



UAI
UNIVERSIDAD ADOLFO IBÁÑEZ

**ANATOMY OF THE “LAS MÁQUINAS” WILDFIRE USING
REMOTE SENSING TOOLS**

JORGE ALBERTO VALDIVIA GAVILÁN

JUNE 2022



UAI
UNIVERSIDAD ADOLFO IBÁÑEZ

**ANATOMY OF THE “LAS MÁQUINAS” WILDFIRE USING
REMOTE SENSING TOOLS**

JORGE ALBERTO VALDIVIA GAVILÁN

SUPERVISOR : PEDRO RESZKA C, PhD.
CO-SUPERVISOR : MARÍA THOMSEN, PhD.
EXTERNAL EXAMINER : ALBERT SIMEONI, PhD.
EXTERNAL EXAMINER : ANDRÉS FUENTES, PhD.

A thesis submitted in partial fulfillment
of the requirements for the degree of

Master of Science in Engineering, Energy and Environment

JUNE 2022

In memoriam

To all the people who lost their lives during the wildfires in the summer of 2017, Central and Southern Chile.

Ricardo Salas Martínez
Wilfredo Salgado Donoso
Sergio Faúndez Vergara
Rolf Kher
Fredí Fernández
Mauricio Roca
Hernán Avilés
Juan Eduardo Bizama Zanhueza
Daniel Vera
Nibaldo Pérez
The person who died at his home in Santa Olga

May their deaths not be in vain.

Acknowledgment

I would like to acknowledge and give my warmest thank to my supervisor Dr. Pedro Reszka who made this work possible, for his patience, motivation, enthusiasm, and immense knowledge. His guidance and advice carried me through all the stages of writing my project. I could not have imagined having a better advisor and mentor for my M.Sc. study.

I would also like to give special thanks to my mother, Valeria, my father, Jorge, my friends Jean Pierre, Alejandra, Felipe, Macarena, Carola, Ian, Diego, my sister Florencia, and my fellow labmates Nicolás, Danielle, Nicole, Israel and Joaquín, for the continuous support and understanding when undertaking my research and writing my project.

I wish to extent my special thanks to the Ortega-Bustamante family, who took care of me like my second family. My heart is with you.

... “Reminds me of those ghost stars in the sky.
You know, the ones that still shine their light upon us
long after they are gone.”

Abstract

In the austral summer of 2017, Central and Southern Chile was severely affected by a series of wildfires, burning an area of 575,000 ha (5,750 km²), leaving 11 dead, more than 4,000 people affected and destroying over 1,000 structures. One of the fires, named the “Las Máquinas” wildfire, has been the largest single event ever recorded in Chilean history, burning an area of around 193,000 ha (1,930 km²) and killing 4 people.

In this work, the anatomy of the “Las Máquinas” wildfire is studied by using the advantages given by Earth Observation tools. By definition, *anatomy* corresponds to “a study of the structure or internal workings of something”. For this purpose, the *pre*-, *per*- and *post*-fire conditions were described using open-access satellite imagery obtained from multiple remote sensing instruments, giving a new perspective to the description of this event. In addition, the Canadian Fire Weather Index (FWI) was calculated for the entire region of interest on a daily basis, based on remotely sensed data and physical simulations.

The findings suggest that within the region of interest (ROI), there was abundant and healthy vegetation in terms of the Normalized Difference Vegetation Index (NDVI). Moreover, some affected municipalities had not experienced wildfires for several years prior to the event, and therefore a large amount of fuel availability was observed. In terms of the flora, Empedrado was the most affected municipality, lowering its average NDVI from 0.67 to 0.36. The species affected were mainly *Pinus radiata*, *Vachellia caven* and *Nothofagus glauca*, whose total burned area was 129,700, 13,700 and 13,500 ha, respectively.

On average, the maximum temperatures at the whole ROI achieved values of around 29°C in December 2016, the month prior to the event, being the highest since 1979. Additionally, the standardized precipitation index (SPI) indicates that there had been a severe and persisting drought since 2009.

Burned area was calculated using Landsat-8, Sentinel-2 and combined Aqua/Terra-MODIS images. From MODIS data, the total burned area was 193,804 ha (1,938 km²), while Landsat-8 and Sentinel-2 burned area was studied for multiple threshold values of the delta Normalized Burn Ratio (dNBR). High severity dNBR values were found mainly in Constitución and Empedrado municipalities, particularly close to the village of Santa Olga, which was completely decimated by the wildfire on the night of January 25th. According to MODIS data, only on that night, the fire propagation left a total burned area of 85,000 ha (850 km²). Using both the VIIRS-SNPP and MODIS products, the fire radiative power indicated that there were some locations where the total amount of energy released by the wildfire exceeded 2,000 MW, mainly in the Constitución municipality and within a 7 km radius of Santa Olga around the time the village was destroyed. During the event, the air quality was studied by using the VIIRS-SNPP Deep Blue Aerosol product, and the results exhibited an elevated presence of both high altitude smoke and pyrocumulonimbus clouds. Furthermore, carbon emissions for January 2017 resulted in mean values of 197.49 g·C·m⁻², with maximum values of 1,270 g·C·m⁻², 3,750% higher than in previous years for the same month.

The Canadian Fire Weather Index (FWI) was calculated using near-surface air temperature derived from multiple linear regression models, machine learning regression algorithms, and from a physically-based surface energy balance. Overall, the best performing models were those using the machine learning random forests regression. The FWI was computed using Aqua, Terra, VIIRS-SNPP, Energy balance and through an approximation approach which simplifies its calculation (FWI_{app}). In general, all FWI results exhibited the same behavior, achieving the highest FWI values on January 25th, 2017.

The results show that with this methodology it is possible to estimate a daily landscape-scale FWI at a medium resolution derived from Earth Observation tools without strongly overestimating nor underestimating its value compared to the FWI calculated at weather stations.

TABLE OF CONTENTS

Acknowledgment	iv
Abstract	v
Table of Contents	ix
List of Figures	xi
List of Tables	xii
Nomenclature	xiii
Symbols	xv
1. Introduction	16
1.1. Research problem	17
1.1.1. General objective	18
1.1.2. Specific objectives	18
2. State of the art	19
2.1. Chilean Mediterranean ecosystem	19
2.2. Las Máquinas wildfire	20
2.3. Remote sensing	21
2.3.1. Spectral indices	22
2.3.2. Satellite sensors and products	24
2.3.2.1. NASA Aqua/Terra MODIS	25
2.3.2.2. NASA/NOAA Suomi-NPP VIIRS	26
2.3.2.3. NASA Landsat-8 OLI	26
2.3.2.4. ESA Sentinel-2 MSI	27
2.3.3. Remote sensing of wildfires	28
2.4. Canadian Fire Weather Index	30
3. Methods & Materials	32
3.1. Area of study	32
3.2. Vegetation	32
3.2.1. Vegetation density and moisture evolution	32
3.2.2. Previous fires	34
3.3. Meteorology	34
3.3.1. Standardized precipitation index	34
3.3.2. Temperature evolution	36
3.4. Per-event analysis	36
3.4.1. Burned area	36
3.4.1.1. Fire evolution	38
3.4.2. Maximum fire radiative power	38
3.4.3. Land use inventory	39
3.4.4. Affected species	39

3.4.5.	Land cover type	39
3.4.6.	Air quality	40
3.4.6.1.	Smoke generation & evolution	40
3.4.6.2.	Aerosol optical depth	42
3.4.6.3.	Carbon emissions	42
3.4.7.	Canadian Fire Weather Index	43
3.4.7.1.	Wind speed	43
3.4.7.2.	Near-surface air temperature	44
3.4.7.3.	NSAT by energy balance	44
3.4.7.4.	NSAT by regression models	46
3.4.7.4.1.	Building the regression dataset	47
3.4.7.4.2.	Training datasets	48
3.4.7.4.3.	Testing datasets	49
3.4.7.5.	Precipitation	49
3.4.7.6.	Relative humidity	49
3.4.7.7.	Calculation of the Fire Weather Index	52
3.4.7.8.	Calculation of the approximated Fire Weather Index	53
4.	Results	54
4.1.	Vegetation	54
4.1.1.	Vegetation evolution	54
4.1.2.	Previous fires	56
4.2.	Meteorology	57
4.2.1.	Temperature evolution	57
4.2.2.	Drought analysis using the SPI	58
4.3.	Las Máquinas wildfire	62
4.3.1.	Burned area	62
4.3.2.	Fire evolution	65
4.3.3.	Maximum fire radiative power	66
4.3.4.	Affected populated areas	69
4.3.5.	Affected species	70
4.3.5.1.	Landcover type	71
4.3.6.	Air quality	75
4.3.6.1.	Smoke	75
4.3.6.2.	Aerosol optical depth	78
4.3.6.3.	Carbon emissions	79
4.3.7.	Canadian fire weather index	80
4.3.7.1.	MODIS regression models for NSAT	80
4.3.7.1.1.	MODIS regression models training	80
4.3.7.1.2.	MODIS regression models validation	83
4.3.7.2.	VIIRS-SNPP regression models for NSAT	86
4.3.7.2.1.	VIIRS regression models training	86
4.3.7.2.2.	VIIRS regression models validation	86
4.3.7.3.	NSAT from surface energy balance	89
4.3.7.4.	Wind speed	91
4.3.7.5.	Relative humidity	94
4.3.7.6.	Precipitation	95
4.3.7.7.	Fire Weather Index from remote sensing data	97

4.3.7.8. Fire Weather Index at weather station	101
4.3.7.9. Fire Weather Index validation	101
4.3.7.10. FWI discussion	104
Conclusion	106
Bibliography	108
Appendix	124
A. Download satellite images	126
A.1. Download via NASA's EarthData	126
A.2. Download MODIS products in R	127
A.3. Download Landsat-8 and Sentinel-2 images	127
B. Work with raster data in R	128
B.1. Geo-processing	128
C. International Geosphere-Biosphere Programme classification	131
D. NDVI and NDWI pre-fire data distribution	132
E. IGBP detail for land-use categories	132
F. Other Fire Weather Index results	135

LIST OF FIGURES

1. Introduction	
1.1. CONAF statistics for fire counts and burned area in Chile	17
2. State of the art	
2.1. Structure of the Canadian Fire Weather Index system	30
3. Methods & Materials	
3.1. General fire location with topography, weather stations, populated areas, and the region of interest (ROI)	33
3.2. Procedure to build NDWI from MOD09GA surface reflectance	34
3.3. Flowchart for the acquisition of burned area derived from Landsat-8 & Sentinel-2 images	38
3.4. Flowchart for working with VIIRS-SNPP Deep Blue Aerosol product in R	41
3.5. Weather stations location within the region of interest	44
3.6. Surface energy balance	45
3.7. Flowchart for the NSAT estimation by regression models	50
3.8. Flowchart for the relative humidity calculation	51
3.9. Flowchart for the Canadian Fire Weather Index (FWI) calculation	53
4. Results	
4.1. NDVI and NDWI evolution per ROI municipality	55
4.2. Map of previous fires location and size	56
4.3. Fire counts and burned area of previous fires within the ROI	57
4.4. Monthly average maximum temperature evolution within the ROI	58
4.5. Monthly SPI from IMERG-GPM and CR ² precipitation data	59
4.6. AUC of the SPI for both IMERG-GPM and CR ² data	60
4.7. Landsat-8 and Sentinel-2 burned area from several dNBR and RBR threshold values . .	62
4.8. Burned area map from Landsat-8, Sentinel-2 and MODIS MCD64A1	64
4.9. Burned area severity from dNBR for Landsat-8 and Sentinel-2	64
4.10. Maps of daily burned area evolution from MODIS MCD64A1	65
4.11. Daily and cumulative burned area evolution derived from MODIS MCD64A1	66
4.12. Maps of daily fire radiative power (FRP) from VIIRS-SNPP	67
4.13. Maps of fire radiative power (FRP) from Aqua/Terra-MODIS	68
4.14. Map of the fire damage and affected populated areas	69
4.15. Santa Olga digital elevation model and slope	70
4.16. Burned area per species within the ROI	71
4.17. IGBP categories evolution from 2001 to 2020 at the ROI	72
4.18. Map of IGBP categories comparison between years 2015 and 2019	73
4.19. Land-use type from LUI against IGBP categories	74
4.20. Map of aerosol types at the Maule region	75
4.21. Map of aerosol types at continental Chile	76
4.22. Daily aerosol type evolution at the Maule region	77
4.23. Daily aerosol type projected area evolution at the Maule region during the event	77

4.24. Daily aerosol optical depth evolution at the Maule region during the event	78
4.25. Average carbon emissions at the Maule region	79
4.26. NSAT Aqua-MODIS regression models results for the training dataset	81
4.27. NSAT Terra-MODIS regression models results for the training dataset	82
4.28. Importance matrix of the random forest regression models for Aqua/Terra-MODIS . . .	83
4.29. NSAT Aqua/Terra-MODIS regression models validation	84
4.30. Weather station NSAT histograms and boxplots at Aqua/Terra-MODIS overpass time . .	85
4.31. NSAT VIIRS-SNPP regression models results for the training dataset	87
4.32. Importance matrix of the random forest regression model for VIIRS-SNPP	88
4.33. NSAT VIIRS regression models validation	88
4.34. Weather station NSAT histograms and boxplots at VIIRS-SNPP overpass time	89
4.35. NSAT calculated by the surface energy balance	90
4.36. NSAT distribution and evolution from all methodologies applied	91
4.37. VIIRS-SNPP DBA wind speed versus WindNinja's simulated wind speed	92
4.38. VIIRS-SNPP DBA wind speed against measured wind speed at the weather stations . . .	93
4.39. Relative humidity distribution and evolution for Aqua/Terra-MODIS and VIIRS-SNPP .	95
4.40. Relative humidity validation against weather station data	96
4.41. Initial conditions of the FPMC, DMC and DC for the FWI calculation	97
4.42. Results for the Canadian Fire Weather Index	98
4.43. FWI maps for Aqua, Terra, VIIRS-SNPP and Energy balance data	99
4.44. Results for the Canadian Fire Weather Index at each weather station	102
4.45. FWI validation against weather station data	103
4.46. FWI ERA-5 against weather station data	104
4.47. Event timeline, daily burned area, FWI and NSAT evolution	105
Appendix	124
D.1. Pre-fire NDVI and NDWI values	132
E.1. Detailed land-use type from LUI against IGBP categories	133
E.2. Species surface area within detailed land-use type category	134
F.1. FWI CFFDRS vs FWI approximated at weather stations	135

