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UNIVERSIDADE  
**COIMBRA**

Nuno Pires

## **INTELLIGENT SYSTEM FOR LOCALISING AND MONITORING FOREST FIRES**

Dissertation in the context of the Master in Informatics Engineering, specialization in Information Systems, advised by Professor Alberto Cardoso and Professor Jacinto Estima and presented to the Department of Informatics Engineering of the Faculty of Sciences and Technology of the University of Coimbra.

January 2024



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**SISTEMA INTELIGENTE PARA LOCALIZAÇÃO  
E MONITORIZAÇÃO DE INCÊNDIOS  
FLORESTAIS**

Dissertação no âmbito do Mestrado em Engenharia Informática,  
especialização em Sistemas de Informação, orientada pelo Professor Alberto  
Cardoso e Professor Jacinto Estima e apresentada ao Departamento de  
Engenharia Informática da Faculdade de Ciências e Tecnologia da  
Universidade de Coimbra.

Janeiro 2024



## **Abstract**

Fire can have disastrous consequences. Decision-support systems play a central role in dealing with forest fires. Its early warning capacity and real-world impact help to protect forests, species, and communities from wildfire.

The presented work proposes a system for forecasting and monitoring forest fires using multiple data sources. Data fusion, aggregation, and enhancement techniques are also mentioned.

The main purpose of the system is to provide important information for emergency decision-making, such as the geolocation, severity, and temporal evolution of a wildfire. It will employ statistical and machine learning methodologies to predict and determine fire occurrence, susceptibility, and risk.

Finally, the system, with the help of data visualisation tools, will show findings and insights.

The document also presents current approaches and obstacles to forest fire prediction, as well as the suggested methodology and analysis of risk.

## **Keywords**

Decision support system, Fire management, Fire forecasting, Machine learning, Spatial and temporal prediction



## **Resumo**

Os incêndios podem ter consequências desastrosas. Os sistemas de apoio à decisão desempenham um papel central na luta contra os incêndios florestais. As suas capacidades de alerta e o seu impacto no mundo real ajudam a proteger as florestas, as espécies e as comunidades.

O trabalho apresentado propõe um sistema de previsão e monitorização de incêndios florestais que utiliza fontes diversas de dados. Onde são utilizadas técnicas de fusão, agregação e melhoramento de dados.

O principal objetivo do sistema é fornecer informações importantes para a tomada de decisões de emergência, tais como a geolocalização, a gravidade e a evolução temporal de um incêndio florestal. O sistema empregará metodologias estatísticas e de aprendizagem automática para prever e determinar a ocorrência, a suscetibilidade e o risco de incêndio.

Finalmente, com a ajuda de ferramentas de visualização de dados, o sistema será capaz de apresentar informações e resultados.

No documento também são analisadas as abordagens actuais e os obstáculos à previsão de incêndios florestais, bem como a metodologia sugerida e a análise de risco.

## **Palavras-Chave**

Sistema de apoio à decisão, Gestão de incêndios, Previsão de incêndios, Aprendizagem automática, Previsão espacial e temporal



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# Chapter 1

## Implementation

### 1.1 Data Sources

#### 1.1.1 Historical record of fires from 1980 to 2015 in mainland Portugal (?) (?) (?)

//describe dataset here, how many entries?

#### 1.1.2 Historical record of fires from 2013 to 2023 in mainland Portugal (?)

Data retrieved from the API endpoint. //describe dataset here, how many entries?

#### 1.1.3 Study area

MUDAR The study area is located in western Sichuan, southwest China, between 26°05'00"N to 34°20'00"N and 97°22'00"E to 104°07'00"E, with a total area of about 300,423 km<sup>2</sup> (Fig. 2a). Belonging to the southeastern edge of the Qinghai-Tibet Plateau, the area is characterized by complex topography, with a low elevation in the south region (around 1500 m a.s.l.) to a high elevation in the north region (around 4500 m a.s.l.). Wildfires only seldom occur above 4000 m a.s.l., so we limited our study area to the region below 4000 m a.s.l. The climate in the study area varies with altitude and ranges from alpine in the northern area to the subtropical semi-humid climate in the southern mountainous area. The alpine climate in the northwestern region faces water scarcity (annual total precipitation of 500–900 mm).

Table 1.1: Field description of Historical fires from 1980 to 2015

Variable	Description
ano	Year of fire occurrence
codigo_sgif	Unique identifier for the fire occurrence
tipo	Kind of wildfire. The available options are: forest, slash-and-burn, false alarm, and agricultural.
distrito	District of fire occurrence.
concelho	Municipality of fire occurrence.
freguesia	Parish of fire occurrence.
local	Location of fire occurrence.
ine	Not described or explained anywhere.
x   y	Wildfire location.
data_alerta	Wildfire warning date.
hora_alerta	Wildfire warning hour.
data_extincao	Wildfire complete extinguishment date.
hora_extincao	Hour of wildfire complete extinguishment.
data_primeira_intervencao	Date of first fire intervention
hora_primeira_intervencao	Hour of first fire intervention
fonte_alerta	Authority or group of people who reported the fire first.
nut	A Unique identifier for a given nomenclature of territorial units for statistics.
area_povoamento	Burnt settlement area.
area_mato	Burnt bush area.
area_agricola	Burnt agricultural area.
area_pov_mato	Sum of burned area from the burnt settlement area and burnt agricultural area.
area_total	Total burnt area.
reacendimento	Describes if a given fire is a re-ignition from a previous wildfire.
queimada	Identifies if a fire is a slash-and-burn.
falso_alarme	Identifies if it is a false alarm.
fogacho	Identifies if it is a specific type of fire named a blaze.
incendio	Identifies if it is a fire.
causa	Numerical identifier for the fire cause.
tipo_causa	Description of fire cause. The available options are unknown, deliberate, natural, negligent fire, and undefined.

### 1.1.4 Open-meteo hourly weather variables (?)

Historical Weather (?) from ( ? ), ( ? ) and ( ? )

### **1.1.5 Fire danger indices historical data from the Copernicus Emergency Management Service (?)**

The dataset "Fire danger indices historical data from the Copernicus Emergency Management Service" (?) provided by ECMWF, contains full historical reconstruction of weather conditions suitable for the origin, spread, and sustainability of natural occurring fires.

It embodies fire danger indices from three distinct models created in Canada, United States and Australia. The fire danger indices are obtained from historical simulations and weather forecast provided by the dataset ECMWF ERA5 reanalysis.

The available data starts from January 1940 and it extends all the way through 2023, but the data records are regularly extended with time as ERA5 forcing data becomes available. The variables contained in the dataset are expressed in the table ??.

### **1.1.6 Forest Inventory 2015 (??)**

Forest Inventory 2015 contains 579422 occurrences of forest inventory for mainland Portugal. The data was gathered using aerial images and ground surveys that covered mainland Portugal. //describe dataset here

## **1.2 Additional sources of Data**

The python library geopy (?) was used to geolocate multiple locations, resolving district, parish, municipalities, and localities to sets of coordinates. Geopy utilises multiple geocoding web services like OpenStreetMap Nominatim and Google Geocoding API to resolve locations.

The Google Maps service (?) was used to manually check if the extracted data from Open-Meteo corresponded to the intended location. It was also used to analyse some errors that were found in the location of some entries.

## **1.3 Creating the dataset**

The dataset described in ?? is composed of multiple files describing historical occurrences since 1980 until 2015. Prior to 2001, the fields from each file became unstandardized, and there's no explicit parameter mentioning a natural wildfire cause. Therefore, the time frame considered was from 2001 to 2012. The latter years were rejected due to the fact that entries from ?? do not contain any explicit latitude and longitude. They rely on territorial entities such as districts, municipalities, parishes, and NUTS to describe locations.

The second historical wildfire dataset ?? is also composed of multiple files. Its time frame is from 2013 until 2023. Unlike dataset ??, entries do contain an explicit latitude and longitude values. It also features descriptive territorial entities.

### **1.3.1 Entry selection**

Entries whose cause was deliberate or negligent fire were excluded. The fire causes contained, by order of importance, in the dataset are: natural, reignition, unknown, and undefined. Entries that were undefined as causes differed from those with unknown causes because their cause field was blank, and entries that had unknown causes were explicitly described as unknown.

falta: tabela com o número de entradas antes e depois

### **1.3.2 Geocoding places from 2001 to 2012 historical wildfire locations**

The dataset entries featured in ?? contain no direct field leading up to the real site location coordinates. To tackle this issue, an algorithm with the help of the geopy library (?) was made to resolve the names of historical wildfire places to a set of coordinates.

Using multiple combinations, attempts were made to geocode the location, featuring the combinations in the table ???. The district, municipality, parish, and local (if available) of each entry were utilized for this purpose. Sometimes, the name of the exact wildfire locality was enclosed in brackets, requiring processing using strings to extract it.

These combinations caused errors in the location of some entries because the geocoders returned coordinates in other countries, such as Spain and Brazil, due to similar names in some locations. The entries that produced errors underwent recalculation, with the addition of "Portugal" at the end. An example of this usage is *Parish, District, Portugal*.

After each entry was resolved, their latitude and longitude were added as values in the columns LAT and LON of each corresponding file.

A very minor sample of entries couldn't be geocoded using this method. Therefore they were manually geocoded from the Google Maps service.

### **1.3.3 Retrieving historical meteorological data**

In order to retrieve historical meteorological data, a Python script was made. It went through each historical fire location and downloaded weather data about the entire day regarding the wildfire. The weather data contained all the fields described in ??.

### 1.3.4 Linking historical wildfires with historical weather data

Dizer número de instâncias Every unit from each field was specified in the retrieved data, so it had to be removed. Dizer que NA ficou com NC no dataset.

### 1.3.5 Matching each historical wildfire with tree species

O que mudei no dataset inicial das trees dfTreesDRP['stateProvince'] = dfTreesDRP['stateProvince'].replace('Bragança District', 'Bragança') dfTreesDRP['locality'] = dfTreesDRP['locality'].replace('Ovadas e Panchora', 'Ovadas e Panchorra') Continha um erro, Ovadas e Panchora não existe.

variáveis das trees que foram usadas: scientificName,locality,stateProvince,occurrenceStatus,in haversine formula da distância (? ).

Multiple tests were made for distance, 120metres, 500 metres.

Especies que estavam na mesma freguesia ou concelho foram associadas sem fazer cálculo de distância. Para combater espécies duplicadas, só se adicionava uma espécie se esta não estivesse contida na entrada do fogo. Distrito, usava-se uma distância de 1000 metros.

As restantes entradas que não obtiveram correspondência com os outros métodos anteriores, foi feita uma análise das espécies que estavam mais perto, neste passo foram detetados erro, alguns valores tabulados do icnf não correspondiam à realidade, e alguns valores em ?? foram mal calculados.

Devido ao tamanho do dataset das árvores o script de python utilizado dividiu os anos em chunks e com multiprocessamento foi calculado as espécies de árvores perto do fogo.

### 1.3.6 Locations in the middle of the sea.

Between 2013 and 2023, some of the featured locations were in the middle of the ocean. Although having a real-life location set explicitly in the file when using services like Google Maps, its coordinates were undeniably wrong. These multiple geolocation errors were discovered when trying to pin multiple species of trees ?? to a single location with a distance function calculator. The algorithm yielded values that were outside of the range spectrum of 1500km. Leading to the manual confirmation of these errors with the help of the Google Maps service.

### 1.3.7 Dataset description

2001: 25982 2002: 25650 2003: 25138 2004: 21189 2005: 34578 2006: 19175 2007: 15615 2008: 9905 2009: 17399 2010: 14431 2011: 14913 2012: 11841 2013: 11899

2014: 3833 2015: 8431 2016: 7782 2017: 10412 2018: 5559 2019: 4040 2020: 3953  
2021: 2610 2022: 4040 2023: 2499 TOTAL : 300874

Natural Fires 2001: 44 2002: 13 2003: 96 2004: 16 2005: 3 2006: 67 2007: 50 2008: 28  
2009: 106 2010: 138 2011: 102 2012: 56 2013: 77 2014: 38 2015: 138 2016: 67 2017:  
104 2018: 114 2019: 128 2020: 95 2021: 103 2022: 115 2023: 72 TOTAL: 1770

Reignition Fires - Averiguar os zeros 2001: 0 2002: 0 2003: 0 2004: 0 2005: 0 2006:  
0 2007: 0 2008: 0 2009: 0 2010: 0 2011: 0 2012: 2256 2013: 2430 2014: 305 2015: 1505  
2016: 1347 2017: 1714 2018: 712 2019: 580 2020: 524 2021: 201 2022: 480 2023: 247  
TOTAL: 12301

Unknown Fires 2001: 215 2002: 221 2003: 234 2004: 268 2005: 377 2006: 1557 2007:  
3577 2008: 3253 2009: 4422 2010: 6071 2011: 5915 2012: 4041 2013: 4133 2014: 2273  
2015: 3834 2016: 3497 2017: 5266 2018: 2949 2019: 2506 2020: 2480 2021: 2101 2022:  
3154 2023: 1863 TOTAL: 64207

NA Fires

## **1.4 Python libraries used in the conception of the dataset**

requests pandas os to check if files already existed.

## **1.5 Entry Selection**

Specify how many entries raw files have.

Table 1.2: Field description of Historical fires from 2013 to 2024

Variable	Description
CODIGO id	Unique identifier for the fire occurrence
DISTRITO	District of fire occurrence.
TIPO	Kind of wildfire. The available options are: forest and agricultural fire.
ANO	Year of fire occurrence
AREAPOV	Burnt settlement area.
AREAMATO	Burnt bush area.
AREAAGRIC	Burnt agricultural area.
AREATOTAL	Total burnt area.
REACENDIMENTOS	Boolean value for reignition.
FOGACHO	Boolean value for small fire.
NCCO	Non specified identifier.
NOMECCO	Not described or explained anywhere.
DATAALERTA	Wildfire warning date.
HORAALERTA	Wildfire warning hour.
LOCAL	Location of fire occurrence
CONCELHO	Municipality of fire occurrence.
FREGUESIA	Parish of fire occurrence
FONTEALERTA	Authority or group of people who reported the fire first.
INE	Not described or explained anywhere.
X   Y	Wildfire location.
DIA	Day of the fire occurrence.
MES	Month of fire occurrence.
HORA	Fire hour of occurrence.
OPERADOR	Not described or explained anywhere.
PERIMETRO	Not described or explained anywhere.
APS	Not described or explained anywhere.
CAUSA	Numerical identifier for the fire cause.
TIPOCAUSA	Description of fire cause. The available options differ from year to year.
distrito	District of fire occurrence.
local	Local of fire occurrence
data_alerta	Wildfire warning date.
hora_alerta	Wildfire warning hour.
data_extincao	Wildfire complete extinguishment date.
hora_extincao	Hour of wildfire complete extinguishment.
data_primeira_intervencao	Date of first fire intervention
hora_primeira_intervencao	Hour of first fire intervention
fonte_alerta	Authority or group of people who reported the fire first.
nut	A Unique identifier for a given nomenclature of territorial units for statistics.
area_pov_mato	Sum of burned area from the burnt settlement area and burnt agricultural area.
reacendimento	Describes if a given fire is a re-ignition from a previous wildfire.
queimada	Identifies if a fire is a slash-and-burn.
falso_alarme	Identifies if a false alarm.
fogacho	Identifies if it is a specific type of fire named a blaze.
incendio	Identifies if it is a fire.
causa	Numerical identifier for a fire cause.

Table 1.3: Hourly weather variables from Open-meteo

Variable	Unit	Description
Temperature	°C	Air temperature 2 metres above ground.
Relative Humidity	%	Relative humidity 2 metres above ground.
Dew	°C	Dew point 2 metres above ground.
Apparent Temperature	°C	Apparent temperature is the result of a wind chill factor, relative humidity, and solar radiation.
Pressure	hPa	Atmospheric air pressure reduced to mean sea level.
Surface Pressure	hPa	Surface pressure reduced to mean sea level.
Precipitation	mm	Sum of preceding hour precipitation including rain, showers, and snow.
Rain	mm	Preceding hour of liquid precipitation.
Snowfall	cm	Preceding hour of snowfall amount.
Cloud cover low	%	Fog and low level clouds up to an altitude of 2 kilometres.
Cloud cover mid	%	Clouds floating at a medium level with altitudes ranging from 2 kilometres to six kilometres.
Cloud cover high	%	Clouds floating at an altitude of 6 kilometres.
Shortwave radiation	W/m <sup>2</sup>	Shortwave solar radiation.
Direct radiation	W/m <sup>2</sup>	Direct solar radiation.
Direct normal irradiance	W/m <sup>2</sup>	Direct solar irradiance.
Diffuse radiation	W/m <sup>2</sup>	Diffuse solar radiation.
Global tilted irradiance	W/m <sup>2</sup>	Total radiation received on a tilted pane.
Sunshine duration	Seconds	Duration of sunshine in seconds.
Wind speed at 10m	km/h	Speed of the wind, 10 metres above ground.
Wind speed at 100m	km/h	Speed of the wind, 100 metres above ground.
Wind direction at 10m	°	Wind direction at 10 metres above ground.
Wind direction at 100m	°	Wind direction at 100 metres above ground.
Wind gusts	km/h	Wind gusts at 10 metres above ground.
Evapotranspiration	mm	Evapotranspiration value for the required irrigation for plants calculated from temperature, wind speed, humidity, and solar radiation.
Weather code	WMO code	Numeric codes for weather conditions.
Snow depth	meters	The depth of snow on the ground.
Vapour pressure deficit	kPa	Vapour pressure deficit in kilopascal.
Soil temperature	°C	Average soil temperature ranging from 0 to 7cm, 7 to 28cm, 28 to 100cm, and 100 to 255cm below ground.
Soil moisture	m <sup>3</sup> / m <sup>3</sup>	Average soil moisture ranging from 0 to 7cm, 7 to 28cm, 28 to 100cm, and 100 to 255cm depths.

Table 1.4: Fire danger indices from historical data

Variable	Unit	Description
Build-up index	Dimensionless	Weighted combination of the Duff moisture code and Drought code.
Burning index	Dimensionless	Measure that explains how difficult it is to control a fire.
Danger rating	Dimensionless	Equivalent to the FWI but with class level definitions of very low, low, medium, high, very high and extreme.
Drought code	Dimensionless	Component representing fuel availability, and the influence of recent temperatures and rainfall events on fuel availability.
Duff moisture code	Dimensionless	Moisture content in loosely-compacted organic layers of moderate depth. Duff moisture code fuels are affected by rain, temperature and relative humidity.
Energy release component	$J/m^2$	Available energy within the burning front at the head of a fire.
Fine fuel moisture code	Dimensionless	Moisture content in litter. Representative of the top litter layer less than 1-2 cm deep.
Fire daily severity index	Dimensionless	A numerical assessment of the difficulty of controlling flames.
Fire danger index	Dimensionless	Metric that hold the chances of a fire starting.
Fire weather index	Dimensionless	Combination of Initial spread index and Build-up index. Numerical rating of the potential fire intensity.
Ignition component	%	Probability of a firebrand that will require suppression action.
Keetch-Byram drought index	Dimensionless	The total impact of evapotranspiration and precipitation in causing cumulative moisture shortage in deep duff and higher soil layers.
Spread component	Dimensionless	Measure of the spead at which a headfire would spread.

Table 1.5: Forest Inventory 2015

Variable	Description
gbifID   datasetKey   occurrenceID	Identifiers for the occurrence of trees and the dataset.
kingdom	Kingdom classification of a given Tree.
phylum	Phylum classification of a given Tree.
class	Taxonomic class.
order	Taxonomic Order of a Tree.
genus	Tree genus.
species	Data containing the species of a given tree.
taxonRank	Data containing the highest taxonomic rank available for a given tree group.
scientificName   verbatimScientificName	Scientific name for the available taxonomic classification.
verbatimScientificNameAuthorship	Scientific name authorship for the available taxonomic classification.
countryCode	Country code of Portugal.
locality	Name of a locality containing a given tree.
stateProvince	Name of a district containing a given tree.
occurrenceStatus	Describes if a tree is still present.
decimalLatitude	Latitude for the tree occurrence.
decimalLongitude	Longitude for the tree occurrence
coordinateUncertaintyInMeters	Uncertainty for a given tree location in metres.
eventDate   year	Year of event record.
taxonKey	Taxonomic key for the highest available classification for a tree
speciesKey	Individual key for a given tree species if available.
speciesKey	Individual key for a given tree species if available.
institutionCode	Unique identifier for ICNF.
collectionCode	Unique collection identifier for the institutionCode.

Table 1.6: Combinations for local geocoding

Combination
Local, District
Local, Parish, District
Local, Parish, Municipality
Local, Parish, Municipality, District
Parish, Municipality, District
Local, Parish, District

# Chapter 2

## Graphs

### 2.1 Fire Weather Index variables

FFMC: Time lag is 2/3 day DMC: Time Lag is 12 days DC:Time lag is 52 days (AICC) dá indicação do teor de umidade nas camadas profundas (10 a 20 cm), estimando indiretamente a intensidade dos fogos devido à secura dos combustíveis.

