

Article

Investigating FWI Moisture Codes in Relation to Satellite-Derived Soil Moisture Data across Varied Resolutions

Hatice Atalay , Ayse Filiz Sunar  and Adalet Dervisoglu *

Geomatics Engineering, Civil Engineering Faculty, Istanbul Technical University, 34469 Istanbul, Türkiye; atalayhat@itu.edu.tr (H.A.); fsunar@itu.edu.tr (A.F.S.)

* Correspondence: adervisoglu@itu.edu.tr

Abstract: In the Mediterranean region, particularly in Antalya, southern Türkiye, rising forest fire risks due to climate change threaten ecosystems, property, and lives. Reduced soil moisture during the growing season is a key factor increasing fire risk by stressing plants and lowering fuel moisture content. This study assessed soil moisture and fuel moisture content (FMC) in ten fires (2019–2021) affecting over 50 hectares. The Fire Weather Index (FWI) and its components (FFMC, DMC, DC) were calculated using data from the General Directorate of Meteorology, EFFIS (8 km), and ERA5 (≈ 28 km) satellite sources. Relationships between FMCs, satellite-based soil moisture datasets (SMAP, SMOS), and land surface temperature (LST) data (MODIS, Landsat 8) were analyzed. Strong correlations were found between FWI codes and satellite soil moisture, particularly with SMAP. Positive correlations were observed between LST and FWIs, while negative correlations were evident with soil moisture. Statistical models integrating in situ soil moisture and EFFIS FWI (R : -0.86 , -0.84 , -0.83 for FFMC, DMC, DC) predicted soil moisture levels during extended fire events effectively, with model accuracy assessed through RMSE (0.60–3.64%). The SMAP surface (0–5 cm) dataset yielded a lower RMSE of 0.60–2.08%, aligning with its higher correlation. This study underlines the critical role of soil moisture in comprehensive fire risk assessments and highlights the necessity of incorporating modeled soil moisture data in fire management strategies, particularly in regions lacking comprehensive in situ monitoring.



Citation: Atalay, H.; Sunar, A.F.; Dervisoglu, A. Investigating FWI Moisture Codes in Relation to Satellite-Derived Soil Moisture Data across Varied Resolutions. *Fire* **2024**, *7*, 272. <https://doi.org/10.3390/fire7080272>

Academic Editors: António Vieira, Washington Rocha and Marcos Francos

Received: 20 May 2024

Revised: 11 July 2024

Accepted: 1 August 2024

Published: 5 August 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: fire weather index; fuel moisture codes; soil moisture; SMAP; SMOS; correlations; Antalya

1. Introduction

In recent years, wildfires have become more widespread globally, increasingly linked to the impacts of climate change. In Mediterranean countries such as Spain, Portugal, Greece, and Türkiye, the risk of forest fires is increasing due to higher temperatures, unpredictable weather patterns, climate change and changes in land cover [1–7]. For example, in Portugal, natural fires are more likely to occur in the summer months when temperatures are high and relative humidity is low [8]. Similarly, in Spain, temperatures are projected to increase by 3.7–5.3 °C by the end of the 21st century compared to the period 1961–2010 under a high emission scenario [9]. In Greece, with the ongoing increase in greenhouse gas emissions, the temperature is projected to rise by 4.3 °C by the end of the 21st century compared to mid-20th-century levels [10]. The importance of temperature anomalies as a significant risk factor is also highlighted in Türkiye’s 2021 Climate Assessment report, which notes that 2021 was the fourth warmest year, with temperatures 1.4 °C above the 1981–2010 average [11,12]. Besides temperature anomalies, this increased risk is also related to moisture dynamics in vegetation, soil, and atmosphere, which are other critical factors significantly affecting ignition probability and fire behavior.

Several meteorologically based indices have been developed to explain the relationship between forest fires and climatic conditions, as well as to calculate weather-based fire danger [13,14]. Major fire danger rating systems in different countries use estimates of

moisture levels in mineral and/or organic soil layers to assess wildfire risk [15,16]. For example, the Canadian Fire Weather Index (FWI), a key part of the Canadian Forest Fire Weather Index System (CFFWIS), is one of the most widely used indices. The FWI, a numerical rating of fire intensity, is weather-dependent and serves as a good indicator of fire danger, measuring both the ease of fire spread and the availability of fuel due to drought conditions [17]. It also includes moisture codes that account for moisture content stored in the organic layers of forest floors, helping to evaluate fire potential based on factors such as fuel moisture [13]. Alongside the Canadian FWI, other significant models used include the European Forest Fire Information System (EFFIS) FWI and ERA5 FWI, which utilize satellite-based products to analyze fire weather conditions and monitor global trends and implement fire danger metrics from the Canadian FWI system [18,19].

Factors like fuel (dead and living vegetation) and fuel moisture significantly impact fire intensity, contributing 21.5% and 16.5%, respectively, to forest fire behavior [20]. The quantity, type, and arrangement of fuel affect fire spread and intensity, while fuel moisture is influenced by soil moisture, rainfall, soil temperature, relative humidity, temperature, and solar radiation [21]. Fuel moisture content (FMC), expressed as a percentage of the oven-dry weight, measures the water content in both live and dead fuels and is essential for improving fire risk indices due to its direct influence on fire ignition, spread, and development [22–24]. Distinguishing between dead and live fuels is important because their FMCs vary based on different factors. Dead fuels are primarily affected by weather and environmental conditions, whereas live fuels are also influenced by soil moisture. Fuels with high moisture content require higher temperatures or prolonged exposure to heat to ignite. Moreover, fire spreads more slowly in wet fuels because evaporated moisture inhibits combustion by diluting flammable gases in the reaction zone and cooling the flames [25–27]. The Canadian FWI system uses three FMCs to represent organic layers at or below the forest floor: the Fine Fuel Moisture Code (FFMC) for fine surface litter (10–20 mm deep), the Duff Moisture Code (DMC) for loosely packed duff (50–100 mm deep), and the Drought Code (DC) for deeper organic materials (100–200 mm deep) [28]. Both the DMC and DC correlate significantly with soil moisture levels in adjacent mineral horizons due to moisture exchange through capillary and vapor transport [29–32]. A study on Siberian forest fires found that the previous summer's moisture levels were a better indicator of burned areas than precipitation anomalies or fire weather indices [33], leading to a modification of the FWI methodology by integrating soil moisture deficit using Sentinel-1 radar satellite data [34]. However, FMC models using precipitation data may not accurately represent soil moisture in topographically complex landscapes or heterogeneous moisture environments [35]. Further research into the relationship between soil moisture content and FMC is necessary to improve the accurate interpolation of FMC observations across diverse environmental conditions, given the limited availability of studies in this research area [35]. Since estimating fuel moisture over a large area is still challenging, soil moisture is used as an indicator of fuel moisture content [36].

Soil moisture or soil water content, representing the water content within the unsaturated soil zone where the soil is not fully saturated but contains a mix of water and air, also plays an important role in fire dynamics. In areas with deep organic horizons, retained moisture functions as both soil and fuel moisture reserves, which is crucial due to the increased flammability of dry organic material. Low soil moisture contributes to rapid wildfire ignition and spread, while optimal levels act as a natural deterrent. Soil moisture's behavior mirrors fuel moisture content, emphasizing its importance in assessing wildfire risk [37–42]. Despite the critical importance of soil moisture data, acquiring in situ soil moisture data presents considerably greater challenges compared to meteorological weather data, and there is limited availability of global observational soil moisture data. Therefore, much of the research in the literature has focused on local and regional case studies [37,43,44]. Studies examining the role of soil moisture in fire dynamics have used model-derived soil moisture information or drought indices like the Keetch–Byram Drought Index or Standardized Precipitation Index [2,39,41]. However, these modeled or

proxy variables have certain drawbacks, such as limited accuracy in capturing localized soil moisture variations and potential discrepancies between modeled data and actual field conditions [45]. Methodologies for monitoring soil moisture are advancing rapidly due to ongoing innovations in in situ and proximal sensors, satellite technologies, and enhanced modeling capabilities [46–48]. In particular, over five decades of experimental and operational studies have demonstrated the application of active and passive microwave remote sensing for monitoring soil moisture. The strength of radar signals increases with higher soil moisture levels, as moist soil alters its electrical properties and enhances interaction with radar waves. This interaction enables radar systems to measure soil moisture across various surfaces and vegetation types accurately. Specialized satellite missions such as the European Space Agency (ESA)'s Soil Moisture Ocean Salinity (SMOS) [49] and the National Aeronautics and Space Administration (NASA)'s Soil Moisture Active Passive (SMAP) [50] use microwave sensors to provide global soil moisture data, enabling comprehensive wildfire risk assessment [49–54].

While weather stations and satellites offer global coverage for monitoring atmospheric conditions, soil monitoring, particularly regarding soil moisture levels, faces limitations due to coverage and technological constraints [55]. The primary drawback of Earth observation (EO) satellites is their global coverage over multiple days, resulting in lower temporal resolution compared to in situ measurements, with a typical return interval of 1–3 days. While this return interval may not pose a significant problem for long-term soil moisture monitoring, it can be a limitation in capturing rapid changes in soil moisture conditions, especially during dynamic events such as sudden rainfall or fire outbreaks. Challenges remain, however, in monitoring soil moisture beyond surface layers and accuracy limitations under dense forest cover [29,56,57]. Improved algorithms show that remote sensing is capable of effectively detecting soil moisture even under forest canopies [58,59]. In addition to low temporal resolution, the lower spatial resolutions (typically 1–9 km) also affect usability. In this context, improvements in algorithms are essential to increase the accuracy and reliability of measurements through downscaling as well as increasing spatial resolution. This approach allows for finer-grained soil moisture data, offering detailed insights into local variability [60].

Understanding the relationship between Land Surface Temperature (LST) and soil moisture is very important for accurately mapping fire hazards. LST is a critical indicator of fire activity, influenced by factors such as solar radiation, vegetation cover, and moisture levels, which impact vegetation dryness. Specifically, LST not only affects vegetation growth and fuel storage but also determines the moisture content of vegetation, directly influencing vegetation flammability [37,38]. Moreover, deviations from typical temperature patterns, as indicated by anomalies in LST, play a significant role in identifying areas prone to fires in relation to soil moisture content. For example, abnormally low surface temperatures may indicate high soil moisture levels, suggesting reduced fire susceptibility [61,62].

The existing literature consistently emphasizes the critical role of soil moisture in improving wildfire hazard assessments [22,36,41,63,64], particularly in providing more accurate estimations of fuel moisture and fuel load compared to traditional drought indices. However, there remains a significant gap in the literature regarding the direct use of soil moisture as an indicator of FMC, or the clear inference of such a relationship. This study aims to address this gap by specifically investigating the correlation between three key moisture-related components of the FWI system—namely, FFMFC, DMC, and DC—using two different satellite-based soil moisture datasets (from SMAP and SMOS), along with in situ soil moisture measurements from ten forest fires that occurred in Antalya between 2019 and 2021. The study innovates by assessing the consistency and establishing models linking regional-scale soil moisture data with these FWI components derived from both in situ and satellite observations. Validation included statistical metrics such as correlation coefficients and Root Mean Square Error (RMSE) against in situ measurements. Furthermore, the relationship between FWI FMCs for each fire and LST data, obtained from MODIS and Landsat 8, as well as in situ observations, was analyzed and compared.

Three key questions guide this investigation:

1. What is the strength of the correlation between FMCs and satellite-derived soil moisture data, and which FMC component performs best?
2. How accurately can soil moisture be predicted using statistical models based on conventional regression applied to each EFFIS FWI fuel moisture code?
3. How do soil moisture dynamics vary across forest fires occurring in different seasons and within diverse land use and land cover (LULC) types in our study area?

2. Materials and Methods

2.1. Study Area

The Mediterranean Basin, known for its frequent forest fires, falls under the Cs (Mediterranean) category of the Köppen–Geiger climate system. This classification signifies mild, rainy winters followed by hot, dry summers, prevalent in countries such as France, Italy, Greece, and Türkiye [65,66]. Forest fires are widespread along the Marmara, Aegean, and Central Mediterranean coastlines in Türkiye, reflecting this climate pattern. For instance, Antalya in southwestern Türkiye, situated in the Mediterranean Csa subtype, experiences summer forest fires due to high temperatures and low humidity (Figure 1). The Mediterranean Csa climate, a variant of Cs with hot, dry summers and mild, wet winters, exhibits summer soil moisture deficiency caused by changes in circulation, air mass, and pressure systems [67].

Türkiye's General Directorate of Forestry reports 63,724 forest fires over the past two decades, with over 90% caused by human activities [68]. Forest fires are primarily driven by 'fuel' availability, posing challenges in assessing forest fuels and vegetation dynamics during fires due to their dynamic disturbance and succession processes [26]. Combustion, propelled by oxygen and heat, spreads rapidly during dry periods when low humidity and high temperatures reduce soil moisture, thereby increasing fuel susceptibility [69]. Conversely, adequate moisture content in vegetation, soil, and the atmosphere acts as a natural deterrent to fire ignition and spread.

