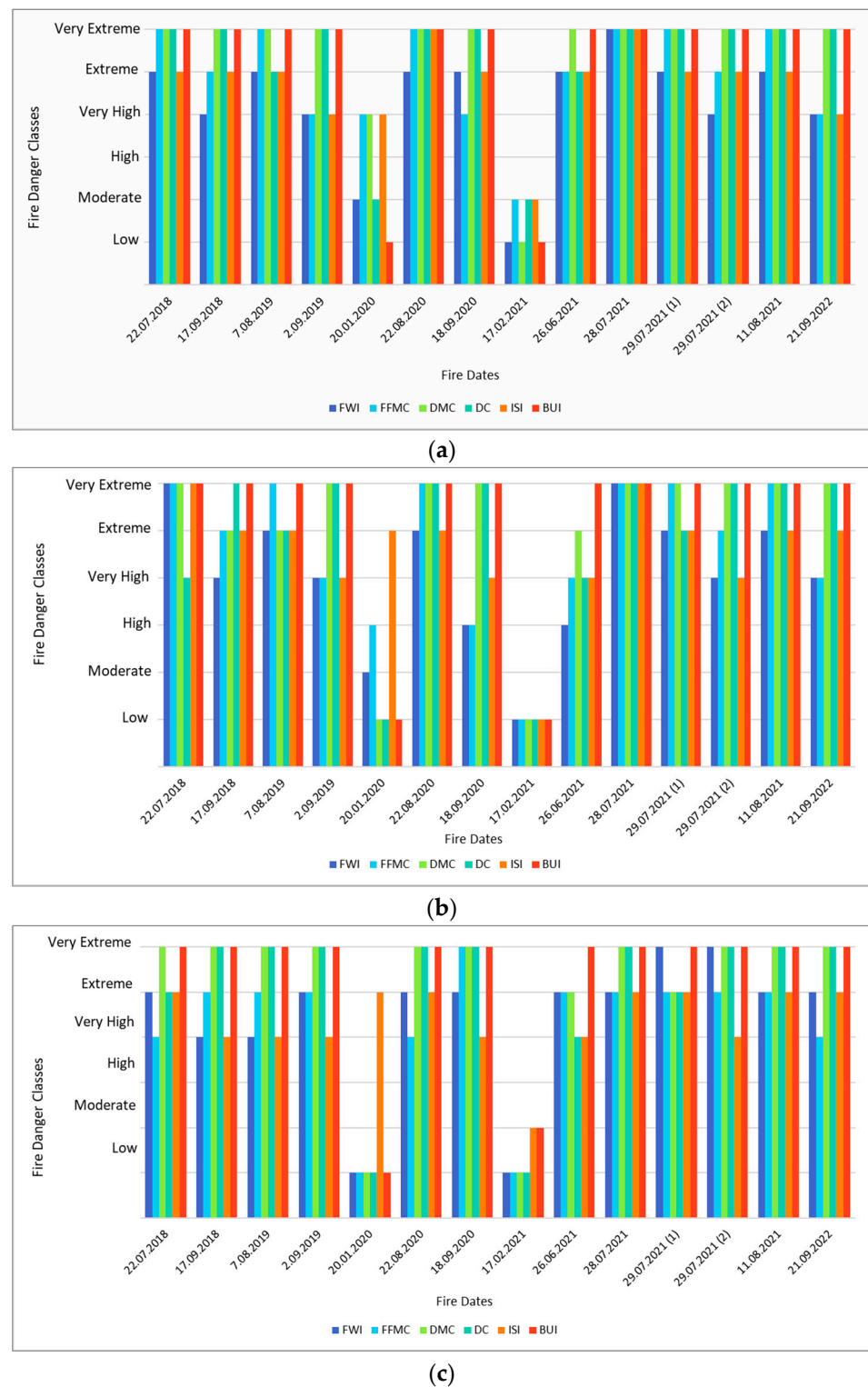


Figure 12. Comparison of each danger class of the six subcomponents used in the FWI system for 14 common fires. (a) In situ FWI. (b) EFFIS FWI. (c) ERA5 FWI.