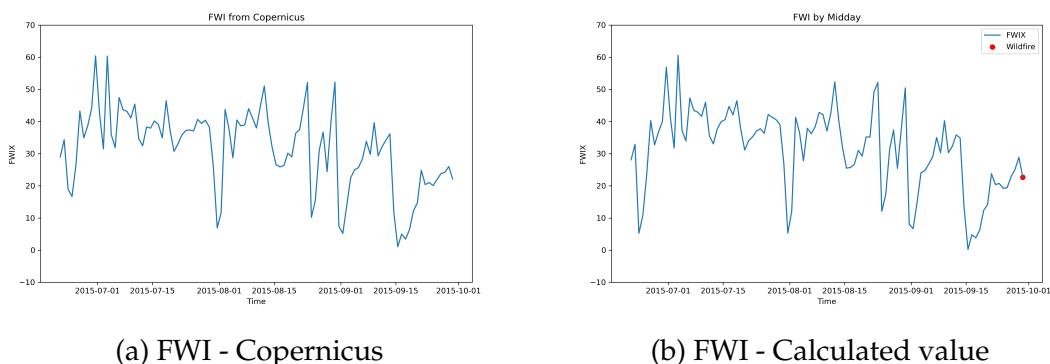
### 2.2 Sample Description

2022: FWI:21.95067024230957 Drought Code (DC): 418.90625 Duff Moisture Code (DMC): 160.0711212158203 Fine Fuel Moisture Code (FFMC): 86.57350158691406

### 2.3 Simulated FWI variables

Este local não teve incêndio

Figure 2.1: Comparison of FWI calculated values and Copernicus



(a) FWI - Copernicus

(b) FWI - Calculated value

Figure 2.2: Comparison of FFMC calculated values and Copernicus

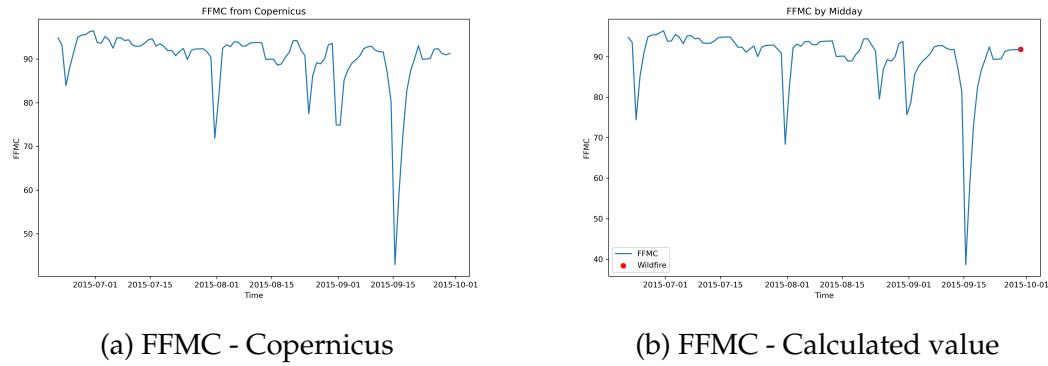


Figure 2.3: Comparison of DMC calculated values and Copernicus

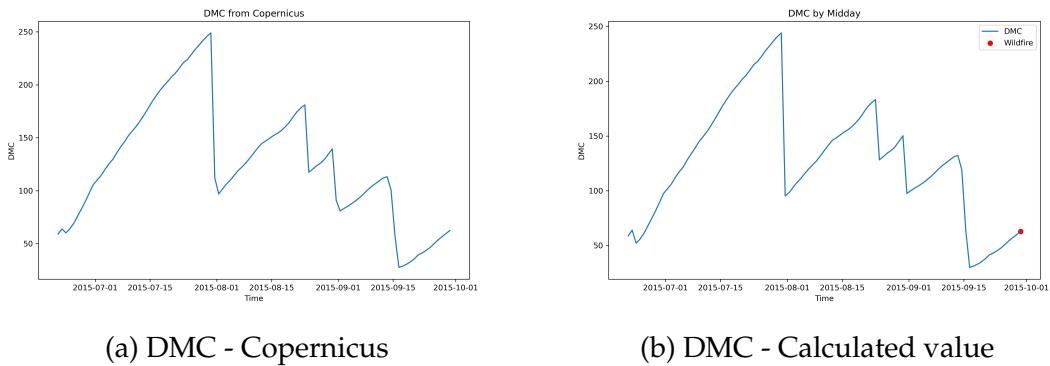


Figure 2.4: Comparison of DC calculated values and Copernicus

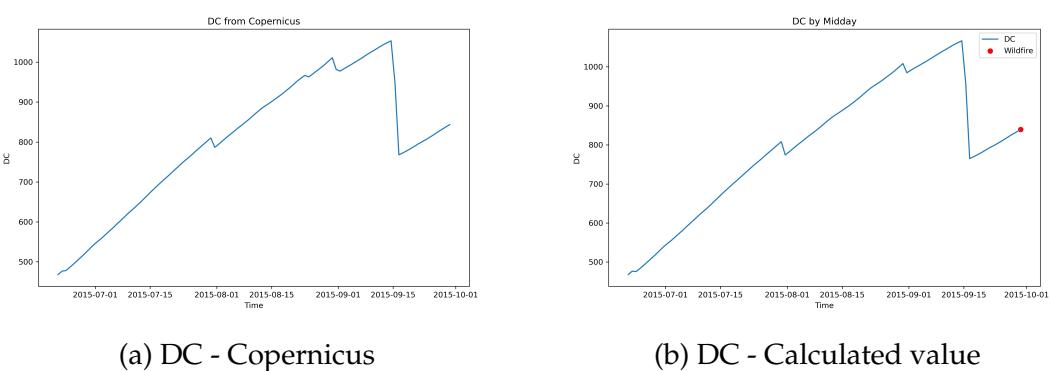


Figure 2.5: Comparison of ISI calculated values and Copernicus

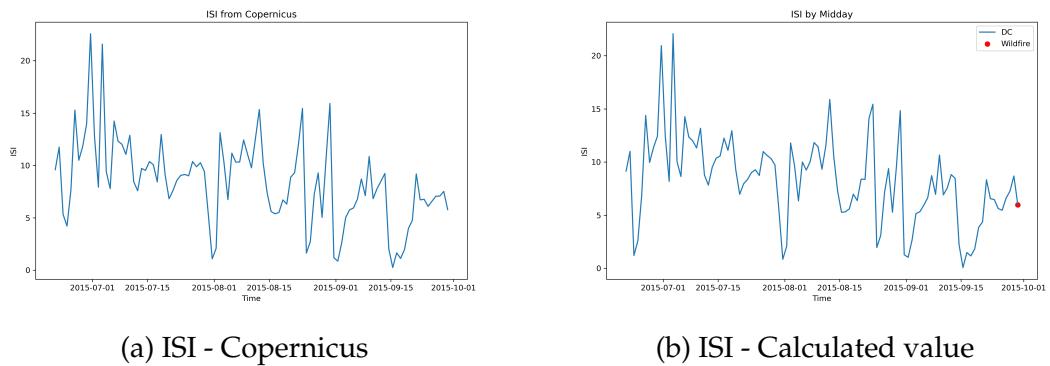
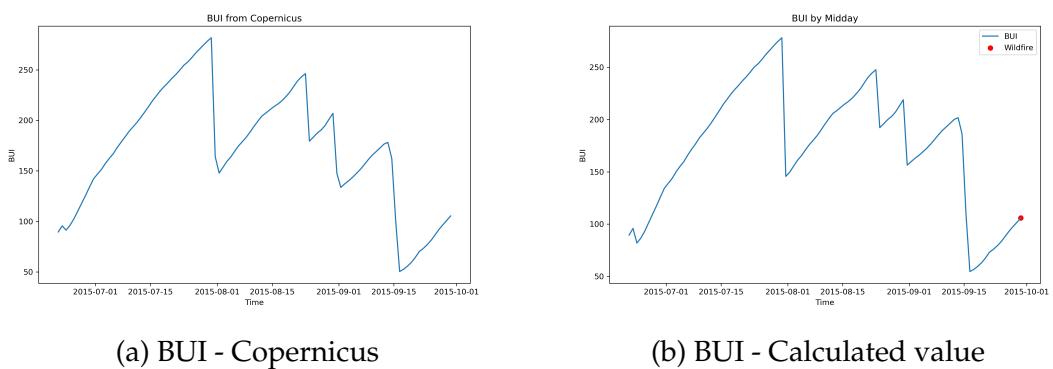


Figure 2.6: Comparison of BUI calculated values and Copernicus



## 2.4 Comparison of Copernicus and Simulated FWI

### 2.4.1 Fogo de 2015

Figure 2.7: Comparison of FWI calculated values and Copernicus at midday

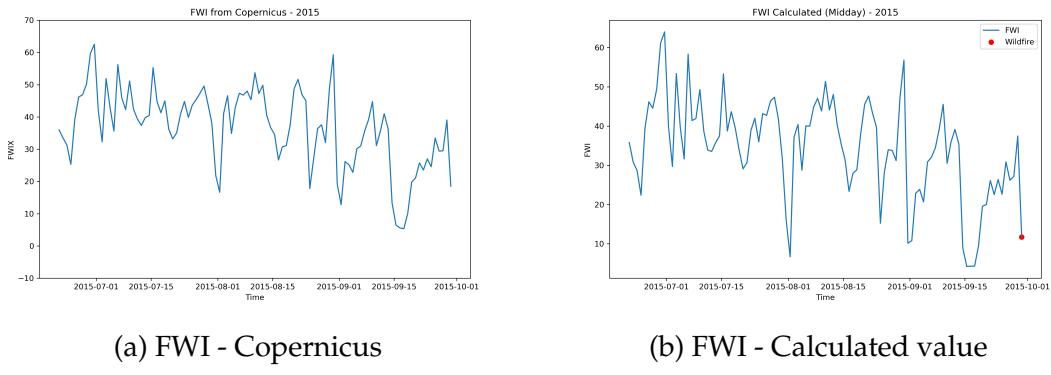


Figure 2.8: Comparison of FFMC calculated values and Copernicus at midday

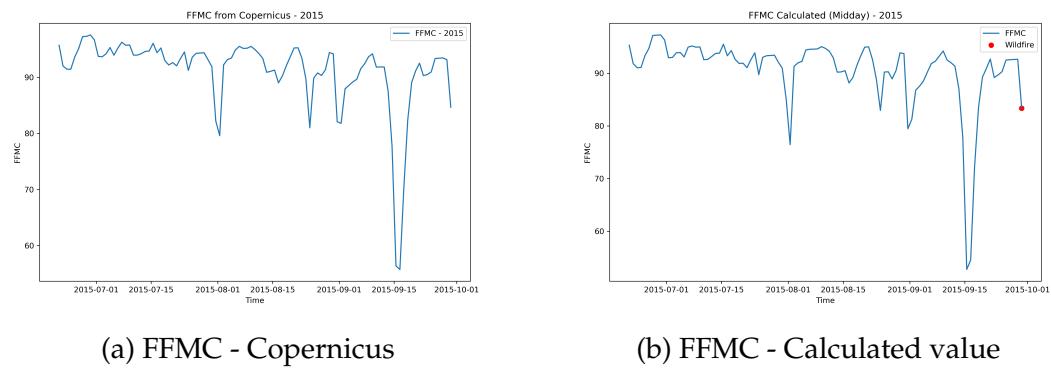


Figure 2.9: Comparison of DMC calculated values and Copernicus at midday

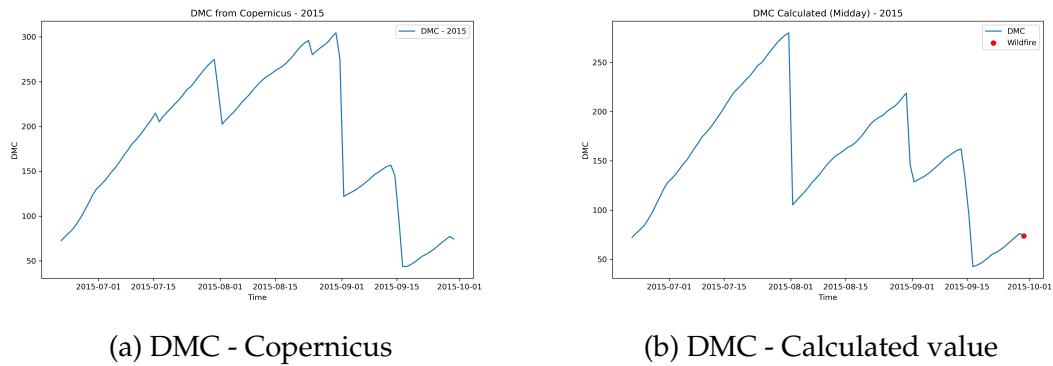


Figure 2.10: Comparison of DC calculated values and Copernicus at midday

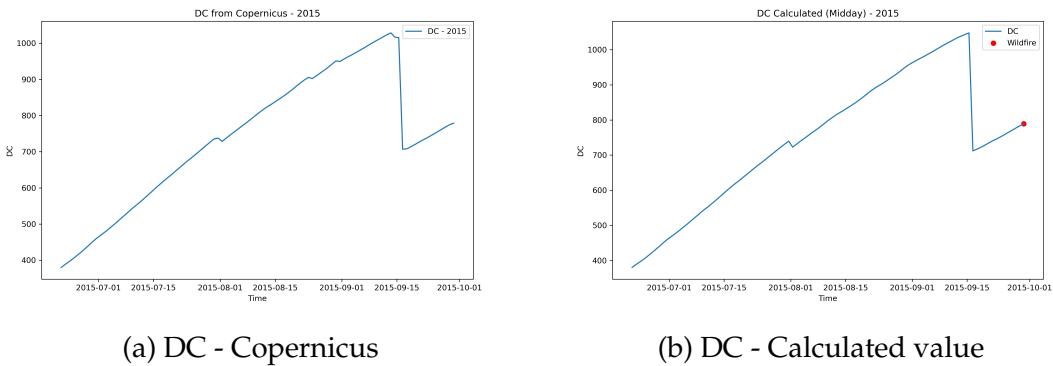


Figure 2.11: Comparison of ISI calculated values and Copernicus at midday

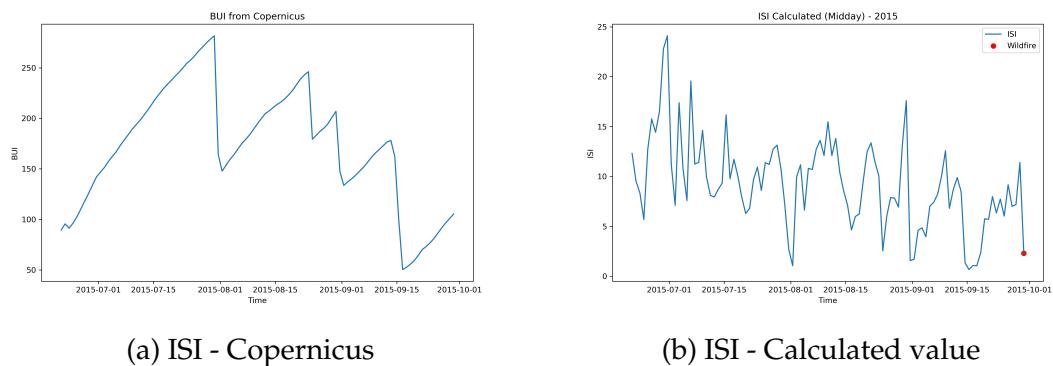
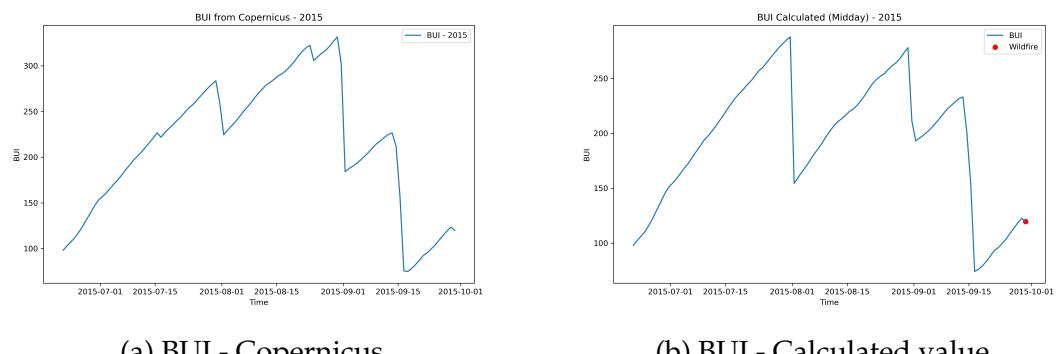
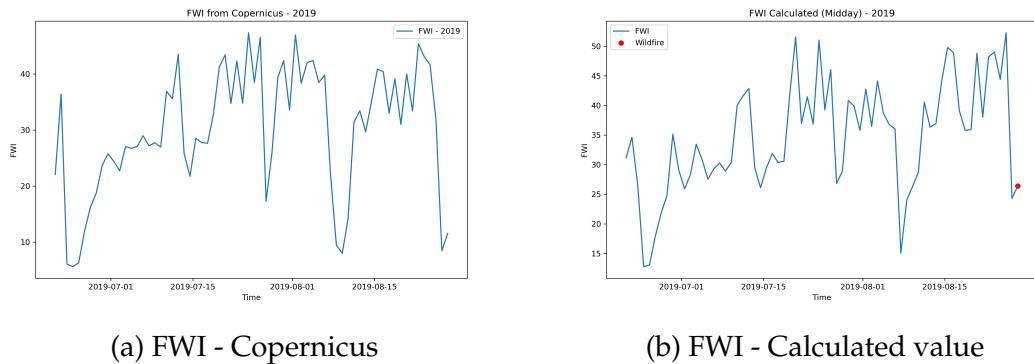