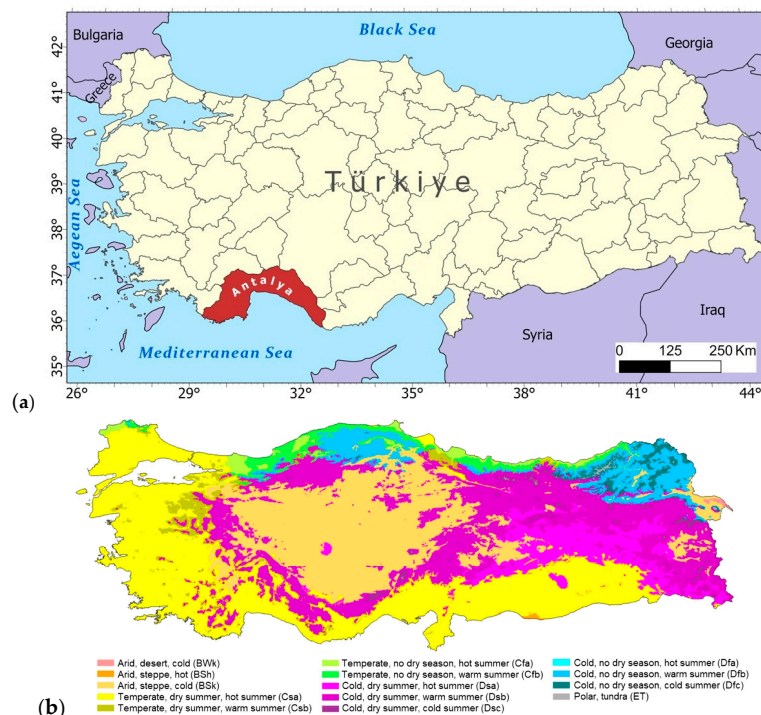


Figure 1. (a) Location of the study area (Antalya region); created using ArcGIS Pro (version 3.1, Esri, Redlands, CA, USA). (b) geographical distribution of climate types in Türkiye based on Köppen–Geiger climate system (the map is retrieved from [70,71]).

By 2023, the number of automatic meteorological stations, also known as automatic weather observation stations (AWOS), collecting hydrometeorological data such as air temperature, relative humidity, wind speed and direction, precipitation, solar radiation, surface pressure, and temperature, reached 1717 [72], with only 366 of these stations measuring soil moisture [73].

This current situation implies a lack of in situ soil moisture data with sufficient spatial and temporal resolution, which can make it difficult to use these data for soil moisture/fire assessment and modelling. In addition, since soil moisture can vary greatly even over small distances [74], point measurements of soil moisture may not represent soil moisture at the landscape scale. In this context, remotely sensed and modeled soil moisture information is clearly a necessity as a complementary strategy for measuring soil moisture [75].

Selected Forest Fires in Antalya Region between 2019–2021

Since EFFIS FWI data became available after 2019, only ten fires varying in size and exhibiting diverse LULC patterns in the Antalya region between 2019 and 2021 are considered for a comparative analysis of the fuel moisture codes determined by the three different FWIs. In the selection process, fires exceeding 50 hectares (based on EFFIS's criteria for assessing the severity of forest fires in Europe [76]) and presenting different fire danger risks were specifically taken into account. Additional detailed information about these ten fires is provided in Table 1, while Figure 2 illustrates their locations and sizes.

Table 1. Forest fire information for the ten forest fires analyzed.

#ID	Start (d/m/y)	Finish (d/m/y)	Burned Area (ha)	Burned Area over the Total Burned Area (%)
1	7 August 2019	7 August 2019	63	0.0877
2	2 September 2019	2 September 2019	56	0.0778
3	20 January 2020	20 January 2020	55	0.0764
4	22 August 2020	22 August 2020	142	0.1973
5	18 September 2020	18 September 2020	78	0.1084
6	17 February 2021	17 February 2021	266	0.3694
7	26 June 2021	26 June 2021	121	0.1681
8	28 July 2021	6 August 2021	54,769	76.0389
9	29 July 2021 (1)	10 August 2021	15,860	22.0277
10	29 July 2021 (2)	30 July 2021	266	0.3694

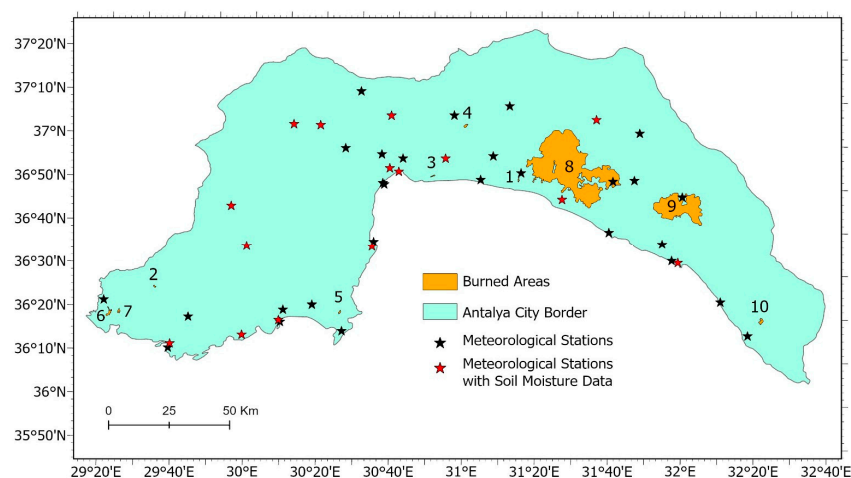


Figure 2. Locations and sizes of ten forest fires analyzed (data sourced from EFFIS), along with meteorological stations in the study area; created using ArcGIS Pro (version 3.1, Esri, Redlands, CA, USA).

There are 62 meteorological stations in the Antalya region. However, due to insufficient data on wind and/or precipitation in 18 stations, and with one station situated at sea, the data from the remaining 43 stations were utilized for analysis. As shown in Figure 2, soil moisture data could only be collected from 15 out of these 43 stations. As reported, these stations may exhibit inconsistencies in soil moisture data responses to precipitation, often attributable to sensor issues stemming from inadequate maintenance [77]. Important meteorological data considered in the analysis for each date are provided in Figure 3. On 29 July, 1 and 2 denote the fires that occurred in two separate locations on the same day. As shown, for Fire #4 event, there is no record for soil moisture, and the main differences in the values are seen due to seasonal changes (i.e., Fire #3 and Fire #6). Moreover, precipitation recorded was 0% for all fires except for Fire #6 event, which had 0.8 mm.

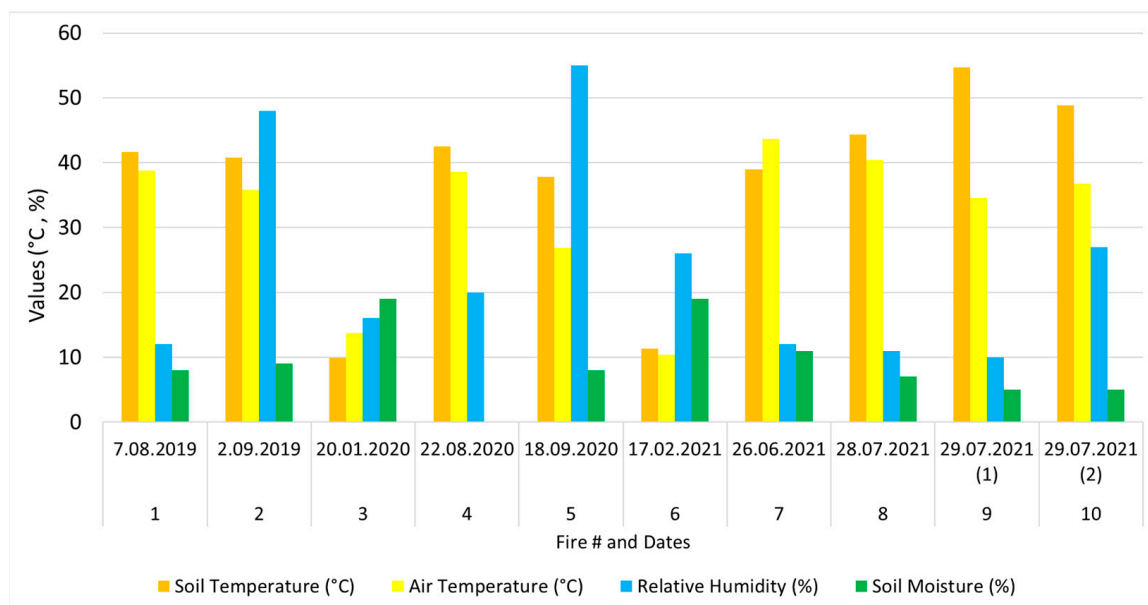


Figure 3. Important meteorological parameters considered for each date in the analysis.

Using LULC data sourced from ESA WorldCover, we examined the distribution of each LULC class within the burned areas of the ten fires analyzed (Figure 4). The analysis reveals that forests are the most severely affected, followed by shrublands and cultivated areas. Interestingly, even wetlands, typically inundated for a considerable part of the year, are susceptible to fires during specific periods (e.g., 20 January 2020 and 17 February 2021). Given the lower proportion of agricultural and residential areas compared to forests in this region, the extent of fire impact is relatively low, highlighting the vulnerability of forest ecosystems to such disasters.

2.2. Data

The data sources utilized in the study are categorized into subsections.

2.2.1. FWI Data

Three different FWI datasets were used in the analysis:

1. Canadian FWI system

The Canadian FWI system, originating in 1970, combined previous wildfire risk indices to address fire behavior factors like spread rate and intensity [1]. Evolving further, the FWI now offers a comprehensive assessment of potential wildfires by incorporating fuel moisture levels and current weather conditions, which include moisture fluctuations across different soil layers on the forest floor.

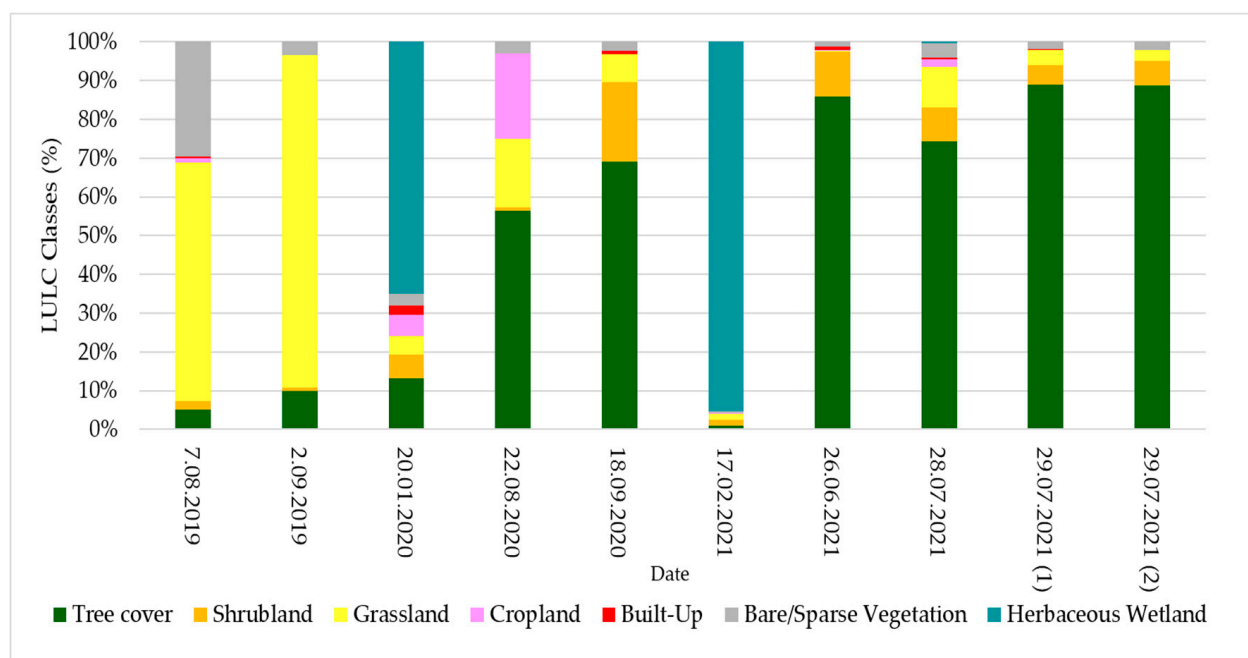


Figure 4. Distribution of LULC classes as a percentage of burned areas in ten fires analyzed.

The Canadian FWI System, based on a standard red and white pine forest, consists of six subcomponents. Three of these (FFMC, DMC, and DC) are fuel moisture codes, while the other three (Initial Spread Index (ISI), Built Up Index (BUI), and FWI) are fire behavior indices [34]. The FFMC, for instance, precisely measures moisture levels in flammable materials such as branches, leaves, dry grasses, bark, and other substances within a depth of 0–2 cm on the forest floor. This provides essential information about the moisture content of deceased organic matter, including debris and residues within this thin layer. DMC evaluates moisture levels in decaying organic matter found 5–10 cm beneath the surface residues and debris layer, providing crucial data on moisture conditions within this specific layer of organic material. DC measures organic moisture content at a 10–20 cm depth in the forest floor [28,65]. Together, these three codes characterize fuel conditions from the surface down to deeper soil layers, covering both litter and organic layers [1].