3.2. Correlation Analysis

An analysis of the relationships among monthly MODIS LST, in situ FWI, and soil moisture is presented in Figure 11. Additionally, the correlations between monthly FWI values obtained by three different methods with each other and with these two parameters were analyzed and summarized in Table 4.

Since the release of microwave radiation by all soil types is influenced by the moisture content, drier soil emits more microwave energy, while wetter soil emits less. This dynamic establishes a significant relationship between soil moisture and the moisture codes (FFMC, DMC, DC) subcomponents of the FWI, determined by the moisture content in the upper layers of the forest floor or organic soil. The Pearson correlation coefficient between in situ FWI and soil moisture was calculated as -93% , indicating a robust inverse relationship with soil moisture levels (Figure 13a).

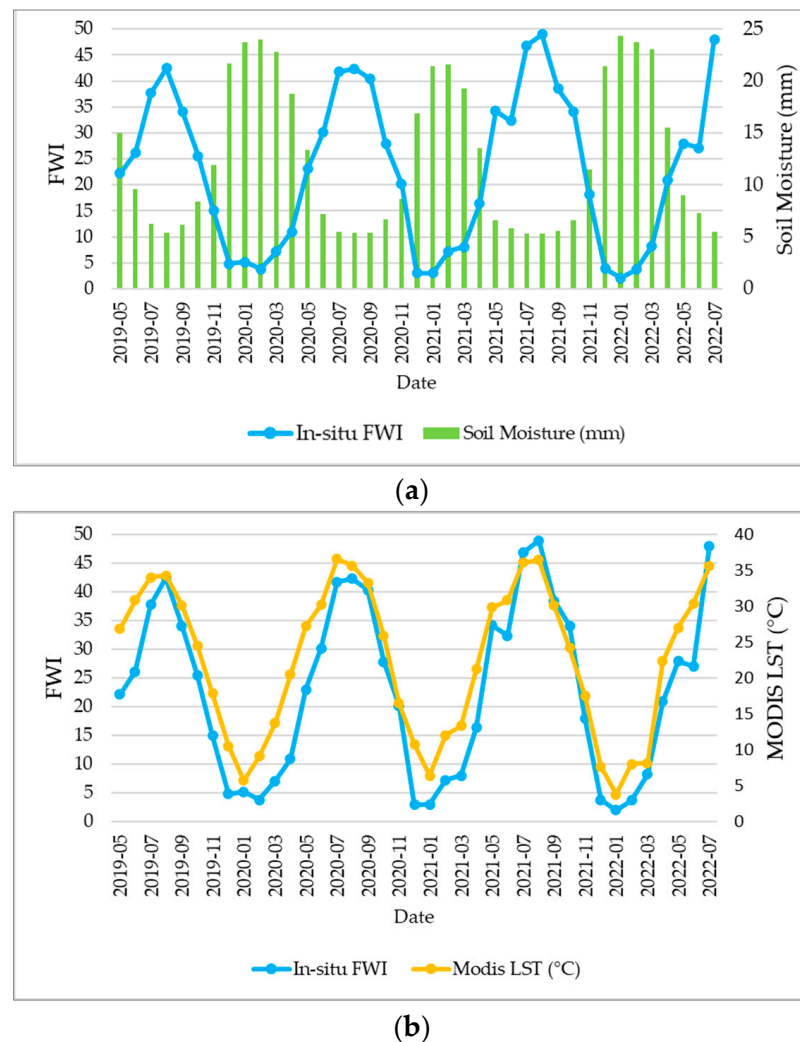


Figure 13. Relationships between monthly in situ FWI and (a) soil moisture and (b) MODIS LST.