Figure 2.12: Comparison of BUI calculated values and Copernicus at midday



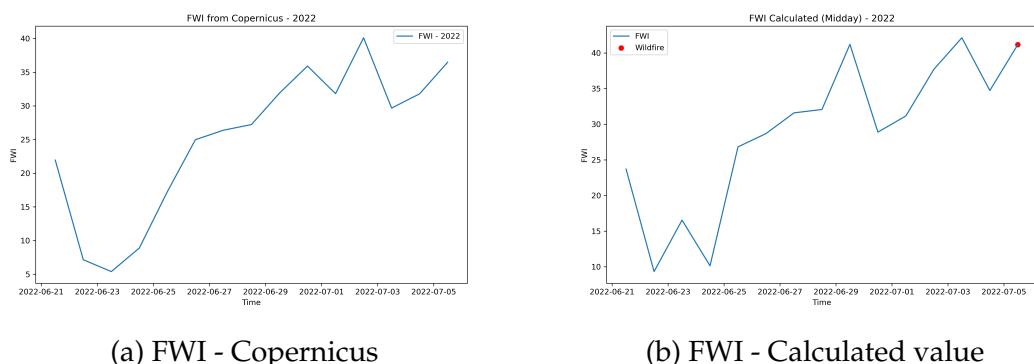
## 2.4.2 Fogo de 2019

Figure 2.13: Comparison of FWI calculated values and Copernicus at midday - 2019



## 2.4.3 Fogo de 2022

Figure 2.14: Comparison of FWI calculated values and Copernicus at midday - 2022



## 2.5 Hourly FWI variables

Figure 2.15: Calculated hourly FWI value for 2015, 2019, and 2022

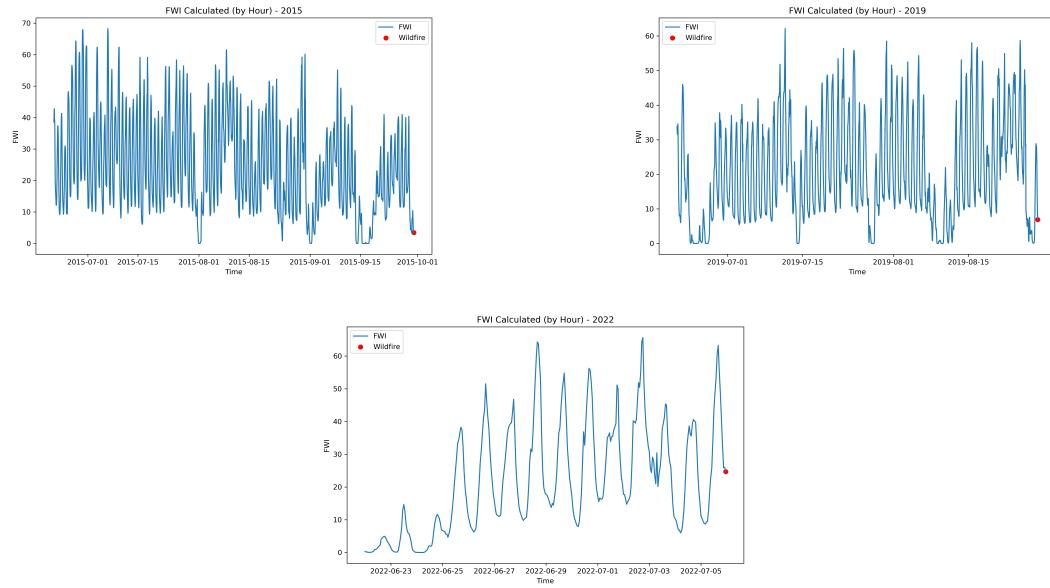


Figure 2.16: Calculated hourly FFMC value for 2015, 2019, and 2022

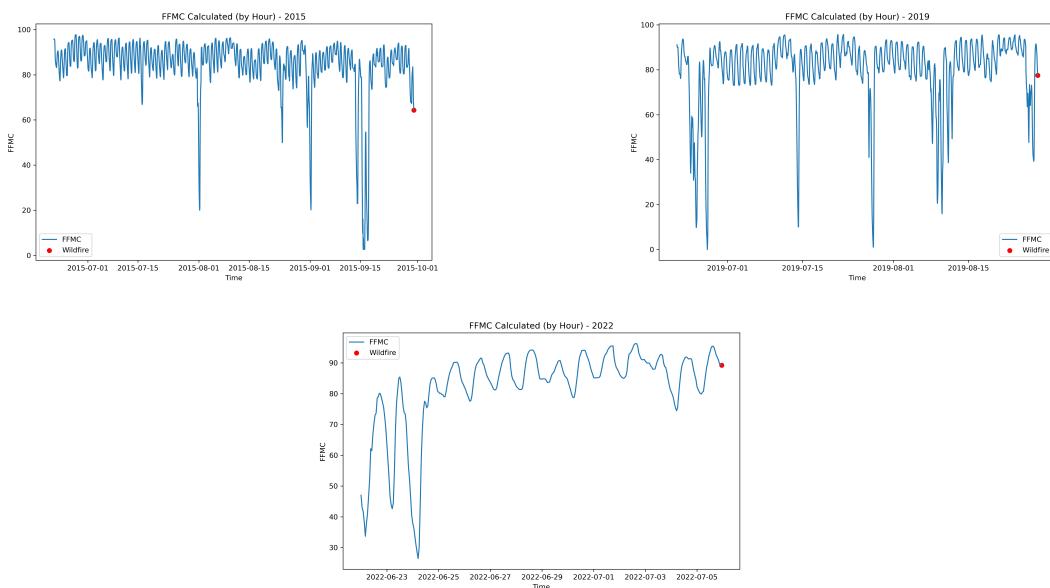


Figure 2.17: Calculated hourly DMC value for 2015, 2019, and 2022

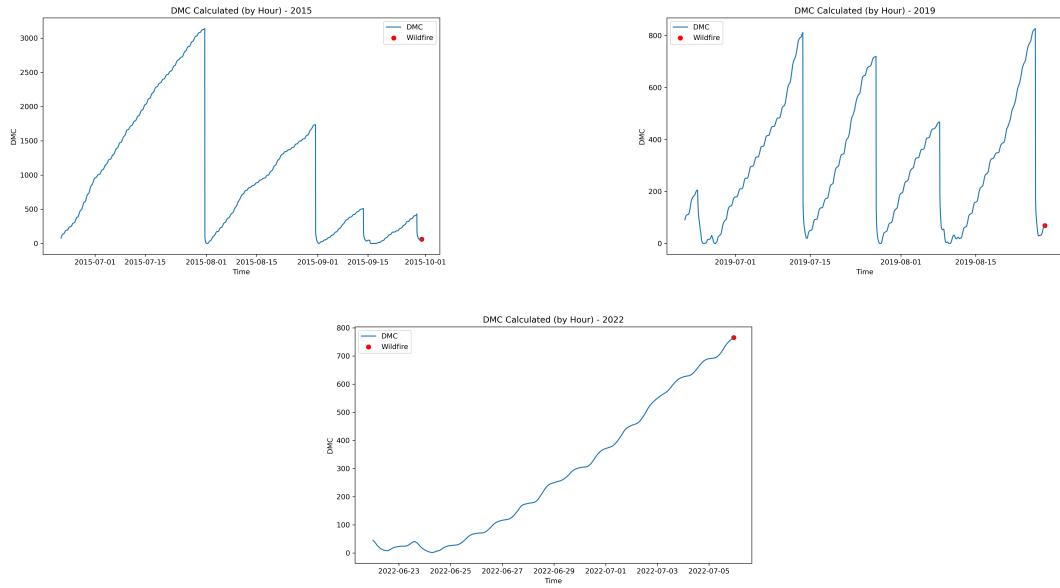


Figure 2.18: Calculated hourly DC value for 2015, 2019, and 2022

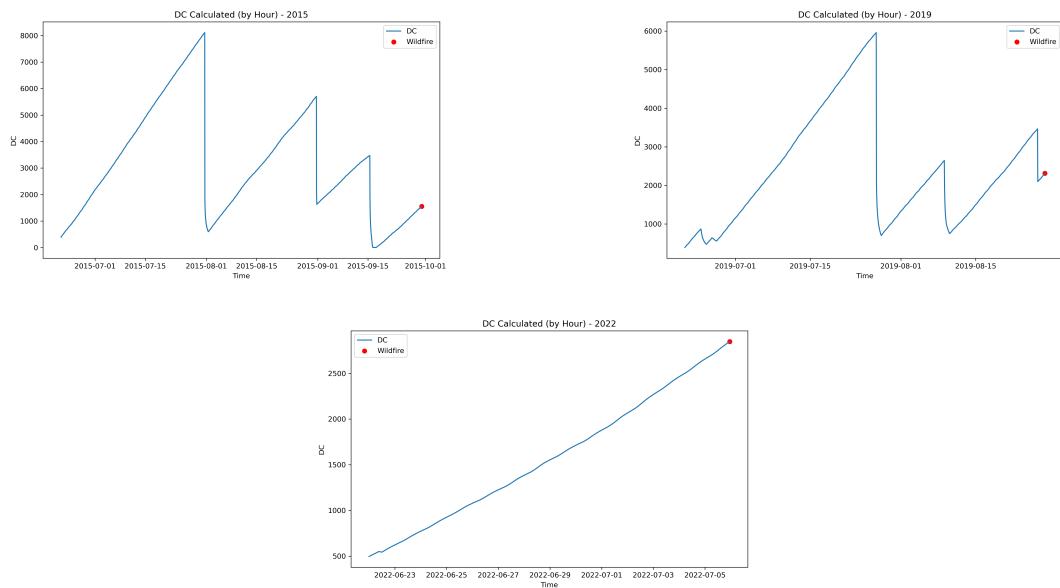


Figure 2.19: Calculated hourly ISI value for 2015, 2019, and 2022

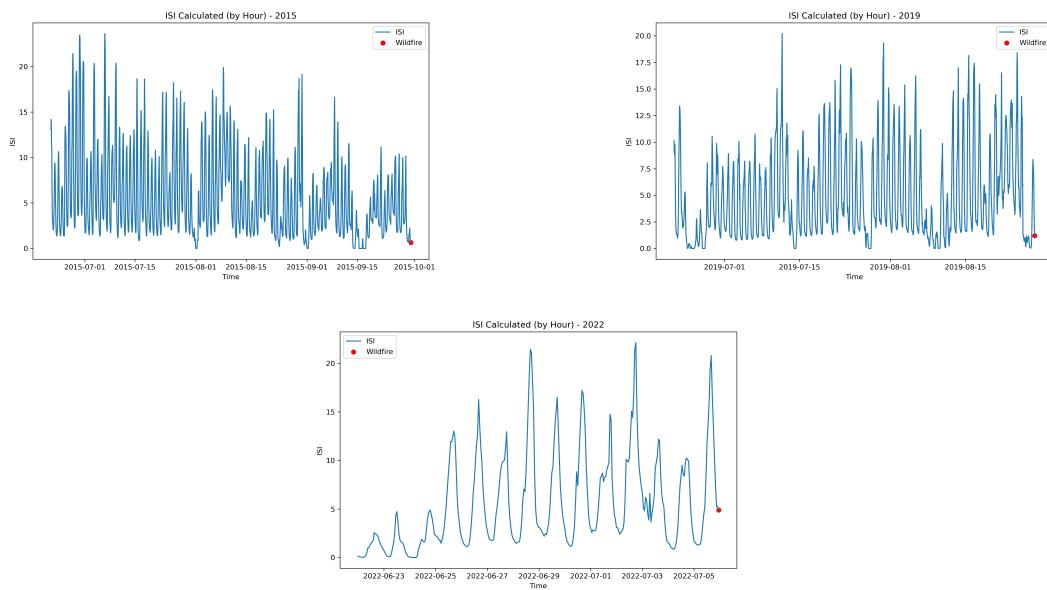
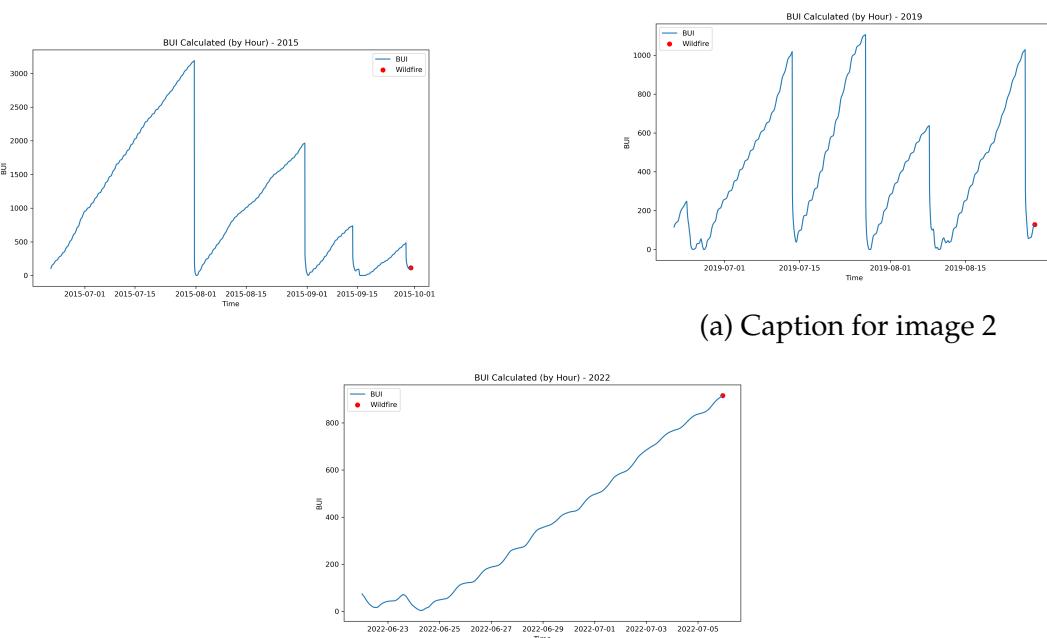