LIST OF TABLES

2. State of the art	
2.1. Selected spectral indices in vegetation studies	22
2.2. General characteristics of Aqua/Terra-MODIS	25
2.3. Aqua/Terra-MODIS bands for land, cloud and aerosols boundaries and properties	25
2.4. General characteristics of the VIIRS-SNPP sensor	26
2.5. VIIRS-SNPP bands for land, cloud and aerosols boundaries and properties.	26
2.6. General characteristics of the Landsat-8 OLI sensor	27
2.7. Landsat-8 OLI bands for land, cloud and aerosols boundaries and properties.	27
2.8. General characteristics of the Sentinel-2 MSI sensor	28
2.9. Sentinel-2 MSI bands for land, cloud and aerosols boundaries and properties	28
2.10. Canadian Fire Weather Index danger classification	31
3. Methods & Materials	
3.1. Drought categories for the SPI	36
3.2. Severity levels and its corresponding dNBR ranges	37
3.3. Classification of the pixel values of the VIIRS-SNPP Deep Blue Aerosol “Aerosol Type Land” layer	42
4. Results	
4.1. Average pre- and post-fire NDVI per municipality within the ROI	54
4.2. Statistical p -value results with the Kolmogorov Smirnov test for the IMERG-GPM and CR^2 data	61
4.3. Satellite products average local time of data acquisition for the regression models	80
4.4. Time difference between satellite-sensors for the relative humidity calculation	94
4.5. FWI tendency analysis	100
Appendix	124
C.1. International Geosphere-Biosphere Programme (IGBP) class descriptions	131

Nomenclature

AOD	<i>Aerosol Optical Depth</i>
BRIFE	<i>Brigadas de Refuerzo de Incendios Forestales</i>
BRIFAR	<i>Brigada Forestal Armada</i>
BUI	<i>Built-up Index</i>
CFFDRS	<i>Canada Forest Fire Danger Rating System</i>
CFS	<i>Canadian Forest Service</i>
CIREN	<i>Centro de Información de Recursos Naturales</i>
CONAF	<i>Comisión Nacional Forestal</i>
CRED	<i>Centre for Research on the Epidemiology of Disasters</i>
CR ²	<i>Center for Climate and Resilience Research</i>
DBA	<i>Deep Blue Aerosol</i>
DC	<i>Drought Code</i>
DMC	<i>Duff Moisture Code</i>
dNBR	<i>delta Normalized Burn Ratio</i>
DOY	<i>Day of Year</i>
DT	<i>Decision Tree</i>
EB	<i>Energy Balance</i>
ECMWF	<i>European Centre for Medium-Range Weather Forecasts</i>
EO	<i>Earth Observation</i>
EPSG	<i>European Petroleum Survey Group (geodetic parameter dataset)</i>
ERA-5	<i>Fifth generation ECMWF reanalysis for the global climate and weather data</i>
ESA	<i>European Space Agency</i>
ESRI	<i>Environmental System Research Institute</i>
FAO	<i>Food and Agriculture Organization</i>
FFMC	<i>Fine Fuel Moisture Code</i>
FMC	<i>Fuel moisture content</i>
FRP	<i>Fire Radiative Power (MW)</i>
FS	<i>Forest Service</i>
FWI	<i>Fire Weather Index</i>
FWI _{app}	<i>Approximated Fire Weather Index</i>
GDP	<i>Gross Domestic Product</i>
GEO	<i>Geostationary Orbit</i>
GFA	<i>Global Fire Atlas</i>
GFED	<i>Global Fire Emissions Database</i>
GIS	<i>Geographic Information System</i>
GPM	<i>Global Precipitation Measurement</i>
IDE	<i>Infraestructura de Datos Espaciales</i>
IGBP	<i>International Geosphere-Biosphere Programme</i>
IMERG	<i>Integrated Multi-satellite Retrievals for GPM</i>

IPCC	<i>Intergovernmental Panel on Climate Change</i>
ISI	<i>Initial Spread Index</i>
LCP	<i>Landscape File</i>
LEO	<i>Low Earth Orbit</i>
LFMC	<i>Live fuel moisture content</i>
LR	<i>Linear Regression</i>
LST	<i>Land Surface Temperature</i>
LUI	<i>Land Use Inventory</i>
ML	<i>Machine Learning</i>
MODIS	<i>Moderate Resolution Imaging Spectroradiometer</i>
MOD	<i>Terra-MODIS product</i>
MYD	<i>Aqua-MODIS product</i>
MSI	<i>Multi-Spectral Instrument</i>
NA	<i>Not-available (missing value)</i>
NASA	<i>National Aeronautics and Space Administration</i>
NBR	<i>Normalized Burn Ratio</i>
NDVI	<i>Normalized Difference Vegetation Index</i>
NDWI	<i>Normalized Difference Water Index</i>
NFDRS	<i>National Fire Danger Rating System</i>
NICC	<i>National Interagency Coordination Center</i>
NIR	<i>Near Infrared (spectrum)</i>
NOAA	<i>National Oceanic and Atmospheric Administration</i>
NRC	<i>Natural Resources Canada</i>
NSAT	<i>Near-surface Air Temperature (°C)</i>
OLI	<i>Operational Land Imager</i>
ONEMI	<i>Oficina Nacional de Emergencias del Ministerio del Interior</i>
PW	<i>Precipitable Water content (cm)</i>
RBR	<i>Relativized Burn Ratio</i>
RF	<i>Random Forests</i>
RH	<i>Relative Humidity (%)</i>
ROI	<i>Region of Interest</i>
SNASPE	<i>Sistema Nacional de Áreas Silvestres Protegidas del Estado</i>
SNPP	<i>Suomi National Polar-orbiting Partnership</i>
SPI	<i>Standardized Precipitation Index</i>
SVM	<i>Support Vector Machines</i>
SVR	<i>Support Vector Regression</i>
SWIR	<i>Short-wave Infrared (spectrum)</i>
TIR	<i>Thermal Infrared</i>
UNDRR	<i>United Nations Office for Disaster Risk Reduction</i>
USDA	<i>United States Department of Agriculture</i>
UTC	<i>Coordinated Universal Time</i>
UTM	<i>Universal Transverse Mercator</i>

VIS	<i>Visible (spectrum)</i>
VIIRS	<i>Visible Infrared Imaging Radiometer Suite</i>
WFAS	<i>Wildland Fire Assessment System</i>
WGS84	<i>World Geodetic System 1984</i>
WS	<i>Weather Station</i>
WUI	<i>Wildland Urban Interface</i>

Symbols

T_a	Ambient temperature ($^{\circ}\text{C}$)
T_s	Surface temperature ($^{\circ}\text{C}$)
T_{dew}	Dew-point temperature ($^{\circ}\text{C}$)
G	Incident irradiation flux from the Sun ($\text{W}\cdot\text{m}^{-2}$)
G_r	Reflected flux from solar irradiation ($\text{W}\cdot\text{m}^{-2}$)
G_a	Absorbed flux from solar irradiation ($\text{W}\cdot\text{m}^{-2}$)
G_t	Transmitted flux from solar irradiation ($\text{W}\cdot\text{m}^{-2}$)
ρ_{λ}	Material reflectance at λ wavelength
α_{λ}	Material absorbance at λ wavelength
τ_{λ}	Material transmittance at λ wavelength
$\dot{q}''_n$	Net surface radiation flux ($\text{W}\cdot\text{m}^{-2}$)
$\dot{q}''_{sens}$	Sensible heat flux to the atmosphere ($\text{W}\cdot\text{m}^{-2}$)
$\dot{q}''_{soil}$	Soil heat flux ($\text{W}\cdot\text{m}^{-2}$)
$\dot{q}''_{lat}$	Latent heat flux ($\text{W}\cdot\text{m}^{-2}$)
ρ	Air density ($\text{kg}\cdot\text{m}^{-3}$)
c_p	Specific heat at constant pressure ($\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$)
r_a	Aerodynamic resistance ($\text{s}\cdot\text{m}^{-1}$)
z	Reference height at which wind speed is measured (m)
z_o	Surface roughness
e_a	Actual water vapor pressure (kPa)
e_s	Saturation vapor pressure (kPa)
B	Fire Weather Index in its intermediate form
U_r	Wind speed ($\text{m}\cdot\text{s}^{-1}$)
u	Wind speed ($\text{km}\cdot\text{h}^{-1}$)

1 | Introduction

For millennia, forests have delivered fuel and building materials to people. Further, people have experienced an increasingly sought out for their lifestyles and amenity values as they choose to live in close proximity to forests (Paton et al., 2015). This closeness among people and forests has increased the wildfire risk in the so-called wildland-urban interface (WUI), which is the zone of transition between unoccupied land and built environment. Furthermore, at the global scale, the impact of wildfires is expected to increase dramatically in the future due to the combined effects of the spreading of the WUI and climate change (Hammer et al., 2007; Simeoni, 2016). According to the Intergovernmental Panel on Climate Change (IPCC) AR6 report (Pörtner et al., 2022), currently there has been an increase in areas burned by wildfires, which are attributed to human-induced climate change in some regions. In the mid to long-term, this situation is expected to worsen.

A wildfire is an uncontrolled fire that burns in wildland vegetation, often in rural areas. It originates from an unplanned ignition, such as lightning, volcanic eruptions, and intentional or accidental human causes. Fire is the rapid oxidation of a material (the fuel) in the exothermic chemical process of combustion, releasing heat, light, and various reaction products. Hence, for a fire to exist, combustion must occur, and thus a flammable or combustible material in combination with sufficient oxidizer such as oxygen and a source of heat must subsist (NWCG, 2022).

Unplanned ignitions are referred as spontaneous and piloted ignition, where the first one corresponds to the fire occurrence without the application of an external heat source, while the second one occurs when there is a heating source (e.g. flame, firebrand), and can happen under lower temperatures than for spontaneous ignition (Mindykowski et al., 2011; NWCG, 2022; Urban & Fernandez-Pello, 2020). Once ignition occurs, propagation is the next concern. Fire propagation can take place from the forest surface (burning shrubland, grassland, small trees, etc) to crown fires (through tree canopies), which is usually associated to catastrophic wildfires involving live vegetation (Butler et al., 2004; McAllister et al., 2012; Scott & Reinhardt, 2001).

Studies have shown that human ignition is to blame for 84% of all wildfires in the United States (Balch et al., 2017). Moreover, US data compiled by the National Interagency Coordination Center (NICC) indicates that the average annual number of wildfires has a tendency to decrease, however the burned area has increased (Hoover & Hanson, 2022), hence wildfires have had a tendency to become more devastating through time in the US. Until the year 2007 the Food and Agriculture Organization indicated that worldwide, more than 90% of the fires are linked directly or indirectly to intentional and unintentional human actions, power lines and machinery (FAO, 2007). In addition, the incidence of major and catastrophic fire events has increased in many regions, with widespread media attention to fires in the Amazon, western North America, the Mediterranean, and Australia (Wu et al., 2021). Furthermore, the likelihood of catastrophic wildfire events will globally increase by a factor of 1.09 to 1.14 in the near-term and 1.31 to 1.57 by the end of the century (UNEP, 2022).

The loss of lives, property, flora and fauna are the primary effects of a wildfire. According to the Centre for Research on the Epidemiology of Disasters (CRED) and the United Nations Office for Disaster Risk Reduction (UNDRR) (Wallemacq & House, 2018), it is estimated that both wildfires and volcanic activities affected 6.2 million people between 1998–2017 with 2,400 attributable deaths worldwide from suffocation, injuries, and burns. The same report states that between 1998–2017, the total expenditure

resulting from wildfires was US\$ 68 billion.

Chile situation is not far from this reality. As it is possible to observe from [Figure 1.1](#), the fire counts (or number of fires) per season has increased since 1964. If a linear regression is applied to fire counts against the years, the slope has a positive value and hence it is possible to observe that there is an upward trend. On the other hand, burned area has also been slightly increasing, however if the wildfire events of 2017 are taken into consideration, all statistics become inaccurate due to the atypical outcomes of these fires. The “Las Máquinas” wildfire was one the events of the 2016–2017 austral summer fire season, which consumed 190,000 ha in a few days, becoming the largest single wildfire recorded in Chilean history. The total expenditure was around US\$ 350 million, which was made between CONAF and the Chilean government ([CONAF, 2017a](#)).

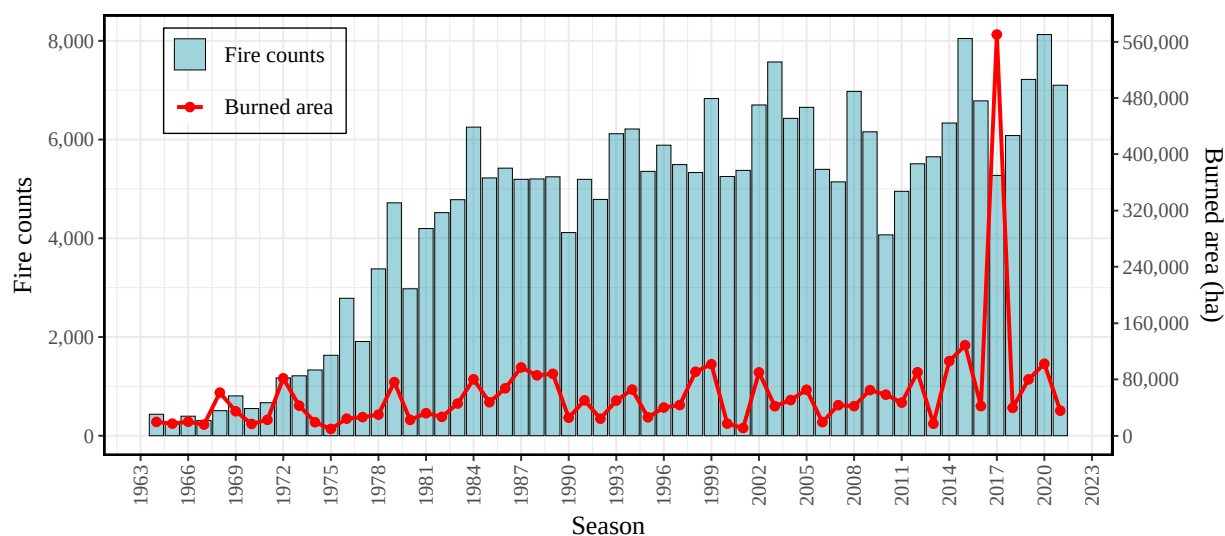


Figure 1.1: Fire counts and burned area for 1964 to 2021 seasons. First year data (1964) represent the 1964-1965 season and so forth. Each fire season starts in September and ends in March. Source: [CONAF \(2022b\)](#).