Monthly daytime land surface temperatures (LSTs) from MODIS Aqua (MODIS/061/MYD11A1) and Terra (MODIS/061/MOD11A1) were calculated for the Antalya region during the period from May 2019 to August 2022. This period was selected because it covers the range of dates available for the correlation analyses in this section. Due to the high correlation (0.99) between both sets of satellite data, only Terra's daily daytime LSTs were utilized in the subsequent correlation analysis. Figure 11 shows a significant correlation between MODIS LST and in situ FWI. This is attributed to the consideration of meteorological values measured at local noon, in line with the prediction of the highest burning conditions during the hottest hours of the day in the Canadian Wildfire Weather Index system. Furthermore, Figure 13b and Table 5 reveal high FWI values in the summer months of 2021, which coincides with the period when the largest fires occurred, compared to other years.

Table 5. Correlation analysis between monthly FWI values obtained by three different methods, SMAP soil moisture, and MODIS LST.

Correlations (r)	In Situ FWI	EFFIS FWI	ERA5 FWI	SMAP Soil Moisture	MODIS LST
In Situ FWI	1	0.98	0.86	−0.93	0.96
EFFIS FWI	0.98	1	0.81	−0.90	0.92
ERA5 FWI	0.86	0.81	1	−0.87	0.93
SMAP Soil Moisture	−0.93	−0.90	−0.87	1	−0.92
MODIS LST	0.96	0.92	0.93	−0.92	1

The Pearson correlation coefficient between in situ FWI and EFFIS FWI is $r = 0.98$ ($p < 0.001$), while the correlation coefficient between in situ FWI and ERA5 FWI is slightly lower at $r = 0.86$ ($p < 0.001$) (Table 5). This difference is thought to be attributed to the lower resolution of the ERA5 data, at approximately 31 km.

As shown in Table 5, the correlations are generally high, ranging from 0.81 to 0.98 ($p < 0.001$). Expectedly, there is a positive correlation between LSTs and FWI values, alongside a negative correlation with soil moisture.

4. Discussions

As is widely known, in the analysis of satellite-based FWI data, exploring the utilization of meteorological data with various spatial resolutions is essential for understanding the complexities of fire danger assessment and for developing effective mitigation strategies. Within this context, this study evaluates the impact of using meteorological satellite data with different spatial resolutions and compares the resulting outcomes. As illustrated in Table 5, a notably higher correlation exists between in situ FWI and EFFIS FWI (0.98) compared to ERA5 FWI. These findings align with numerous studies. For instance, a study by McElhinny et al. (2020) [81] conducted in Canada revealed a robust agreement, showing that the FWI calculated from ERA5 climate data (0.25°) closely aligns with calculations based on weather station data (Spearman correlation: 0.77). Similarly, de Jong et al. (2016) reported a correlation range of 0.61 to 0.85 between FWI (2 km) derived from numerical weather forecasts and FWI derived from station-based meteorological observations in the UK [26]. The high correlation percentages indicate that these datasets can be utilized more effectively in fire danger assessments.

While the Canadian FWI system was initially designed for red pine and white pine forests, the findings of this study demonstrate its effectiveness in this region as well as in other parts of the world. This success is thought to be attributed to the prevalence of red pine (*Pinus brutia*) in the Antalya region. On the other hand, the widespread and quickly flammable nature of red pine, the predominant tree in the Mediterranean ecosystem, has prompted discussions in Türkiye about potential alterations to the forest stand type. Despite these suggestions, experts argue that red pine, present in the Mediterranean basin for thousands of years, has adapted and survived numerous fires. On the other hand, given red pine's self-growing capacity, driven by its excellent germination ability, the potential impacts of replacing red pine with other species (e.g., olive and fruit trees) on the biodiversity of red pine forests should be thoughtfully considered, taking into account both ecological and negative consequences.

5. Conclusions

The occurrence of large-scale fires is increasing in the Mediterranean basin of Türkiye, where ecosystems are highly susceptible to forest fires. In this context, it is crucial to acknowledge that the existing ecosystems in this region will become increasingly more vulnerable due to global warming. Additionally, the annual degradation of a significant proportion of forested areas in the Antalya region of southern Türkiye is of considerable concern. This phenomenon can be attributed to anthropogenic factors associated with the

popularity of the region as a tourist destination or to recurrent events influenced by the Mediterranean climate.