Figure 2.20: Calculated hourly BUI value for 2015, 2019, and 2022



(a) Caption for image 2

## 2.6 Evolution of maximum and minimum daily values of FWI variables

Figure 2.21: Daily max and min FWI values

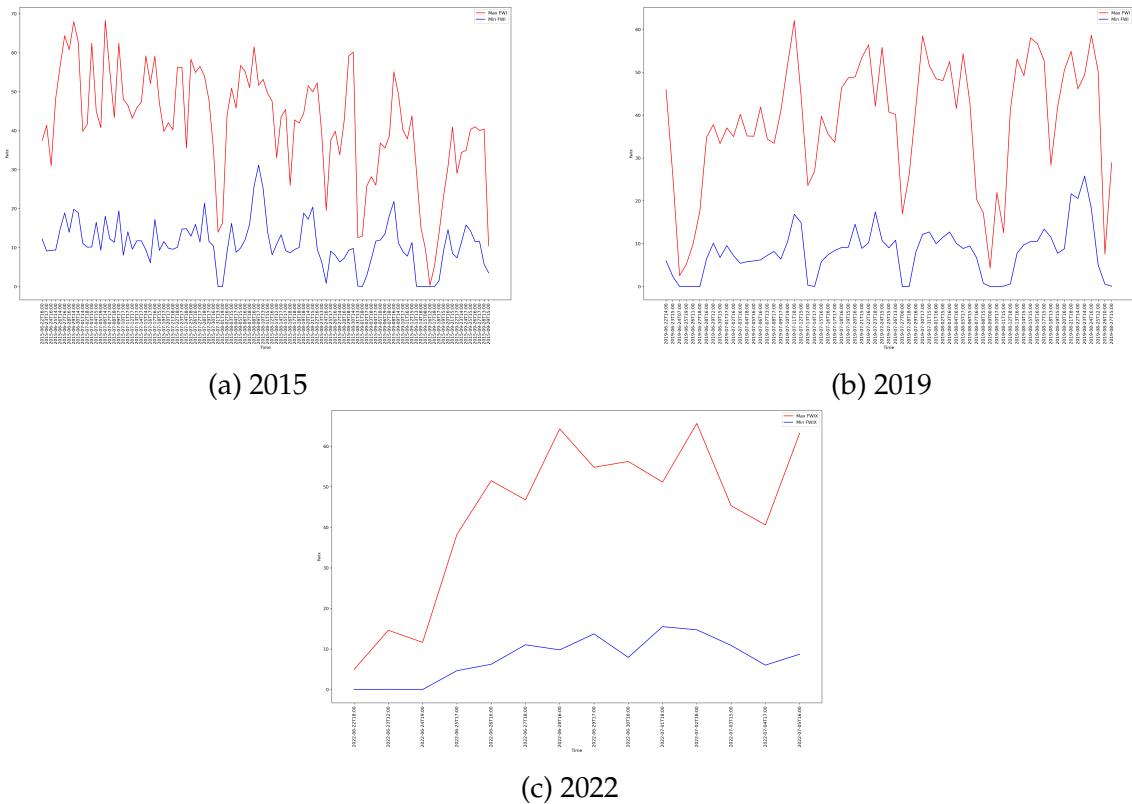


Figure 2.22: Daily max and min FFMC values

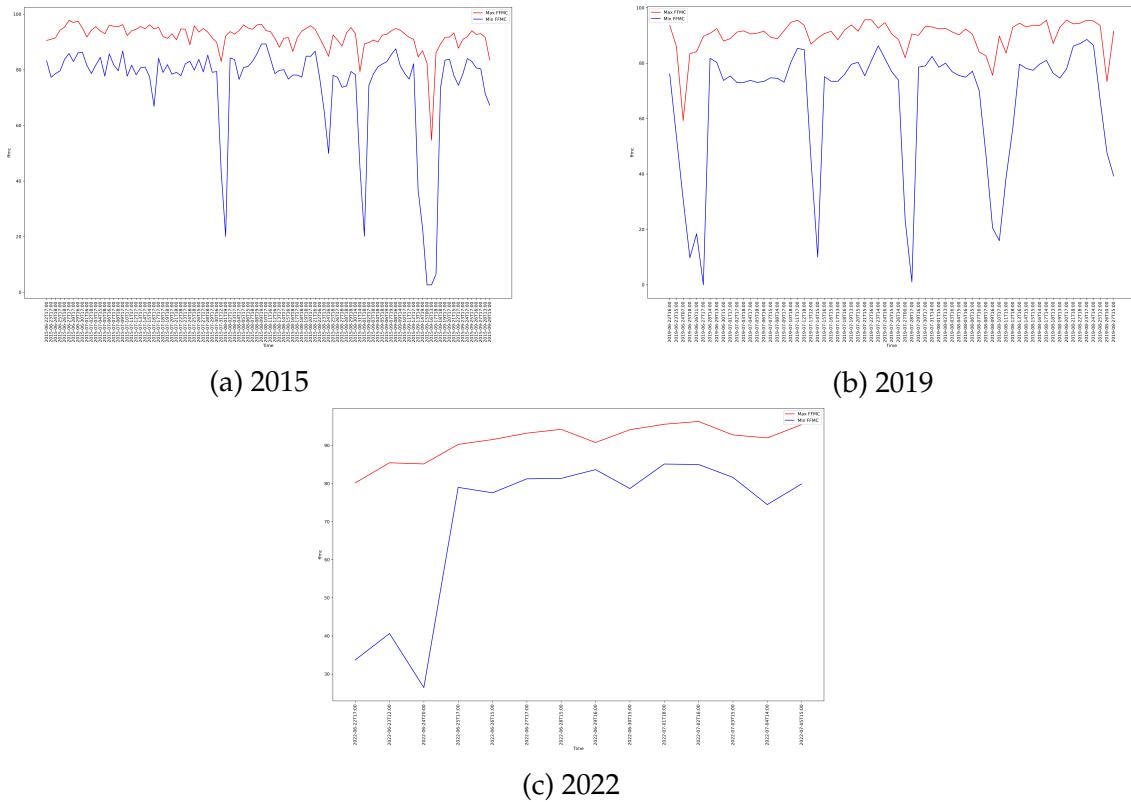


Figure 2.23: Daily max and min DMC values

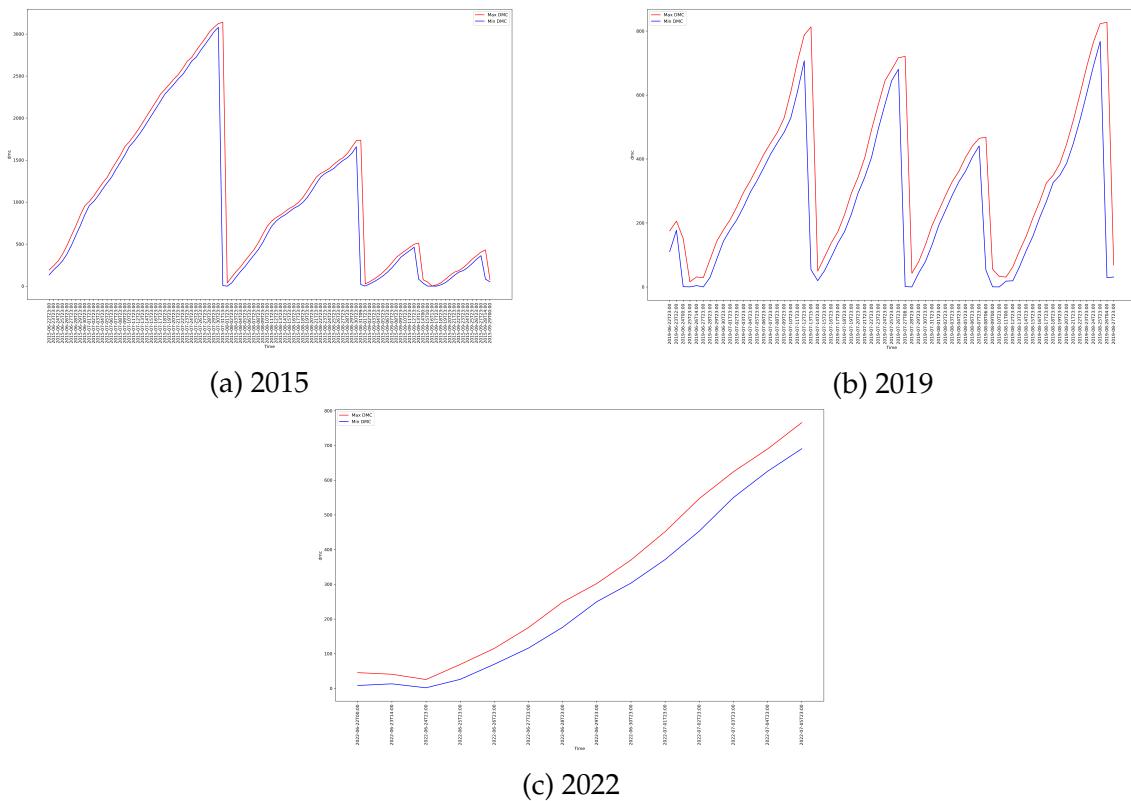


Figure 2.24: Daily max and min DC values

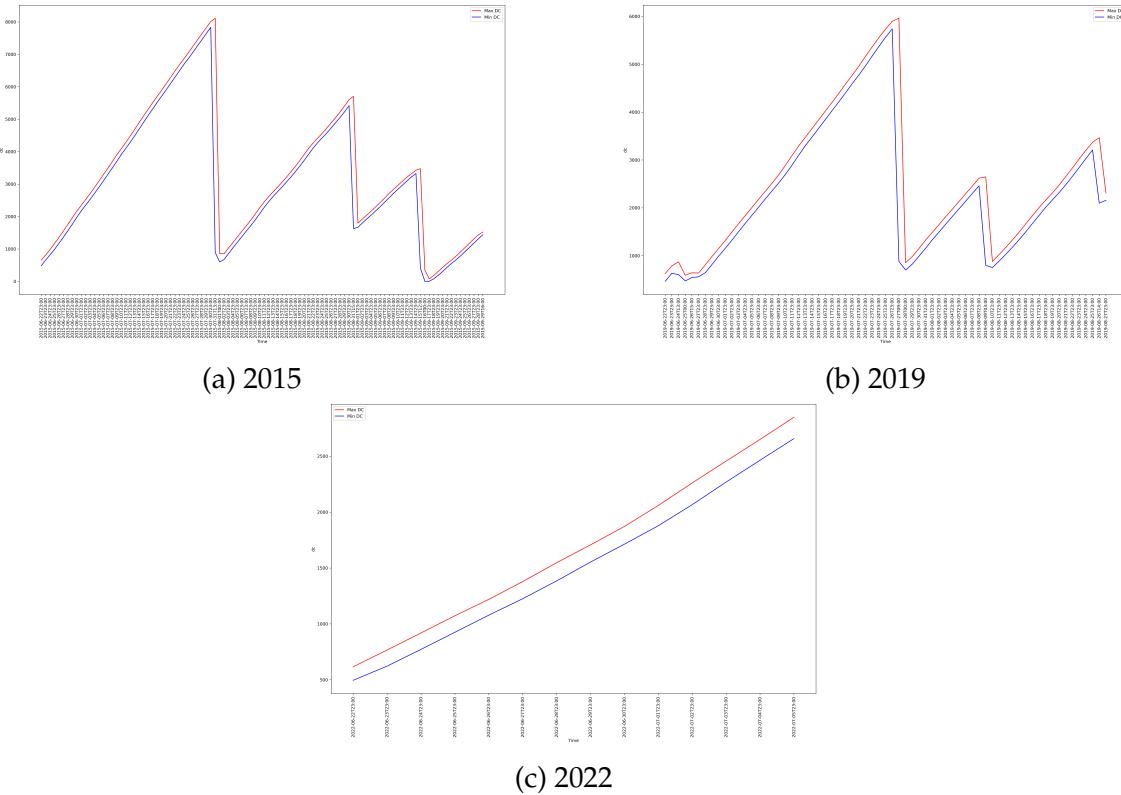


Figure 2.25: Daily max and min ISI values

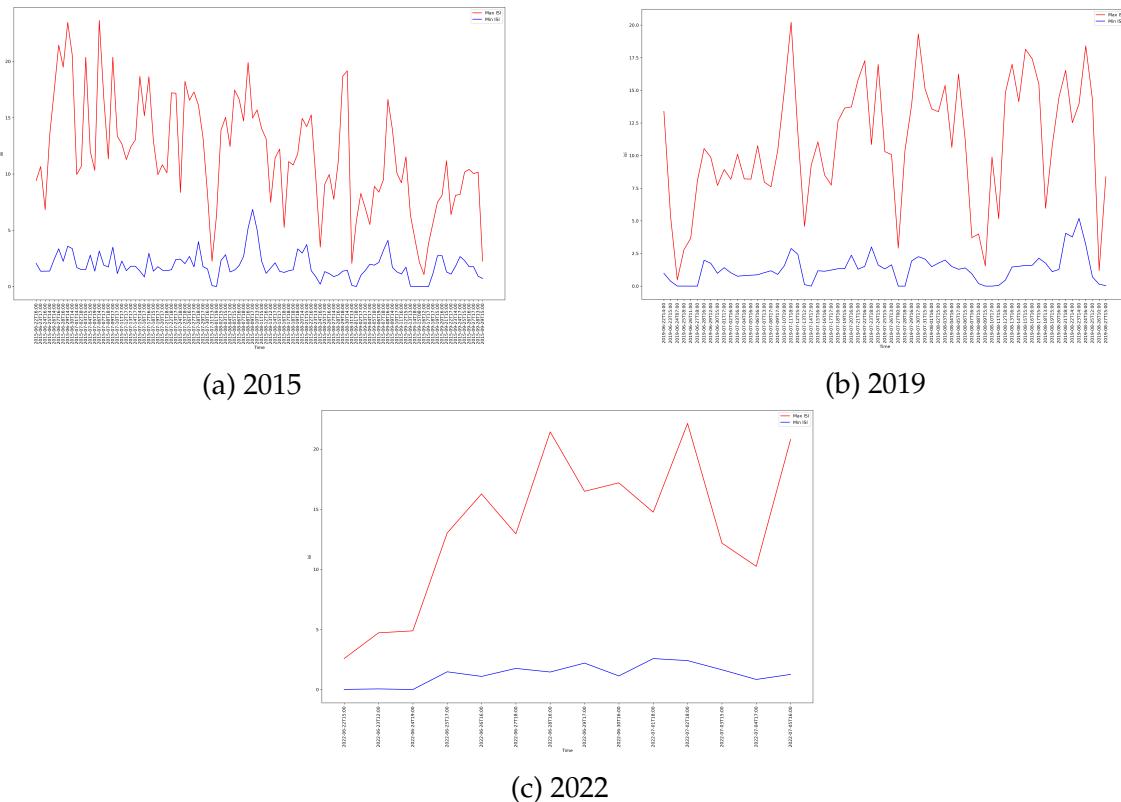
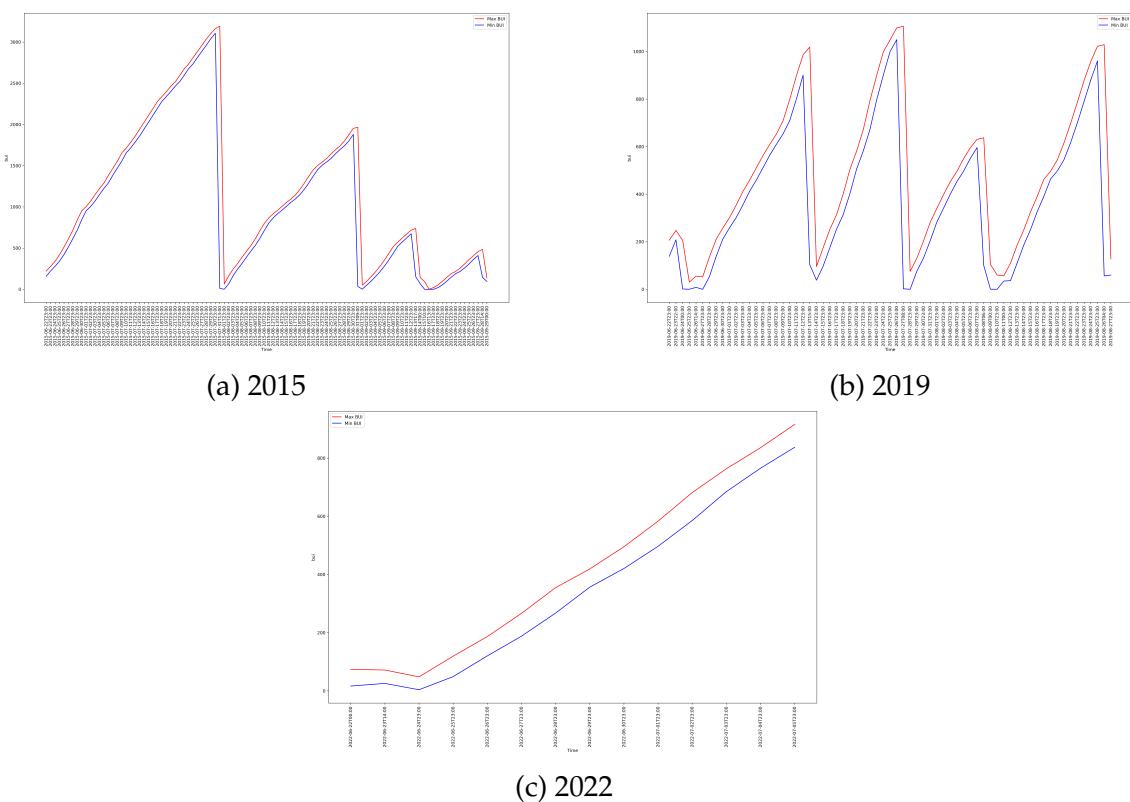


Figure 2.26: Daily max and min BUI values



## 2.7 Before, after and daily maximum value

Figure 2.27: Before, after and daily FWI maximum value

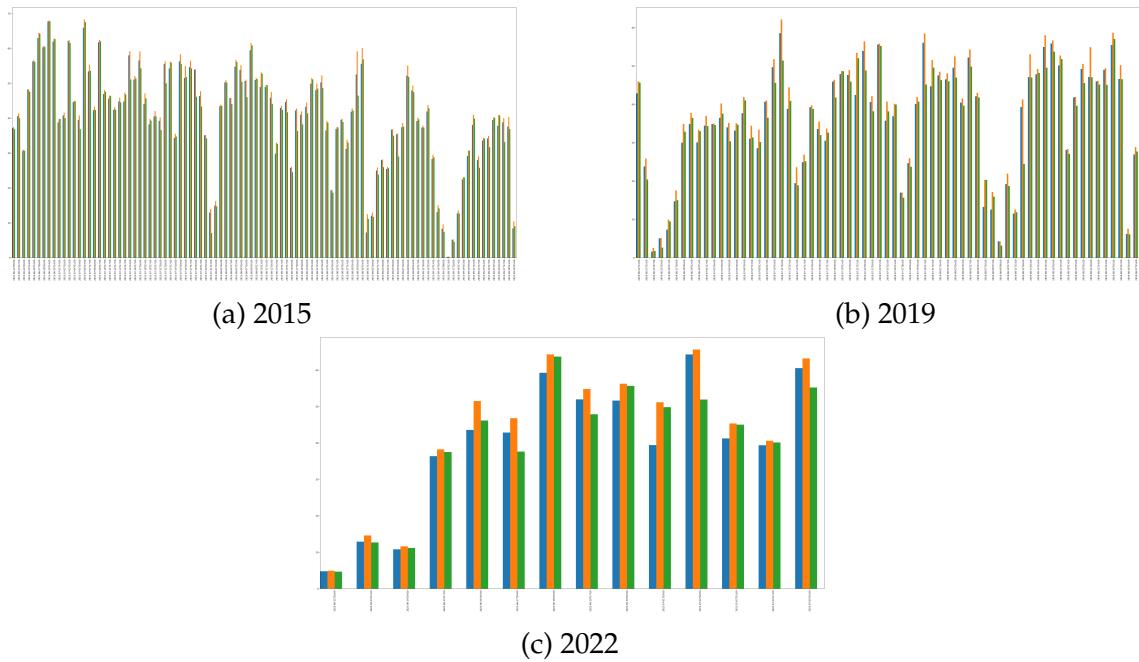


Figure 2.28: Before, after and daily FFMC maximum value

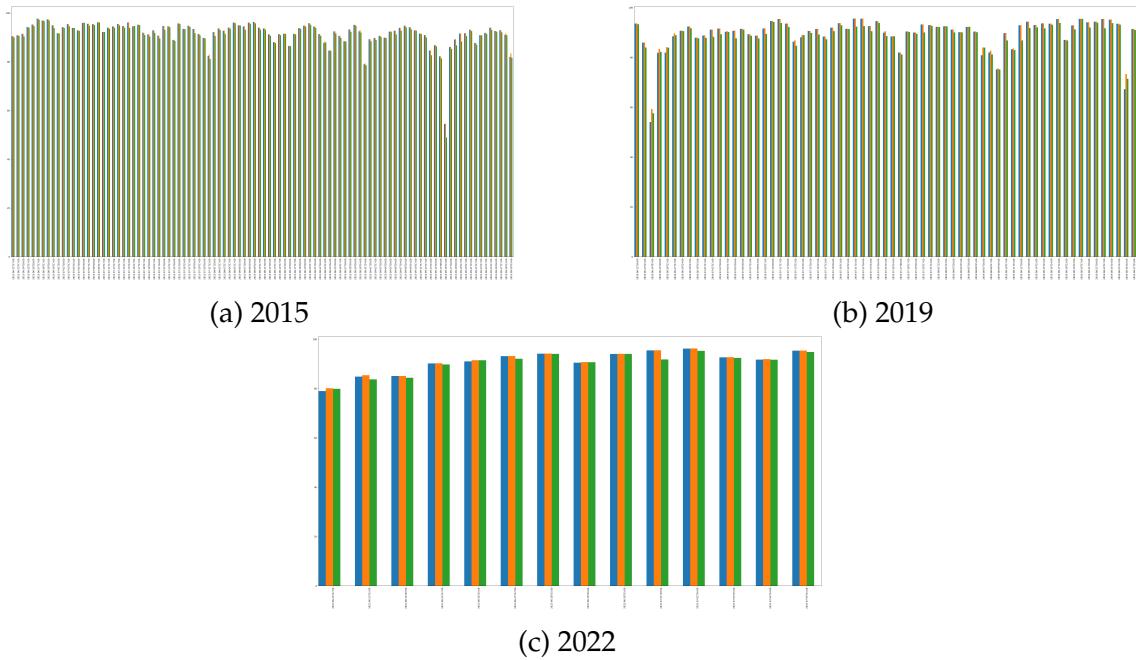


Figure 2.29: Before, after and daily DMC maximum value

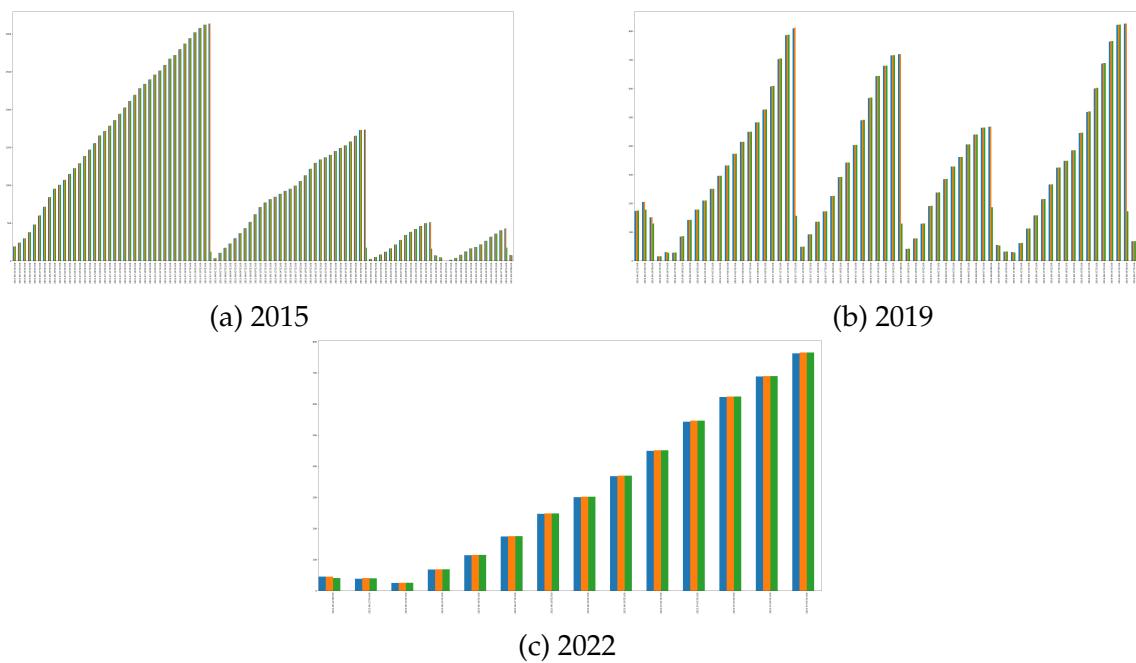


Figure 2.30: Before, after and daily DC maximum value

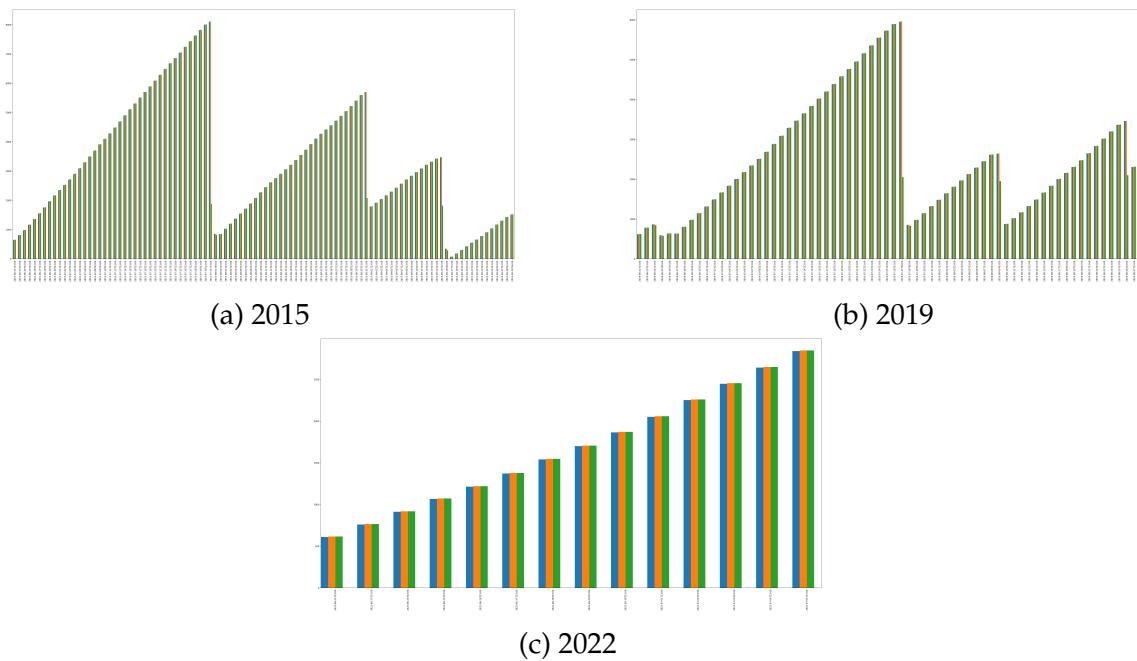


Figure 2.31: Before, after and daily ISI maximum value

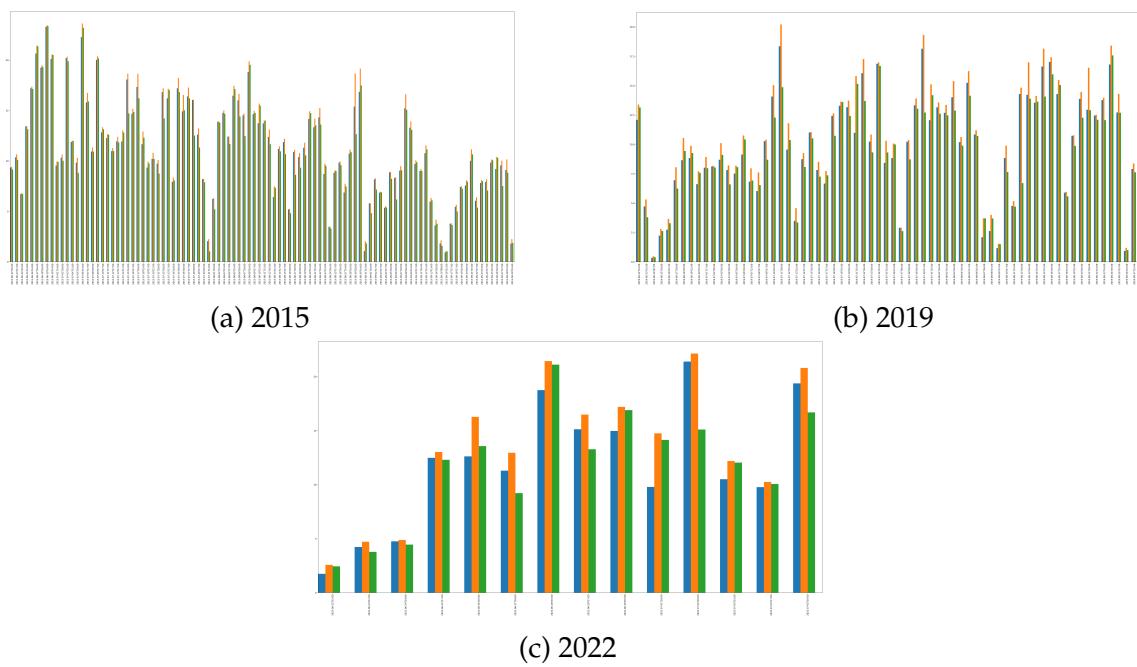
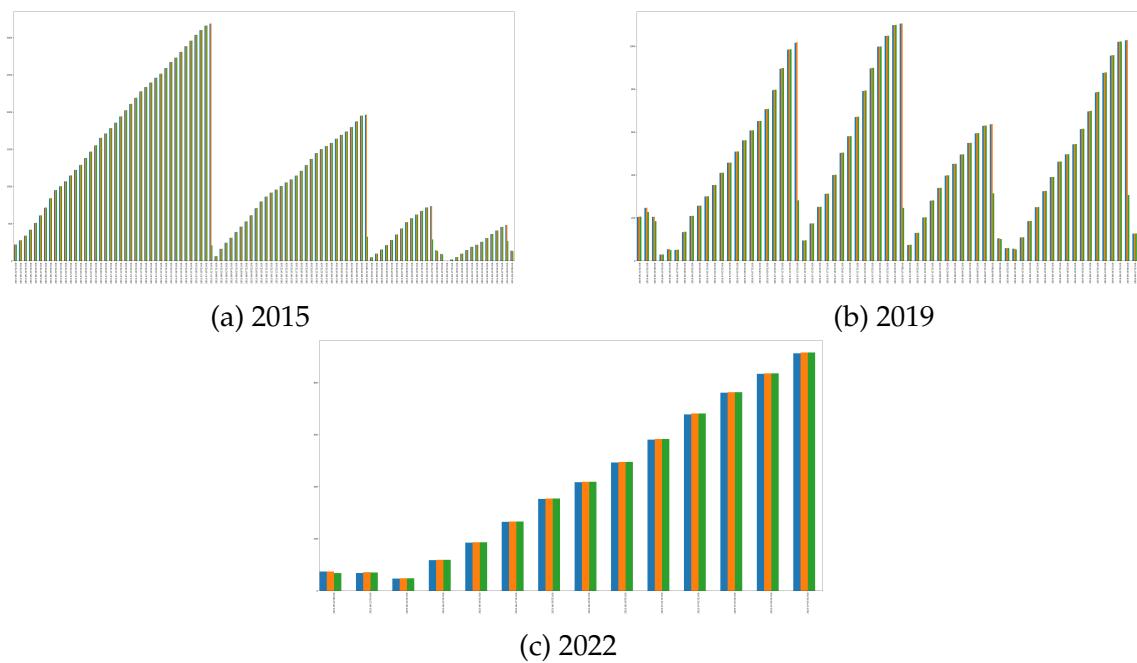