1.1. Research problem

Since the “Las Máquinas” wildfire has been the largest single event ever recorded in Chilean history, the focus of this study consists in analyzing the anatomy of the event solely relying on Earth Observation (EO) tools. The goal of this work is to develop a framework to carry out detailed analyses of catastrophic fires for forensic and public policy purposes, making use of the advantages given by EO satellites, including the observation of large tracts of landscapes with a good spatial resolution, and an ever-increasing temporal resolution, coupled with a sophisticated suite of instruments which allow measuring many parameters simultaneously. For this purpose, an analysis of the landscape conditions before the fire (pre-fire), the propagation of the fire front (per-fire) and the evolution of the vegetation in the years after the event (post-fire), using open-access satellite imagery obtained from multiple remote sensing instruments was carried out, giving a new perspective to the description of this event. Additionally, the pre- and per-fire Canadian Fire Weather Index (FWI) was calculated for the entire Region of Interest on a daily basis, based completely on remotely sensed data and physical simulations.

1.1.1 General objective

Describe the anatomy of the “Las Máquinas” wildfire solely relying on Earth Observation tools at a medium spatial resolution.

1.1.2 Specific objectives

1. Analyze the *pre*-fire conditions based on meteorological data and vegetation vigor evolution.
2. Study the *per*-fire effects and evolution considering the burned area, fire radiative power, air quality, fire weather, affected populated areas and affected species.
3. Examine the *post*-fire consequences.
4. Establish a framework for the analysis of large wildfires using Earth Observation data.

2 | State of the art

This chapter reviews the literature associated with the objectives of this study, which includes the Chilean ecosystem, a description of the “Las Máquinas” wildfire, remote sensing definitions and its use in wildfires, and the Canadian Fire Weather Index as a numeric rating of fire intensity.

2.1. Chilean Mediterranean ecosystem

Chile is located in the western part of South America and is the longest country in the world, being 4,300 km long and 175 km wide (average). Excluding its Pacific islands and Antarctic claim, Chile lies between latitudes 17° and 56°S, and longitudes 66° and 75°W. It is bounded on the north by Perú and Bolivia, on its long eastern border by Argentina and on the west by the Pacific Ocean. Continental Chile has a total surface of 756,096 km² with an estimated population of 19,800,000 inhabitants in 2022 (Carmagnani et al., 2022). According to the World Bank, in December 2020, Chile’s GDP was US\$ 252.9 billion, and GDP per capita was US\$ 13,867 (The World Bank, 2022).

Continental Chile is dominated by natural barriers such as the Andes Mountains at the east and the Pacific Ocean in the west. Facing the Pacific Ocean is the Coastal range that encloses the thin flat Central Valley, where most of the population lives. The climate in Central Chile is prototypical Mediterranean, holding most of the population and economical activities of the country. The once wide spread Valdivian Chilean Rainforest, characterized by a number of endemic tree species of the *Nothofagus* genre, bamboo shrub, the notorious Chilean Palm forest (*Jubaea Chilensis*) and *Cupressaceae* trees in the Andes have given way to arable land and exotic forest plantations in central Chile.

Forestry is one of the main economical activities in Central Chile, with large continuous areas planted with *Pinus radiata* and *Eucalyptus globulus*, destined mainly to the production of pulp and timber. Growing fast, they have a large extent replaced the native Chilean forests. Fire have been traditionally used to clean land for agricultural, silvicultural and urbanistic purposes. Even though some native tree and shrub species display some degree of adaptation to fire, most of the native forest requires much longer recovery times than the exotic species growth cycle, which mean that once burnt, they disappear from a zone due to land use and land cover change (Miranda et al., 2017). *Pinus radiata* trees exhibit serotiny i.e. the ability to release seeds under a external stress trigger such as fire, in concomitance with the release of abundant fine dead leaves (Franzese & Raffaele, 2017; Liacos, 1986; Reszka et al., 2020). *Eucalyptus globulus* on the other hand produces highly flammable oils, bark and dead branches, and bears the capacity to easily re-sprout after a fire (Dos Santos et al., 2015; Reyes & Casal, 2001), so both species are adapted to fire. In spite of this, fire is not considered as an ecological regulator in Chile, since the natural germination or resprout are not the preferred cultivation method of introduced species, so prescribed fire (Fernandes et al., 2013; Liacos, 1986; Miller et al., 2020) is not a viable option in Chile to avoid wildfires, contrary to other regions of the world. Fire is then a hazard to either native as well as exotic forests in Chile (Franzese & Raffaele, 2017). Introduced annual grasses and shrub are also recognized to be well adapted to fire (Contreras et al., 2011), invading ecosystems (Gómez-González et al., 2011) even though not necessarily replacing native species. Burning during the dry season they can abundantly regrow during the wet season, adding fuel material (Bowman et al., 2019; Pauchard et al., 2008; Úbeda & Sarricolea, 2016). An anomalously prolonged drought (Boisier et al., 2016; Flores-Aqueveque et al., 2020; Garreaud et al., 2020) has put enormous stress on water resources and associated agricultural activities in Central Chile,

that has likely produced social unrest (Garreaud et al., 2017) in rural communities. Closely associated are the record temperatures experienced in Chile during the last decade, with all time record maximums during January 2017 (Feron et al., 2019; Urrutia-Jalabert et al., 2018).

The Chilean wildfire season is from November to March (Austral summer), and there is evidence that this season has been increasing (Castillo et al., 2020). Due to the summer climate in Central Chile, natural fires caused by lightning are practically nonexistent. According to CONAF (2022a), 0.82% of wildfires are attributed to natural causes, and 80% to human activity, either accidental or intentional. In addition, 99% of the fires damage exhibits an area under 3.3 ha, while the remaining 1% of the fires damage an average area of 853 ha (CONAF, 2022b). In the recent years, two significant wildfires have been located in the WUI, particularly in the city of Valparaíso (called “The great fire of Valparaíso” in 2014), and near villages within the Maule Region (season 2016–2017, mainly the “Las Máquinas” wildfire), both in Central Chile, where the most affected neighborhoods had mid-to-low income. As stated by Úbeda & Sarricolea (2016), in Chile, as in other countries, the lax nature of regulations in the past saw the building of very low quality constructions with a poor provision of infrastructure in these WUI areas.

2.2. Las Máquinas wildfire

The wildfires of the 2016–2017 season took place in Central and Southern Chile. A total of 681 fires were reported by CONAF, and 417 of them were spotted at the regions of O’Higgins, Maule and Biobío, which became the *critical* regions (CONAF, 2017a). The total burned area of these fires was 575,000 ha (Castillo et al., 2019). As a result, 11 people died, 4,290 were injured, and 1,159 were sheltered. A total of 2,300 structures were destroyed and 25,000 were threatened within the critical regions (CONAF, 2017a; ONEMI, 2017a). In response, 3,297 people fought in the fire line, including brigades from CONAF, BRIFE and BRIFAR (trained military special forces brigadiers), and from international cooperation. Moreover, 64 aircraft were deployed during the emergency, and a total of $\sim 4.3 \times 10^7$ L of water were launched nationwide (CONAF, 2017a).

Only in 14 hours (the night of January 25th, 2017) the fire propagated increasing its burned area in 114,000 ha, i.e. 1.8 times the size of Chilean capital city of Santiago (CONAF, 2017a). These fires took place at the Maule region, particularly among the Cauquenes, Empedrado, San Javier, Chanco and Constitución municipalities. These events acquired the name of the “Las Máquinas” wildfire, since its origin was close to the “Las Máquinas” village within the Cauquenes municipality. On the night of January 25th, the fire propagated north and the village of Santa Olga (located within the Constitución municipality) was completely razed by its flames. This event killed 4 people and destroyed over 1,000 structures (Clarín, 2017; Cooperativa, 2017; Medrano, 2017). A total burned area of 183,946 ha was reported by the authorities (ONEMI, 2017b), becoming the single largest fire in Chilean history.

These wildfires turned into a worldwide episode, since there was no such precedent of the magnitude of these events in Chile. As in over the 80% of wildfires causes in Chile, these event were human-made. In fact, on January 29th of the same year, President Michelle Bachelet (Chilean President between 2014–2018) announced that there were 43 people arrested (BioBio, 2017). Nevertheless, ignition should not be the only variable to take into consideration, since the magnitude, propagation and effects of the event are related to other constituents, which have been widely studied (Balocchi et al., 2020; Bowman et al., 2019; Castillo et al., 2020, 2019; CONAF, 2017a; Garcia-Chevesich et al., 2019; Garreaud et al., 2020; González et al., 2020). Among these, and as stated by CONAF (2017a), January was a “month of records”. Temperatures reached values of 37.3°C in the Maule Region (specifically in the city of Curicó), being this the highest

temperature registered in over 91 years. Moreover, since 2009–2010 a severe and prolonged drought has been detected (CONAF, 2017a; Garreaud et al., 2020). Using the fifth generation of ECMWF (European Centre for Medium-Range Weather Forecasts) atmospheric reanalysis of the global climate data (ERA-5), the Center for Climate and Resilience Research (CR², Chile), analyzed meteorological variables seven days prior and after the event (González et al., 2020). The results showed that the occurrence of large fires in Central and Southern Chile were favored by heat waves, characterized by low humidity and the absence of cloud cover, strong southerly winds and intense easterly winds in the foothills. In addition, Bowman et al. (2019) studied, among other variables, the Canadian Fire Weather Index (FWI) using ERA-Interim reanalysis data for all the fires that took place in Central Chile, and their findings showed maximum FWI values of around 60 between January 20 and 28, 2017.

2.3. Remote sensing

There are multiple definitions of what remote sensing is. For example, Lintz & Simonett (1976) establish that remote sensing is the acquisition of physical data of an object without touch or contact. Another interesting definition is the one made by Campbell & Wynne (2011), which is the following. “Remote sensing is the practice of deriving information about Earth’s and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the Earth’s surface”. However, this would be an appropriate definition if remote sensing was studied only from satellite-derived information, yet remote sensing also applies to laboratory–scale studies using, for example, spectrometers, which do not acquire images. Nevertheless, and because of the scope of this work, remote sensing will refer to the spectral information acquisition from a satellite sensor and/or satellite product.

A satellite image has more physical information than the commonly-known “RGB images” taken by a professional camera or even a phone camera. RGB images are a composition of the red, green and blue bands within the visible electromagnetic spectrum. Most satellite sensors carry those bands within their optical sensors, but there is much more information through different regions of the spectrum i.e. there are bands outside the visible region. For example, NASA’s Terra and Aqua satellites were launched in 1999 and 2002, respectively, and they carry one of the most used open-access information sensor-data which is the Moderate Resolution Imaging Spectroradiometer (MODIS). The MODIS sensor has 36 spectral bands ranging from 0.4 μm to 14.4 μm (NASA, 2022a). This spectral information refers to reflectance, transmittance or absorbance information-retrievals within a specific spectral resolution (bandwidth), spatial resolution (pixel size), and at a certain temporal resolution (time it takes for the satellite to pass through the same location) which is dependent of both the satellite and optical sensor. Say the incident irradiation flux from the Sun G is decomposed. The result would be the following (Bergman et al., 2011; Chuvieco, 2010).

$$G = G_r + G_a + G_t \quad (2.1)$$

where G_r , G_a and G_t correspond to the reflected, absorbed and transmitted fluxes, respectively. When radiation is incident upon a semitransparent medium, portions of the irradiation may be reflected, absorbed, and transmitted. Transmission refers to radiation passing through the medium, while absorption occurs when radiation interacts with the medium. Finally, reflection is the process of incident radiation being redirected away from the surface, with no effect on the medium (Bergman et al., 2011, Chapter 12). Hence, if expression (2.1) is divided by the incident irradiation flux,

$$1 = \rho_\lambda + \alpha_\lambda + \tau_\lambda \quad (2.2)$$

where ρ_λ , α_λ and τ_λ are the reflected, absorbed and transmitted irradiation fractions at a certain wavelength λ , respectively. In order to quantify these values, sophisticated optical instruments are required. These are called spectrometers or radiometers. A radiometer is used to measure the amount of electromagnetic energy among a certain wavelength range. Generally, radiometers are used to detect and measure the amount of energy outside the visible spectrum, specially in the ultraviolet (UV) or infrared (IR) regions. Spectrometers, like radiometers, are instruments that are also used to measure an specific wavelength range. However, the difference between them is that spectrometers use an optical grating or prism and multiple sensors to break down the incoming energy into different wavelength or components (Konika Minolta, 2019).

Most optical Earth Observation (EO) satellite systems obtain physical reflectance information from the Earth's surface within the visible (VIS $\sim$ 400–700 nm), near infrared (NIR $\sim$ 700–1200 nm) and short-wave infrared (SWIR $\sim$ 1200–2500 nm) bands, and others even include thermal infrared (TIR $\sim$ 3–35 μ m) bands. Some examples are the MODIS sensor (NASA, 2022a), Landsat-8 Operational Land Imager (OLI) sensor (USGS, 2022a), Sentinel-2 MultiSpectral Instrument (MSI) sensor (ESA, 2022a), NASA/NOAA Suomi-NPP Visible Infrared Imaging Radiometer Suite (VIIRS) sensor (NASA, 2022b), among others. As a result, the output of a satellite image is known as a raster or matrix, where each cell or pixel has a certain value. These rasters are stacked within a satellite image, and hence each raster stacked layer represents the data for an specific multi-spectral band.

When applied to vegetated surfaces, the spectral characteristics are a function of the leaf composition, age and phenology, plant architecture, illumination intensity and viewing angles (Suarez et al., 2015). The vegetation spectrum can be divided into several wavelength regions. The main responsible of the leaf low reflectance in the visible region is the leaf pigment pool (chlorophylls, carotenoids and xanthophylls; Suarez et al., 2015). In the NIR region the leaf absorption/reflection is mainly dependent on the leaf cell structure, and in the SWIR, absorption/reflection is due to vegetation water content and other compounds concentration (Ceccato et al., 2002a,b; Chuvieco, 2010; Danson & Bowyer, 2004; Peñuelas & Filella, 1998; Peñuelas et al., 1997).

Hence, remote sensing is a robust tool that can capture physical spectral information within a certain resolution. This is useful to study multiple variables such as land surface temperatures (Hulley & Hook, 2018; Wan et al., 2015), evapotranspiration (Running et al., 2017), vegetation vigor (Gitelson et al., 1996; Hardisky et al., 1983; Huete et al., 2002; Rouse et al., 1973; Tucker, 1979), vegetation water content (Gao, 1996; Peñuelas et al., 1997), biochemical composition (Gitelson et al., 2003, 2006, 2001) and so forth. Most of these variables are indirectly explained through the use of the so-called spectral indices, which are explained in the following section.

2.3.1 Spectral indices

A spectral index can be defined as a mathematical relationship between physical reflectance to indirectly explain or estimate (being an independent variable) the behavior of the response to a dependent variable, like biochemical or biophysical information of vegetation (Salas & Henebry, 2013).