In Figure 5, the three moisture codes delineate the fuel moisture content across three categories of forest floor fuels within the “standard” mature pine stand [28]. Surface soil moisture refers to the water in the upper 10 cm of soil, while root zone soil moisture denotes the water available to plants, typically considered to be within the upper 200 cm of soil. The key characteristics of these moisture indices are outlined in Table 2.

Table 2. The key characteristics of three fuel moisture codes in the Canadian FWI system [28].

Features	Fuel Moisture Codes		
	FFMC	DMC	DC
Fuel association	Litter and other dried fine fuels	Moderately deep, loosely compacted organic layers	Deep, compact organic layers
Fire potential indicator	Easy ignition	Probability of lightning fires; fuel consumption in moderate duff	Mop-up difficulty; fuel consumption of deep organic material
Depth (cm)	0–2	5–10	10–20
Fuel loading (t/ha)	5	50	440

Table 2. Cont.

Features	Fuel Moisture Codes		
	FFMC	DMC	DC
24 h rainfall threshold (mm)	0.5	1.4	2.8
Time-lag constant	16 h	12 days	52 days
Required Weather Inputs			
Temperature	✓	✓	✓
Relative Humidity	✓	✓	
Windspeed	✓		
Rain	✓	✓	✓

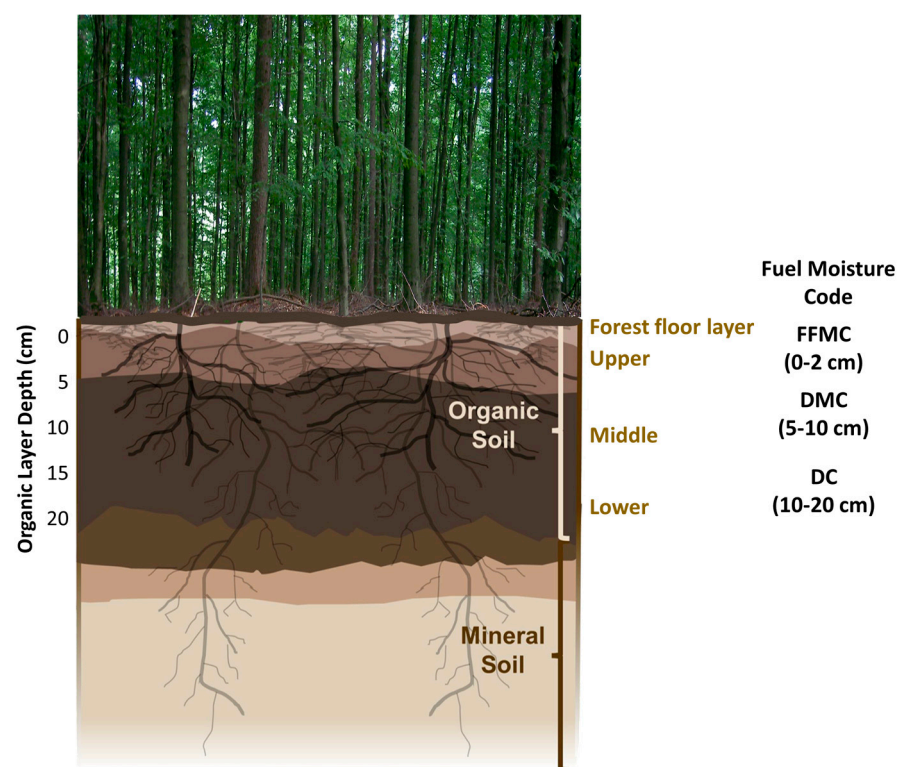


Figure 5. Categorization of forest floor fuels based on the fuel moisture codes of the FWI System [28].

In this study, Canadian FWI calculations were performed using in situ data from 43 meteorological stations in the Antalya region, including hourly temperature ($^{\circ}\text{C}$), humidity (%), wind speed (m/s), and precipitation ($\text{mm} = \text{kg/m}^2$) for the years 2019–2021, acquired from the General Directorate of Meteorology.

2. EFFIS FWI

The Joint Research Centre (JRC) of the European Commission established a research group in 1998 to advance methods for forest fire danger assessment and burnt area mapping in Europe, leading to the creation of the EFFIS in 2000. EFFIS integrates the FWI from the European Centre for Medium-Range Weather Forecasts (ECMWF) and MeteoFrance models for short-term forecasts. Since 2007, FWI has been integrated into EFFIS at the EU level under the Copernicus Emergency Management Service (CEMS). EFFIS provides FWI forecasts as well as monthly and seasonal temperature and rainfall anomaly forecasts for Europe and the Mediterranean region, enabling fire danger assessment.

In this study, EFFIS FWI values at an 8 km resolution were utilized along with the delineation of burn area boundaries, obtained from the EFFIS data center through its web platform (<https://effis.jrc.ec.europa.eu/>, accessed on 20 February 2024) [76].

3. ERA5 FWI

ERA5, a product of ECMWF, provides comprehensive historical weather and climate data from 1940 to the present [78]. ERA5 FWI employs the Canadian FWI System, replacing previous indices derived from ERA-Interim [79,80]. Developed collaboratively by the JRC and ECMWF as part of the Global Wildfires Information System (GWIS), ERA5 FWI consists of seven indices that assess various aspects of fuel moisture and the influence of wind on fire ignition likelihood and behavior [81].

In this study, ERA5 FWI data with a spatial resolution of approximately $0.25^\circ \times 0.25^\circ$ (equivalent to roughly a 28 km grid cell size) were obtained through the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) in NetCDF format (<https://cds.climate.copernicus.eu/>, accessed on 20 February 2024).

2.2.2. Soil Moisture Data

Two different datasets were utilized in the analysis:

- In situ soil moisture data

Soil moisture data for each fire were estimated using the Kriging interpolation method, utilizing observations from nearby meteorological stations. Due to the scarcity of data collected from a small number of stations, this interpolation approach is well suited for mapping a variable of interest or generating continuous surfaces, especially effective when fewer spatial sample points are available [82]. Soil moisture at these stations is recorded at soil depths of 0–20 cm and on weekly, daily, and hourly time scales.

- Satellite-derived soil moisture data

1. SMAP soil moisture data: SMAP Level-4 (L4) soil moisture data, derived from SMAP L1C (NASA, Jet Propulsion Laboratory, Pasadena, CA, USA) Radiometer Half-Orbit 36 km EASE-Grid Brightness Temperatures (SPL1CTB) and GEOS-5 Forward Processing (FP) Model Data from NASA's GMAO, integrates daily surface meteorology and precipitation corrections using NOAA's Climate Prediction Center data [83]. For more technical details, refer to the NASA user guide [84] and related work [83].

This study utilized SMAP L4 data, providing global estimates of surface soil moisture (0–5 cm) and root zone soil moisture (0–100 cm) at 9 km spatial resolution and 3 h temporal resolution from 2019 to 2021. The dataset, accessed via Google Earth Engine (GEE), includes both directly sensed surface soil moisture and modeled root-zone soil moisture [85]. SMAP L-band brightness temperatures from descending satellite passes were integrated into a global cylindrical 9 km EASE-Grid 2.0 projection [86,87], with a preference for descending orbits to align with SMOS product ascents. Additionally, SMAP L4 includes supplementary research products such as surface meteorological variables, soil temperature, evapotranspiration, and net radiation, which were not validated in this study.

2. SMOS soil moisture data: Data originate from the SMOS mission initiated by ESA in November 2009. This mission employs an L-band two-dimensional synthetic aperture radiometer equipped with multi-angle and full polarimetric capabilities for microwave radiometry, allowing it to measure soil moisture and ocean salinity levels from space. The SMOS Level 4 (L4) global surface soil moisture data offer estimates for surface (0–5 cm) soil moisture, typically with a mean latency of around 2.5 days [83].

In this study, we employed daily ascending orbit SMOS L4 global surface soil moisture data at a spatial resolution of 1 km, focusing specifically on the 0–5 cm depth range. These data were obtained through a downscaling algorithm developed and distributed by the Barcelona Expert Centre (BEC) through SMOS-BEC data distribution and visualization service (<http://bec.icm.csic.es>, accessed on 20 February 2024), enabling finer resolutions ranging from 100 m to 1 km [60]. For more comprehensive details on the Level 4 retrieval process, refer to the BEC SMOS Soil Moisture Products Description file provided in [60].

2.2.3. Meteorological Data

Air temperature and soil temperature data collected from the meteorological stations were used in the analysis.

2.2.4. Satellite-Derived Land Surface Temperature (LST) Data

Satellite-derived LST data are effective in assessing burn severity in large-scale Mediterranean wildfires by identifying high-risk areas with increased temperature and altered soil moisture [64,65]. This study uses two satellite-derived LST datasets to evaluate and correlate soil and fuel moisture, aiding fire risk assessment and management.

1. MODIS Daily LST: The MOD11A1 V6.1 product, accessible through NASA LP DAAC at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center and via the GEE platform, provides daily global LST and emissivity values at a spatial resolution of 1 km within a 1200 by 1200 km grid [88]. LST pixel values are derived from GEE using the Generalized Split-Window algorithm under clear-sky conditions, with a confidence level of at least 95% over land at an elevation of up to 2000 m or at least 66% over land at an elevation greater than 2000 m, and with a confidence level of at least 66% over lakes [89]. For more detailed information, please refer to the MOD11 User Guide V6 at [90].
2. Landsat 8 LST: Landsat 8 Thermal Infrared Sensor (TIRS) data, with a spatial resolution of 100 m, are utilized for deriving LST. For Landsat 8, band 10 (B10) is employed as the thermal band, while the red (B4) and near-infrared (NIR) bands (B5) are used to calculate Normalized Difference Vegetation Index (NDVI) in LST data retrieval based on the Mono Window algorithm. Similar to MODIS LST data, Landsat 8 LST data were obtained through the GEE platform [91].

2.2.5. ESA World Cover Data

This dataset provides the initial global land cover products, validated in quasi-real-time, utilizing Sentinel-1 and Sentinel-2 data at a spatial resolution of 10 m for 2020 and 2021. It was retrieved through the GEE [92].

2.3. Methodology

The flowchart in Figure 6 outlines the methodology used. For each of ten fires from 2019 to 2021, FWI values, representing a numerical rating of fire intensity, were calculated using the Canadian FWI system, EFFIS, and ERA5.

Only three fuel moisture codes were analyzed in this study: FPMC, derived from air temperature, relative humidity, wind, and precipitation; DMC, calculated from air temperature, relative humidity, and precipitation; and DC, calculated from air temperature and precipitation data [28]. Correlations between these three moisture-related components of the FWI system and two different satellite-based soil moisture datasets (from SMAP and SMOS) and in situ soil moisture data were then analyzed for ten wildfires that occurred in Antalya between 2019 and 2021. Moreover, the study also looked into analyzing the relationships with two weather-related factors, soil temperature and air temperature, during the same timeframe, along with utilizing LST data from MODIS and Landsat 8 sources. Models that showed strong correlation with in situ soil moisture data underwent validation using information from the Fire #8 event, which began on 28 July 2021 and lasted for ten days. Since the study primarily analyzed data starting from 28 July 2021, the dataset covering the subsequent 9 days starting from 29 July was considered. Their performance was assessed using the RMSE.

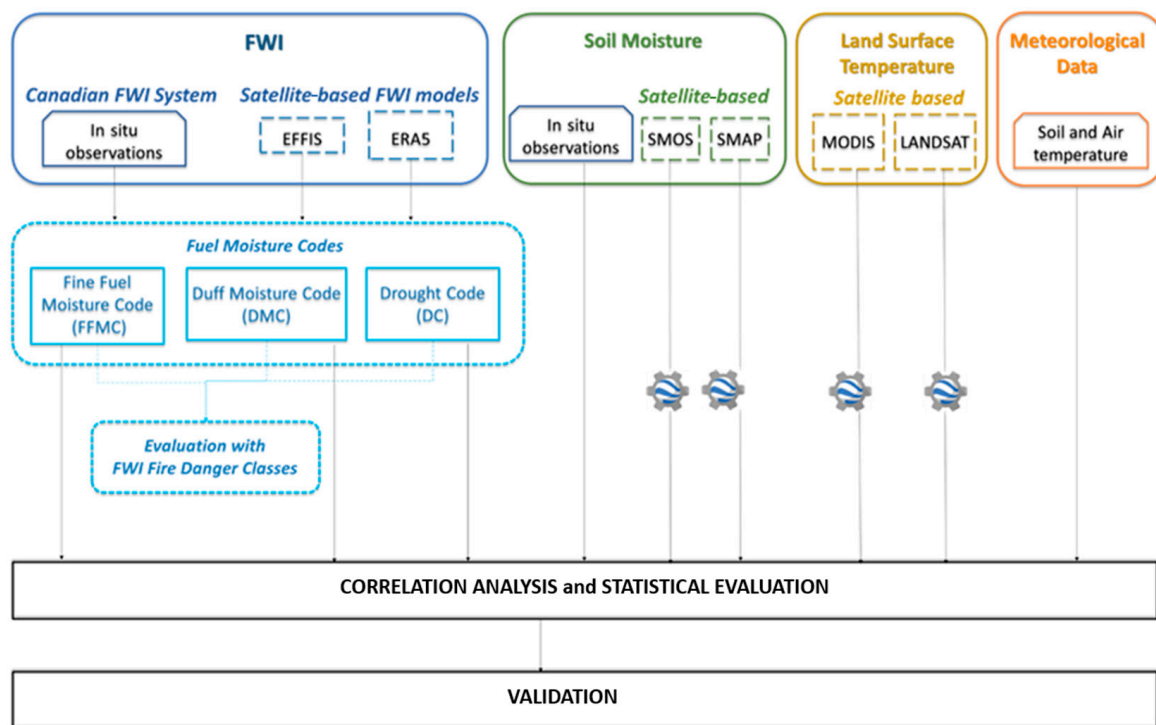


Figure 6. Flowchart of the study.