Figure 2.32: Before, after and daily BUI maximum value



## 2.8 Difference between the daily maximum and minimum values of the FWI variables

Figure 2.33: Daily difference of max and min FWI values

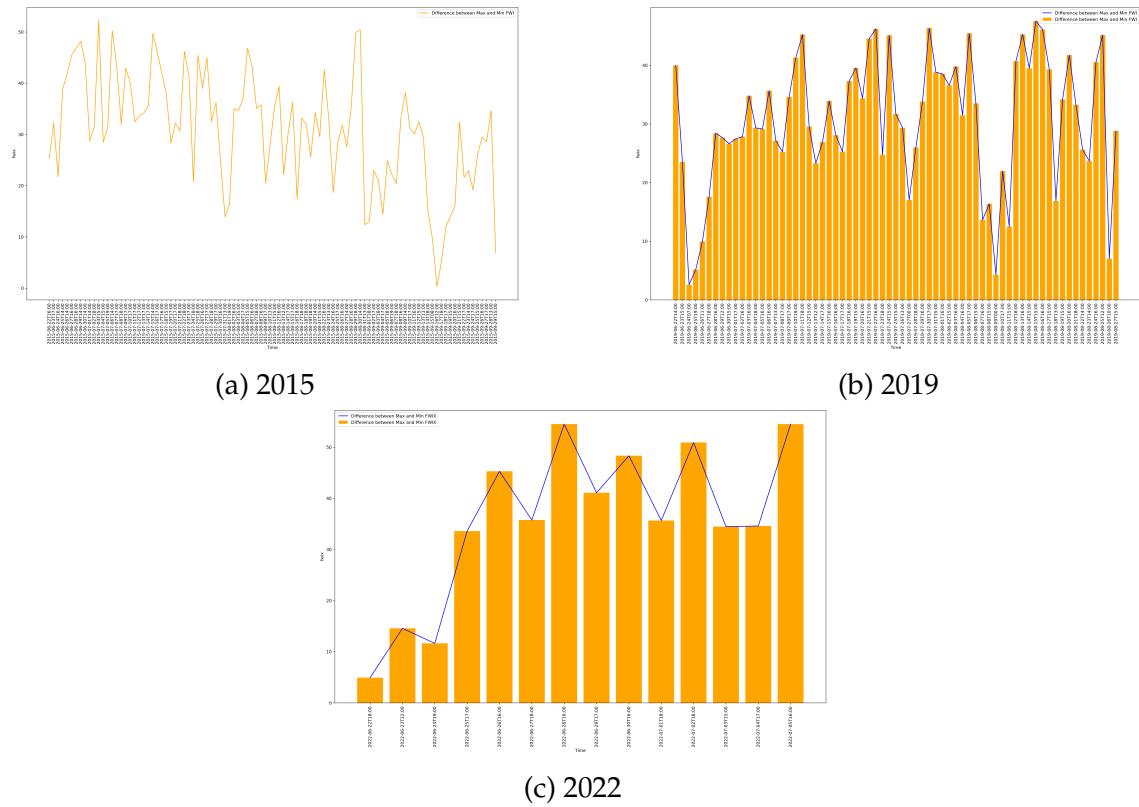


Figure 2.34: Daily difference of max and min FFMC values

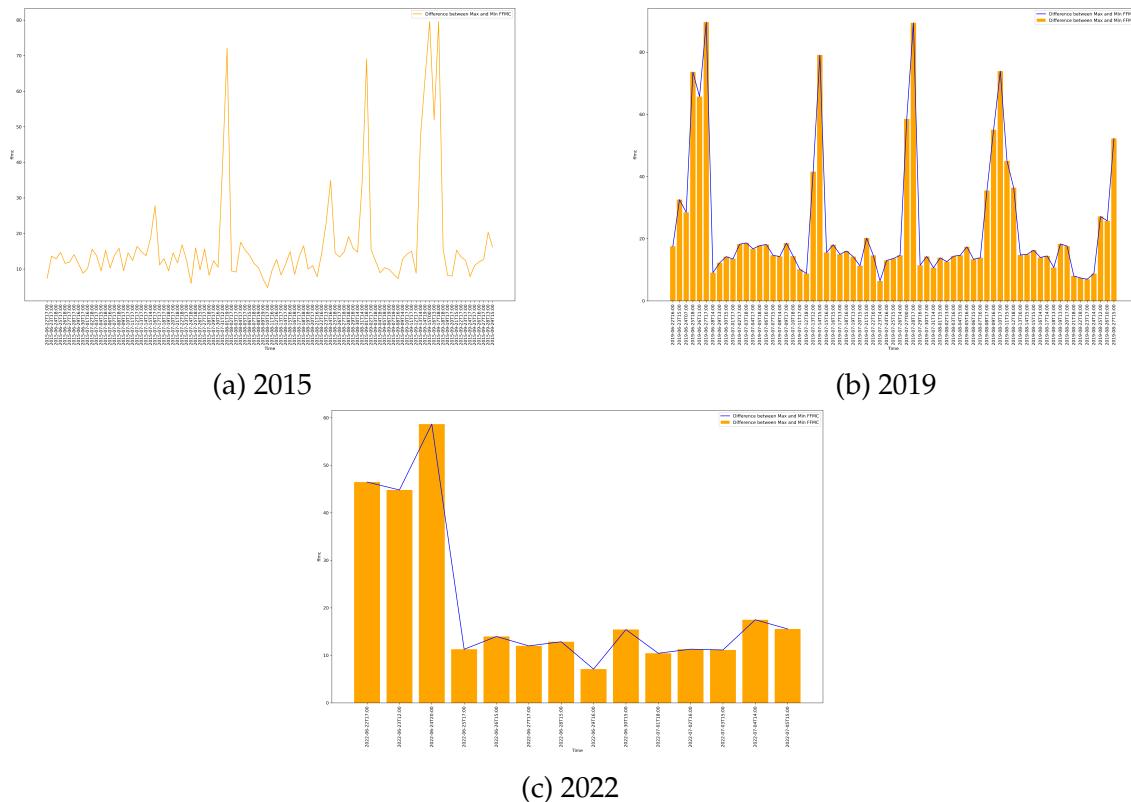


Figure 2.35: Daily difference of max and min DMC values

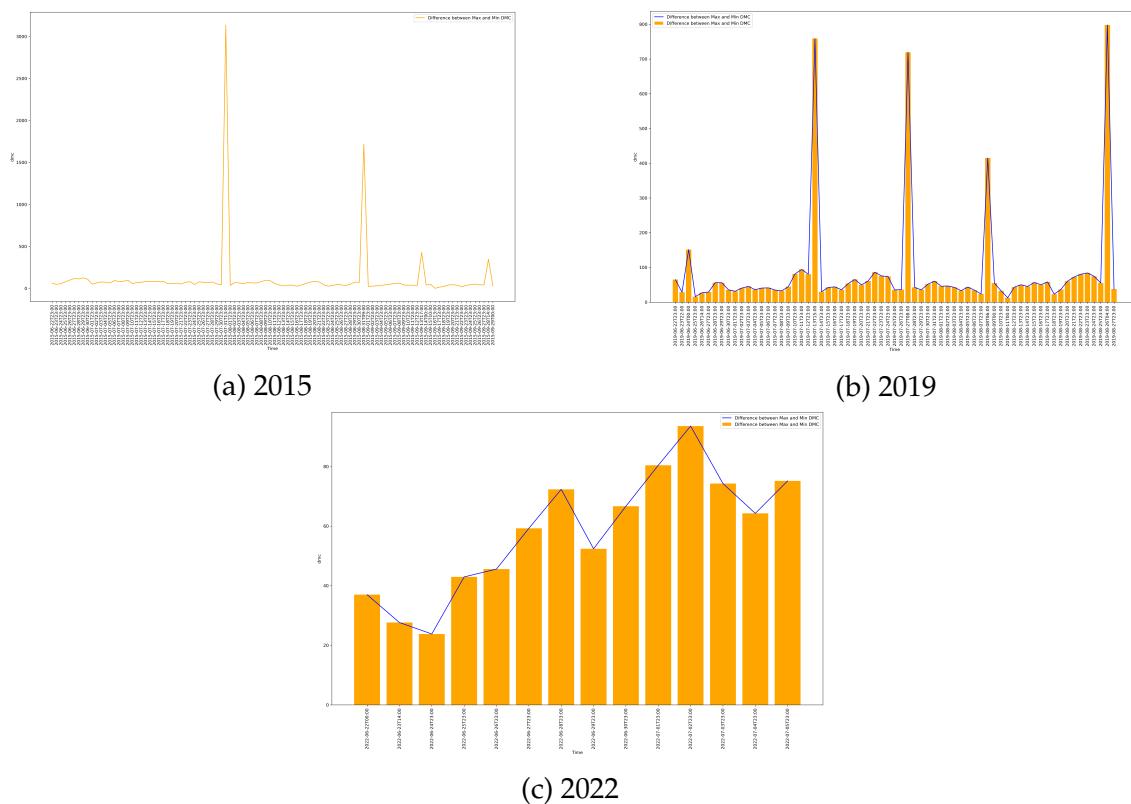


Figure 2.36: Daily difference of max and min DC values

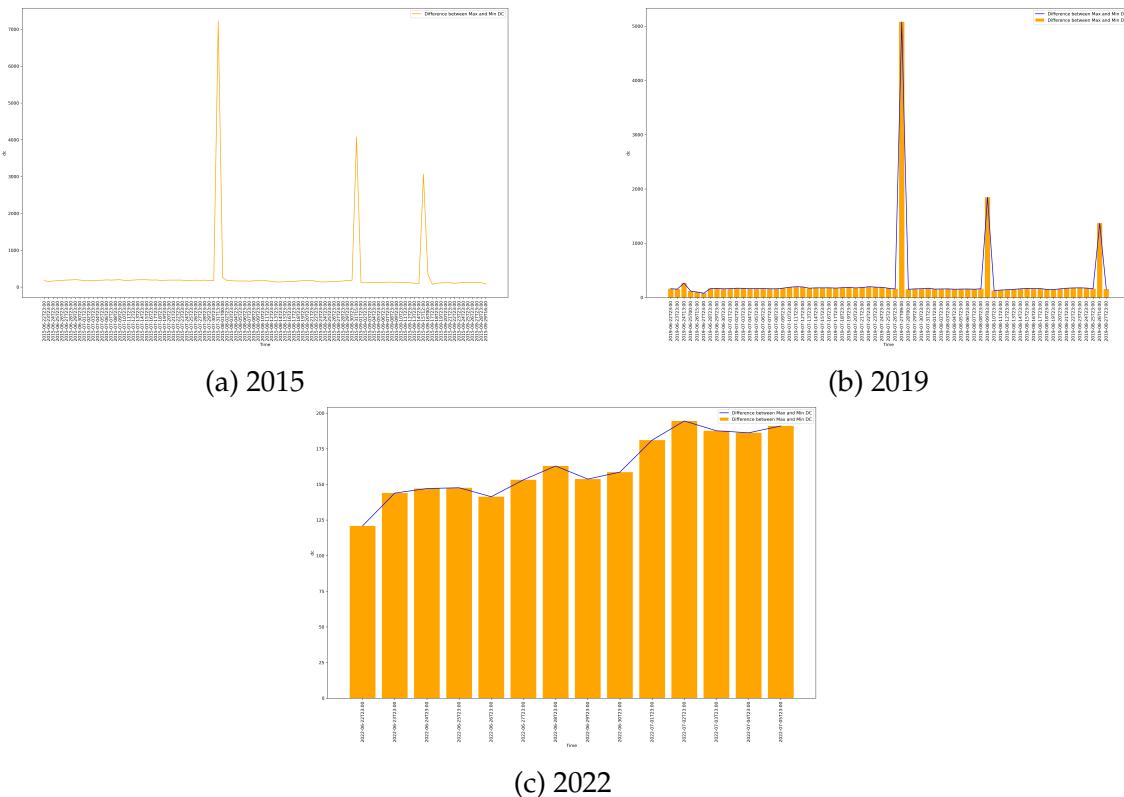


Figure 2.37: Daily difference of max and min ISI values

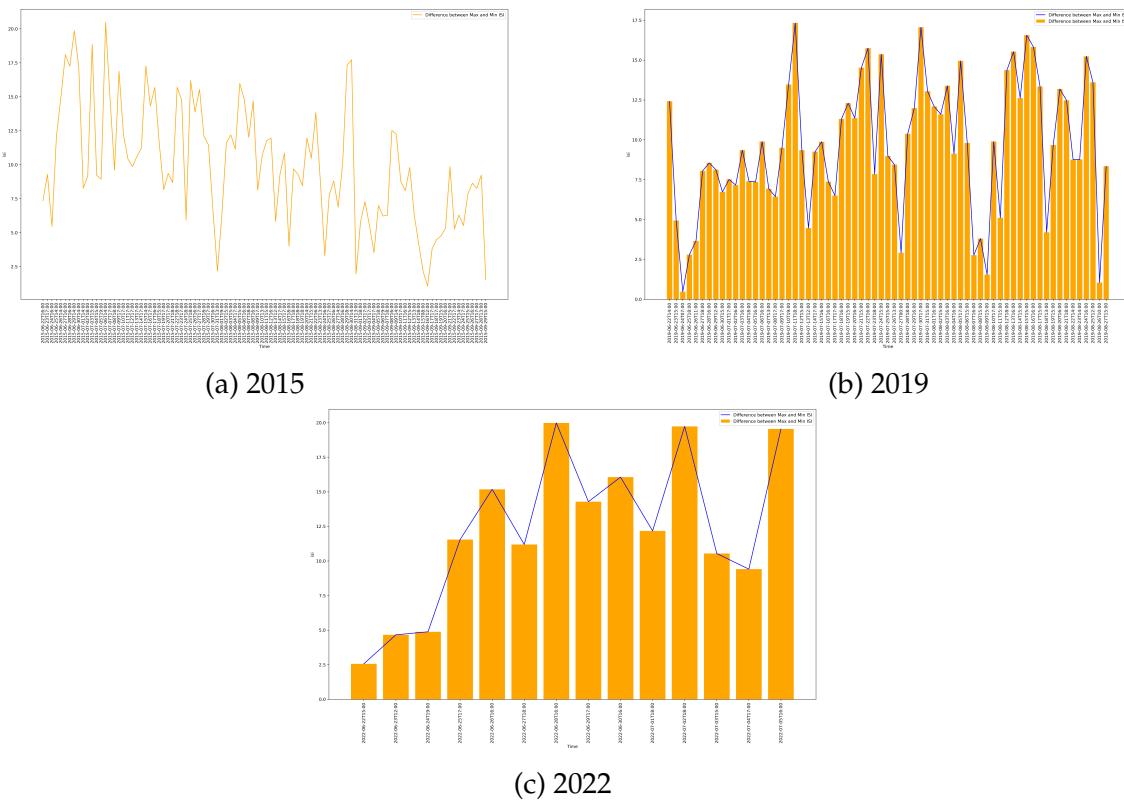
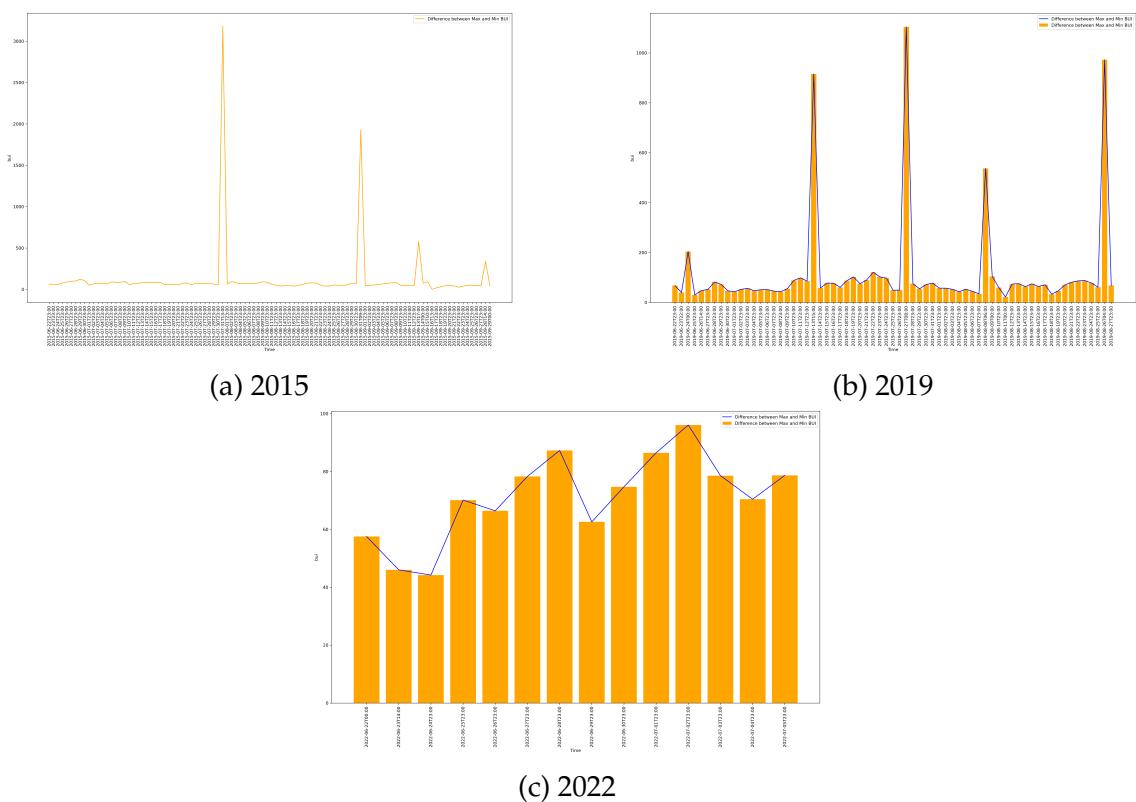