For vegetation, spectral indices seek to explain variables including the chlorophyll and carotenoid content (e.g. Gitelson et al., 2003; Gitelson & Merzlyak, 1994; Mishra & Mishra, 2012), or variables related to vegetation moisture content (e.g. Ceccato et al., 2002a,b; Gao, 1996; Hardisky et al., 1983; Huete et al., 2002; Hunt Jr & Rock, 1989; Peñuelas et al., 1997; Wang et al., 2004), among others. Table 2.1 exhibits some spectral indices with their corresponding formula and author.

Table 2.1: Selected spectral indices used in vegetation studies, focusing on the photosynthetic pigments and moisture content indirect retrieval. ρ_λ corresponds to physical reflectance at wavelength λ (in nm).

Spectral index	Name	Formula	Author
I.G.I [†]	Gitelson Index ^{**}	$\frac{\rho_{775}}{\rho_{718}} - 1$	Gitelson et al. (2003)
WI [‡]	Water Index	$\frac{\rho_{900}}{\rho_{970}}$	Peñuelas et al. (1997)
NDVI [*]	Normalized Difference Vegetation Index	$\frac{\rho_{850} - \rho_{680}}{\rho_{850} + \rho_{680}}$	Rouse et al. (1973)
D.I.I [†]	Datt Index ^{**}	$\frac{\rho_{780} - \rho_{710}}{\rho_{780} - \rho_{680}}$	Datt (1999)
NDI [†]	Normalized Difference Index	$\frac{\rho_{750} - \rho_{705}}{\rho_{750} + \rho_{705}}$	Gitelson & Merzlyak (1994)
NDWI [‡]	Normalized Difference Water Index	$\frac{\rho_{860} - \rho_{1240}}{\rho_{860} + \rho_{1240}}$	Gao (1996)
MSI [‡]	Moisture Stress Index	$\frac{\rho_{820} - \rho_{1600}}{\rho_{820} + \rho_{1600}}$	Hunt Jr & Rock (1989)
NDII [‡]	Normalized Difference Infrared Index	$\frac{\rho_{850} - \rho_{1650}}{\rho_{850} + \rho_{1650}}$	Hardisky et al. (1983)
NMDI [‡]	Normalized Multi-band Drought Index	$\frac{\rho_{860} - (\rho_{1640} - \rho_{2130})}{\rho_{860} + (\rho_{1640} - \rho_{2130})}$	Wang & Qu (2007)

[†] Indices that have been used to estimate photosynthetic pigments.

[‡] Indices that have been used to estimate moisture content.

^{*} Indices developed to determine vegetation vigor.

^{**} Indices that do not have an established name.

Usually, in order to develop a spectral index a laboratory bench scale analysis is carried out. This means that optical instruments like spectrometers are used to retrieve the reflective spectrum within the instrument spectral resolution for a certain sample. Furthermore, the precision of these instruments in terms of spectral resolution is high, meaning that these apparatuses obtain spectral information categorized as hyperspectral data, since spectral-bands are non-existent or quite narrow, thus reflectance is acquired at a certain wavelength λ . This is not the case for most satellite sensors, whose resulting information is categorized as multispectral, thus a reflectance value is obtained for a certain bandwidth or wavelength range. Therefore, if a particular spectral index is going to be applied to satellite data, special consideration must be taken to use the corresponding bands whose central bandwidth wavelength value is the closest to the spectral index wavelength value. For example, if NDVI is going to be calculated from MODIS reflectance information (Vermote & Wolfe, 2015), the reflectance values to be used are those at the 850 and 680 nm wavelengths (see Table 2.1), which corresponds to MODIS Band 2 (B2) and Band 1 (B1), respectively. However, the bandwidths of these bands are 841–867 nm and 620–670 nm (NASA, 2022a).

From Table 2.1 it is possible to observe that there are multiple mathematical expressions to calculate a spectral index. The most common ones are the so-called *normalized differences*, such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), among others. Nevertheless, there are multiple methods to generate a spectral index. In recent years, new techniques have been applied to create or adjust spectral indices from machine learning algorithms using both classification and regression in supervised and unsupervised models (e.g. Arevalo-Ramirez et al., 2020; Ramos et al., 2020; Wang et al., 2017b).

2.3.2 Satellite sensors and products

There is a vast amount of satellites orbiting the Earth, from low Earth orbit (LEO) to geostationary orbit (GEO). Most Earth Observation (EO) satellites operate in the LEO since it is the closest to the planet surface allowing the satellite sensor to take images of higher resolution. Satellites in this orbit travel at a speed of around $7.8 \text{ km}\cdot\text{s}^{-1}$, and thus it takes them around 90 minutes to circle Earth (ESA, 2022b).

Satellite information or images are obtained by a sensor, and these images usually undergo several processing procedures. For example, NASA's EarthData defines a total of 10 levels for some products (e.g. Landsat-8; NASA, 2021). "Level 0" data corresponds to reconstructed, unprocessed instrument data. "Level 1A" refers to data that has undergone a radiometric and geometric calibration, and so forth. These are usually called satellite-derived products, and in the case of MODIS and VIIRS sensors, a product refers to a much advanced post-processing method, including the application of several algorithms (e.g. radiative transfer models) to estimate, for example, aerosol optical depth (Hsu et al., 2019), evapotranspiration (Running et al., 2017), land surface temperature (Hulley & Hook, 2018; Wan et al., 2015), vegetation indices (Didan, 2015; Didan & Barreto, 2018), total precipitable water content (Gao & Kaufman, 2015), etc. A list of all NASA's EarthData products (including VIIRS and MODIS) can be found in the following website: https://lpdaac.usgs.gov/product_search/?view=list (accessed in May 2022).

Furthermore, there are several types of resolutions within a satellite-sensor and hence for their products. These are the following (Chuvieco, 2010).

- 1) Spatial resolution. Refers to the size of the smallest feature that can be detected by a satellite sensor or displayed in a satellite image. It is usually represented by a single value representing the length of one side of a square, which is the image pixel. For example, Landsat-8 satellite images have a 30 m spatial resolution, meaning that each pixel represents an area of $30 \times 30 \text{ m}$ on the ground.
- 2) Temporal resolution. Refers to the time it takes the satellite to fly through the same location. For example, NASA's Aqua/Terra satellites have a temporal resolution of 1 day i.e. it is possible to acquire daily images from their sensor data.
- 3) Spectral resolution. Indicates the bandwidth value of the spectral bands that a satellite-sensor can distinguish. For example, band number 1 of the MODIS sensor has a bandwidth or spectral resolution of 50 nm. Within this definition is possible to distinguish between multispectral (spectral bands) and hyperspectral (usually lower than 8 nm, and in some cases under 1 nm) information.
- 4) Radiometric resolution. Corresponds to the sensitivity of a sensor i.e. to its ability to detect variations within the spectral radiance that it captures. For example, the MODIS sensor aboard NASA's Terra and Aqua satellites has a radiometric resolution of 12-bit, offering a total of $2^{12} = 4,096$ codification levels per pixel.

A description and procedure on how to download several satellite images or products is detailed in Appendix A, which can be through data-hubs or using R language (R Core Team, 2021). In addition,

the work with raster or Geographic Information System (GIS) data is detailed in [Appendix B](#), which is completely done in R language.

In the following sections, and for the sake of simplicity, only the satellite sensors that are used in this work are described, which are all open-source and widely used.

2.3.2.1 NASA Aqua/Terra MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument is operating on both the Terra and Aqua spacecraft. The Terra satellite was launched on December 18, 1999 while the Aqua on May 4, 2002. It has a viewing swath width of 2,330 km and views the entire surface of the Earth every one to two days. Its detectors measure 36 spectral bands and it acquires data at three spatial resolutions: 250 m, 500 m, and 1,000 m ([USGS, 2022b](#)). The general characteristics of MODIS sensor can be appreciated in [Table 2.2](#), while the MODIS bands used for land, cloud and aerosol boundaries and properties are shown in [Table 2.3](#).

Table 2.2: General characteristics of Aqua/Terra-MODIS. Obtained from [Justice et al. \(2002\)](#).

Orbit	705 km, sun-synchronous, near-polar nominal descending equatorial crossing at 10:30 local time.
Swath	2,330 km $\pm$ 55° cross-track.
Spectral bands	36 bands, between 0.405 and 14.385 μ m with onboard calibration subsystems.
Radiometric resolution	12 bits.
Spatial resolution at nadir	250 m (bands 1–2), 500 m (bands 3–7), 1,000 m (bands 8–36).
Repeat coverage	daily, every 2 day for $< 30^\circ$ latitude.

On the other hand, MODIS uses a Sinusoidal grid tiling system, which are 10° by 10° at the equator. The tiles are enumerated for horizontal (h) from 0 to 35, and for vertical (v) from 0 to 17. For example, Central Chile is within the horizontal 12 and vertical 12, which corresponds to tile: h12v12.

Table 2.3: MODIS bands for land, cloud and aerosols boundaries and properties within the VIS/NIR/SWIR spectrum.

Band	Spectral range (nm)	Center (nm)	Bandwidth (nm)	Spatial resol. (m)	Description
1	620 – 670	645	50	250	Red
2	841 – 876	858	35	250	NIR
3	459 – 479	469	20	500	Blue
4	545 – 565	555	20	500	Green
5	1230 – 1250	1240	20	500	SWIR 1
6	1628 – 1652	1640	24	1,000	SWIR 2
7	2105 – 2155	2130	50	1,000	SWIR 3

2.3.2.2 NASA/NOAA Suomi-NPP VIIRS

The Visible Infrared Imaging Radiometer Suite (VIIRS) is aboard two satellites: Suomi National Polar-orbiting Partnership (Suomi NPP) and National Oceanic and Atmospheric Administration-20 (NOAA-20). Suomi NPP, which contains five instruments including VIIRS, was launched from Vandenberg Air Force Base on October 28, 2011. It was the first in a series of four Joint Polar Satellite System (JPSS) satellites, a collaborative mission between NOAA and NASA, that carries the VIIRS instrument. Its data products are developed by NASA and are distributed by NASA's Land Processes Distributed Active Archive Center (LP DAAC, [USGS, 2022c](#)). The general characteristics of the VIIRS sensor can be appreciated in [Table 2.4](#), while the VIIRS bands used within the VIS/NIR and SWIR regions are shown in [Table 2.5](#). Finally, the VIIRS sensor uses the same Sinusoidal grid tiling system as MODIS.

Table 2.4: General characteristics of the VIIRS-SNPP sensor. Obtained from [NASA \(2022b\)](#).

Orbit	830 km, sun-synchronous, polar orbiting crossing at 13:30 local time
Swath	3000 km
Spectral bands	22 bands, between 0.415 and 12.013 μm
Radiometric resolution	12 bits
Spatial resolution at nadir	750 m
Repeat coverage	nearly global coverage every day

Table 2.5: VIIRS-SNPP bands for land, cloud and aerosols boundaries and properties within the VIS/NIR/SWIR spectrum.

Band	Spectral range (nm)	Center (nm)	Bandwidth (nm)	Spatial resol. (m)	Description
M1	402 – 422	412	20	750	VIS 1
M2	436 – 454	445	18	750	VIS 2
M3	478 – 498	488	20	750	Blue
M4	545 – 565	555	20	750	Green
M5	662 – 682	672	20	750	Red
M6	739 – 754	746	15	750	NIR 1
M7	846 – 885	865	39	750	NIR 2
M8	1230 – 1250	1240	20	750	SWIR 1
M9	1371 – 1386	1379	15	750	SWIR 2
M10	1580 – 1640	1610	60	750	SWIR 3
M11	2225 – 2275	2250	50	750	SWIR 4

2.3.2.3 NASA Landsat-8 OLI

The Operational Land Imager (OLI) is one of the two sensors aboard the Landsat-8 satellite. Landsat 8 launched on February 11, 2013, from Vandenberg Air Force Base, California, on an Atlas-V 401 rocket, with the extended payload fairing (EPF) from United Launch Alliance ([NASA, 2022c](#)). Landsat-8 OLI collects data for visible, near infrared, and short wave infrared spectral bands as well as a panchromatic band, and its products are distributed by the United States Geological Survey (USGS), which can be found in USGS EarthExplorer. The general characteristics of the OLI sensor are presented in [Table 2.6](#), while the OLI bands used within the VIS/NIR and SWIR regions are shown in [Table 2.7](#).

Table 2.6: General characteristics of the Landsat-8 OLI sensor. Obtained from [NASA \(2022c\)](#).

Orbit	705 km, sun-synchronous, polar orbiting crossing at 10:00 local time.
Swath	185 km cross-track.
Spectral bands	9 bands, between 0.435 and 2.294 μm .
Radiometric resolution	12-bit scaled to 16-bit integers.
Spatial resolution at nadir	30 m.
Repeat coverage	16 days.

On the other hand, OLI products uses the Worldwide Reference System-2 (WRS-2) path/row system, with a swath overlap (or sidelap) varying from 7% at the equator to a maximum of approximately 85% at extreme latitudes. For example, path/row = 233/085 images cover most part of the Maule region, Chile.

Table 2.7: Landsat-8 OLI bands for land, cloud and aerosols boundaries and properties within the VIS/NIR/SWIR spectrum.

Band	Spectral range (nm)	Center (nm)	Bandwidth (nm)	Spatial resol. (m)	Description
1	430 – 450	440	20	30	Aerosol
2	450 – 510	500	20	30	Blue
3	530 – 590	560	60	30	Green
4	640 – 670	655	30	30	Red
5	850 – 880	865	30	30	NIR
6	1570 – 1650	1610	80	30	SWIR 1
7	2110 – 2290	2180	180	30	SWIR 2
8	500 – 680	590	180	15	Panchromatic
9	1360 – 1380	1370	20	30	Cirrus

2.3.2.4 ESA Sentinel-2 MSI

The MultiSpectral Instrument (MSI) is aboard the Copernicus Sentinel-2A and 2B satellites, which launched on June 23, 2015, and March 7, 2017, respectively. The MSI measures the Earth's reflected radiance in 13 spectral bands from VIS-NIR to SWIR ([ESA, 2022a](#)), and its data is processed, archived and distributed by the Payload Data Ground Segment (PDGS) in Copernicus Open Access Hub. The general characteristics of MSI sensor are displayed in [Table 2.8](#), while the MSI bands in [Table 2.9](#).

MSI products are $100 \times 100 \text{ km}^2$ ortho-images in UTM/WGS84 projection. The UTM (Universal Transverse Mercator) system divides the Earth's surface into 60 zones. Each UTM zone has a vertical width of 6° and horizontal width of 8° . For example, most of the Maule Region of Chile is covered by the following Sentinel-2 tiles: T18HYE, T18HYF, T18HYG and T19HBA.