2.3.1. FWI Fire Danger Classes

The FWI fire danger classes from EFFIS form the basis for the danger maps in this study, ensuring consistent spatial representation of fire risk across Europe, the Middle East, and North Africa. The addition of the “Very Extreme” class was prompted by the June 2021 Mediterranean fires [93]. Details on the class ranges used for fire danger, defined by EFFIS satellite data, are available in previous studies [16]. This study details the thresholds for fire danger classes involving FWI fuel moisture codes specifically, as displayed in Table 3, where each code operates on a relative scale of values indicating increasingly severe burning conditions with higher values [28].

Table 3. Thresholds of the fire danger classes for fuel moisture codes within the FWI system [94].

FWI Fire Danger Classes	FFMC	DMC	DC
Low	<82.7	<15.7	<256.1
Moderate	82.7–86.1	15.7–27.9	256.1–334.1
High	86.1–89.2	27.9–53.1	334.1–450.6
Very High	89.2–93.0	53.1–83.6	450.6–600.0
Extreme	93.0–96.0	83.6–160.7	600.0–749.4
Very Extreme	>96.0	>160.7	>749.4

2.3.2. Correlation Analysis and Model Establishment

Pearson correlation analysis (Equation (1)) measures the linear relationship between two continuous variables using the correlation coefficient (r), which ranges from -1 to 1 . An r value close to 1 indicates a strong positive correlation, while an r value near -1 suggests a strong negative correlation; an r value close to 0 implies no correlation [95].

$$r = \frac{n \sum XY - \sum X \sum Y}{\sqrt{(n \sum X^2 - (\sum X)^2) (n \sum Y^2 - (\sum Y)^2)}} \quad (1)$$

where n denotes the number of variables in the dataset, and X and Y refer to specific variables within the dataset.

In this study, correlation analyses were conducted to evaluate the impact of FWI fuel moisture codes, computed using various input sources, on satellite-based SMAP/SMOS soil moisture, in situ (on-site) soil moisture, MODIS/Landsat 8 LST, and in situ meteorological data, including soil temperature and air temperature. Afterward, a linear model fitting the best straight line to data points in a scatterplot was selected to quantify relationships between variables. The model equation $Y = \beta_0 + \beta_1 X + \epsilon$ represents how the dependent variable Y changes with the independent variable X , where β_0 is the intercept, β_1 is the slope coefficient indicating the relationship strength, and ϵ accounts for error. The error term ϵ accounts for deviations between predicted and actual values, capturing unexplained variability in the data [95].

2.3.3. Validation

The objective of the validation process was to evaluate the robustness of the methodologies employed and to enhance confidence in the interpretation of results about soil moisture dynamics and fire danger assessment within the study area. For validation purposes, the optimal model was selected based on the highest correlation coefficient, which indicated the best fit line between variables and was subsequently used for predictions. Model predictions were then compared with observed data from in situ measurements and independent sources such as satellite data. More specifically, the accuracy of the soil moisture predictions was evaluated against ground-truth measurements obtained from in situ observations and satellite-derived soil moisture data, particularly from SMAP and SMOS datasets. Statistical metrics including correlation coefficients and RMSE were computed to evaluate the agreement between predicted and observed values. RMSE, which indicates the average magnitude of the errors between predicted values and actual observations, is calculated as the square root of the average of the squared differences using Equation (2).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}} \quad (2)$$

where i represents a variable, n is the number of variables, x_i denotes the actual observations, and $\hat{x}_i$ represents the estimated observations.

The fire day data served as the primary dataset in the linear regression model. For validation purposes, the performance of the model was evaluated using data from two fires lasting more than one day, since there were no fires larger than 50 hectares in the region and/or no in situ measurements, even if there were other fires. Specifically, models showing strong correlations with in situ soil moisture data were validated using information from Fire #8 and #9, which lasted 10 and 13 days, respectively. The dataset from the second day onwards of each fire event was evaluated using RMSE, excluding the first day, which had already been included in the model establishment.

After calculating RMSE, model evaluation utilized leave-one-out cross-validation (LOOCV), where each iteration involves training on $n - 1$ samples and testing on the remaining sample, resulting in n iterations, akin to k -fold cross-validation with $k = n$ [96,97]. LOOCV is computationally intensive due to its exhaustive nature but provides unbiased error estimates and consistent results by using all sample combinations for training. It is preferred for small datasets to maximize the training set size [96,98,99].

3. Results

3.1. Fire Danger Classes

In this study, an analysis was conducted on forest fires larger than 50 hectares that occurred between 2019 and 2021. Firstly, the distribution of these events by month aligns with the typical fire season in Türkiye, which varies regionally and typically extends from May to September. For each of the ten fires, six fire danger classes (Low, Moderate, High,

Very High, Extreme, and Very Extreme) were determined using three distinct datasets of the FWI system, including their fuel moisture codes. These calculations are presented in Table 4, enabling a comparative analysis of fire danger assessments derived from different sources (Canadian FWI system, EFFIS, ERA5) and using various fuel moisture codes (FFMC, DMC, DC) within the FWI system.

Table 4. Fire danger classes calculated for both FWI and FWI’s fuel moisture codes from three different FWI datasets.

#ID	Fire Danger Class											
	Canadian FWI System				EFFIS FWI				ERA5 FWI			
	FWI	Fuel Moisture Codes			FWI	Fuel Moisture Codes			FWI	Fuel Moisture Codes		
		FFMC	DMC	DC		FFMC	DMC	DC		FFMC	DMC	DC
1	E	VE	VE	E	E	VE	E	E	VH	VH	VE	VE
2	VH	VH	VE	VE	VH	VH	E	VE	VH	E	VE	VE
3	M	VH	L	L	M	H	L	L	M	H	L	L
4	E	VE	VE	VE	E	VE	VE	VE	E	E	VE	VE
5	E	VH	VE	VE	H	H	VE	VE	VH	VH	VE	VE
6	L	M	L	L	L	L	L	L	L	L	L	L
7	E	E	VE	VE	H	VH	E	VH	VH	VH	E	VH
8	VE	VE	VE	VE	VE	VE	VE	E	E	E	VE	VE
9	E	VE	VE	VE	E	VE	VE	E	E	E	E	E
10	VH	VH	VE	VE	VH	E	VE	VE	VH	E	VE	VE

Fire Danger Class: Low (L)—Moderate (M)—High (H)—Very High (VH)—Extreme (E)—Very Extreme (VE).

Firstly, concerning the general FWI index, as depicted in Table 4, it is evident that the EFFIS FWI demonstrates better consistency with the Canadian FWI compared to the ERA5 FWI, which incorporates data from a meteorological satellite with lower spatial resolution.

Upon examining the ten forest fires outlined in Table 4, an analysis of fire danger assessment within burned areas reveals some differences between FWI models and data sources. Consistency in fire danger classes is generally observed across the three fuel moisture codes in the three FWI datasets, with variations typically limited to 1–2 ranges. This agreement is evident in the classification of some fires as very extreme, extreme, very high, and low risk. However, interesting results have been noted in some fires. For instance, Fires #3 and #6 are notably different from the others due to variations in both their LULC classes (Figure 4) and the seasons during which they occurred (i.e., winter season; 20 January 2020 and 17 February 2021). Since the main LULC class of Fire #6 is herbaceous wetland, the FWI and moisture codes are classified as “Low”. In contrast, the main LULC class of Fire #3 is mixed, including tree cover, shrubland, cropland and grassland alongside wetland areas. In particular, the higher FFMC codes observed compared to Fire #6 are associated with higher surface moisture levels at 0–2 cm depths in the forest floor, where combustibles and other materials are abundant. However, in the lower layers, the other two fuel moisture codes remain “low”.

On the other hand, the consistency of fire danger classes is higher, especially for large fires occurring in various areas, such as Fires #8 and #9, which persisted for longer durations (i.e., 10 days and 13 days on 28 July 2021 and 29 July 2021, respectively).

3.2. Analysis

Table 5 presents the correlations between the three fuel-moisture-related components of the FWI system and soil moisture datasets for the ten fires. As indicated in Table 5, the Pearson correlation coefficient between the three FWI fuel moisture codes and daytime

satellite-based soil moisture levels reveals a strong inverse relationship. In terms of their relationship with in situ soil moisture data, it is important to note that in situ soil moisture measurements typically cover depths of 0–20 cm. Consequently, the three fuel codes exhibit varying degrees of correlation with these data. The highest correlation values (ranging from -0.80 to -0.97) are observed with EFFIS FWI, while the Canadian FWI system shows comparatively lower correlations (ranging from -0.64 to -0.77).

Table 5. Correlations between FWI fuel moisture codes and various soil moisture datasets.

	ERA5 FWI			EFFIS FWI			Canadian FWI System			SMOS	SMAP
	FFMC 0–2 cm	DMC 5–10 cm	DC 10–20 cm	FFMC 0–2 cm	DMC 5–10 cm	DC 10–20 cm	FFMC 0–2 cm	DMC 5–10 cm	DC 10–20 cm	L4 0–5 cm	L4 0–5 cm
SMOS L4 0–5 cm	-0.87	-0.45	-0.65	-0.85	-0.70	-0.68	-0.79	-0.68	-0.70	1	0.79
SMAP L4 0–5 cm	-0.86	-0.64	-0.81	-0.86	-0.84	-0.83	-0.84	-0.81	-0.85	0.79	1
In situ soil moisture 0–20 cm (%)	-0.85	-0.66	-0.84	-0.80	-0.97	-0.88	-0.64	-0.76	-0.77	0.71	0.87

When assessing forest floor moisture levels, in situ soil moisture demonstrates the strongest correlation with both satellite-based FFMCI datasets (-0.85 and -0.80 for ERA5 and EFFIS, respectively). Moreover, for all three fuel moisture codes across all three datasets, DC consistently demonstrated the highest correlation, with values ranging from -0.77 to -0.88 . Regarding satellite-derived soil moisture, in general, correlations with SMAP data were found to be stronger than those with SMOS data. Although the SMAP soil moisture product provides data for two different depths (0–5 cm and 0–100 cm), only the upper layer was considered due to FMCs being collected between 0–20 cm for consistency with the penetration depth. Within the 0–5 cm moisture level, the highest correlations were observed between the FFMCI values of all FWIs, ranging from -0.84 to -0.86 . Slightly lower correlations were observed between the DMC and DC values of all FWIs, ranging from -0.64 to -0.85 .

A reasonable agreement was found between the SMOS product measured from 0–5 cm data and the corresponding fuel moisture codes, alongside in situ measurements. Particularly, the highest correlation was observed in FFMCI data obtained from the thin layer (0–2 cm) of deceased organic matter, encompassing debris and residues, showing correlations ranging from -0.79 to -0.87 with the forest floor moisture layer. Additionally, the SMOS product demonstrated the highest correlation (-0.79) with SMAP level 4 (0–5 cm) data. In terms of their relationship with in situ soil moisture data, the correlation was relatively lower (-0.70), primarily due to differences in the penetration depth of the L-band from in situ instruments.

Additionally, Table 6 displays the correlations between the three fuel-moisture-related components of the FWI system and four other relevant parameters. Specifically, these parameters include two separate satellite-derived LST datasets—MODIS and Landsat 8—as well as in situ soil and air temperature data.

Table 6 shows a significant correlation between MODIS/Landsat 8 LST and the three moisture-related components of the FWI system. As can be seen, there is a positive correlation between LSTs and FWI fuel moisture codes, along with a negative correlation between soil moisture. A slightly higher correlation was observed with MODIS LST data (min/max: $0.61/0.89$) compared to Landsat 8 LST (min/max: $0.43/0.85$). No particular correlation was observed with any of the FWI moisture codes for all FWI datasets. Both LST datasets exhibited higher correlations with SMAP data (-0.90 to -0.94) compared to SMOS data (-0.71 to -0.78).

Table 6. Correlations of FMCs and soil moisture datasets with other relevant parameters.