Figure 2.38: Daily difference of max and min BUI values



## 2.9 3-day time frame mean block tendency graphs of FWI variables

Figure 2.39: FWI mean tendency graph

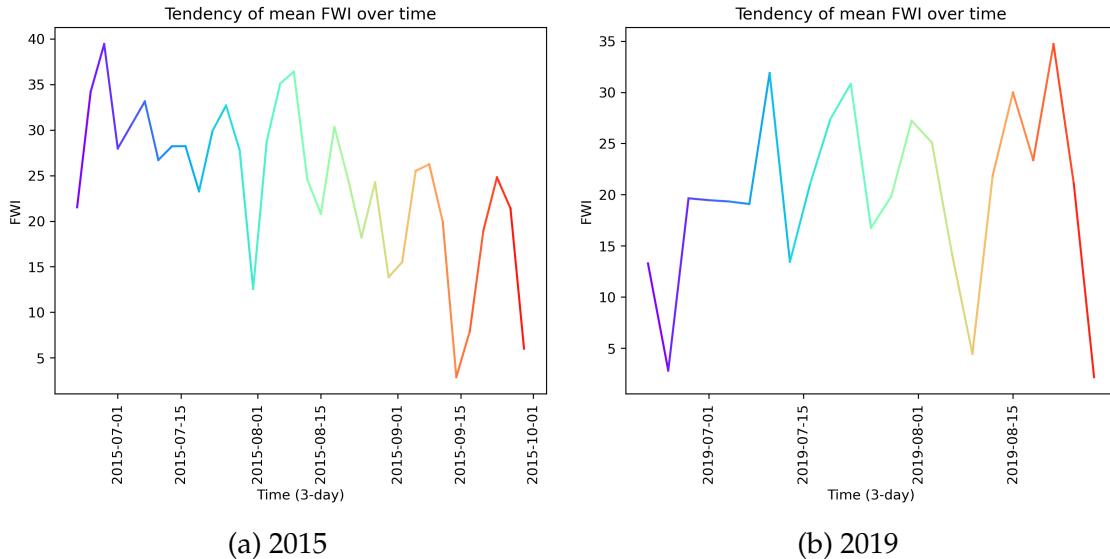


Figure 2.40: FFMC mean tendency graph

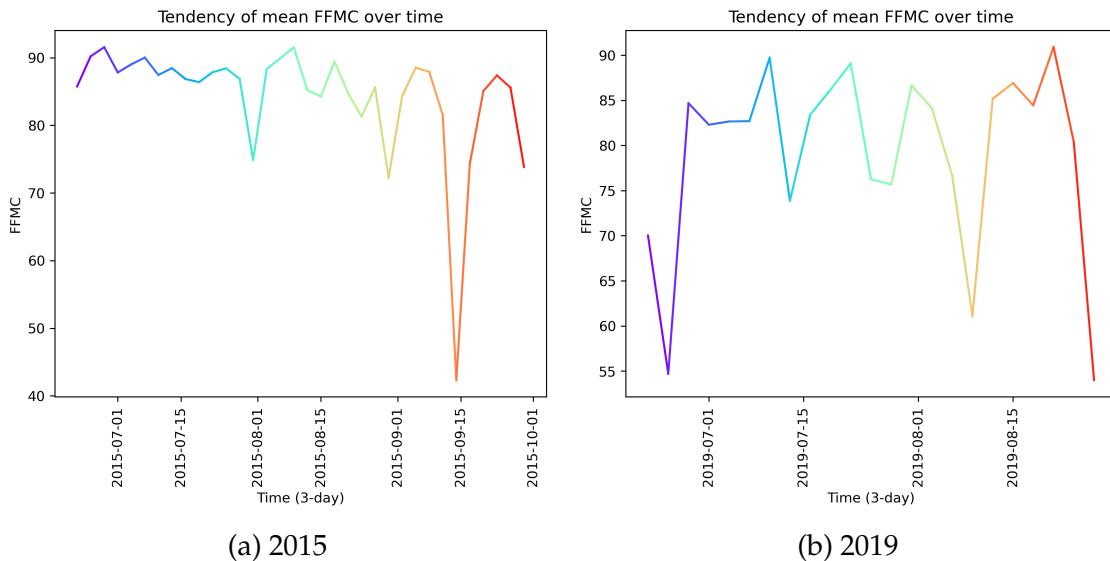


Figure 2.41: DMC mean tendency graph

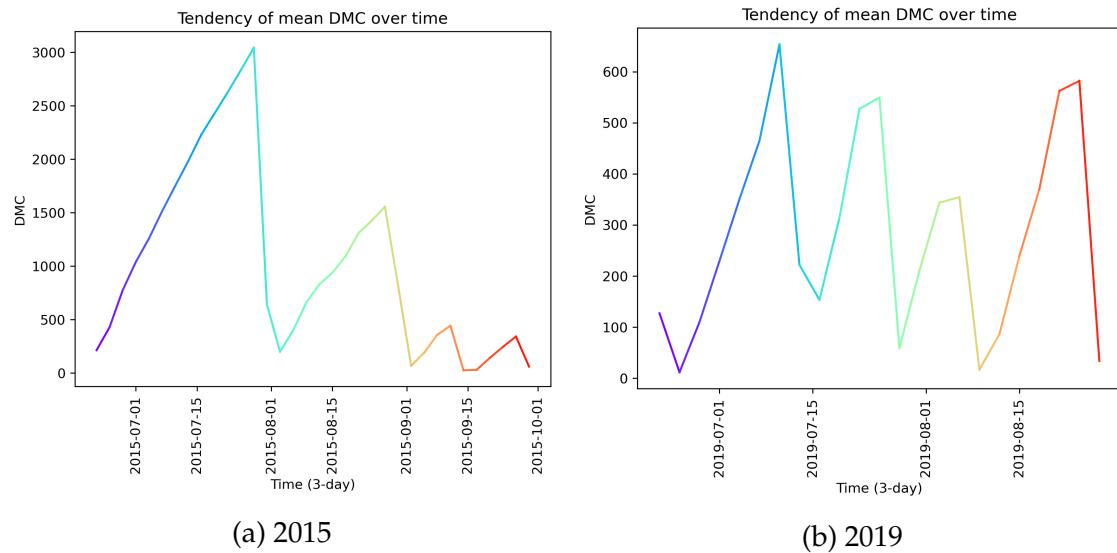


Figure 2.42: DC mean tendency graph

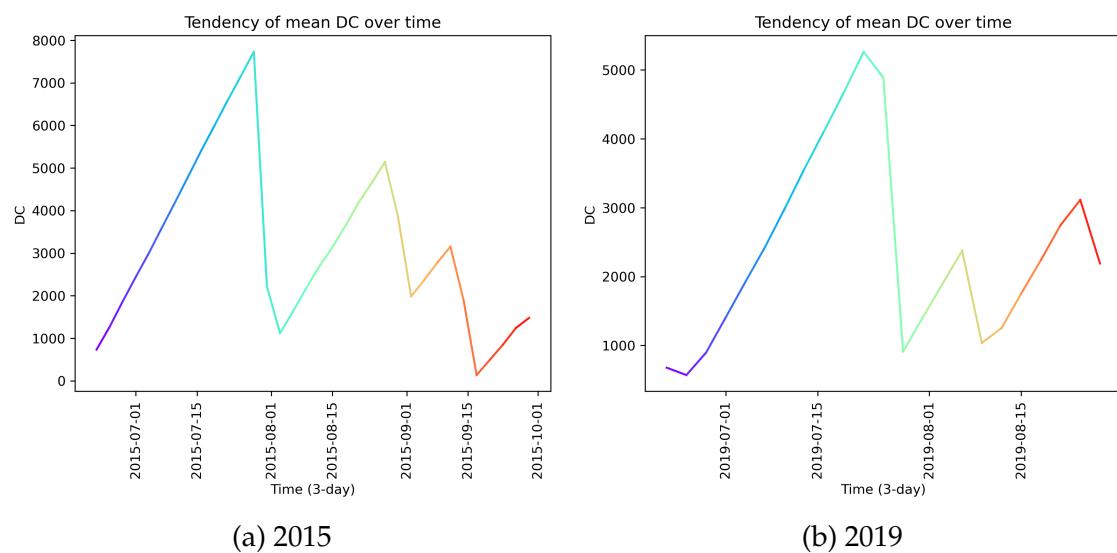


Figure 2.43: ISI mean tendency graph

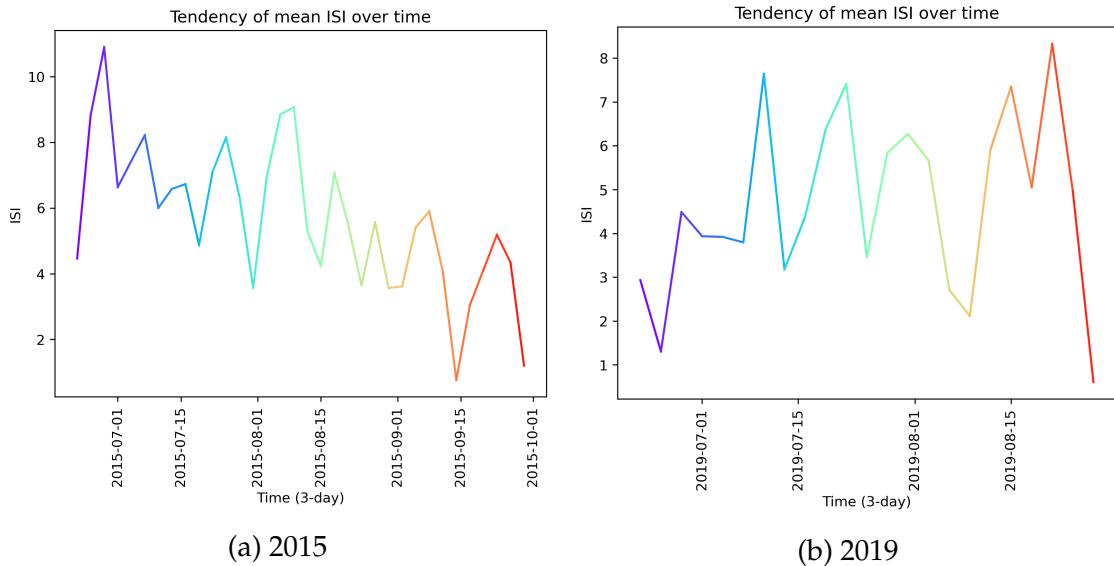
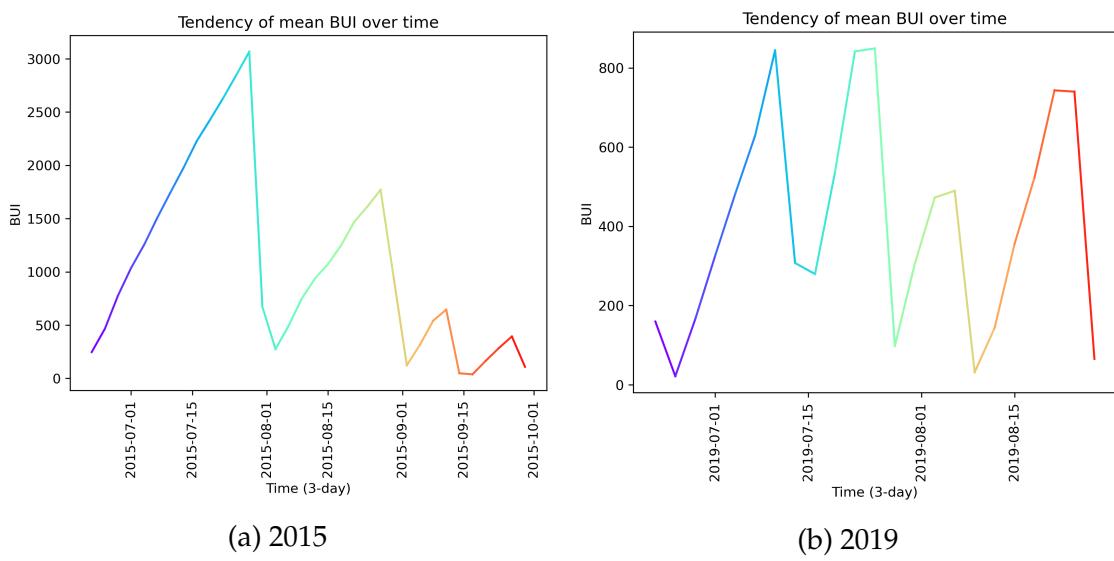


Figure 2.44: BUI mean tendency graph



## 2.10 Comparison of mean FWI variables 15 days prior to the wildfire

Figure 2.45: FWI values 15 days prior to wildfire

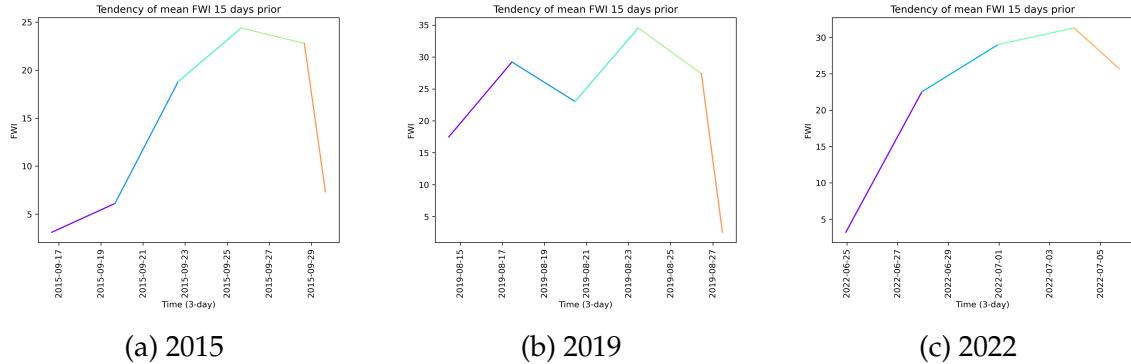


Figure 2.46: FFMC values 15 days prior to wildfire

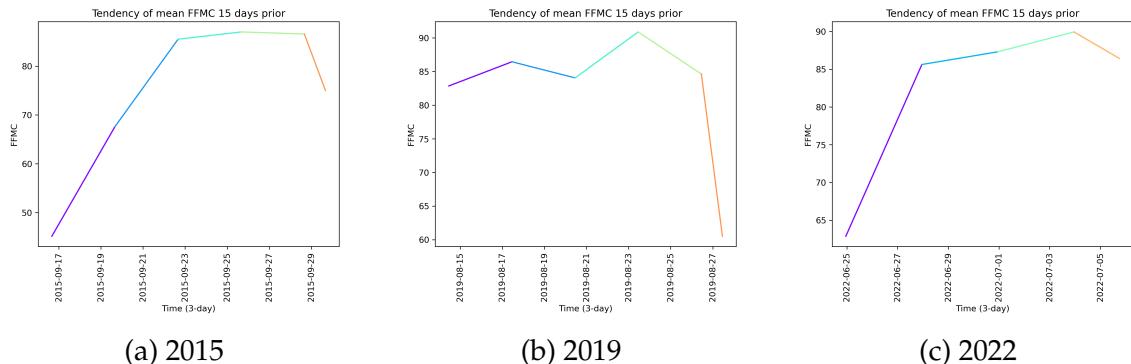


Figure 2.47: DMC values 15 days prior to wildfire

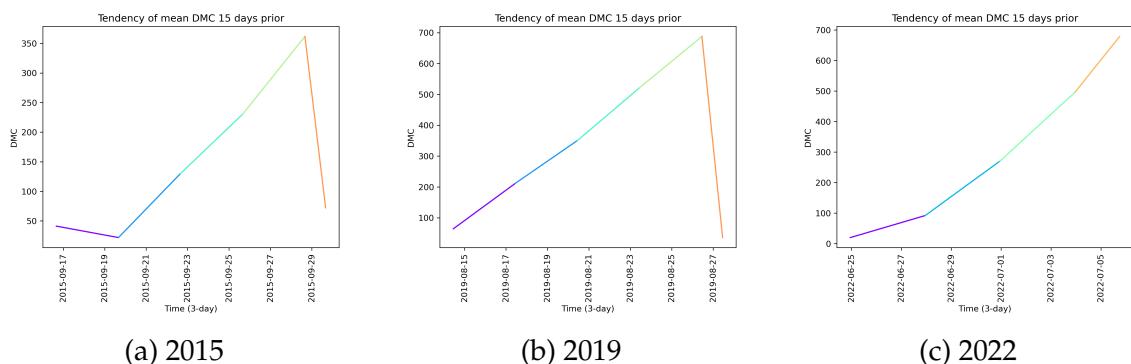


Figure 2.48: DC values 15 days prior to wildfire

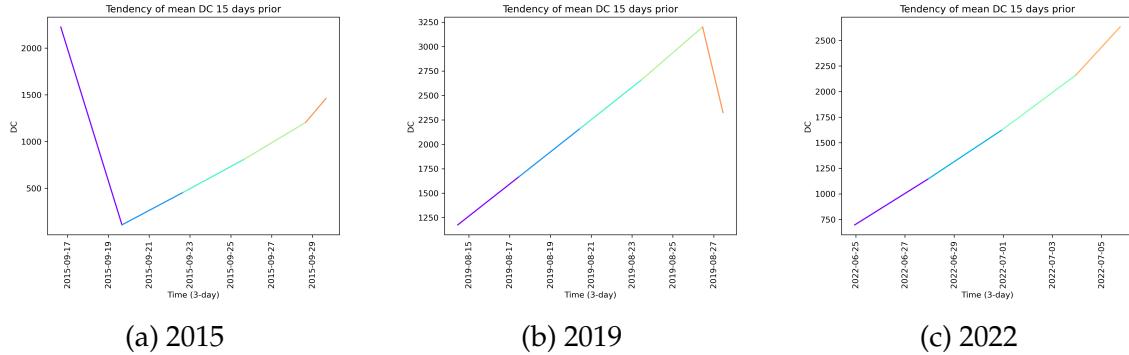


Figure 2.49: ISI values 15 days prior to wildfire

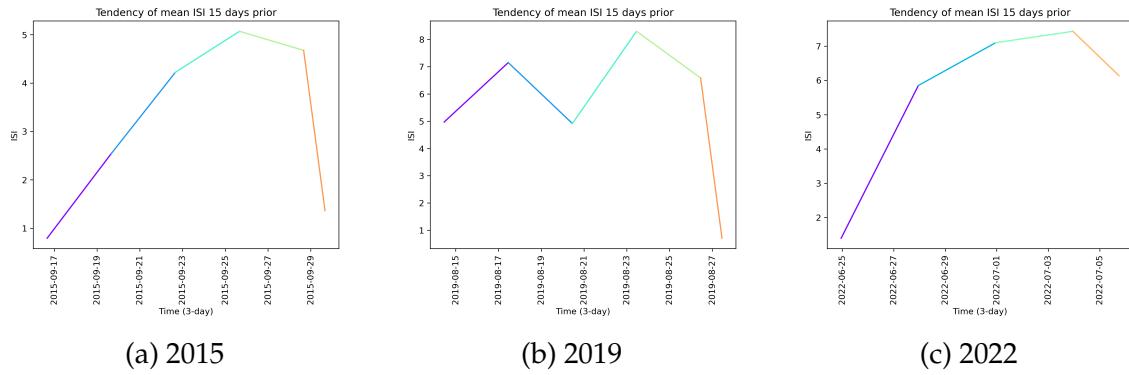
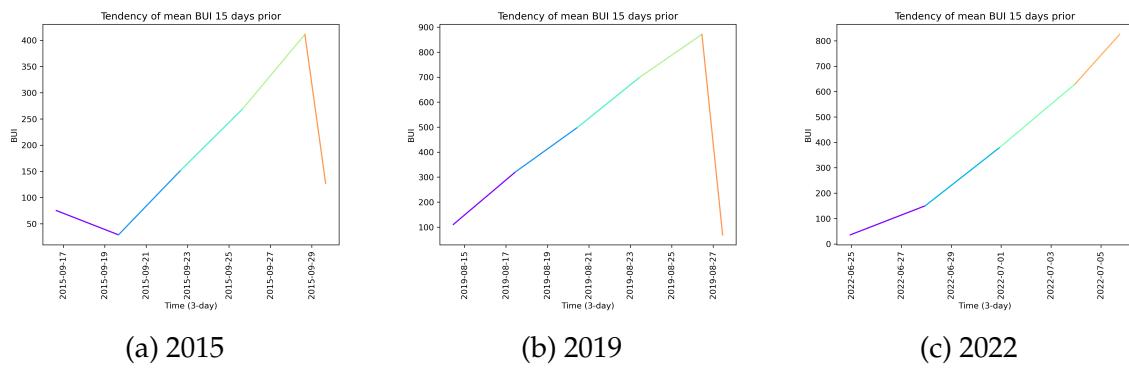


Figure 2.50: BUI values 15 days prior to wildfire



## 2.11 Comparison of mean FWI variables 3 days prior to the wildfire

Figure 2.51: FWI values 3 days prior to wildfire

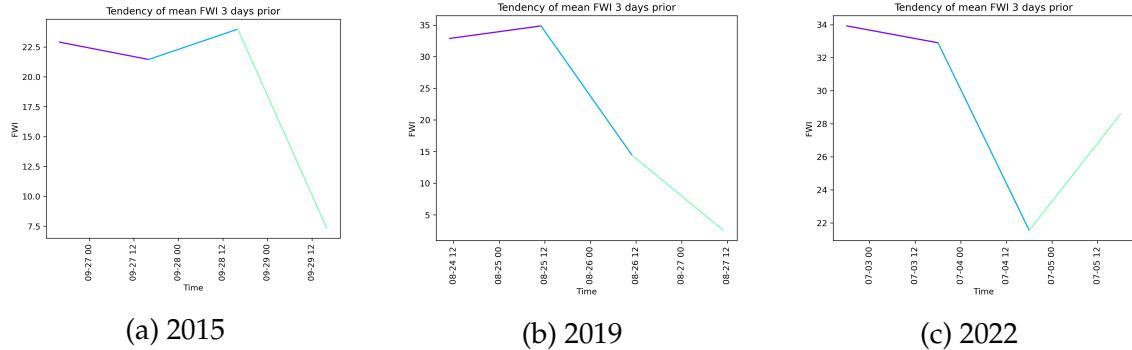


Figure 2.52: FFMC values 3 days prior to wildfire

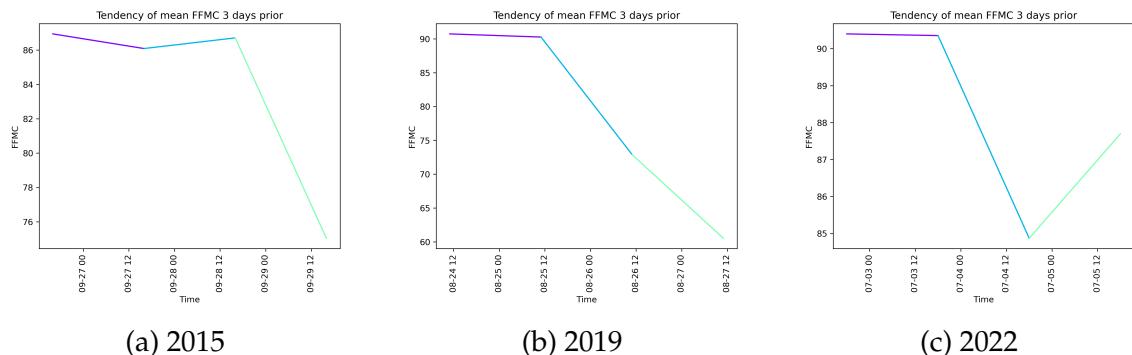


Figure 2.53: DMC values 3 days prior to wildfire

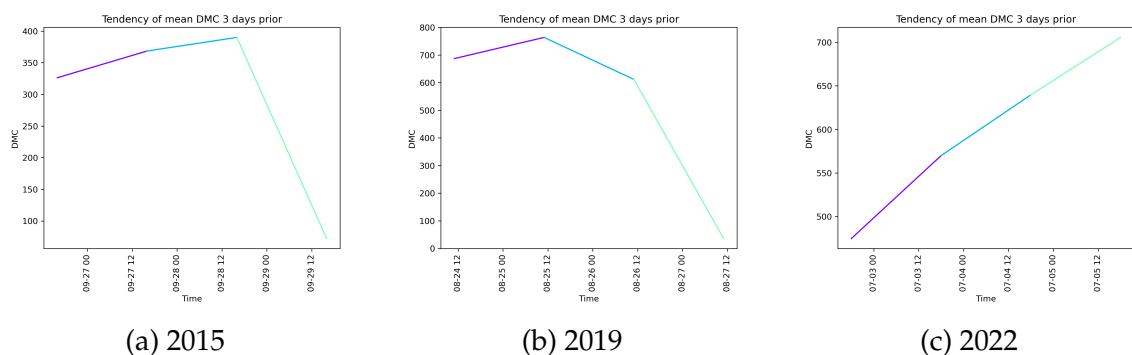


Figure 2.54: DC values 3 days prior to wildfire

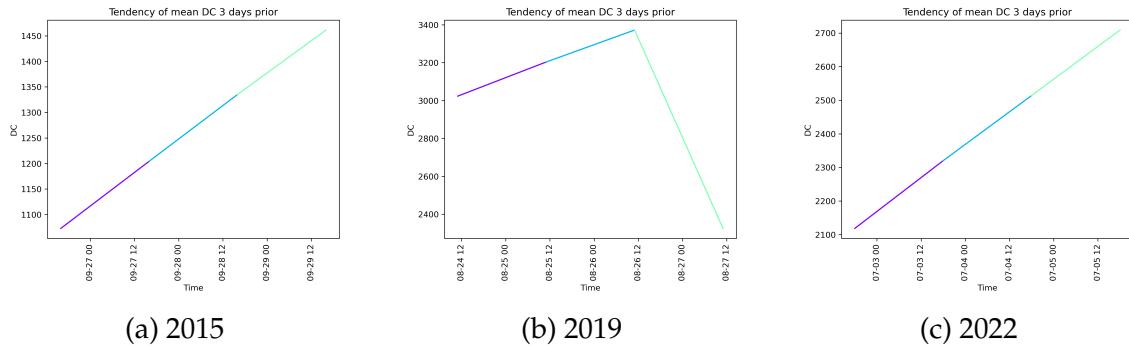


Figure 2.55: ISI values 3 days prior to wildfire

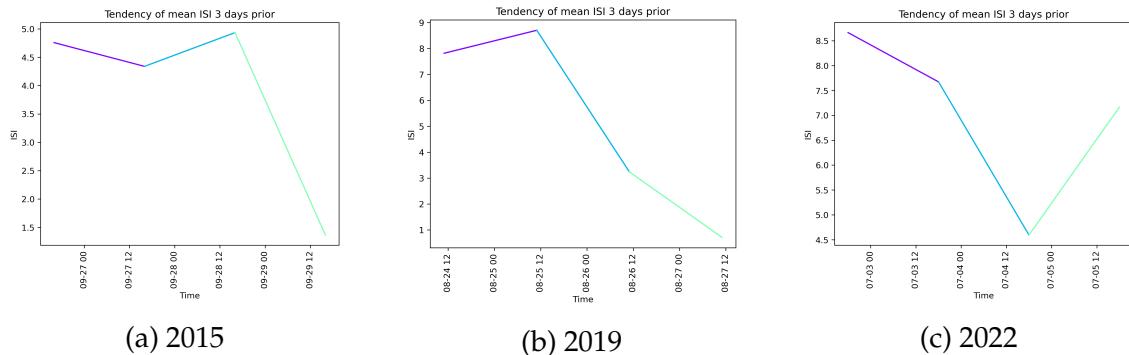
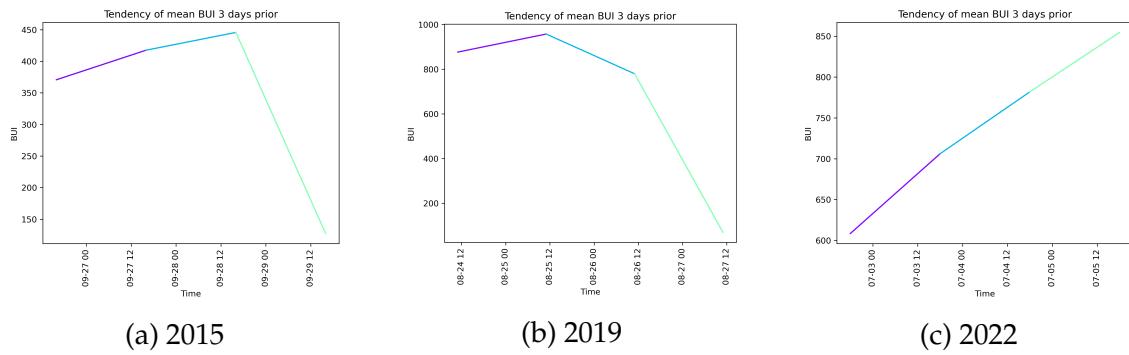


Figure 2.56: BUI values 3 days prior to wildfire



## 2.12 Polyfit FWI trend Analysis

### 2.12.1 All-time FWI trend with 3-days polyfit block

Figure 2.57: All-time FWI polyfit trend

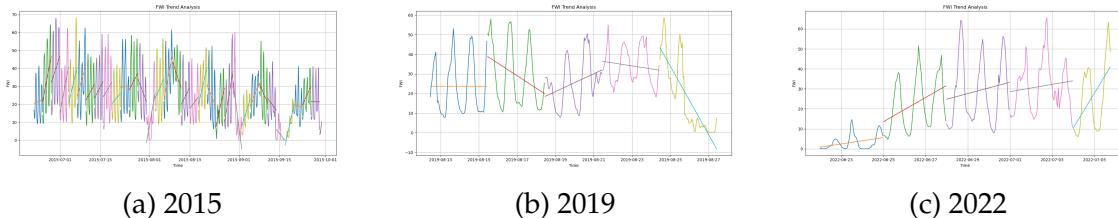


Figure 2.58: All-time FFMC polyfit trend

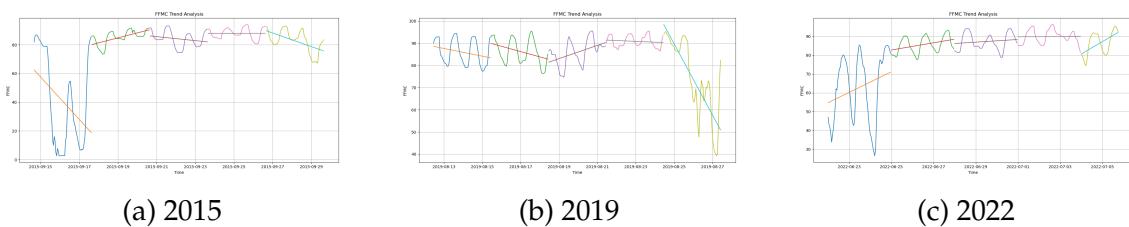
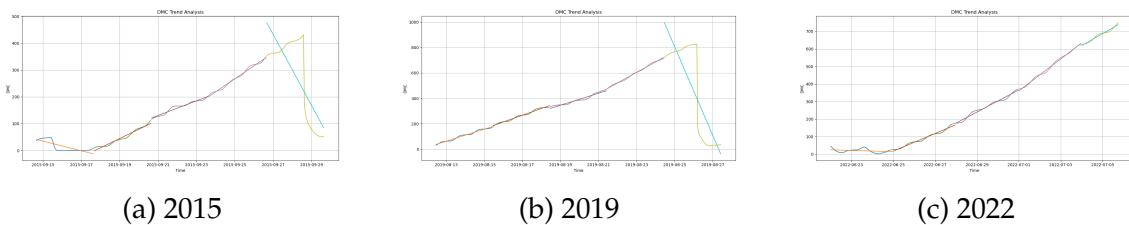


Figure 2.59: All-time DMC polyfit trend



### 2.12.2 15-days polyfit trend

15 dias com declive da reta para 3 dias.