Table 2.8: General characteristics of the Sentinel-2 MSI sensor. Obtained from [ESA \(2022a\)](#).

Orbit	786 km, sun-synchronous, two-polar orbiting crossing at 10:30 local time.
Swath	290 km cross-track.
Spectral bands	12 bands, between 0.421 and 2.377 μm .
Radiometric resolution	12-bit.
Spatial resolution at nadir	see Table 2.9 .
Repeat coverage	10 days.

Table 2.9: Sentinel-2 MSI bands for land, cloud and aerosols boundaries and properties within the VIS/NIR/SWIR spectrum. Re_i correspond to “red edge” i bands, NIRn to narrow-NIR, and W. vapor to water vapor band.

Band	Spectral range (nm)	Center (nm)	Bandwidth (nm)	Spatial resol. (m)	Description
1	421.7 – 463.7	442.7	21	60	Aerosol
2	426.4 – 558.4	492.4	66	10	Blue
3	523.8 – 595.8	559.8	36	10	Green
4	633.6 – 695.6	664.6	31	10	Red
5	689.1 – 719.1	704.1	15	20	Re_1
6	725.5 – 755.5	740.5	15	20	Re_2
7	762.8 – 802.8	782.8	20	20	Re_3
8	726.8 – 938.8	832.8	106	10	NIR
8A	843.7 – 885.7	864.7	21	20	NIRn
9	925.1 – 965.1	945.1	20	60	W. vapor
10	1342.5 – 1404.5	1373.5	31	60	Cirrus
11	1522.7 – 1704.7	1613.7	91	20	SWIR-1
12	2027.4 – 2377.4	2202.4	175	20	SWIR-2

2.3.3 Remote sensing of wildfires

In wildfires, the fuel is defined as vegetation, both live and dead, susceptible of burning, which is needed, for example, as input variables for fire behavior prediction models ([Anderson, 1982](#); [Cocero et al., 2004](#); [Scott & Burgan, 2005](#)). However, the data-scale required for the latter is at the so-called “landscape scale”. The variables that play a relevant role in a wildfire are vast, from vegetation that burns, fuel moisture content, biochemical composition, fire weather, and so forth, and the use of remote sensing in wildfires relies in the acquisition or estimation of those variables ([Burgan et al., 1998](#); [Chuvieco et al., 2002](#); [Keane et al., 2001](#); [Reszka et al., 2020](#); [Salas & Chuvieco, 1995](#); [Yebra et al., 2013](#)). Usually, spectral indices at a laboratory bench-scale are studied to explain such variables, which are then scaled to the UAV/satellite level (e.g. [Ceccato et al., 2002a,b](#); [Valdivia, 2017](#); [Vaughan, 2001](#)).

In wildfire detection, remote sensing has demonstrated to be a powerful tool. An example of this is the MODIS MCD64A1 product ([Giglio et al., 2015](#)), which corresponds to the combined Terra+Aqua-MODIS Burned Area product at 500 m spatial resolution. This product has been used for generating databases such as the Global Fire Atlas database ([Andela et al., 2019a,b](#)), the Global Fire Emissions database ([Giglio et al., 2015, 2013](#); [Van Der Werf et al., 2017](#)), and actively used by NASA’s Fire Information for Resource Management System (FIRMS) to provide active fire data for near-real time monitoring and applications

(FIRMS, 2022).

Furthermore, remote sensing has several advantages. For example, a global coverage, at a fine, medium and coarse spatial resolution (e.g. fine: Sentinel-2 MSI, medium: Terra/Aqua-MODIS, coarse: Aqua's Atmospheric Infrared Sounder-AIRS), and at a daily-to-medium temporal resolution (e.g. daily: Terra/Aqua-MODIS, 16-day: Landsat-8). Depending on the satellite-sensor, the spectral bands can be used to obtain several spectral indices at diverse regions of the electromagnetic spectrum, which can be used to study the variables mentioned before. In addition, most of these images are completely free to use, and there is a wide community in the "GIS world" (Geographic Information System; e.g. GIS Stack-Exchange).

Nowadays, most fire danger systems study both the fire weather and the dead fuels condition. The fire weather corresponds to meteorological variables that directly affect both ignition and propagation of the fire, such as the ambient temperature, wind speed, precipitation, and relative humidity. Dead fuel conditions refer to the study of variables including the fine dead fuel moisture content, dry matter content, etc, which are used in fire danger systems like the Canadian Forest Fire Weather Index (FWI) System (NRC, 2021; Van Wagner, 1974, 1987), and in the US National Fire Danger Rating System (NFDRS, Burgan, 1979, 1988; Cohen & Deeming, 1985).

McAllister et al. (2012) studied the flammability of live fuels (pine needles) with the basis that the most unpredictable and uncontrollable wildfires are those that occur in the tree-canopies of living fuels (crown fires), and discuss how little is known about the combustion processes of these fires. The study developed by Dennison et al. (2008) showed a relation between live fuel moisture content (LFMC) and large wildfires in Santa Monica (California, US). Their findings suggest that large wildfires (with a burned area over 1,000 ha) only occur when the LFMC was under 77%. Therefore, the study of live fuels should also be taken into consideration. A review of this variable was carried out by Yebra et al. (2013), where they state that satellite information provides the opportunity to estimate the live fuel moisture content through large areas at both good spatial and temporal resolutions (e.g. Chuvieco et al., 2002; Peterson et al., 2008; Wang et al., 2013; Yebra et al., 2008).

With remote sensing it is possible to acquire information such as monthly cumulative precipitation or even daily precipitation (Huffman et al., 2014), vegetation vigor/density with spectral indices such as the NDVI (Rouse et al., 1974), vegetation water content (Gao, 1996), and many more that, for example, derive from physical radiative transfer models (e.g. aerosol optical depth and aerosol type from SNPP/VIIIRS, Hsu et al., 2019) or reanalysis data (e.g. ECMWF ERA-5 Reanalysis).

As stated by Cocero et al. (2004), "By means of remote sensing, today it is possible, for example, to determine through time series the historic configuration of an area as well as its environmental gradients which are the biogeochemical phenomena that directly influence vegetation and fuel dynamics".

2.4. Canadian Fire Weather Index

The first wildfire hazard prediction systems emerged in Canada and the USA. For the US, the prediction system is called “National Fire Danger Rating System” (NFDRS; Bradshaw et al., 1983; Burgan, 1979; Cohen & Deeming, 1985), whose objective is to evaluate the probability of a wildfire event at a certain period of time and provide guidelines about its growth (Salas & Cocero, 2004). Canada’s prediction system is called “Canadian Forest Fire Danger Rating System” (CFFDRS; Van Wagner, 1974, 1987), whose purpose is similar to the NFDRS, however there is a slight difference, since the CFFDRS incorporates the Fire Weather Index (FWI), which consists of six components that account for the effects of fuel moisture and weather conditions on fire behavior (NRC, 2021). Its structure can be observed in Figure 2.1.

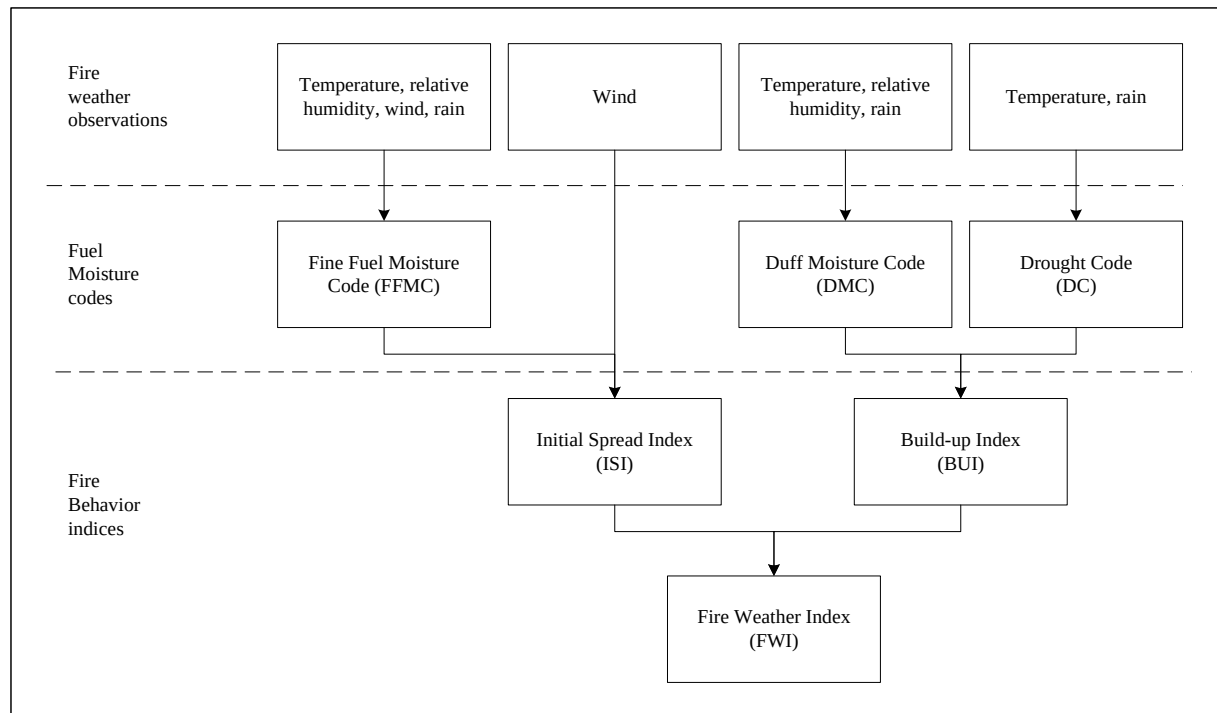


Figure 2.1: Structure of the Fire Weather Index system.

Therefore, the Canadian FWI uses the meteorological variables ambient temperature, relative humidity, wind speed and 24-hours accumulated rainfall at noon to calculate three sub-indices: the Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC) and Drought Code (DC). These indices estimate the humidity of three layers, the top layer of fine fuel, a second of the duff, and the third of the soil, respectively (Lawson & Armitage, 2008; Van Wagner, 1987; Van Wagner & Pickett, 1985; Wang et al., 2015; Wotton et al., 2009). Hence, the first iteration of the FWI must include these values, and the following FWI estimation will modify it using meteorological data. The definition of the last three variables are mentioned below (Van Wagner, 1974, 1987; Van Wagner & Pickett, 1985).

1. Fine Fuel Moisture Code (FFMC; unitless) of the previous day. This variable corresponds to a numeric rating of the moisture content of litter and other cured fine fuels in a forest stand, in a layer of dry weight about $0.25 \text{ kg}\cdot\text{m}^{-2}$. This code indicates a relative ease of ignition and the flammability of fine fuels.
2. Duff Moisture Code (DMC; unitless) of the previous day. The DMC is a numeric rating of the

average moisture content of loosely compacted, decomposing organic matter weighing about $5 \text{ kg}\cdot\text{m}^{-2}$ when dry. This code gives an indication of fuel consumption in moderate duff layers and medium-size woody material.

3. Drought Code (DC; unitless) of the previous day. The DC is a numeric rating which represents a deep layer of compact organic matter weighing around $25 \text{ kg}\cdot\text{m}^{-2}$ when dry. This code is a useful indicator of seasonal drought effects on forests fuels and the amount of smoldering in deep duff layers and large logs.

The FWI can be categorized into 6 classes of danger as shown in [Table 2.10](#) ([Climate Adapt, 2020](#)).

Table 2.10: Canadian Fire Weather Index danger classification. Obtained from [Climate Adapt \(2020\)](#).

Classification	FWI values
Very low danger	0 – 5.2
Low danger	5.2 – 11.2
Moderate danger	11.2 – 21.3
High danger	21.3 – 38.0
Very high danger	38.0 – 50.0
Extreme danger	> 50.0

[Avila et al. \(2022\)](#) studied both a modified FWI for Central Chile as well as an approximation under certain weather conditions. The Fire Weather Index approximated (FWI_{app}) can be used if the following requisites are satisfied:

- No rainfall
- Low humidity
- High temperatures
- Little variations among the meteorological conditions from one day to another

Hence, if these conditions are satisfied, the humidity derived from the FFMC is approximated using the drying equilibrium humidity, and some terms such as the $m^{5.31}$ value within the FFMC equation (see Eq. (25) of [Van Wagner & Pickett, 1985](#)) are discarded considering low humidities ([Avila et al., 2022](#)). Moreover, the Build-up Index (BUI) can be approximated to $2 \times \text{DMC} \approx 2N \times K$, where N is the number of days and K is the log drying rate. Thus, if the latter is solved, the Fire Weather Index can be estimated only based on the ambient temperature, relative humidity and wind speed.

3 | Methods & Materials

The following chapter will focus on the methodology used for the calculation of the variables to be covered in the study of the pre-, per-, and post-conditions of the “Las Máquinas” wildfire.

3.1. Area of study

The “Las Máquinas” wildfire was the biggest event of the fires that took place in January 2017, and occurred in the Maule region, which is located in the central part of continental Chile ($35^{\circ} 25' 36''\text{S}$, $71^{\circ} 39' 78''\text{O}$), with an area of $30,296.1 \text{ km}^2$ (see [Figure 3.1](#)). By 2017, the region concentrated around 250,000 ha of exotic forest plantations, mostly of *Pinus radiata* ([CONAF, 2017b](#)), small regions of the rare *Nothofagus alessandrii* and *Jubaea Chilensis*, as well as a large SNASPE (protected area) zone unscathed by the fires. Native and exotic shrub species ([McWethy et al., 2018](#)), as well as arable and grasslands complement the landscape of the Maule region.

The event took place in the Cauquenes, Chanco, Constitución, Empedrado and San Javier municipalities within the Maule region, which correspond to the five zones shown in [Figure 3.1](#) delimited by a thick black line with a gray hatched fill, and will be denominated as the **Region of Interest** or ROI.

3.2. Vegetation

There have been numerous studies that have indicated that the frequency, spatial extent, and duration of a fire show a close association with climate variability on seasonal to inter-annual and decadal time scales (e.g. [Cardil et al., 2021](#), [Shen et al., 2019](#), [Verdon et al., 2004](#), [Fasullo et al., 2018](#)). Therefore, the analysis of the pre-event weather, hydrology, vegetation state and their evolution within the region of interest is pertinent to study the anatomy of the wildfire.

3.2.1 Vegetation density and moisture evolution

Spectral indices such as the Normalized Difference Vegetation Index (NDVI, [Rouse et al., 1974](#)) and the Normalized Difference Water Index (NDWI, [Gao, 1996](#)) are used to study the vegetation density/vigor and moisture content, respectively.