	ERA5 FWI			EFFIS FWI			Canadian FWI System			SMOSL4 0–5 cm	SMAP L4 0–5 cm
	FFMC 0–2 cm	DMC 5–10 cm	DC 10–20 cm	FFMC 0–2 cm	DMC 5–10 cm	DC 10–20 cm	FFMC 0–2 cm	DMC 5–10 cm	DC 10–20 cm		
Soil Temperature 5 cm	0.86	0.48	0.77	0.81	0.98	0.82	0.68	0.81	0.79	−0.70	−0.87
Air Temperature	0.85	0.45	0.66	0.82	0.84	0.68	0.79	0.87	0.84	−0.73	−0.90
MODIS LST	0.86	0.61	0.82	0.82	0.89	0.84	0.76	0.88	0.89	−0.78	−0.94
Landsat 8 LST	0.77	0.43	0.72	0.80	0.85	0.77	0.73	0.78	0.80	−0.71	−0.90

A similar relationship trend was also observed with two meteorological datasets, air temperature and soil temperature. Both in situ temperature datasets exhibited higher correlations with SMAP data (−0.87 to −0.90) compared to SMOS data (−0.70 to −0.73).

As a general conclusion, given that the Canadian FWI system and its subcomponents were initially designed for red pine and white pine forests, the predominance of red pine (*Pinus brutia*) in the Antalya region likely enhances the efficacy and applicability of these codes within this particular geographical area.

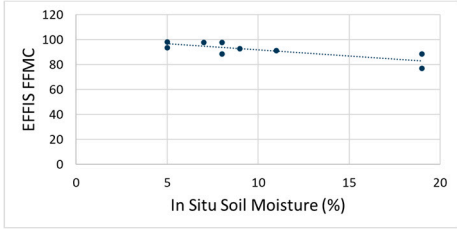
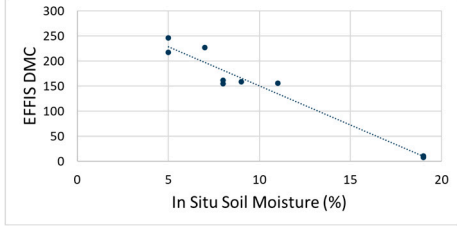
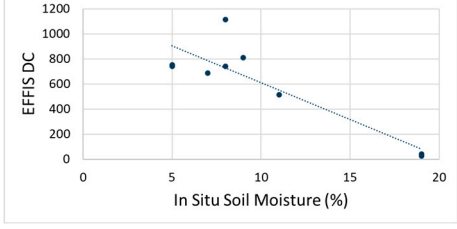
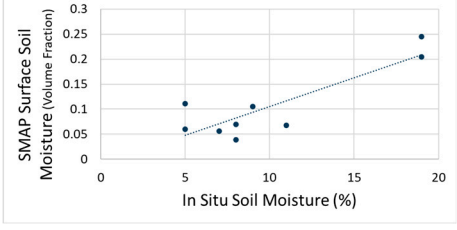
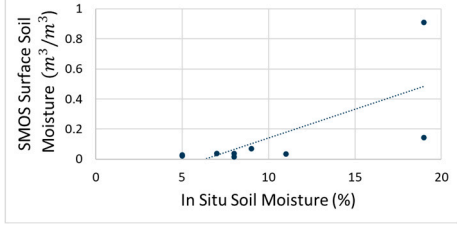
3.3. Model Establishment and Validation

In the model establishment, in situ soil moisture was selected as the dependent variable, while the independent variables comprised three EFFIS FWI moisture codes and two satellite-derived soil moisture datasets. EFFIS FWI was chosen over other FMC datasets due to its highest correlation with in situ soil moisture. Linear models ($Y = \beta_0 + \beta_1 X$) were developed by fitting straight lines to the data points. The corresponding equations, correlation coefficients, and scatter plots, which provide deeper insights and visually depict relationships between variables, are summarized in Table 7.

As demonstrated, among the EFFIS FMCs, the EFFIS DMC moisture codes exhibit a strong linear relationship with in situ soil moisture, characterized by a clear alignment of data points along a trend line. In contrast, SMOS shows significant scatter, indicating weak correlation and high variability, possibly due to unaccounted factors, measurement errors, non-linearity, or outliers. This variability can generally be attributed to factors such as soil and fuel moisture heterogeneity, local climatic variations, differences in LULC types, and a limited sample size not fully representing seasonal changes. Measurement errors in both satellite-derived and in situ soil moisture data may also contribute. Despite these factors, the model offers valuable insights into the general trends and relationships between fuel moisture and in situ soil moisture. However, further refinement and additional data are necessary to enhance accuracy.

While data from ten fire days were used to construct the linear regression model, two fires lasting longer than one day (Fires #8 and #9) were considered for the validation step. First, the Fire #8 event, which began on 28 July 2021, and lasted ten days, was selected as the first test fire area. The Fire #9 event, started on 29 July 2021, and lasting until 7 August 2021, was considered as the second test fire event. Since the start dates of both test fires were utilized in the analyses, the subsequent dates were considered in the validation analysis. For both fire events, the three fuel moisture codes of the EFFIS FWI that showed the strongest correlation with in situ soil moisture were selected for validation. Soil moisture was estimated by applying the established linear models (Table 7) derived from conventional regression to the EFFIS FWI fuel moisture codes calculated for the other days. The RMSE of the model was then calculated based on the difference between the predicted soil moisture values and the in situ measurement data (Table 8).

Table 7. Linear regression models used for different datasets.

Dependent Variable	Independent Variable	Linear Regression Models	r	Scatterplots
In Situ Soil moisture	EFFIS FMC	$-0.6467 \times \text{FFMC} + 69.403$	−0.80	
	EFFIS DMC	$-0.0501 \times \text{DMC} + 18.704$	−0.97	
	EFFIS DC	$-0.0131 \times \text{DC} + 18.042$	−0.88	
	SMAP Soil Moisture	$65.035 \times \text{SMAP} + 3.1826$	0.87	
	SMOS Soil Moisture	$13.179 \times \text{SMOS} + 8.2203$	0.71	

The validation analysis was expanded to include satellite-based soil moisture estimations. Therefore, the process mentioned above was also performed for the two satellite-based surface soil moisture estimation datasets. Table 8 provides a summary of the validation analyses conducted for the three fuel moisture codes and the examined satellite-based soil moisture datasets.

Since the in situ soil moisture is recorded at 0–20 cm soil depths, the SMAP surface (0–5 cm) dataset yielded a lower RMSE of 0.60% and 2.08%, aligning with its higher correlation. The results also indicate that dry soil conditions led to longer duration fires in these two fire regions due to the importance of fuel dehydration.

Table 8. The results of validation analyses for three FMCs and satellite-based surface soil moisture (# represents the fire number, as previously provided in earlier sections).

Fire #	Dates	Nearest Station	Distance to the Fire Zone (km)	In Situ Soil Moisture (%)	RMSE (%)
EFFIS FWI FPMC					
# 8	29 July 2021–6 August 2021	17,954	13	7	1.40
# 9	30 July 2021–6 August 2021	17,310	23	5	1.53
EFFIS FWI DMC					
# 8	29 July 2021–6 August 2021	17,954	13	7	1.85
# 9	30 July 2021–6 August 2021	17,310	23	5	0.79
EFFIS FWI DC					
# 8	29 July 2021–6 August 2021	17,954	13	7	1.41
# 9	30 July 2021–6 August 2021	17,310	23	5	2.77
SMAP Surface Zone					
# 8	29 July 2021–6 August 2021	17,954	13	7	0.60
# 9	30 July 2021–6 August 2021	17,310	23	5	2.08
SMOS Surface Zone					
# 8	29 July 2021–6 August 2021	17,954	13	7	1.80
# 9	30 July 2021–6 August 2021	17,310	23	5	3.64

When the two fire events were considered together in the validation analysis, errors were acquired for fuel moisture codes as follows: 1.46% (FFMC), 1.45% (DMC), and 2.16% (DC). For satellite-based surface soil moisture, the estimates were 1.49% (SMAP) and 2.82% (SMOS).

Model accuracy was also evaluated using LOOCV, where each data point served as a validation set while the remaining data were used for training. This method was chosen due to the dataset's small size and the proven effectiveness of LOOCV for small datasets. The RMSE values and correlation coefficients obtained, given in Table 9, are consistent with conventional results. Specifically, the lowest RMSE was observed with the DMC model, while the highest RMSE was associated with the SMOS model. This cross-validation method highlights the varying degrees of predictive accuracy across different variables and underlines the importance of selecting the most suitable predictors for model optimization.

Table 9. RMSE values and correlation coefficients obtained from LOOCV for different models used.

Data	Leave-One-Out Cross-Validation	
	RMSE	Correlation
FFMC	3.61	0.72
DMC	1.37	0.96
DC	3.35	0.77
SMAP	3.06	0.80
SMOS	24.6	0.62

The findings underline the paramount significance of integrating soil moisture information derived from both fuel moisture codes and satellite-based soil moisture data, as employed in this study. This is particularly crucial in regions where the availability of ground-based point measurement networks is limited.

4. Discussion

Microwave emissions, driven by the dielectric contrast between dry and wet soil particles, are crucial for soil moisture measurement. They vary with soil moisture levels across different soil types—drier soil emits higher microwave energy, while wetter soil emits less. This variation is integral to the FMCs used in the FWI to assess moisture content in the upper layers of the forest floor or organic soil [100,101]. Our findings show that EFFIS FWI has the highest correlation with in situ soil moisture data, while the Canadian

FWI system has lower correlations. This discrepancy can be attributed to the enhanced spatial coverage and resolution of gridded remote sensing data over weather station-based estimates, especially in regions with sparse weather stations [102,103].

In assessing forest floor moisture, in situ soil moisture shows strong correlations with satellite-based ERA5 and EFFIS FPMC datasets, which aligns well with Chaparro et al. (2016) [52]. Across all three fuel moisture codes, DC consistently shows the highest correlations (-0.77 to -0.88), which aligns with previous studies such as that of D'Orangeville et al. (2016) [31], reporting correlations of 0.6 – 0.8 between measured soil moisture and DC estimates in Canadian forests. Studies focusing on surface organic layers also indicate significant correlations between DMC, DC, and soil moisture levels in adjacent mineral horizons [29–32].

Analysis of satellite-derived soil moisture correlations revealed that SMAP data consistently showed stronger relations compared to SMOS, aligning with findings in the literature [104,105]. In this study, strong correlations were observed within the 0 – 5 cm depth of the SMAP soil moisture product, particularly with FPMC values across all FWIs. These findings are consistent with previous research highlighting the robust relationship between soil moisture and FWIs. Additionally, lower correlations were noted for DMC and DC values, which can be attributed to complex moisture exchange mechanisms between mineral and organic soil layers [106]. The high correlation coefficient ($r = -0.87$) observed for in situ soil moisture data with SMAP at the same depth further supports the validity of these findings, aligning with similar studies [104,107]. The SMOS product demonstrated reasonable agreement with FMCs and in situ measurements within the 0 – 5 cm soil moisture layer. Notably, the highest correlations were found again with FPMC data from the thin layer of organic matter. In addition, SMOS also aligned well with SMAP level 4 data. However, its correlation with in situ soil moisture data was relatively lower in comparison to SMAP due to SMOS having a higher radiometric error (4 K versus 1.3 K) and being more affected by radio frequency interference (RFI) due to its non-interferometric retrieval technique [104]. Another study [108] affirmed reasonable agreement between SMOS estimates and in situ measurements within the 0 – 5 cm layer ($\text{RMSE} = 11.6\%$).

Our study provides initial insights into the interaction between soil and fuel moisture, highlighting the significant advantage of integrating satellite data with in situ measurements to manage fire hazard and risk, particularly in regions with limited meteorological stations. This approach aids policymakers in developing targeted land use and fire risk strategies, thereby enhancing community resilience through the integration of satellite and in situ data. However, further research is essential to generalize the findings from this study [39], considering the multitude of factors influencing forest fires and their complex interactions. As is known, fire occurrence is shaped by diverse factors with varying temporal and spatial characteristics, complicating the isolation of soil moisture's specific role. Additionally, the relationship between soil moisture and other environmental factors (e.g., temperature, wind, vapor pressure deficit, precipitation) further complicates understanding the relationship between fuel moisture and soil moisture. This complexity is particularly evident in wet soil conditions, during wetting and drying cycles, across different soil types, and in the presence of leaf litter layers [22]. Studies supporting these insights are relatively scarce and often limited to specific geographic areas. Therefore, conducting comprehensive research across different geographical regions and on a larger scale is crucial, considering the challenges outlined below.

1. Data availability and resolution issues

The availability and resolution of data present significant challenges for both in situ measurements and remote sensing applications. Direct measurement of soil moisture in situ is prone to uncertainties and can be costly, resulting in sparse data coverage in both temporal and spatial domains. Errors related to instrumentation and representation, such as measurement technique, dataset homogeneity, instrument installation depth and method, calibration methods, and measurement intervals, etc., can influence the accuracy of in situ observations [22,109].

Remote sensing faces challenges with the availability and resolution of soil moisture data, where a trade-off between fine temporal and coarse spatial resolution is necessary, making it challenging to balance temporal frequency and spatial detail [110]. The limited spatial resolution of passive microwave instruments like SMOS or SMAP hinders the effective use of soil moisture estimates at the local scale, specifically regarding how representative an in situ measurement can be for satellite observations characterized by a spatial resolution of about 1 km or more [111,112]. Hence, high to moderate spatial resolution satellite data is necessary to scale up in situ measurements before utilizing coarse resolution data to estimate fuel moisture codes on a finer scale; however, inconsistencies in performance and model parameters with various downscaling techniques have led to differences in the spatial and temporal representation of soil moisture, resulting in challenges [110,113].