## 2.13 15-days Weather Variables

## 2.14 3-days Weather variables

Figure 2.60: All-time DC polyfit trend

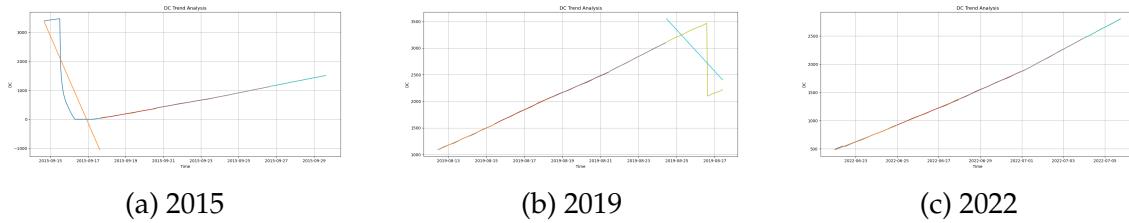


Figure 2.61: All-time ISI polyfit trend

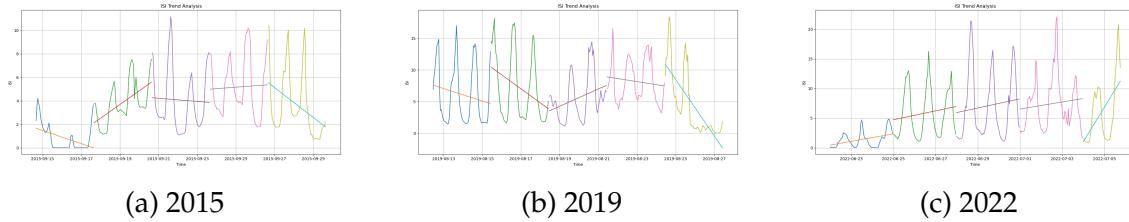


Figure 2.62: 15-days FWI polyfit trend

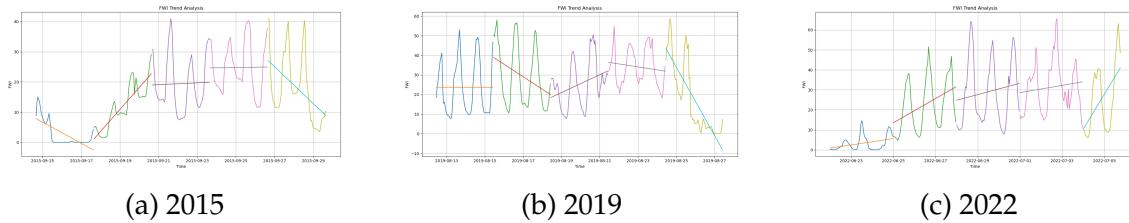


Figure 2.63: 15-days FFMC polyfit trend

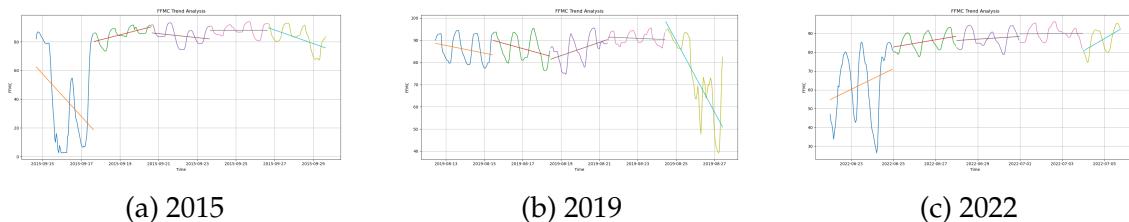


Figure 2.64: 15-days DMC polyfit trend

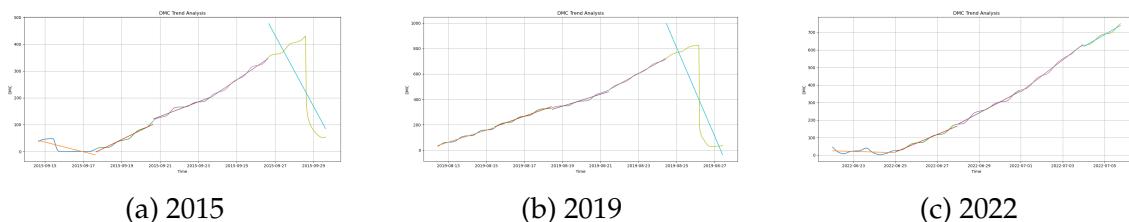


Figure 2.65: 15-days DC polyfit trend

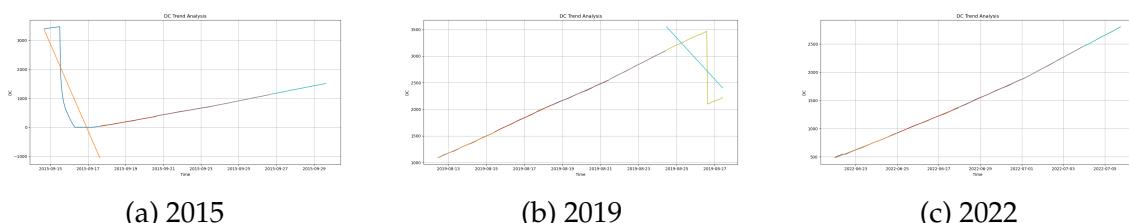


Figure 2.66: 15-days ISI polyfit trend

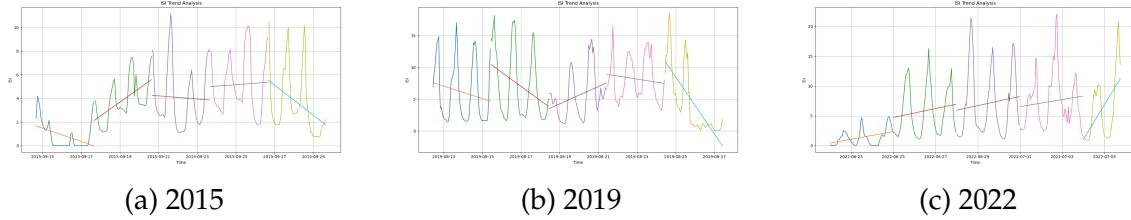


Figure 2.67: 15-days BUI polyfit trend

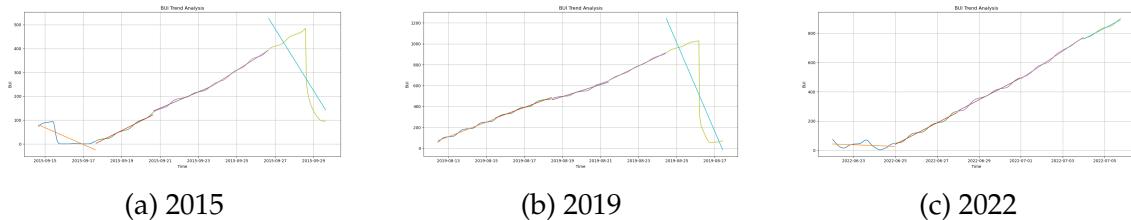


Figure 2.68: 15-days temperature, humidity, and dew

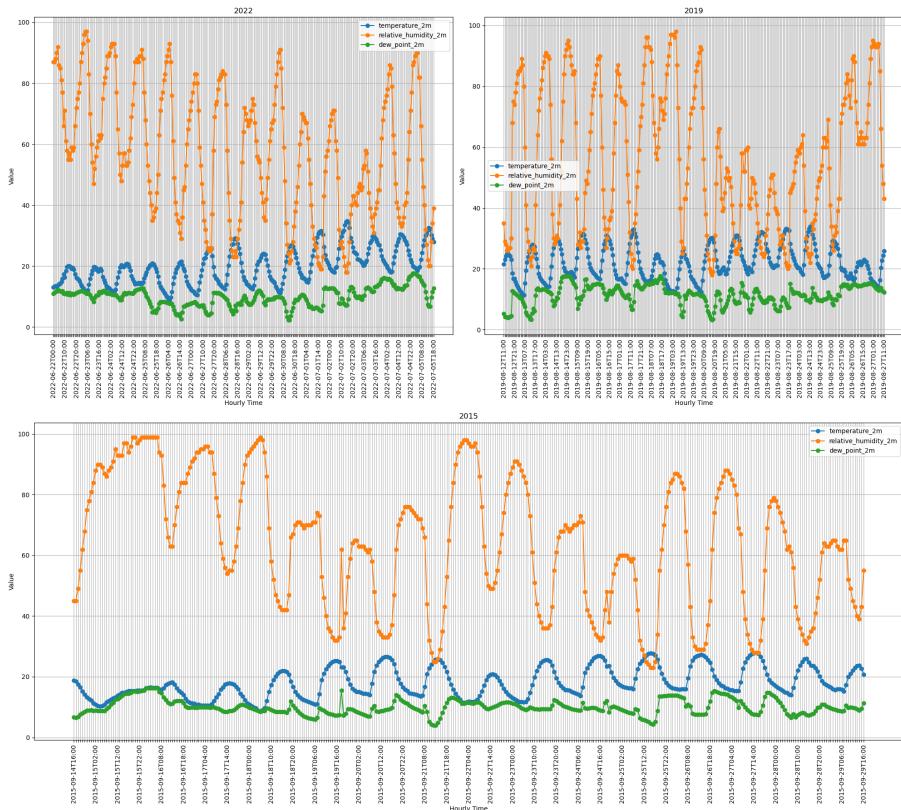


Figure 2.69: 15-days soil temperature at different depths

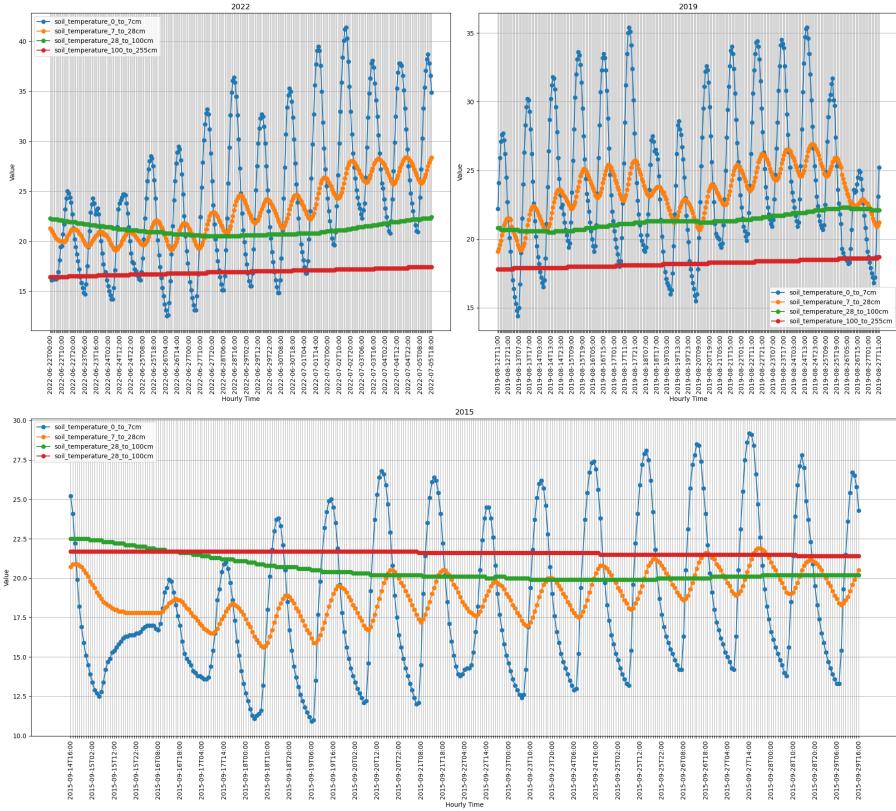


Figure 2.70: 15-days soil moisture at different depths

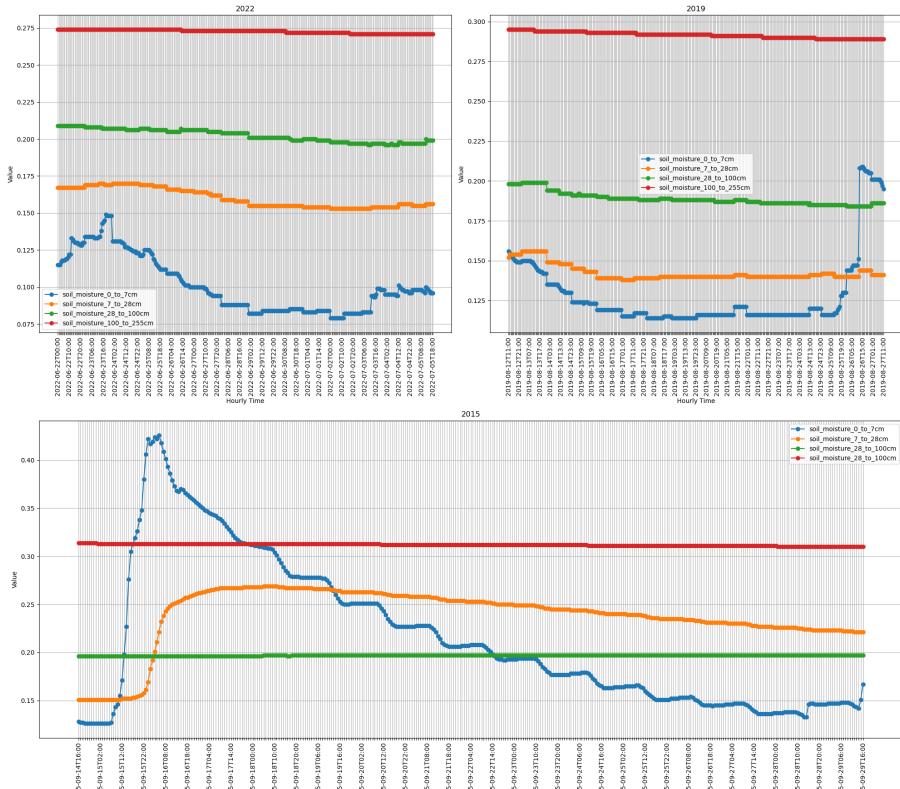


Figure 2.71: 15-days precipitation and pressure

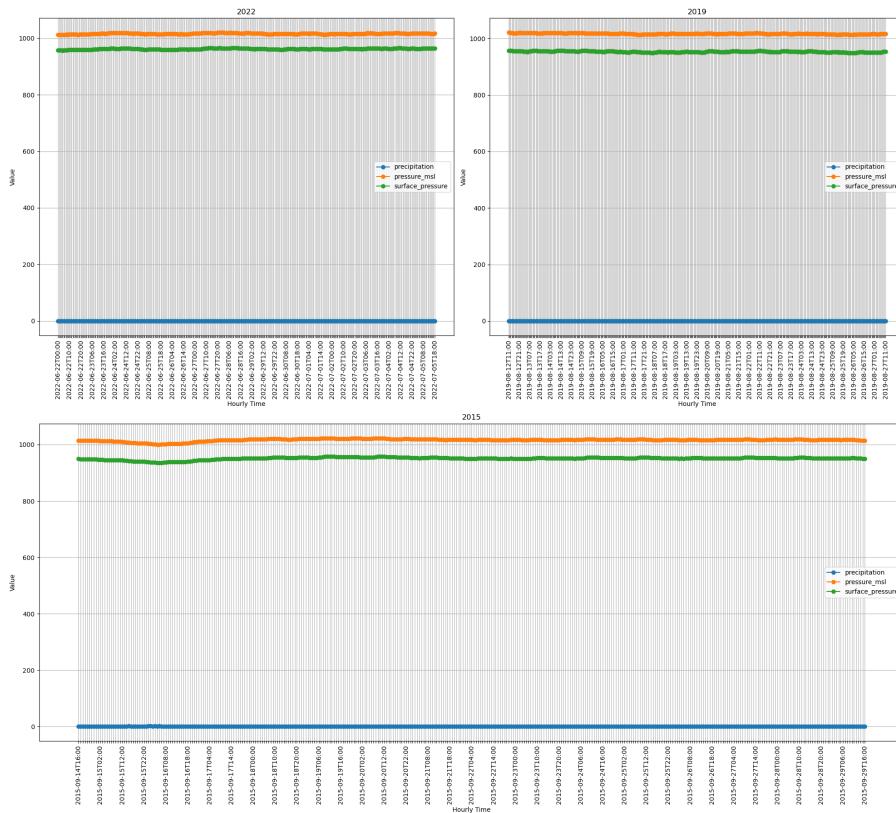


Figure 2.72: 15-days wind gusts, evapotranspiration, and vapour pressure deficit