The NDVI data was downloaded using `MODIS.sp()` ([Busetto & Ranghetti, 2016](#)) in R (cf. [Appendix A](#)) from January 2010 to January 2022, and corresponds to the product MODIS MOD13A1 - Vegetation Indices 16 Days at a 500 m pixel resolution. The images were reprojected from MODIS Sinusoidal coordinates to EPSG:32719 (WGS84 UTM zone 19-South) and the resampling was done using a bilinear interpolation. The MODIS tile that covers the whole region of interest corresponds to 12-12-12-12 (xmin, xmax, ymin, ymax), or h12v12. All the downloaded images were cropped and masked to the extent of the five municipalities (Cauquenes, Chanco, Constitución, Empedrado and San Javier) where the fire took place (see [Section 3.1](#) and [Figure 3.1](#)). Later, all the NDVI values (counts) over 0.3 and under 1.0 within the ROI from each image were stored in a comma separated value (*.csv) file, since for $\text{NDVI} \geq 0.3$ it means that pixels corresponds to healthy vegetation ([El-Gammal et al., 2014](#)). Once the latter filter was carried out, a raster extraction procedure was performed (see [Appendix B](#)), and the average NDVI value for each municipality within the ROI was obtained per image.

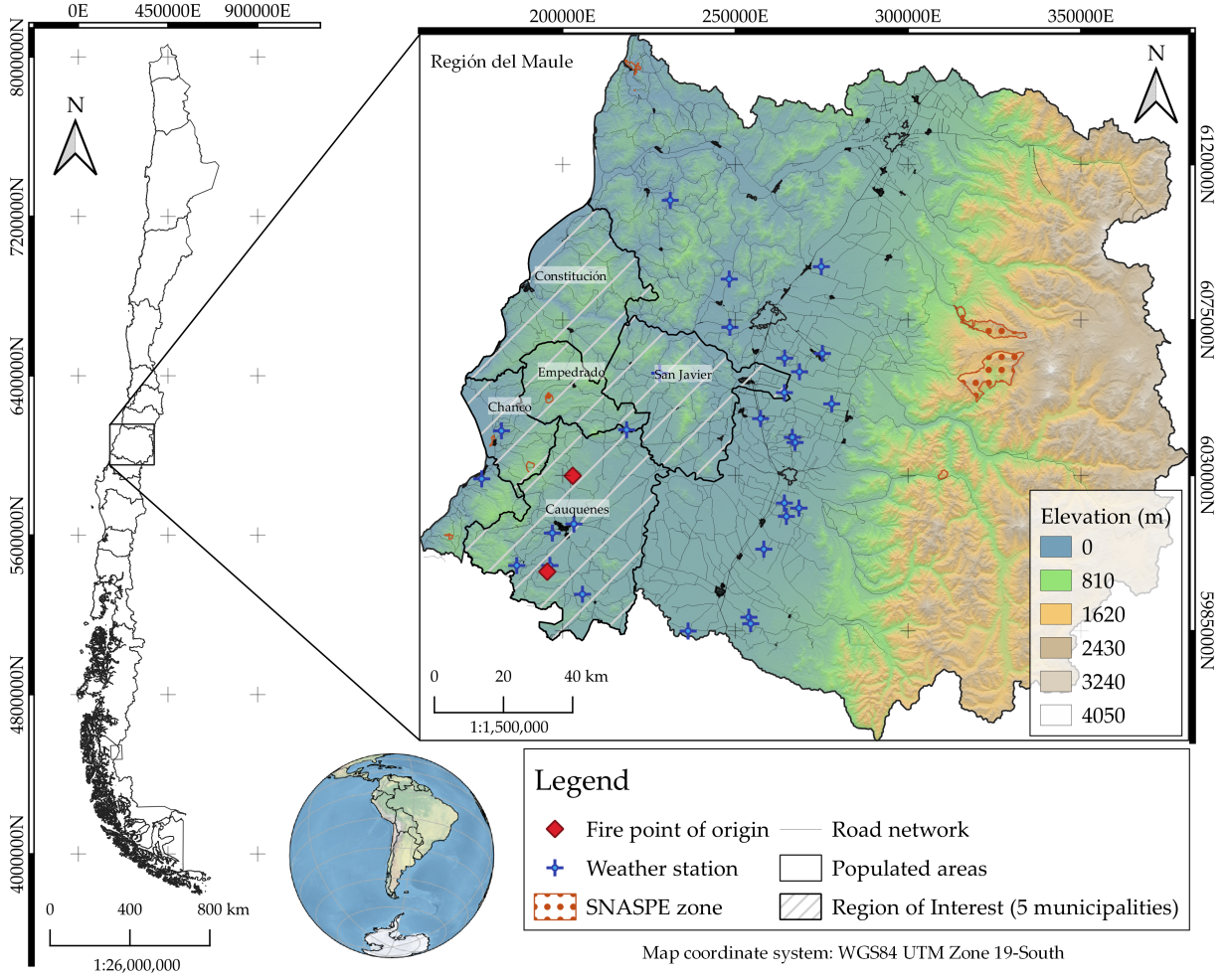


Figure 3.1: General fire location with topography, weather stations, populated areas, and the region of interest (ROI).

Since there is no product for NDWI, it was computed from MODIS Land Surface Reflectance product (MOD09GA; [Vermote & Wolfe, 2015](#)). As in the case of NDVI, the Land Surface Reflectance products are downloaded using `MODISTsp()`. The product category is “Radiation Budget Variables - Land Surface Reflectance”, and the product name is “Surface Reflectance 8 Days” at 500 m resolution. NDWI is calculated using the following formula ([Gao, 1996](#)).

$$\text{NDWI} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} = \frac{\rho_{860} - \rho_{1240}}{\rho_{860} + \rho_{1240}} = \frac{B2 - B5}{B2 + B5} \quad (3.1)$$

Where ρ_{860} and ρ_{1240} are the reflectance at 860 and 1240 nm, and B2, B5 are the corresponding MODIS bands for those wavelength values (see [Table 2.3](#)). The procedure for computing the NDWI with MOD09GA is shown in [Figure 3.2](#).

The NDVI data was averaged and extracted for each one the municipalities within the ROI and stored in an R data frame (which was saved afterwards as a *.csv text file for further analysis).

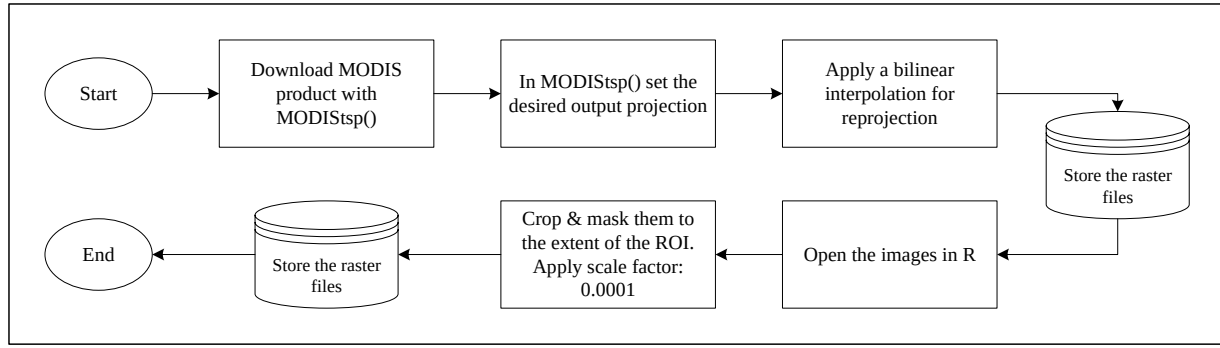


Figure 3.2: Procedure to build NDWI from MODIS MOD09GA surface reflectance product. Scale factor is applied to obtain NDWI values ranging from $\text{NDWI} \in [-1, 1]$.

3.2.2 Previous fires

Previous fire can give an idea of the amount of vegetation (or fuel) available. These were studied using the Global Fire Atlas, which is a global database that tracks the day-to-day dynamics of individual fires to determine the timing and locations of ignitions, fire size, duration, daily expansion, fire line length, speed, and direction of spread based on MODIS MCD64A1 burned area product (Andela et al., 2019a,b; Giglio et al., 2015).

The data is available from 2003 to 2016, and can be downloaded from: <https://doi.org/10.3334/ORNLDAAC/1642> (last access in May 2022). Each dataset has several ESRI shapefiles and raster (*.tif) images. For this study, the ESRI shapefiles containing ignitions are used. The *.dbf files (database file) within each shapefile data and for each year were opened as a data frame in R using the “foreign” package (R Core Team, 2022). Each data frame was filtered by the latitude and longitude of the extent of the ROI (see Section 3.1). As a result, a data frame where each row corresponds to a fire that took place in the ROI was acquired, which also includes the fire size, location and year. This file was saved as an ESRI shapefile for further analysis.

3.3. Meteorology

3.3.1 Standardized precipitation index

There are numerous indicators based on rainfall that are used to study/monitor drought (Naresh Kumar et al., 2009; Smakhtin & Hughes, 2007). However, one of the most widely used indices is based on the deviation of rainfall from normal i.e. long term mean, which is called Standardized Precipitation Index (SPI). This index was developed by McKee et al. (1993) and measures normalized anomalies in precipitation and has been recommended as a key drought indicator by the World Meteorological Organization (Stagge et al., 2015).

The SPI quantifies observed precipitation as a standardized departure from a selected probability distribution function that models the raw precipitation data. The raw precipitation data are typically fitted to a gamma or a Pearson Type III distribution, and then transformed to a standard normal distribution ($\mu = 0, \sigma = 1$). The SPI values can be interpreted as the number of standard deviations by which the observed anomaly deviates from the long-term mean (McKee et al., 1993; Stagge et al., 2015). Thus, the SPI values are expressed in standard deviations with positive SPI values indicating greater than median precipitation (i.e. wet conditions) and negative values indicating less than median precipitation (i.e. dry

conditions) (Edwards & McKee, 1997; Naresh Kumar et al., 2009).

As stated by McKee et al. (1993), a long-term series of precipitation accumulations is required to estimate an appropriate probability density function (at least 30 years). Nevertheless, and since the scope of this work relies in the use of remote sensing tools, the Integrated Multi-satellitE Retrievals for Global Precipitation Measurements (IMERG-GPM) satellite images are used (Huffman et al., 2019a), and the data starts from year 2000 (June) to the present. The images were downloaded from NASA's EarthData hub (see Appendix A). The product name used was the "GPM IMERG Final Precipitation Monthly Data" at a $0.1^\circ \times 0.1^\circ$ spatial resolution (≈ 10 km) version 6 (Huffman et al., 2019a). Once the images are downloaded, the following steps are required to calculate the SPI.

- 1) Using the `ncdf4` package (Pierce, 2021) in R, the first step is to open the *.H5 image files.¹ Once opened, the latitude, longitude and precipitation variables are retrieved and saved for each image metadata. Close the file afterwards.
- 2) The following step was to open the image as a raster granule using the `raster` package (Hijmans, 2020). For this, it is necessary to explicitly set the extent of the image using the latitude and longitude obtained in the previous step, as well as the projection of the image (which is WGS84 Geographic coordinates or EPSG:4326).
- 3) Since the images are a "Global Earth Observation System of Systems" (GEOSS) i.e. world data, the next step was to crop and mask the resulting raster to the extent of a smaller area. For this purpose a ESRI Shapefile (extent-box) of the Maule region in WGS84 Geographic projection was used (see Appendix B.1).
- 4) Afterwards, a raster reprojection was carried out from WGS84 Geographic coordinates to WGS84 UTM Zone 19-South. Resampling was done using a bilinear interpolation for the precipitation data.
- 5) The resulting image was cropped and masked once again but now to the extent of the ROI (which is an ESRI Shapefile containing the five municipalities under study, whose projection is WGS84 UTM Zone 19-South).
- 6) Finally, for the whole ROI, a mean precipitation value was calculated i.e. each pixel data within the ROI was stored and the mean was computed. This value was saved to an R data frame (which is a generic data object in R to store the tabular data), as well as the year and month of the image.
- 7) Through a `for` loop, each *.H5 data-file was processed. As a result, a data frame with three columns (year, month, mean precipitation) and 192 rows (from january 2001 to december 2016) was obtained.

To obtain the SPI, the following procedure was carried out.

- i. First, this analysis is based on the Pearson Type III distribution, i.e. a 3-parameter Gamma distribution function (Guttman, 1999). This was carried out by using the SPEI package (Beguería & Vicente-Serrano, 2017) in R.
- ii. Since the data was already acquired and saved as an R data frame with three columns: year, month, and mean precipitation for the ROI, the procedure is straightforward considering that the only two inputs required are the mean precipitation and the scale (which was settled to 3 for the Pearson Type III distribution). Once computed, the output is the SPI calculated for each month and year.

Finally, the SPI drought categories can be seen on Table 3.1.

¹N.B: the `ncdf4` library opens both NetCDF files and HDF5 files.

Table 3.1: Drought categories for the SPI (McKee et al., 1993).

SPI	Drought category
0 to -0.99	Mild drought
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
-2.00 or less	Extreme drought

3.3.2 Temperature evolution

Temperature evolution was studied using the maximum monthly temperature from 1979 to 2019 grid product of the Center for Climate and Resilience Research (CR², downloaded from: <https://www.cr2.cl/datos-productos-grillados/>, last access in May 2022; CR2, 2022), which is in *.NetCDF format. The product was built using statistical regionalization of the ERA-Interim atmospheric reanalysis data, yet adding functions to consider local information (such as topography and temperature observations) and surface temperature estimates by MODIS Land Surface Temperature product (MCD11A1; Wan et al., 2015).

The workflow is basically the same as the one used in the SPI calculation (see Section 3.3.1), since the temperature files were opened with the same package used to open the GPM-IMERG precipitation files in *.HDF5 format, i.e. the ncdf4 package (Pierce, 2021).

The product contains maximum average monthly temperatures of all Chile, i.e. around 480 rasters of continental Chile, in WGS84 Geographic projection at $0.05^\circ \times 0.05^\circ$ (≈ 5 km) spatial resolution. The data was reprojected to WGS84 UTM Zone 19-South using the raster library, and the data-pixels within the ROI were all extracted and averaged to obtain the maximum mean temperature value for each monthly dataset. Finally, the results were stored in a data frame for further analysis.

3.4. Per-event analysis

The *per-fire* analysis consists in the study *during* the wildfire.