Moreover, satellite-based measurements mainly reflect soil moisture conditions in the top few centimeters of the soil, with lower temporal resolution compared to in situ networks, resulting in discrepancies between them [56,110]. In contrast, in situ soil moisture measurements represent conditions deeper into the soil profile, such as root zone conditions, and cover various vegetation types (e.g., grasslands, shrublands, and forests). However, the primary limitation of in situ measurements is their small spatial coverage, which may not adequately reflect the heterogeneous soil moisture conditions in the surrounding terrain.

2. FWI system and fuel types

The FWI system assesses fire danger based on a standardized model using mature pine stands as the reference fuel type, which has been supported by numerous studies. For instance, in one study [114], a positive correlation was found between the fuel moisture content of pine needle litter and soil moisture measured in the 0–40 cm soil layer. This correlation was stronger in un-thinned and un-pruned stands ($r = 0.91$) than in thinned and pruned stands ($r = 0.45$). However, the FWI system overlooks the diverse fuel types present seasonally or across different regions, potentially limiting its ability to capture the complexity of fire behavior. Moreover, while satellite-derived live FMC estimates provide an averaged moisture value for the canopy, differentiating between moisture from dead and live biomass is not possible, despite its importance, highlighted by studies showing that soil moisture dynamics influence vegetation, which directly affects dead fuel moisture content [115]. This underlines the challenge posed by various vegetation and forest floor materials, which significantly influence wildfire behavior and intensity.

In addition, the FWI system calculates a daily value for each of these components, meaning that the system provides a snapshot of fire potential for the whole day, rather than real-time or hourly updates on fire danger [34].

Despite these challenges, the high consistency observed in this study can be mainly attributed to the similar behavior of soil moisture and fuel moisture content during ten different dated fire events under dry and similar meteorological conditions.

- Future trends

Advancements in remote sensing, machine learning, and artificial intelligence promise to greatly enhance future research on soil moisture and fire danger. For instance, the upcoming NASA-ISRO NISAR mission, originally scheduled to be launched in 2024, will provide quad-polarized, dual-band data (L-band at 24 cm and S-band at 9 cm), advancing soil moisture retrieval beyond current dual-polarized SAR missions. Progress in automated machine learning and physics-informed approaches further enhances prediction accuracy by automating learning processes and integrating physical principles into model optimization. Hence, integrating precise in situ measurements, advanced satellite data, and cutting-edge machine learning techniques will significantly improve soil moisture product accuracy, spatial resolution, and temporal resolution [96].

5. Conclusions

The Mediterranean basin of Türkiye is increasingly vulnerable to large-scale fires, stressing the need to understand moisture dynamics in vegetation, soil, and the atmosphere.

These dynamics are crucial for predicting ignition and fire behavior, especially as global warming intensifies their impact. The lack of in situ soil moisture data in Türkiye poses a significant challenge to accurate modeling, as point measurements are insufficient due to substantial variations. This study underlines the importance of utilizing remotely sensed and modeled soil moisture information. Our study pioneers investigating the relationship between regional-scale soil moisture data and the three moisture-related components of the FWI, using in situ and satellite observations for ten forest fires in Antalya (2019–2021). The main findings are as follows:

1. High negative correlations (-0.80 to -0.97) were observed between EFFIS FWI fuel moisture codes and in situ soil moisture; the Canadian FWI system and ERA5 FWI showed comparatively lower correlations.
2. Satisfactory correlations were found between FWI fuel moisture codes and satellite-derived soil moisture datasets, with SMAP outperforming others.
3. There was a positive correlation between LSTs and FWIs, a negative correlation with soil moisture, and higher correlations (0.61 to 0.89) with MODIS LST compared to Landsat 8 LST due to compatible spatial resolution with the FWI dataset.
4. The findings are region-specific and may not generalize to areas with different soil and vegetation characteristics.

Overall, the study offers valuable insights into the potential of satellite-based fuel and soil moisture estimations for fire events, while acknowledging limitations and uncertainties inherent in soil moisture's dynamic nature. Further research is needed to fully understand the relationship between fuel and soil moisture under various conditions, such as different soil types, wetting and drying cycles, and the presence of live and dead fuel layers. Incorporating additional topographical variables like slope, aspect, and altitude, as well as different land uses, is essential to improve the understanding of factors influencing fuel moisture in Turkish Mediterranean forests. Despite being preliminary, the results indicate that considering soil moisture could significantly enhance fuel moisture predictions compared to current practices that overlook soil moisture fluctuations.

Author Contributions: Conceptualization, A.F.S.; methodology, A.F.S. and H.A.; software, H.A.; data curation, H.A.; writing—original draft, H.A., A.F.S. and A.D.; writing—review and editing, A.F.S. and A.D.; supervision, A.F.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

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). SMOS-BEC soil moisture data were downloaded from <http://bec.icm.csic.es> (accessed on 20 February 2024). Data for SMAP soil moisture and land surface temperature were obtained through the Google Earth Engine platform (accessed on 20 February 2024).

Acknowledgments: The authors thank Istanbul Technical University (ITU) for the 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.

References

1. De Rigo, D.; Libertà, G.; Durrant, T.H.; Vivancos, T.A.; San-Miguel-Ayanz, J. Forest Fire Danger Extremes in Europe under Climate Change: Variability and Uncertainty. Ph.D. Thesis, Publications Office of the European Union, Luxembourg, 2017. [CrossRef]

2. Russo, A.; Gouveia, C.M.; Páscoa, P.; DaCamara, C.C.; Sousa, P.M.; Trigo, R.M. Assessing the Role of Drought Events on Wildfires in the Iberian Peninsula. *Agric. For. Meteorol.* **2017**, *237*, 50–59. [\[CrossRef\]](#)
3. Acar, Z.; Gonencgil, B. Forest Fires in Southern Turkey July–August 2021. *Rev. Climatol.* **2023**, *23*, 46–57. [\[CrossRef\]](#)
4. García-Llamas, P.; Suárez-Seoane, S.; Fernández-Manso, A.; Quintano, C.; Calvo, L. Evaluation of Fire Severity in Fire Prone-Ecosystems of Spain under Two Different Environmental Conditions. *J. Environ. Manag.* **2020**, *271*, 110706. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Niccoli, F.; Altieri, S.; Kabala, J.P.; Battipaglia, G. Fire Affects Tree Growth, Water Use Efficiency and Carbon Sequestration Ecosystem Service of Pinus Nigra Arnold: A Combined Satellite and Ground-Based Study in Central Italy. *Forests* **2023**, *14*, 2033. [\[CrossRef\]](#)
6. Atalay, H.; Dervisoglu, A.; Sunar, F. Fire Weather Index and Forest Fire Danger Mapping: Insights from a Case Study in Antalya-Manavgat Forest, Türkiye. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2024**, *48*, 53–59. [\[CrossRef\]](#)
7. G20 Climate Risk Atlas. 2021. Available online: <https://www.g20climaterisks.org/> (accessed on 28 July 2024).
8. Meira Castro, A.C.; Nunes, A.; Sousa, A.; Lourenço, L. Mapping the Causes of Forest Fires in Portugal by Clustering Analysis. *Geosciences* **2020**, *10*, 53. [\[CrossRef\]](#)
9. Garrido-Perez, J.M.; García-Herrera, R.; Barriopedro, D.; Ordóñez, C. Shifting Summer Holidays in Spain as an Adaptation Measure to Climate Change. *Sci. Total Environ.* **2023**, *904*, 166879. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Moshou, H.; Drinia, H. Climate Change Education and Preparedness of Future Teachers—A Review: The Case of Greece. *Sustainability* **2023**, *15*, 1177. [\[CrossRef\]](#)
11. 2021 Climate Assessment. Available online: <https://www.mgm.gov.tr/FILES/iklim/yillikiklim/2021-iklim-raporu.pdf> (accessed on 13 May 2024).
12. 2022 Climate Assessment. Available online: <https://mgm.gov.tr/FILES/iklim/yillikiklim/2022-iklim-raporu.pdf> (accessed on 13 May 2024).
13. de Groot, W.J.; Wotton, B.M.; Flannigan, M.D. Wildland Fire Danger Rating and Early Warning Systems. In *Wildfire Hazards, Risks and Disasters*; Elsevier: Amsterdam, The Netherlands, 2015; pp. 207–228. [\[CrossRef\]](#)
14. Zacharakis, I.; Tsihrintzis, V.A. Environmental Forest Fire Danger Rating Systems and Indices around the Globe: A Review. *Land* **2023**, *12*, 194. [\[CrossRef\]](#)
15. Kumar, V.; Dharssi, I. *Sources of Soil Dryness Measures and Forecasts for Fire Danger Rating*; Bureau of Meteorology: Melbourne, VIC, Australia, 1987; Volume 15, pp. 2729–2746. ISBN 978-0-642-70672-0.
16. 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. [\[CrossRef\]](#)
17. Di Giuseppe, F.; Pappenberger, F.; Wetterhall, F.; Krzeminski, B.; Camia, A.; Libertá, G.; San Miguel, J. The Potential Predictability of Fire Danger Provided by Numerical Weather Prediction. *J. Appl. Meteorol. Climatol.* **2016**, *55*, 2469–2491. [\[CrossRef\]](#)
18. Gallo, C.; Eden, J.M.; Dieppois, B.; Drobyshev, I.; Fulé, P.Z.; San-Miguel-Ayanz, J.; Blackett, M. Evaluation of CMIP6 Model Performances in Simulating Fire Weather Spatiotemporal Variability on Global and Regional Scales. *Geosci. Model Dev. Discuss.* **2022**, *2022*, 3103–3122. [\[CrossRef\]](#)
19. San-Miguel-Ayanz, J.; Schulte, E.; Schmuck, G.; Camia, A.; Strobl, P.; Liberta, G.; Giovando, C.; Boca, R.; Sedano, F.; Kempeneers, P. Comprehensive Monitoring of Wildfires in Europe: The European Forest Fire Information System (EFFIS). In *Approaches to Managing Disaster-Assessing Hazards, Emergencies and Disaster Impacts*; IntechOpen: London, UK, 2012. [\[CrossRef\]](#)
20. Moustakas, A.; Davlias, O. Minimal Effect of Prescribed Burning on Fire Spread Rate and Intensity in Savanna Ecosystems. *Stoch Environ. Res. Risk Assess* **2021**, *35*, 849–860. [\[CrossRef\]](#)
21. Masinda, M.M.; Li, F.; Liu, Q.; Sun, L.; Hu, T. Prediction Model of Moisture Content of Dead Fine Fuel in Forest Plantations on Maoer Mountain, Northeast China. *J. For. Res.* **2021**, *32*, 2023–2035. [\[CrossRef\]](#)
22. Sharma, S.; Dhakal, K. Boots on the Ground and Eyes in the Sky: A Perspective on Estimating Fire Danger from Soil Moisture Content. *Fire* **2021**, *4*, 45. [\[CrossRef\]](#)
23. Nelson, R.M., Jr. Water Relations of Forest Fuels. In *Forest Fires*; Academic Press: Cambridge, MA, USA, 2001; pp. 79–149. [\[CrossRef\]](#)
24. Masinda, M.M.; Li, F.; Qi, L.; Sun, L.; Hu, T. Forest Fire Risk Estimation in a Typical Temperate Forest in Northeastern China Using the Canadian Forest Fire Weather Index: Case Study in Autumn 2019 and 2020. *Nat. Hazards J. Int. Soc. Prev. Mitig. Nat. Hazards* **2022**, *111*, 1085–1101. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Van Wagtenonk, J. Fire as a Physical Process. In *Fire in California's Ecosystems*; University of California Press: Berkeley, CA, USA, 2006; pp. 38–57, ISBN 978-0-520-24605-8.
26. Talucci, A.C.; Meigs, G.W.; Knudby, A.; Krawchuk, M.A. Fire Severity and the Legacy of Mountain Pine Beetle Outbreak: High-Severity Fire Peaks with Mixed Live and Dead Vegetation. *Environ. Res. Lett.* **2022**, *17*, 124010. [\[CrossRef\]](#)
27. Jurdao, S.; Chuvieco, E.; Arevalillo, J.M. Modelling Fire Ignition Probability from Satellite Estimates of Live Fuel Moisture Content. *Fire Ecol.* **2012**, *8*, 77–97. [\[CrossRef\]](#)
28. De Groot, W.J. Interpreting the Canadian Forest Fire Weather Index (FWI) System. In Proceedings of the Fourth Central Region Fire Weather Committee Scientific and Technical Seminar, Winnipeg, MB, Canada, 4 April 1998; p. 8.
29. Krueger, E.S.; Levi, M.R.; Achieng, K.O.; Bolten, J.D.; Carlson, J.D.; Coops, N.C.; Holden, Z.A.; Magi, B.I.; Rigden, A.J.; Ochsner, T.E. Using Soil Moisture Information to Better Understand and Predict Wildfire Danger: A Review of Recent Developments and Outstanding Questions. *Int. J. Wildland Fire* **2022**, *32*, 111–132. [\[CrossRef\]](#)