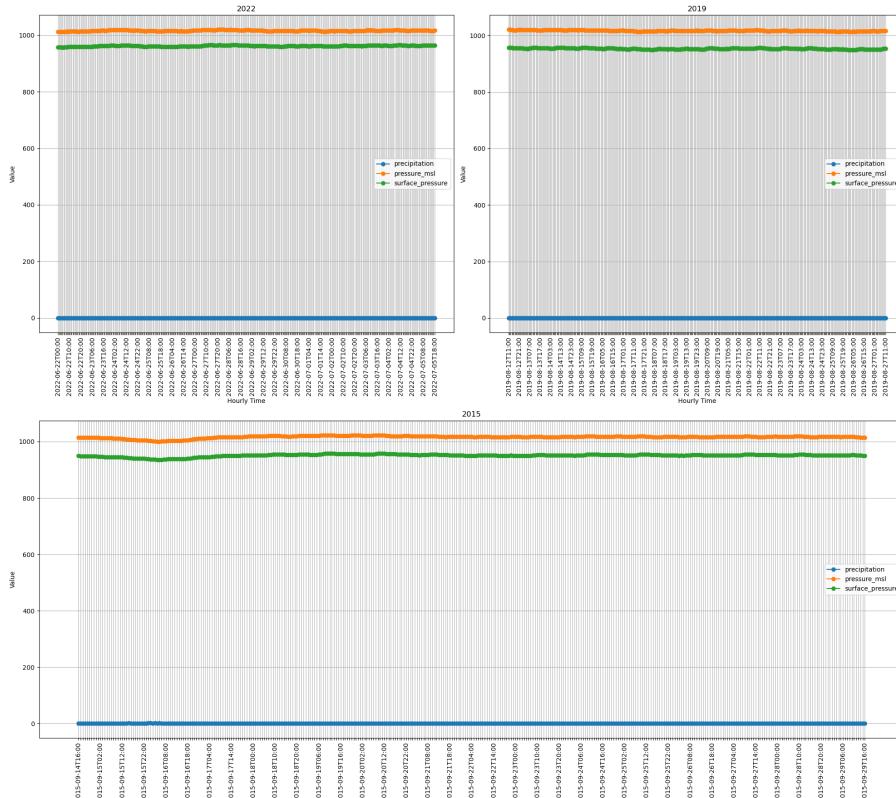


Figure 2.73: 3-days temperature, humidity, and dew

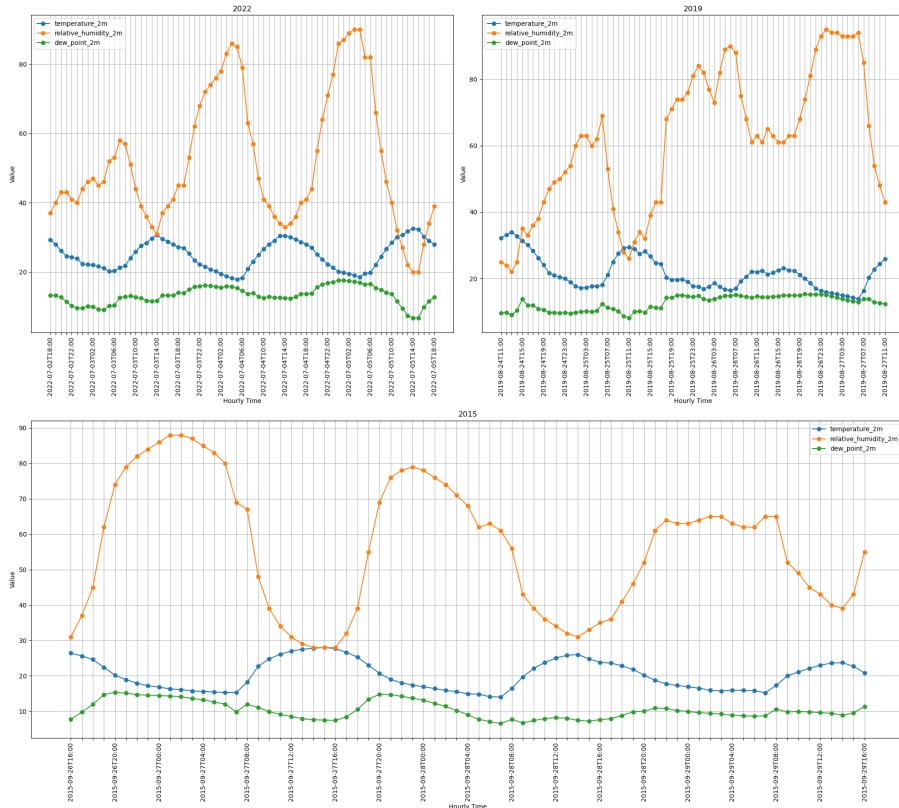


Figure 2.74: 3-days soil temperature at different depths

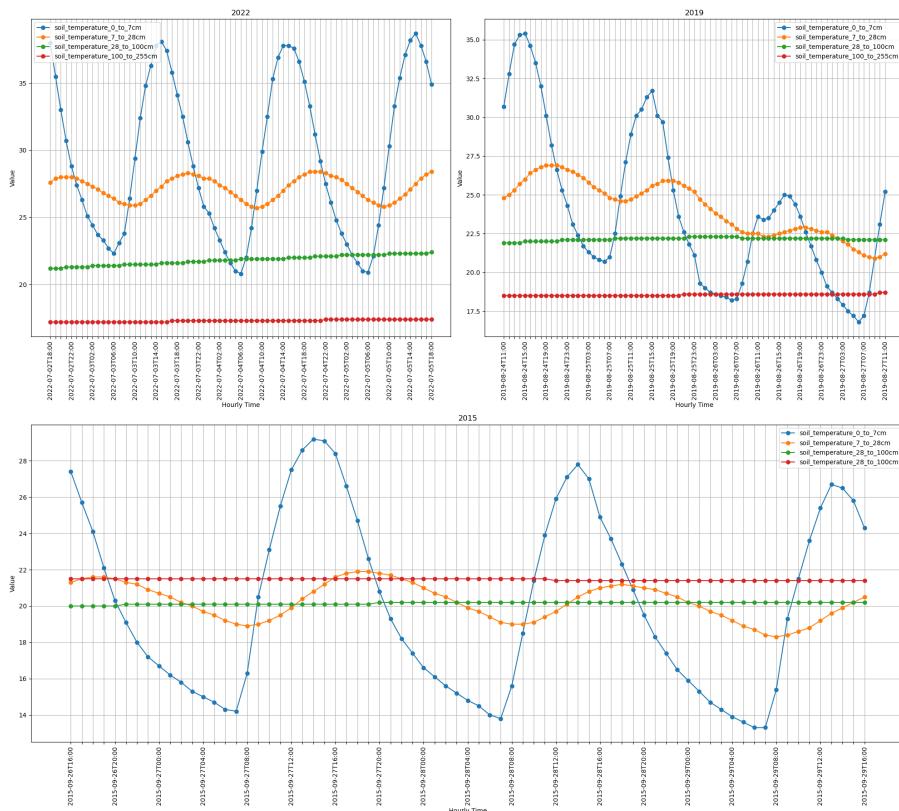


Figure 2.75: 3-days soil moisture at different depths

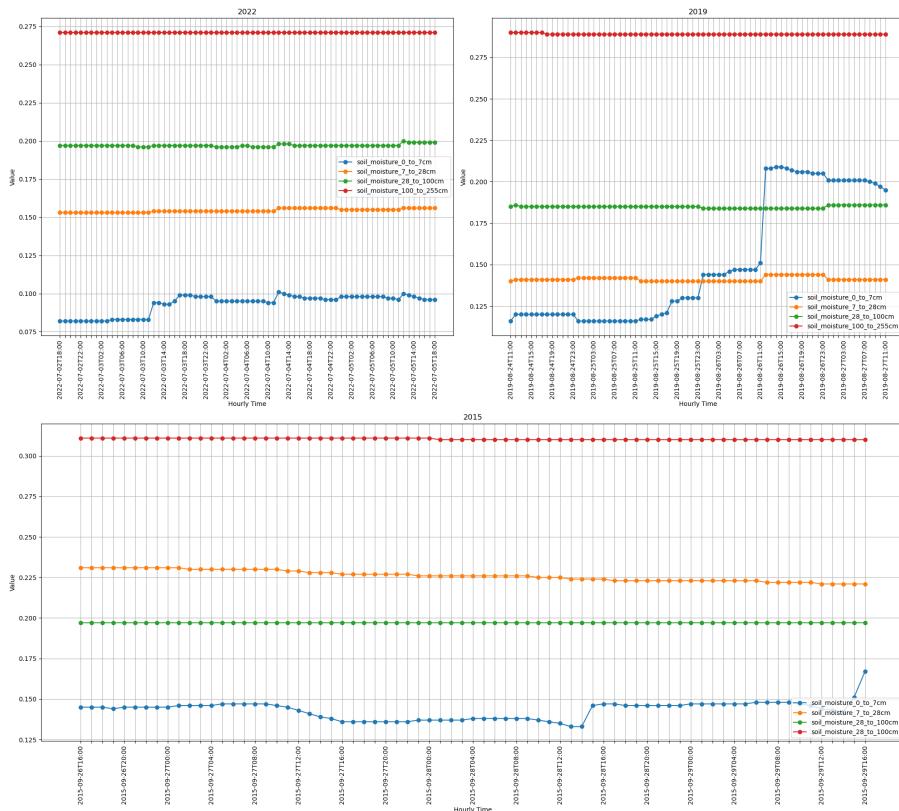


Figure 2.76: 3-days precipitation and pressure

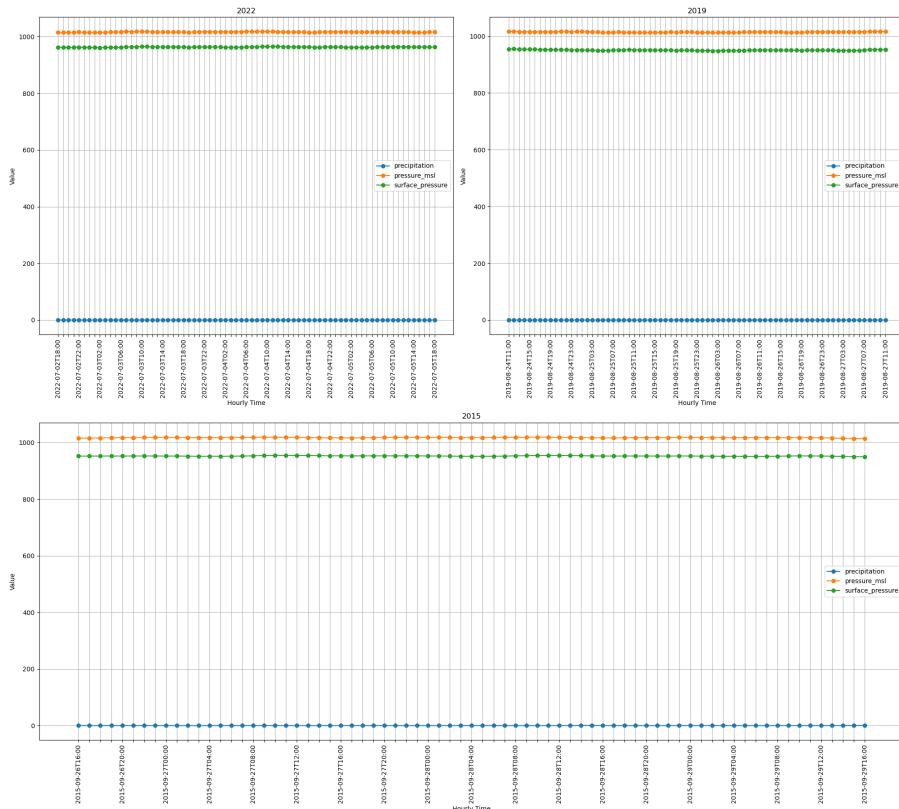


Figure 2.77: 3-days wind gusts, evapotranspiration, and vapour pressure deficit

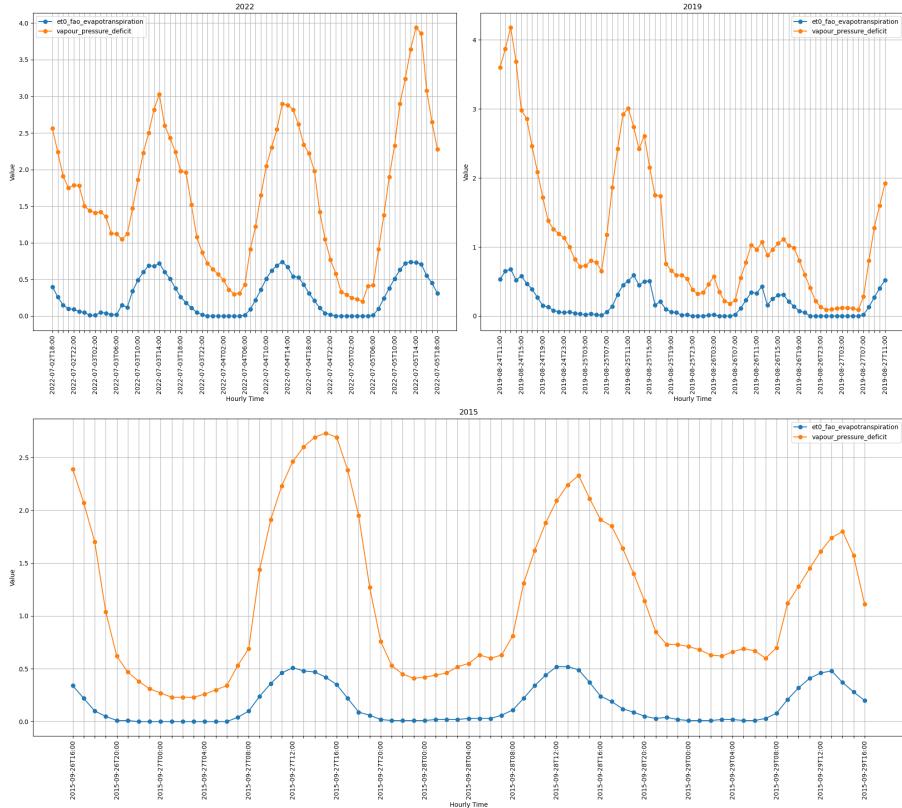


Figure 2.78: 3-days shortwave, direct, and diffuse radiation

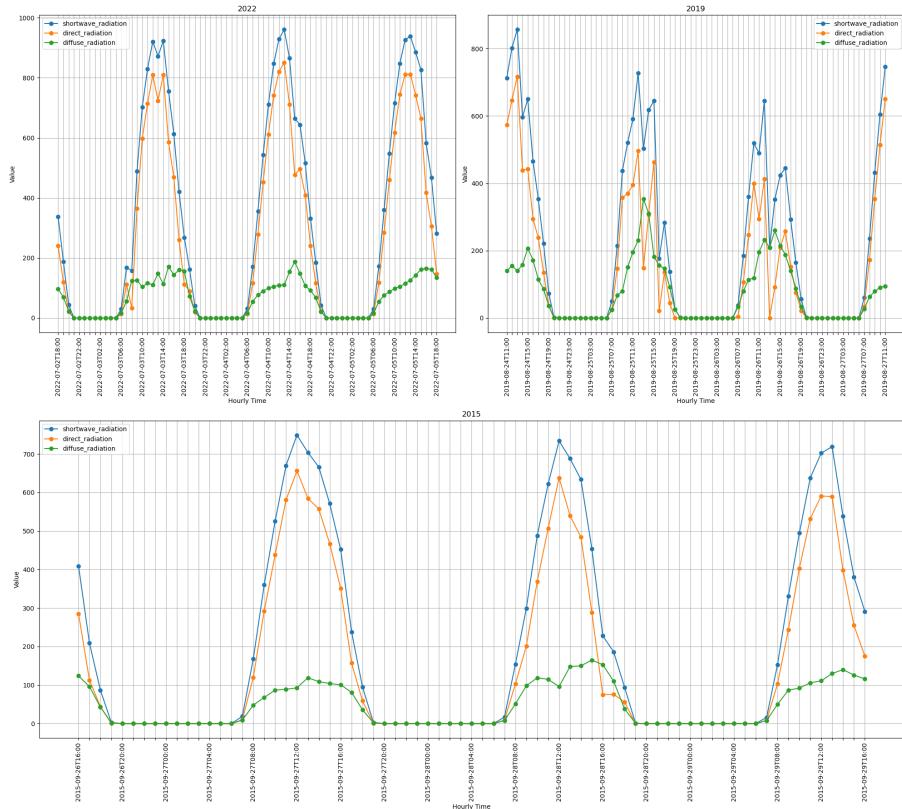


Figure 2.79: 3-days direct, global, and instant irrardice

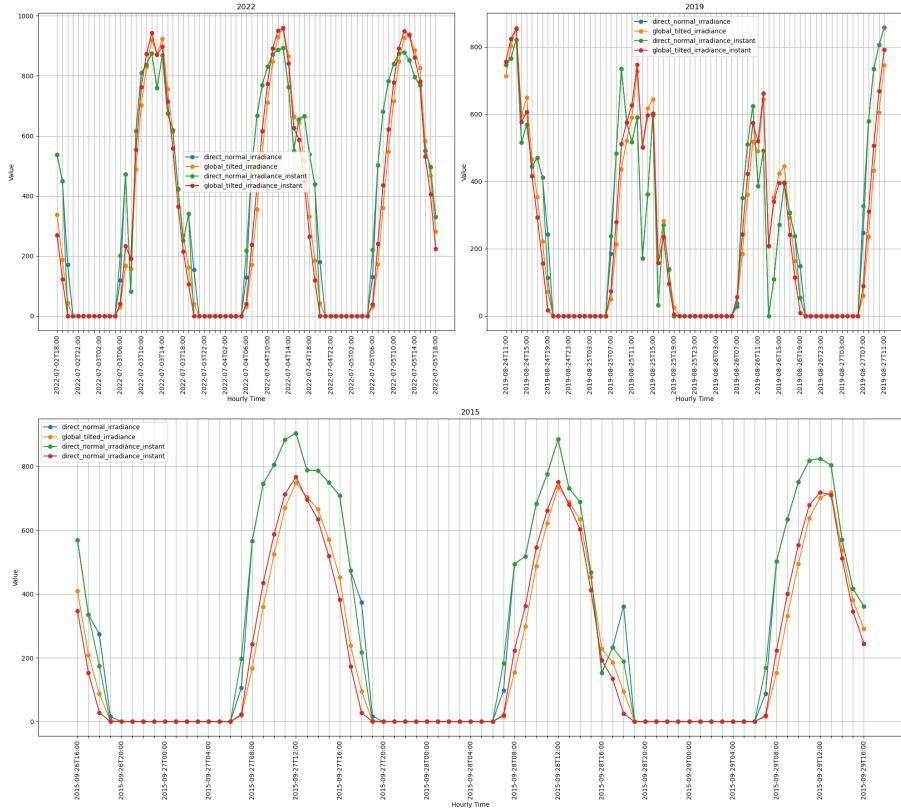


Figure 2.80: 3-days cloud covers at different heights

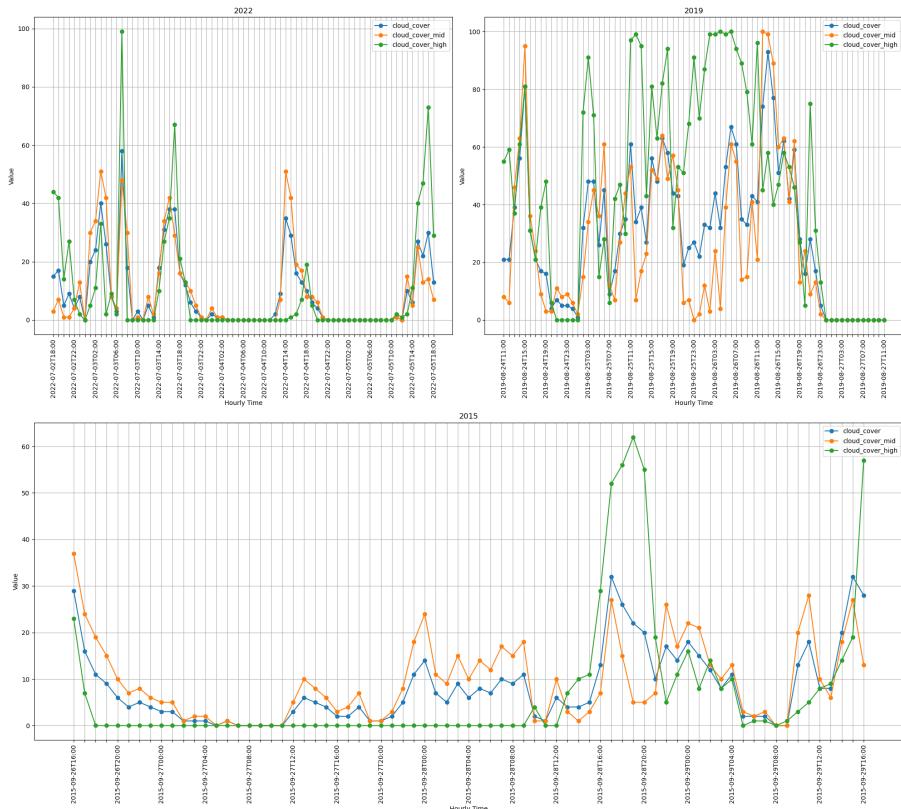


Figure 2.81: 3-days terrestrial, direct, and instant radiation

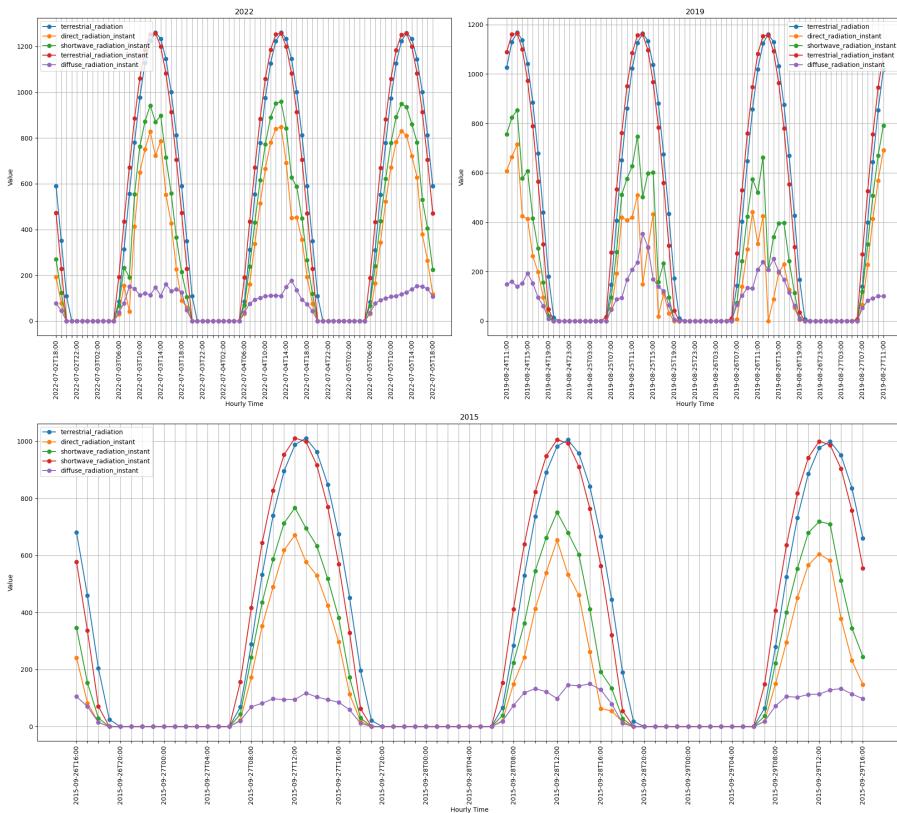
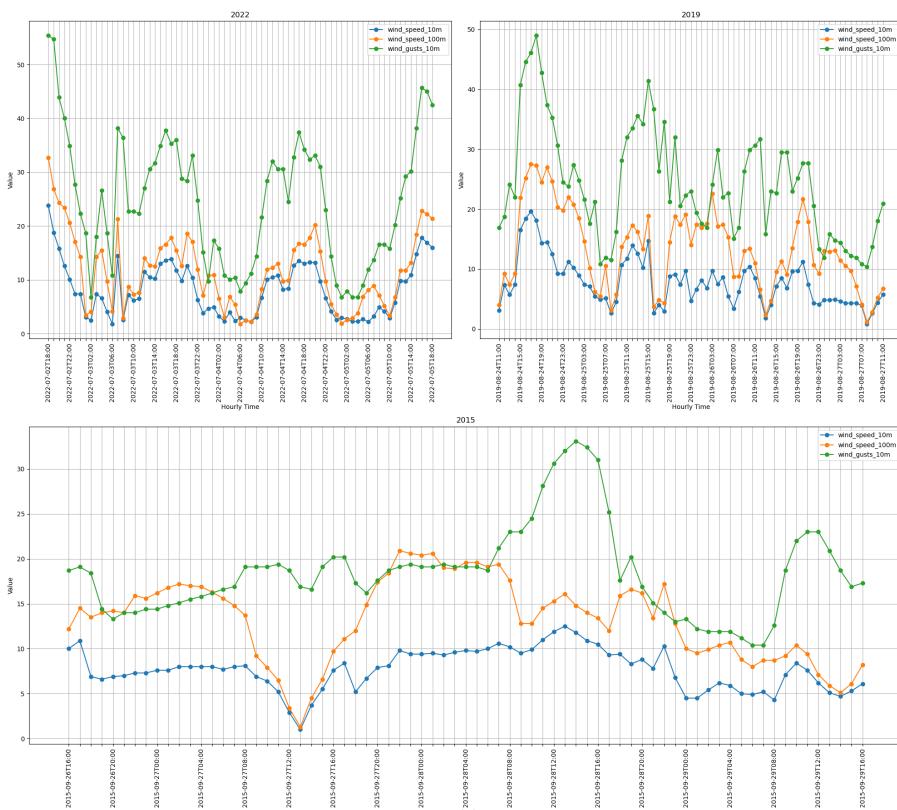


Figure 2.82: 3-days wind speed at different heights





# References

[AICC] AICC. Predictive services - fuels / fire danger - fwi defined.