3.4.1 Burned area

Three different satellite products were used to calculate the burned area of the event: MODIS (product MCD64A1 v006 burned area monthly; Giglio et al., 2015), Landsat-8 OLI images of Level-2 data (surface reflectance with atmospheric correction), and Sentinel-2 MSI data at Level-1C. The sen2r package (Ranghetti et al., 2020) was used in R to perform atmospheric, terrain and cirrus correction at the Top-Of-Atmosphere (TOA) for Sentinel-2 data, delivering Bottom-Of-Atmosphere (BOA) reflectance images. MODIS MCD64A1 was studied with daily images from January 20th to February 4th (2017) to quantify the total burned area. Landsat-8 and Sentinel-2 images were obtained from USGS EarthExplorer, while MODIS images were downloaded using the MODISTsp() (Busetto & Ranghetti, 2016) package in R.

Pre- and post-fire Landsat-8 and Sentinel-2 images were acquired from ~ 1 month prior and after the event. Three images (three for pre-fire and three for post-fire) of each satellite sensor were assembled to build the ROI (all images had $< 0.5\%$ cloud pixels within the ROI). For Landsat-8 these three images were path/row: 001/084, 001/085 and 233/085, while for Sentinel-2 the tiles were T18HYE, T18HYF and

T18HYG. For the MODIS MCD64A1 product, tile h12v12 contained all the ROI's extent. Each mosaic (and tile h12v12 for MODIS data) was cropped and masked to the extent of an ESRI shapefile of the ROI. For both Landsat-8 and Sentinel-2 BOA data the following spectral indices were computed: Normalized Difference Vegetation Index (NDVI; [Rouse et al., 1974](#)) Normalized Difference Water Index² (NDWI; [McFeeters, 1996](#)), Normalized Burn Ratio (NBR; [Key & Benson, 1999, 2006](#)) and its temporal difference between pre- and post-fire, i.e. the delta Normalized Burn Ratio (dNBR; [Key & Benson, 2006](#)), which can represent the optimal separation of burned pixels from unburned ones and provide an scaled index representing the burn severity ([Van Wagtenonk et al., 2004](#)). The normalized burn ratio can be calculated using the following expression ([Key & Benson, 2006](#)).

$$\text{NBR} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} \quad (3.2)$$

where NIR and SWIR correspond to the near-infrared and short-wave infrared bands for the specific satellite-sensor product. For Landsat-8 data, the long-SWIR Band 7 (SWIR2) and NIR band 5 were used, while for Sentinel-2 data, the SWIR-2 Band 12 and NIR Band 8A (narrow-NIR) were used. The dNBR is computed using the following equation.

$$\text{dNBR} = \text{NBR}_{\text{prefire}} - \text{NBR}_{\text{postfire}} \quad (3.3)$$

Since the dNBR is an absolute difference, and thus can present problems in areas with low pre-fire vegetation cover, the Relativized Burn Ratio (RBR; [Parks et al., 2014](#)) was also calculated. This can be determined by the following expression.

$$\text{RBR} = \left(\frac{\text{dNBR}}{\text{NBR}_{\text{prefire}} + 1.001} \right) \quad (3.4)$$

Threshold values for each index (θ for dNBR and ψ for RBR) relied on the following assumptions: (i) NDWI must be lower than zero, and (ii) NDVI pre-fire must be greater than 0.25, meaning that only vegetation and non-water pixels can burn. Several threshold values for dNBR and RBR were studied. Severity level according to dNBR values are shown in [Table 3.2](#), while a flowchart of the burned area procedure is shown in [Figure 3.3](#).

Table 3.2: Severity levels and its corresponding dNBR ranges. Obtained from [Key & Benson \(2006\)](#).

Severity level	dNBR range
Enhanced regrowth, high	-0.500 to -0.251
Enhanced regrowth, low	-0.250 to -0.101
Unburned	-0.100 to 0.090
Low severity	0.100 to 0.269
Moderate-low severity	0.270 to 0.439
Moderate-high severity	0.440 to 0.659
High severity	0.660 to 1.35

²N.B: this index is the NDWI for water bodies, not water within vegetation as the NDWI proposed by [Gao \(1996\)](#).

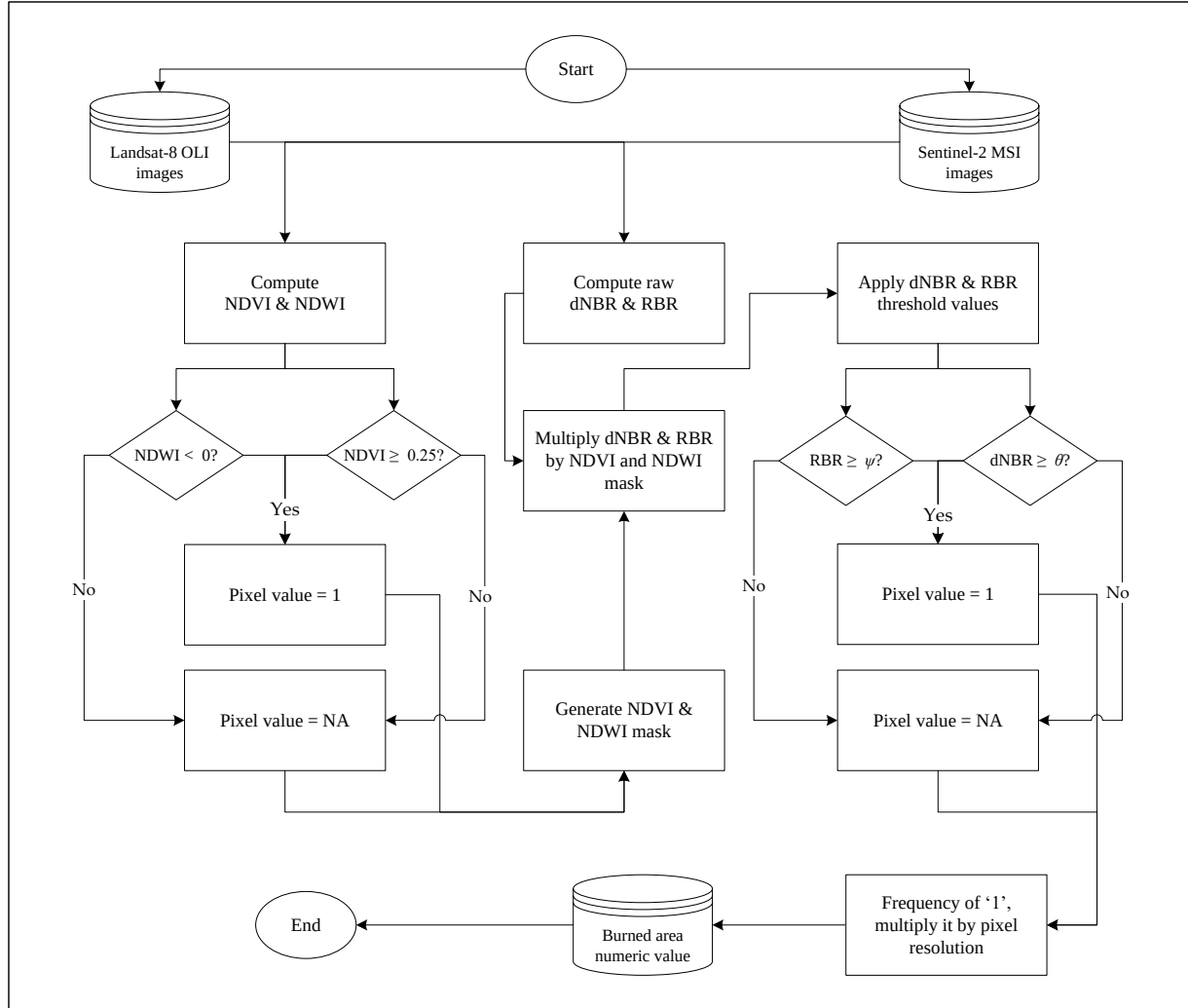


Figure 3.3: Flowchart for the acquisition of burned area derived from Landsat-8 OLI and Sentinel-2 MSI sensors. θ and ψ correspond to the threshold values for the dNBR and RBR, respectively.

3.4.1.1 Fire evolution

The MODIS MCD64A1 is a monthly fire-anomaly product (Giglio et al., 2015). If there was a fire during a particular month, the corresponding monthly image will display a pixel value where the fire took place, and the value of the latter corresponds to the numeric Julian day (also known as day of year, DOY, from 1–365 for non-leap years) in which the event took place, otherwise, the image is filled with NA cells, i.e. “not available” or missing data. Thus, it is possible to filter pixels within fires that occurred on an specific day, and hence build daily-rasters with this information. As a result, the damage per day is obtained during the “Las Máquinas” wildfire time frame. These images were studied from January 20 to February 4, 2017.

3.4.2 Maximum fire radiative power

One of the most important variables for characterizing wildfires is fire radiative power (FRP), which is retrieved from the radiance at the 4 μm spectral band (mid-infrared) of satellite sensors and represents the radiative energy that is released from actively burning fires and can also indicate fuel consumption and fire emissions (Klein et al., 2019; Li et al., 2018). FRP product can be obtained for both MODIS and

VIIRS sensors. However, there are some differences. The MODIS MOD14A1 corresponds to an 8-day fire anomaly product at 1000 m spatial resolution (Giglio et al., 2015), while VIIRS VNP14A1 corresponds to daily fire anomalies at the same spatial resolution of the MODIS product (Schroeder & Giglio, 2018). In the study developed by Li et al. (2018), the results indicated that the VIIRS fire characterization capability is similar across swath, whereas MODIS is strongly dependent on satellite view zenith angle, and that the VIIRS and MODIS FRP relationship varies between different spatial scales. In fire clusters, MODIS and VIIRS FRP estimates are very comparable, except for large boreal forest fires where VIIRS FRP is approximately 47% smaller.

Since the objective is to study the evolution of the fire radiative power during the event, the VIIRS product suits better for accomplishing this task. VIIRS VNP14A1 was downloaded via NASA's EarthData hub (see Appendix A). The downloaded images are in Hierarchical Data Format-5 (*.h5). Since it is not a trivial procedure to reproject Sinusoidal coordinates, NASA's HDF-EOS to GeoTiff Conversion Tool (HEG) was used. HEG output corresponds to raster images in WGS84 Geographic projection, that can now be analyzed in R. Note that the mask layer of the product (fire mask) was used to consider only fire-related pixels within the FRP raster images.

3.4.3 Land use inventory

The National Land Use Inventory (LUI) was developed by CONAF (2016), whose last update was done in year 2016. This LUI comes as an ESRI shapefile data (vector file), which has over 20 variables. Some of them are the land-type, land-use type, species, forest type, canopy height, etc. This data file is used for several pre-fire and post-fire analyses, including the affected species and land cover type.

3.4.4 Affected species

Affected species were obtained using both the Chilean Land Use Inventory (LUI; CONAF, 2016) and the total burned area obtained from MODIS MCD64A1 product (see Section 3.4.1). The procedure consisted in the following.

- a) The LUI (which is a polygon or vectorized dataset) was cropped to the extent of the ROI. Afterwards, the data was separated by layers among the *species* variable. The results correspond to multiple polygon files (or shapefiles) of the different species within the ROI. This was executed using the *raster* package (Hijmans, 2020) in R.
- b) The resulting burned area raster of MODIS burned area product was *vectorized* i.e. the raster was converted to a vector-polygon or "shapefile".
- c) The resulting polygons of the first step were *rasterized* i.e. converted to raster data, and were cropped and masked to the extent of the burned area polygon. All the pixels within the burned area polygon were extracted, multiplied by the pixel resolution and converted to hectares. As a result, an R "data frame" table with the species and its corresponding burned area is obtained.

3.4.5 Land cover type

Land cover classification was obtained using the MODIS MCD12Q1 product (Friedl & Sulla-Menashe, 2019). This product corresponds to combined Aqua/Terra-MODIS data that provides global land cover types at yearly intervals since 2001. The product comes in *.hdf (hierarchical data format) format with layers including six different classification schemes, such as: Annual International Geosphere-Biosphere Programme (IGBP), Annual University of Maryland (UMD), Annual Leaf Area Index (LAI) classification,

among others. The one used for this study was the International Geosphere-Biosphere Programme (IGBP). Each image has pixel values ranging from 1 to 17, and each one corresponds to a particular IGBP classification (Sulla-Menashe & Friedl, 2018), which can be seen in [Appendix C](#) (cf. [Table C.1](#)). For example, if a pixel value is “1”, then that pixel is dominated by evergreen conifer trees with a canopy height greater than 2 m and a tree cover > 60%. All the images were downloaded using MODISTsp in R (see [Appendix A](#)).

3.4.6 Air quality

Aerosols are solid and liquid particles suspended in the atmosphere, which have significant effects on global climate change, directly by scattering or absorbing solar shortwave radiation and indirectly by modifying cloud properties. Recently, the Deep Blue Aerosol (DBA) algorithm has been successfully applied to the Visible Infrared Imaging Radiometer Suite (VIIRS) to expand the long-term aerosol records over land and ocean (He et al., 2021; Sundström et al., 2015; Wei et al., 2019). In the following sections the VIIRS-SNPP Deep Blue Aerosol product will be used to calculate the smoke generation and its evolution as well as the aerosol optical depth (AOD).

3.4.6.1 Smoke generation & evolution

Smoke was studied using the VIIRS-SNPP Deep Blue Aerosol (DBA) L2 6-km product (Sayer et al., 2018). The deep blue algorithm uses the blue wavelength channels possessed by the VIIRS, MODIS and SeaWiFS satellite sensors. However, the algorithm has achieved better results with the VIIRS sensor with a higher spatial resolution, improved smoke mask, dust aerosol optical depth (AOD) models, among others (He et al., 2021). At the blue wavelengths, the surface reflectance is dark and fairly stable and thus helps retrieve AOD over otherwise bright surfaces, such as deserts, barren rocks, and urban areas (NASA LAADS, 2018). Assuming a lambertian and homogeneous surface, the algorithm calculates (1) the total radiance at the top-of-atmosphere, which is estimated as a function of the surface reflectance depending on the land cover type, and (2) the aerosol retrievals based on look-up tables generated by the radiative transfer model for a range of solar and satellite viewing geometry as well as aerosol and surface conditions (Hsu et al., 2013, 2019, 2004).

Daily images from January 20 to February 10, 2017, were downloaded from NASA’s EarthData hub. The product is in NetCDF format, and the layer used was the “Aerosol Type Land”. Working with these products is not straightforward, since there is no projection assigned to the NetCDF files. The procedure is described below. In addition, a flowchart is shown in [Figure 3.4](#).

1. Using the `ncdf4` package (Pierce, 2021) in R, the NetCDF files were opened. The problem is that these products do not come with the coordinate system incorporated in the metadata and hence it is not possible to assign a projection or even reproject it to the desired coordinate system. Therefore, the longitude, latitude and the aerosol type value were extracted from the NetCDF files (since these are variables within the product), and stored in an R data frame table.
2. An empty raster was created to a smaller ROI (using the longitude and latitude values). The projection of the latter raster layer was settled to geographic coordinates i.e. WGS84 (latlong) or EPSG:4326.
3. Finally, the `gstat` package (Pebesma, 2004) was used to interpolate the information within the R data frame table with the empty raster. The following steps were carried out for the interpolation.