30. Pellizzaro, G.; Cesaraccio, C.; Duce, P.; Ventura, A.; Zara, P. Relationships between Seasonal Patterns of Live Fuel Moisture and Meteorological Drought Indices for Mediterranean Shrubland Species. *Int. J. Wildland Fire* **2007**, *16*, 232–241. [\[CrossRef\]](#)
31. D'Orangeville, L.; Houle, D.; Duchesne, L.; Côté, B. Can the Canadian Drought Code Predict Low Soil Moisture Anomalies in the Mineral Soil? An Analysis of 15 Years of Soil Moisture Data from Three Forest Ecosystems in Eastern Canada. *Ecohydrology* **2016**, *9*, 238–247. [\[CrossRef\]](#)
32. Miller, E.A. A Conceptual Interpretation of The Drought Code of The Canadian Forest Fire Weather Index System. *Fire* **2020**, *3*, 23. [\[CrossRef\]](#)
33. Forkel, M.; Beer, C.; Thonicke, K.; Cramer, W.; Bartalev, S.; Schmulilius, C. Extreme Fire Events Are Related to Previous-Year Surface Moisture Conditions in Permafrost-Underlain Larch Forests of Siberia. *Environ. Res. Lett.* **2012**, *7*, 044021. [\[CrossRef\]](#)
34. Kussul, N.; Fedorov, O.; Yailymov, B.; Pidgorodetska, L.; Kolos, L.; Yailymova, H.; Shelestov, A. Fire Danger Assessment Using Moderate-Spatial Resolution Satellite Data. *Fire* **2023**, *6*, 72. [\[CrossRef\]](#)
35. Rakhmatulina, E.; Stephens, S.; Thompson, S. Soil Moisture Influences on Sierra Nevada Dead Fuel Moisture Content and Fire Risks, 2021. *For. Ecol. Manag.* **2021**, *496*, 119379. [\[CrossRef\]](#)
36. Kumar, V.; Dharssi, I. Evaluation and Calibration of a High-Resolution Soil Moisture Product for Wildfire Prediction and Management. *Agric. For. Meteorol.* **2019**, *264*, 27–39. [\[CrossRef\]](#)
37. Bartsch, A.; Balzter, H.; George, C. The Influence of Regional Surface Soil Moisture Anomalies on Forest Fires in Siberia Observed from Satellites. *Environ. Res. Lett.* **2009**, *4*, 045021. [\[CrossRef\]](#)
38. Jensen, D.; Reager, J.T.; Zajic, B.; Rousseau, N.; Rodell, M.; Hinkley, E. The Sensitivity of US Wildfire Occurrence to Pre-Season Soil Moisture Conditions across Ecosystems. *Environ. Res. Lett.* **2018**, *13*, 014021. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Sungmin, O.; Hou, X.; Orth, R. Observational Evidence of Wildfire-Promoting Soil Moisture Anomalies. *Sci. Rep.* **2020**, *10*, 11008. [\[CrossRef\]](#)
40. Seneviratne, S.I.; Corti, T.; Davin, E.L.; Hirschi, M.; Jaeger, E.B.; Lehner, I.; Orlowsky, B.; Teuling, A.J. Investigating Soil Moisture–Climate Interactions in a Changing Climate: A Review. *Earth-Sci. Rev.* **2010**, *99*, 125–161. [\[CrossRef\]](#)
41. Krueger, E.S.; Ochsner, T.E.; Quiring, S.M.; Engle, D.M.; Carlson, J.D.; Twidwell, D.; Fuhlendorf, S.D. Measured Soil Moisture Is a Better Predictor of Large Growing-Season Wildfires than the Keetch–Byram Drought Index. *Soil Sci. Soc. Am. J.* **2017**, *81*, 490–502. [\[CrossRef\]](#)
42. Burapapol, K.; Nagasawa, R. Mapping Soil Moisture as an Indicator of Wildfire Risk Using Landsat 8 Images in Sri Lanna National Park, Northern Thailand. *J. Agric. Sci.* **2016**, *8*, 107–119. [\[CrossRef\]](#)
43. Dorigo, W.A.; Wagner, W.; Hohensinn, R.; Hahn, S.; Paulik, C.; Xaver, A.; Gruber, A.; Drusch, M.; Mecklenburg, S.; van Oevelen, P. The International Soil Moisture Network: A Data Hosting Facility for Global in Situ Soil Moisture Measurements. *Hydrol. Earth Syst. Sci.* **2011**, *15*, 1675–1698. [\[CrossRef\]](#)
44. Gruber, A.; Dorigo, W.A.; Zwieback, S.; Xaver, A.; Wagner, W. Characterizing Coarse-Scale Representativeness of in Situ Soil Moisture Measurements from the International Soil Moisture Network. *Vadose Zone J.* **2013**, *12*, 1–16. [\[CrossRef\]](#)
45. Heim, R.R., Jr. A Review of Twentieth-Century Drought Indices Used in the United States. *Bull. Am. Meteorol. Soc.* **2002**, *83*, 1149–1166. [\[CrossRef\]](#)
46. Lakhankar, T.; Krakauer, N.; Khanbilvardi, R. Applications of Microwave Remote Sensing of Soil Moisture for Agricultural Applications. *Int. J. Terraspace Sci. Eng.* **2009**, *2*, 81–91.
47. Periasamy, S.; Shanmugam, R.S. Multispectral and Microwave Remote Sensing Models to Survey Soil Moisture and Salinity. *Land Degrad. Dev.* **2017**, *28*, 1412–1425. [\[CrossRef\]](#)
48. Konings, A.G.; Rao, K.; Steele-Dunne, S.C. Macro to Micro: Microwave Remote Sensing of Plant Water Content for Physiology and Ecology. *New Phytol.* **2019**, *223*, 1166–1172. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Kerr, Y.H.; Waldteufel, P.; Wigneron, J.-P.; Delwart, S.; Cabot, F.; Boutin, J.; Escorihuela, M.-J.; Font, J.; Reul, N.; Gruhier, C. The SMOS Mission: New Tool for Monitoring Key Elements of the Global Water Cycle. *Proc. IEEE* **2010**, *98*, 666–687. [\[CrossRef\]](#)
50. Entekhabi, D.; Njoku, E.G.; O'Neill, P.E.; Kellogg, K.H.; Crow, W.T.; Edelstein, W.N.; Entin, J.K.; Goodman, S.D.; Jackson, T.J.; Johnson, J. The Soil Moisture Active Passive (SMAP) Mission. *Proc. IEEE* **2010**, *98*, 704–716. [\[CrossRef\]](#)
51. Chaparro, D.; Vayreda, J.; Martinez-Vilalta, J.; Vall-llossera, M.; Banque, M.; Camps, A.; Piles, M. SMOS and Climate Data Applicability for Analyzing Forest Decline and Forest Fires. In Proceedings of the 2014 IEEE Geoscience and Remote Sensing Symposium, Quebec City, QC, Canada, 13–18 July 2014; pp. 1069–1072. [\[CrossRef\]](#)
52. Chaparro, D.; Piles, M.; Vall-llossera, M. Remotely Sensed Soil Moisture as a Key Variable in Wildfires Prevention Services: Towards New Prediction Tools Using SMOS and SMAP Data. In *Satell. Soil Moisture Retrieval: Techniques and Applications*; Elsevier: Amsterdam, The Netherlands, 2016; p. 249. [\[CrossRef\]](#)
53. Chaparro, D.; Vall-llossera, M.; Piles, M. *A Review on European Remote Sensing Activities in Wildland Fires Prevention. Remote Sensing of Hydrometeorological Hazards*; CRC Press: Boca Raton, FL, USA, 2017; pp. 237–260. ISBN 9781315154947.
54. Thomas Ambadan, J.; Oja, M.; Gedalof, Z.; Berg, A.A. Satellite-Observed Soil Moisture as an Indicator of Wildfire Risk. *Remote Sens.* **2020**, *12*, 1543. [\[CrossRef\]](#)
55. Chaparro, D.; Vall-llossera, M.; Piles, M.; Camps, A.; Rüdiger, C.; Riera-Tatché, R. Predicting the Extent of Wildfires Using Remotely Sensed Soil Moisture and Temperature Trends. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2016**, *9*, 2818–2829. [\[CrossRef\]](#)

56. Abbaszadeh, P.; Moradkhani, H.; Gavahi, K.; Kumar, S.; Hain, C.; Zhan, X.; Duan, Q.; Peters-Lidard, C.; Karimiziarani, S. High-Resolution SMAP Satellite Soil Moisture Product: Exploring the Opportunities. *Bull. Am. Meteorol. Soc.* **2021**, *102*, 309–315. [CrossRef]
57. Djamai, N.; Magagi, R.; Goita, K.; Hosseini, M.; Cosh, M.H.; Berg, A.; Toth, B. Evaluation of SMOS Soil Moisture Products over the CanEx-SM10 Area. *J. Hydrol.* **2015**, *520*, 254–267. [CrossRef]
58. Colliander, A.; Cosh, M.H.; Kelly, V.R.; Kraatz, S.; Bourgeau-Chavez, L.; Siqueira, P.; Roy, A.; Konings, A.G.; Holtzman, N.; Misra, S.; et al. SMAP Detects Soil Moisture Under Temperate Forest Canopies. *Geophys. Res. Lett.* **2020**, *47*, e2020GL089697. [CrossRef]
59. Ayres, E.; Colliander, A.; Cosh, M.H.; Roberti, J.A.; Simkin, S.; Genazzio, M.A. Validation of SMAP Soil Moisture at Terrestrial National Ecological Observatory Network (NEON) Sites Show Potential for Soil Moisture Retrieval in Forested Areas. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2021**, *14*, 10903–10918. [CrossRef]
60. Pablos, M.; González-Haro, C.; Piles, M.; Portal, G.; Team, B.E.C. *BEC SMOS Soil Moisture Products Description (V1.0): PD-SM-L3v4-L4v6*; CSIC-Instituto de Ciencias del Mar (ICM): Barcelona, Spain, 2022. [CrossRef]
61. Matin, M.A.; Chitale, V.S.; Murthy, M.S.; Uddin, K.; Bajracharya, B.; Pradhan, S. Understanding Forest Fire Patterns and Risk in Nepal Using Remote Sensing, Geographic Information System and Historical Fire Data. *Int. J. Wildland Fire* **2017**, *26*, 276–286. [CrossRef]
62. Pan, J.; Wang, W.; Li, J. Building Probabilistic Models of Fire Occurrence and Fire Risk Zoning Using Logistic Regression in Shanxi Province, China. *Nat. Hazards* **2016**, *81*, 1879–1899. [CrossRef]
63. Wang, W.; Quan, X. Estimation of Live Fuel Moisture Content from Multiple Sources of Remotely Sensed Data. *IEEE Geosci. Remote Sens. Lett.* **2023**, *20*. [CrossRef]
64. Sharma, S.; Carlson, J.D.; Krueger, E.S.; Engle, D.M.; Twidwell, D.; Fuhlendorf, S.D.; Patrignani, A.; Feng, L.; Ochsner, T.E. Soil Moisture as an Indicator of Growing-Season Herbaceous Fuel Moisture and Curing Rate in Grasslands. *Int. J. Wildland Fire* **2020**, *30*, 57–69. [CrossRef]
65. Calda, B.; An, N.; Turp, M.T.; Kurnaz, M.L. Effects of Climate Change on the Wildfires in the Mediterranean Basin. *Int. J. Adv. Eng. Pure Sci.* **2020**, *32*, 15–32. [CrossRef]
66. Kottek, M.; Grieser, J.; Beck, C.; Rudolf, B.; Rubel, F. World Map of the Köppen-Geiger Climate Classification Updated. *Meteorol. Z.* **2006**, *15*, 259–263. [CrossRef]
67. Turunçoğlu, U.U.; Türkeş, M.; Bozkurt, D.; Önal, B.; Şen, Ö.L.; Dalfes, H.N. Climate. In *The Soils of Turkey*; Kapur, S., Akça, E., Günal, H., Eds.; Springer International Publishing: Cham, Switzerland, 2018; pp. 25–44. ISBN 978-3-319-64392-2.
68. Çolak, E.; Sunar, F. Evaluation of Forest Fire Risk in the Mediterranean Turkish Forests: A Case Study of Menderes Region, Izmir. *Int. J. Disaster Risk Reduct.* **2020**, *45*, 101479. [CrossRef]
69. Flannigan, M.D.; Wotton, B.M.; Marshall, G.A.; De Groot, W.J.; Johnston, J.; Jurko, N.; Cantin, A.S. Fuel Moisture Sensitivity to Temperature and Precipitation: Climate Change Implications. *Clim. Change* **2016**, *134*, 59–71. [CrossRef]
70. Beck, H.E.; Zimmermann, N.E.; McVicar, T.R.; Vergopolan, N.; Berg, A.; Wood, E.F. Present and Future Köppen-Geiger Climate Classification Maps at 1-Km Resolution. *Sci. Data* **2018**, *5*, 312. [CrossRef] [PubMed]
71. Yilmaz, M. Consistency of Spatiotemporal Variability of MODIS and ERA5-Land Surface Warming Trends over Complex Topography. *Environ. Sci. Pollut. Res.* **2023**, *30*, 94414–94435. [CrossRef]
72. T.C. Ministry of Environment, Urbanisation and Climate Change Eighth National Communication and Fifth Biennial Report of Türkiye Under the UNFCCC. Available online: <https://iklim.gov.tr/db/english/dokumanlar/eight-national--8230-1105-20230601110557.pdf> (accessed on 13 May 2024).
73. Meteoroloji Genel Müdürlüğü. Available online: <https://mevbis.mgm.gov.tr/mevbis/ui/index.html#/Login> (accessed on 28 June 2024).
74. Famiglietti, J.S.; Ryu, D.; Berg, A.A.; Rodell, M.; Jackson, T.J. Field Observations of Soil Moisture Variability across Scales. *Water Resour. Res.* **2008**, *44*, 2006WR005804. [CrossRef]
75. Naseri, S.; Farhadi Bansouleh, B.; Hassanpour, B.; Azari, A. Field-Scale Evaluation of Remote Sensing Soil Moisture Retrievals Using a Multi-Satellite Approach. *J. Spat. Sci.* **2024**, *69*, 181–202. [CrossRef]
76. EFFIS-Welcome to EFFIS. Available online: <https://effis.jrc.ec.europa.eu/> (accessed on 20 February 2024).
77. Bektaş, A.; Yilmaz, M.T.; Şimşek, O. İstasyonlarda Ölçülen Toprak Nemi Değerlerinin Hidrolojik Model ve Uydu Verileri Yardımıyla Değerlendirilmesi. TÜBİTAK CAYDAG project (No: 114Y676). 2018. Available online: <https://iopscience.iop.org/article/10.1088/1748-9326/7/4/044021> (accessed on 30 July 2024).
78. Barratt, M. NWP-Driven Fire Danger Forecasting for Copernicus. Available online: <https://www.ecmwf.int/en/newsletter/147/meteorology/nwp-driven-fire-danger-forecasting-copernicus> (accessed on 6 January 2024).
79. Hersbach, H.; Bell, B.; Berrisford, P.; Hirahara, S.; Horányi, A.; Muñoz-Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Schepers, D.; et al. The ERA5 Global Reanalysis. *Q. J. R. Meteorol. Soc.* **2020**, *146*, 1999–2049. [CrossRef]
80. Vitolo, C.; Di Giuseppe, F.; Krzeminski, B.; San-Miguel-Ayanz, J. A 1980–2018 Global Fire Danger Re-Analysis Dataset for the Canadian Fire Weather Indices. *Sci. Data* **2019**, *6*, 190032. [CrossRef]
81. Vitolo, C.; Di Giuseppe, F.; Barnard, C.; Coughlan, R.; San-Miguel-Ayanz, J.; Libertá, G.; Krzeminski, B. ERA5-Based Global Meteorological Wildfire Danger Maps. *Sci. Data* **2020**, *7*, 216. [CrossRef] [PubMed]
82. Kleijnen, J.P.C.; Beers, W.C.M.V. Application-Driven Sequential Designs for Simulation Experiments: Kriging Metamodelling. *J. Oper. Res. Soc.* **2004**, *55*, 876–883. [CrossRef]