In this study, an analysis of temporal and spatial changes in fire danger dynamics in the Mediterranean basin of Türkiye was conducted using three different FWIs over the period between 2000 and 2023, taking into account the climate and weather conditions. For twenty-six different forest fires, FWI values calculated with meteorological data taken from the fire zones on the days of the fires were predominantly (85.71%) between high and very extreme categorizations of fire danger classes. Although the FWI system was developed in Canada, its effectiveness has been demonstrated by the results of this study in our country, as well as in many parts of the world.

The main findings are as follows: (i) The use of FWIs proves the high effectiveness in fire danger mapping of areas susceptible to wildfires. (ii) Generally, high correlations (ranging from 0.81 to 0.98) were observed between FWIs, with the correlation between in situ FWI and EFFIS FWI (98%) being considerably higher compared to ERA5 FWI. (iii) Correlations between FWIs and two other parameters (i.e., SMAP soil moisture and MODIS LST) were also high, ranging from 0.87 to 0.96. As expected, a positive correlation was obtained between LSTs and FWIs, while a negative correlation was found with soil moisture. (iv) The study underlines the importance of accurate FWIs and precise fire danger class thresholds for effective environmental proactive protection and management strategies. In this context, it is evident that fire danger classes and thresholds need to be applied to different regions for the generalization and validation of their accuracy.

Literature studies project that large forest fires will continue to occur in Türkiye and the Mediterranean Basin in the future due to the presence of undisturbed forest areas, increased fuel load in forests, and more frequent and severe meteorological conditions as a result of climate change. However, the FWI system commonly used in many studies focuses only on meteorological variables when assessing fire danger class. This means that differences in fuel types, complex topographic features, the use of low spatial resolution satellite data, modelling uncertainties in FWI calculations at local meteorological stations, or the inclusion of land cover types are ignored. These specific limitations highlight the necessity for refining FWI boundaries across different danger classes, offering a distinct advantage in developing more accurate fire danger models, particularly in the context of a changing climate. In terms of future research, several targets are planned to be explored: (i) investigating the impact of FWIs on stand types and topography; (ii) satellite sensors with better spatial resolutions for LST and soil moisture retrievals; and (iii) testing the fire danger classes in different regions characterized by diverse climatic conditions and geographic characteristics to assess its generalizability and applicability. More precisely, next steps should include the analysis of other forest fires, especially in the Marmara and Aegean regions and the Mediterranean, in order to gain a deeper understanding of the influence of climatic factors on fire occurrence and to facilitate the development of region-specific fire prevention and management strategies.

Author Contributions: Conceptualization, Adalet Dervisoglu and Ayse Filiz Sunar; Methodology, Adalet Dervisoglu and Ayse Filiz Sunar; Software, Hatice Atalay; Data Curation, Hatice Atalay; Writing—original draft, Hatice Atalay, Adalet Dervisoglu and Ayse Filiz Sunar; writing—review and editing, Adalet Dervisoglu and Ayse Filiz Sunar; supervision, Ayse Filiz Sunar. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The in-situ meteorological data utilized in this study were obtained from the General Directorate of Meteorology (Turkish State Meteorological Service) on an hourly basis. Due to special conditions set by the data provider, these data cannot be further distributed to third parties without explicit permission. EFFIS data are publicly available and can be retrieved from <https://effis.jrc.ec.europa.eu/> (accessed on 20 February 2024). Similarly, ERA5 data can be obtained from <https://cds.climate.copernicus.eu/> (accessed on 20 February 2024). Soil moisture and land surface temperature data acquired via the Google Earth Engine platform.

Acknowledgments: The authors thank Istanbul Technical University (ITU) for the financial support provided under the Scientific Research Project Funding for ITU BAP Project number MAB-2023-44581. We also thank the General Directorate of Meteorology for providing data support.

Conflicts of Interest: The authors declare no conflicts of interest.

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