83. Reichle, R.H.; Liu, K. *Observation-Corrected Precipitation Estimates in GEOS-5*; Global Modeling and Assimilation Office, Goddard Space Flight Center: Greenbelt, MD, USA, 2014; No. GSFC-E-DAA-TN19768.
84. SMAP L4 9 Km EASE-Grid Surface and Root Zone Soil Moisture Land Model Constants, Version 3: 3-Hourly Analysis Update, 3-Hourly Geophysical Data, and Land Model Constants. Available online: https://nsidc.org/sites/default/files/multi_spl4_smau-v003-userguide_1.pdf (accessed on 13 May 2024).
85. Marigo, O.; Faye, G.; Manuela, G.; Pellarin, T.; Mbaye, M.; Tine, D.; Mougin, E.; Mbengue, F.; Thiam, A.; Diop, B.; et al. Spatio-Temporal Analysis of Surface and Root Zone Soil Moisture Derived from SMAP and SMOS Microwave Satellite Data Using in-Situ Measurements in Senegal. *Am. J. Environ. Prot.* **2022**, *10*, 8–21. [\[CrossRef\]](#)
86. NASA Data Products | Data. Available online: <https://smap.jpl.nasa.gov/data> (accessed on 13 May 2024).
87. Google Earth Engine Data Catalog SPL4SMGP.007 SMAP L4 Global 3-Hourly 9-Km Surface and Root Zone Soil Moisture | Earth Engine Data Catalog. Available online: https://developers.google.com/earth-engine/datasets/catalog/NASA_SMAP_SPL4SMGP_007 (accessed on 13 May 2024).
88. Google Earth Engine Data Catalog MOD11A1.061 Terra Land Surface Temperature and Emissivity Daily Global 1 km | Earth Engine Data Catalog. Available online: https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD11A1 (accessed on 13 May 2024).
89. Wan, Z.; Dozier, J. A Generalized Split-Window Algorithm for Retrieving Land-Surface Temperature from Space. *IEEE Trans. Geosci. Remote Sens.* **1996**, *34*, 892–905. [\[CrossRef\]](#)
90. Wan, Z. MODIS Land Surface Temperature Products Users' Guide. Available online: https://lpdaac.usgs.gov/documents/715/MOD11_User_Guide_V61.pdf (accessed on 13 May 2024).
91. Avdan, U.; Jovanovska, G. Algorithm for Automated Mapping of Land Surface Temperature Using LANDSAT 8 Satellite Data. *J. Sens.* **2016**, *2016*, 1480307. [\[CrossRef\]](#)
92. ESA WorldCover 10m V200 | Earth Engine Data Catalog. Available online: https://developers.google.com/earth-engine/datasets/catalog/ESA_WorldCover_v200 (accessed on 16 January 2024).
93. Fire Danger Forecast. Available online: <https://effis.jrc.ec.europa.eu/about-effis/technical-background/fire-danger-forecast> (accessed on 13 May 2024).
94. Fire Danger Forecast GWIS. Available online: <https://gwis.jrc.ec.europa.eu/about-gwis/technical-background/fire-danger-forecast> (accessed on 14 May 2024).
95. Asuero, A.G.; Sayago, A.; González, A.G. The correlation coefficient: An overview. *Crit. Rev. Anal. Chem.* **2006**, *36*, 41–59.
96. Christias, P.; Mocanu, M. A Machine Learning Framework for Olive Farms Profit Prediction. *Water* **2021**, *13*, 3461. [\[CrossRef\]](#)
97. Yang, S.; Zeng, A.; Tigabu, M.; Wang, G.; Zhang, Z.; Zhu, H.; Guo, F. Investigating Drought Events and Their Consequences in Wildfires: An Application in China. *Fire* **2023**, *6*, 223. [\[CrossRef\]](#)
98. Cheng, H.; Garrick, D.J.; Fernando, R.L. Efficient Strategies for Leave-One-out Cross Validation for Genomic Best Linear Unbiased Prediction. *J. Anim. Sci. Biotechnol.* **2017**, *8*, 38. [\[CrossRef\]](#)
99. Shi, M.; Li, H.; Zhang, Z.; Lee, E.W.M. Development and Application of an Intelligent Approach to Reconstruct the Location of Fire Sources from Soot Patterns Deposited on Walls. *Fire* **2023**, *6*, 303. [\[CrossRef\]](#)
100. Njoku, E.G.; Entekhabi, D. Passive Microwave Remote Sensing of Soil Moisture. *J. Hydrol.* **1996**, *184*, 101–129. [\[CrossRef\]](#)
101. Bircher, S.; Skou, N.; Jensen, K.H.; Walker, J.P.; Rasmussen, L. A Soil Moisture and Temperature Network for SMOS Validation in Western Denmark. *Hydrol. Earth Syst. Sci.* **2012**, *16*, 1445–1463. [\[CrossRef\]](#)
102. Field, R.D.; Spessa, A.C.; Aziz, N.A.; Camia, A.; Cantin, A.; Carr, R.; de Groot, W.J.; Dowdy, A.J.; Flannigan, M.D.; Manomaiphiboon, K. Development of a Global Fire Weather Database. *Nat. Hazards Earth Syst. Sci.* **2015**, *15*, 1407–1423. [\[CrossRef\]](#)
103. Gale, M.G.; Cary, G.J.; Van Dijk, A.I.; Yebra, M. Untangling Fuel, Weather and Management Effects on Fire Severity: Insights from Large-Sample LiDAR Remote Sensing Analysis of Conditions Preceding the 2019–20 Australian Wildfires. *J. Environ. Manag.* **2023**, *348*, 119474. [\[CrossRef\]](#) [\[PubMed\]](#)
104. Chen, Y.; Yang, K.; Qin, J.; Cui, Q.; Lu, H.; La, Z.; Han, M.; Tang, W. Evaluation of SMAP, SMOS, and AMSR2 Soil Moisture Retrievals against Observations from Two Networks on the Tibetan Plateau. *JGR Atmos.* **2017**, *122*, 5780–5792. [\[CrossRef\]](#)
105. Cui, C.; Xu, J.; Zeng, J.; Chen, K.-S.; Bai, X.; Lu, H.; Chen, Q.; Zhao, T. Soil Moisture Mapping from Satellites: An Intercomparison of SMAP, SMOS, FY3B, AMSR2, and ESA CCI over Two Dense Network Regions at Different Spatial Scales. *Remote Sens.* **2017**, *10*, 33. [\[CrossRef\]](#)
106. Zhao, L.; Yebra, M.; van Dijk, A.I.J.M.; Cary, G.J.; Hughes, D. Controlled Field Experiment Clarifies the Influence of Soil Moisture on Litter Moisture Content. *Agric. For. Meteorol.* **2022**, *314*, 108782. [\[CrossRef\]](#)
107. Hu, F.; Wei, Z.; Yang, X.; Xie, W.; Li, Y.; Cui, C.; Yang, B.; Tao, C.; Zhang, W.; Meng, L. Assessment of SMAP and SMOS Soil Moisture Products Using Triple Collocation Method over Inner Mongolia. *J. Hydrol. Reg. Stud.* **2022**, *40*, 101027. [\[CrossRef\]](#)
108. Petropoulos, G.P.; Ireland, G.; Srivastava, P.K.; Ioannou-Katidis, P. An Appraisal of the Accuracy of Operational Soil Moisture Estimates from SMOS MIRAS Using Validated in Situ Observations Acquired in a Mediterranean Environment. *Int. J. Remote Sens.* **2014**, *35*, 5239–5250. [\[CrossRef\]](#)
109. Dorigo, W.A.; Xaver, A.; Vreugdenhil, M.; Gruber, A.; Hegyiova, A.; Sanchis-Dufau, A.D.; Zamojski, D.; Cordes, C.; Wagner, W.; Drusch, M. Global Automated Quality Control of in Situ Soil Moisture Data from the International Soil Moisture Network. *Vadose Zone J.* **2013**, *12*, vzj2012-0097. [\[CrossRef\]](#)

110. Adelabu, S.A.; Adepoju, K.A.; Mofokeng, O.D. Estimation of Fire Potential Index in Mountainous Protected Region Using Remote Sensing. *Geocarto Int.* **2020**, *35*, 29–46. [[CrossRef](#)]
111. Moran, M.S.; Peters-Lidard, C.D.; Watts, J.M.; McElroy, S. Estimating Soil Moisture at the Watershed Scale with Satellite-Based Radar and Land Surface Models. *Can. J. Remote Sens.* **2004**, *30*, 805–826. [[CrossRef](#)]
112. Fan, L.; Wigneron, J.-P.; Xiao, Q.; Al-Yaari, A.; Wen, J.; Martin-StPaul, N.; Dupuy, J.-L.; Pimont, F.; Al Bitar, A.; Fernandez-Moran, R. Evaluation of Microwave Remote Sensing for Monitoring Live Fuel Moisture Content in the Mediterranean Region. *Remote Sens. Environ.* **2018**, *205*, 210–223. [[CrossRef](#)]
113. Xu, J.; Su, Q.; Li, X.; Ma, J.; Song, W.; Zhang, L.; Su, X. A Spatial Downscaling Framework for SMAP Soil Moisture Based on Stacking Strategy. *Remote Sens.* **2024**, *16*, 200. [[CrossRef](#)]
114. Pook, E.W.; Gill, A.M. Variation of Live and Dead Fine Fuel Moisture in Pinus Radiata Plantations of the Australian Capital Territory. *Int. J. Wildland Fire* **1993**, *3*, 155–168. [[CrossRef](#)]
115. Resco De Dios, V. Environmental Plant Responses and Wildland Fire Danger. In *Plant-Fire Interactions; Managing Forest Ecosystems*; Springer International Publishing: Cham, Switzerland, 2020; Volume 36, pp. 75–92, ISBN 978-3-030-41191-6.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.