- 3.1. NA values (missing values) were removed from the R data frame.

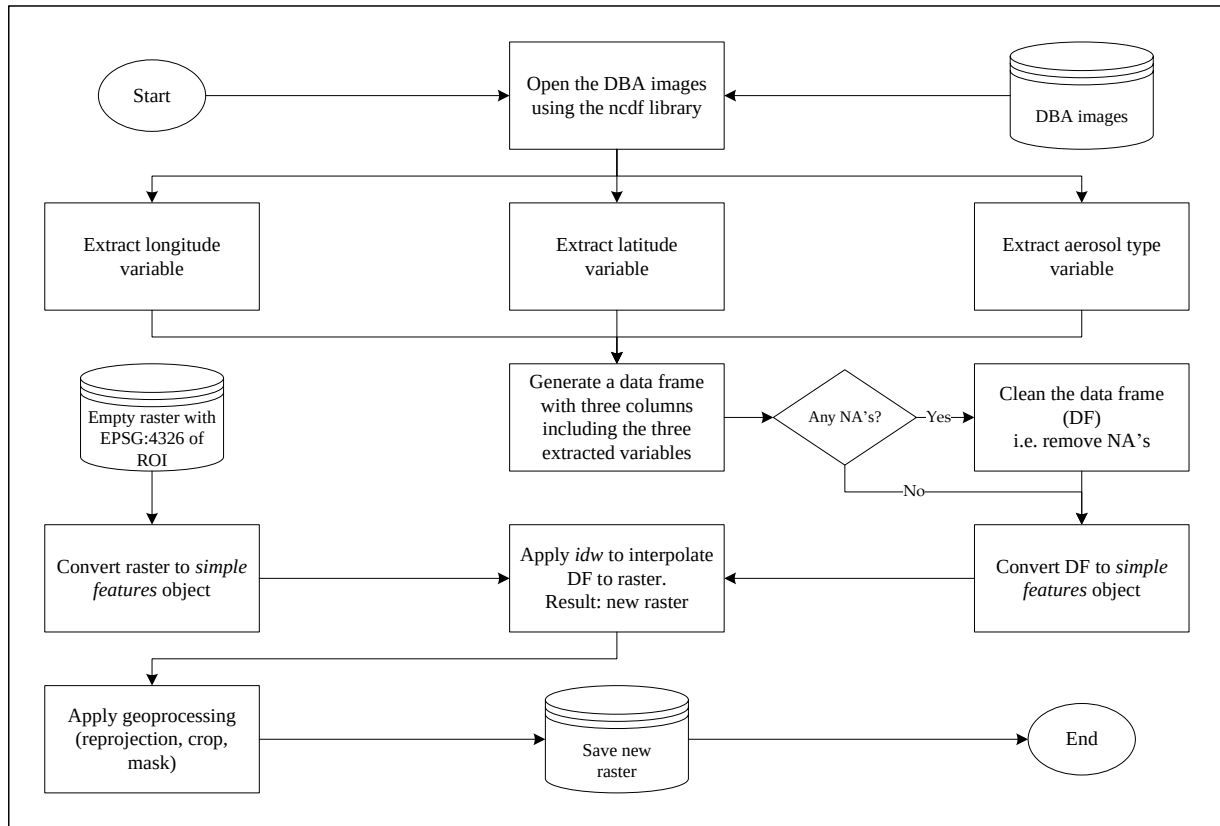


Figure 3.4: Flowchart for working with VIIRS-SNPP Deep Blue Aerosol product in R. DBA stands for “Deep Blue Aerosol” product, DF to R data frame, NA to missing values, and *idw* to inverse distance weighted interpolation.

- 3.2. Using the *sf* package (Pebesma, 2018), the data frame was converted to an *sf* (*simple features*) object.
- 3.3. The empty raster data was also converted to an *sf* object.
- 3.4. Using the *gstat* package, the *idw* (inverse distance weighted interpolation) function was used to interpolate the data, where the *locations* parameter corresponds to the aerosol type data and the *newdata* parameter corresponds to the empty raster data (of the data frame created in the previous step). The result is a data frame with *simple features* and two variables (columns): the index value, and the geometry (longitude and latitude).
- 3.5. The index values were assigned to the empty raster, and the result is a *RasterLayer* which can now be used to extract the data. The following step is to reproject the raster to WGS84 UTM 19-South coordinate system, which was done using the *raster* package. Finally, the resulting grid was cropped and masked to the extent of the Región del Maule shapefile and stored for analysis.

According to the product metadata, the pixel values for the “Aerosol Type Land” layer are those shown in Table 3.3. Therefore, only pixel values of 1, 2 and 3 were considered for the analysis i.e. any other pixel value was settled to NA.

Table 3.3: Pixel values and variable name for VIIRS-SNPP Deep Blue Aerosol layer “Aerosol Type Land” (obtained from the product metadata).

Pixel value	Variable
0	Dust
1	Smoke
2	High altitude smoke
3	Pyrocumulonimbus clouds
4	Non-smoke fine mode
5	Mixed
6	Background

3.4.6.2 Aerosol optical depth

Aerosol optical thickness (or depth, AOD) is the single most comprehensive variable of the remote measurement and assessment of aerosol load in the atmosphere distributed within a column of air. This variable is an essential atmosphere parameters for climate change assessment as well as for total ecological situation study (Filonchyk et al., 2019). The Deep Blue Aerosol (DBA) algorithm is used with the VIIRS-SNPP data to compute the aerosol optical thickness for both land and ocean (the latter using SeaWiFS) (Hsu et al., 2013, 2019; Sayer et al., 2018).

The product used for the analysis correspond to the VIIRS/SNPP Deep Blue Aerosol L2 6-km product (Sayer et al., 2018), which is the same used in Section 3.4.6.1 for computing the studying smoke generation. However, the layer used for this analysis corresponded to the “Aerosol Optical Thickness 550 Land”, which is the Deep Blue aerosol optical thickness at 550 nm over land. The procedure is the same used in Section 3.4.6.1, being the only difference the layer (variable) name and the data-type, since the smoke data was categorical, while the AOD data is a continuous variable with pixel values ranging from 0 to 5. An AOD of less than 0.1 is “clean” - characteristic of clear blue sky, bright sun and maximum visibility. As AOD increases to 0.5, 1.0, and greater than 3.0, aerosols become so dense that sun is obscured. Sources of aerosols include pollution from factories, smoke from fires, dust from dust storms, sea salt, and volcanic ash and smog (NEO, 2022).

3.4.6.3 Carbon emissions

One of the chemical outputs derived from a wildfire is carbon. Fire carbon emissions were obtained from the Global Fire Emissions Database (GFED version 4.0; Van Der Werf et al., 2017). The algorithm used in the product is based on the Carnegie–Ames–Stanford Approach (CASA) biogeochemical model, using the MODIS burned area product (Giglio et al., 2015, 2013) as the input variable. The spatial resolution of the product is $0.25^\circ \times 0.25^\circ$ (≈ 28 km), and the images are stored in hierarchical data format-5 (*.h5). Yearly worldwide images from 2010 to 2017 were downloaded from <https://www.geo.vu.nl/~gwerf/GFED/GFED4/> (visited in April 2022). Each *.h5 file contains, among others, monthly carbon emission data in $\text{g}\cdot\text{m}^{-2}$. The layer used was the “emissions/01/C”, which corresponds to January carbon emissions. The working procedure for this data is the same used for retrieving the Deep Blue Aerosol variables (see Section 3.4.6.1), since the *.h5 files are opened using the ncd4 package (Pierce, 2021) in R.

3.4.7 Canadian Fire Weather Index

In this section, the four parameters that are needed to compute the Canadian Fire Weather Index (FWI) are discussed, and a methodology for their acquisition is described.

3.4.7.1 Wind speed

Wind speed (U_r) at a fine-size mesh resolution (≈ 760 m) was simulated with the WindNinja V3.6.0 software (Firelab, USDA – Forest Service; [Forthofer et al., 2014](#)). The first parameter is the surface input, where a landscape file (LCP) was used. A landscape file is a multi-band raster format commonly used by wildland fire behavior and fire effects models such as FARSITE and FlamMap, and was generated in FlamMap V6.0 software (Firelab, USDA – Forest Service; [Finney, 2006](#)). The LCP consists of a binary file containing a compilation of ASCII (raster) data, which includes the following.

- i. Digital elevation model (DEM). The DEM used was the Alos-Palsar, which has a pixel resolution of 12.5 m and was downloaded from the “Infraestructura de Datos Espaciales de Chile” (IDE-Chile; [CIREN, 2017b](#))
- ii. Slope. The slope was computed in R software using the `raster` library from the DEM file, in degrees.
- iii. Aspect. The aspect was computed in R software using the `raster` library from the DEM file, in degrees.
- iv. Fuel model. The fuel model file was computed using the Chilean land use inventory (LUI; see [Section 3.4.3](#)) of 2016 ([CONAF, 2016](#)). The methodology consisted in classifying the fuels within the “land use” variable of the LUI into one of the [Albini \(1976\)](#) classes. The description of each class was taken from [Anderson \(1982\)](#). For example, a “dense shrubland” is categorized as a fuel model 4, which corresponds to Chaparral 6 feet (within the Chaparral and shrub fields).
- v. Canopy cover. The canopy cover was generated within the four available categories or classes, which are the following. Class 1: 1-20% canopy cover, Class 2: 21-50%, Class 3: 50-80%, and Class 4: 81-100% canopy cover, with zero cover specified by 0. These classes were generated from the “coverage” data within the LUI. For example, a “very-dense” value was cataloged with the canopy cover class 4.

Once each file was ready, they were resampled in R to the DEM resolution and saved as ASCII format. Afterwards, those files were used in FlamMap V6.0 to generate the landscape file.

The wind simulation in WindNinja requires both the surface file (landscape file) and the weather station data. Within the ROI, there are a total of 8 weather stations, whose locations can be seen in [Figure 3.5](#). The data of each one was downloaded from the Chilean National Agroclimatic Network (AGROMET; <https://www.agromet.cl/> – last access in May 2022). It is important to mention that there is a simultaneous study carried out at this point, which corresponds to both the acquisition and analysis of the land surface temperature used for the NSAT estimation (see [Section 3.4.7.2](#)), since the wind simulation is executed at the closest weather station date-time to the satellite overpass time (or to the product acquisition), which depends if the land surface temperature product used is from Aqua or Terra (MYD11A1 or MOD11A1; ([Wan et al., 2015](#))). Hence, for each image the time is acquired from the “Day_view_time” layer of the M*11A1 product. For a particular image at a certain date and time, the weather station data was filtered to match the closest to that date-time and the variables required (e.g. wind direction, wind speed, air temperature, etc) were extracted and stored as a *.csv file following the order of the WindNinja’s weather

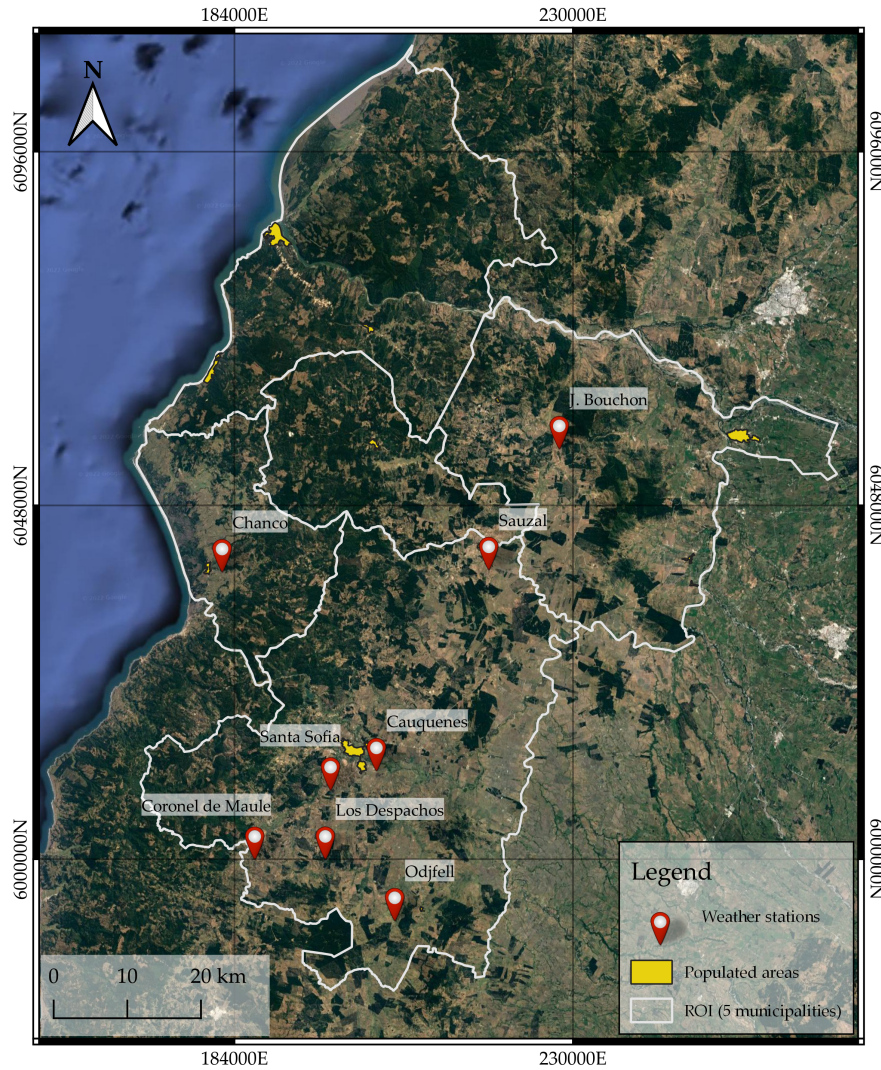


Figure 3.5: Weather stations location within the region of interest (ROI).

station file for the point-initialization wind speed simulation. A mass conservation solver was used (the only available solver in WindNinja for a point-initialization simulation). The output result is a vector (ESRI Shapefile) with wind speed data simulated at 10 m height. The vector file was rasterized (converted to raster) in R using the `raster` library for further analysis.

3.4.7.2 Near-surface air temperature

Two methodologies were studied to estimate the Near-surface air temperature (NSAT), which are (i) a physically-based surface energy balance, and (ii) a statistical approach using regression models and machine learning regression algorithms.

3.4.7.3 NSAT by energy balance

The thermodynamic equilibrium between turbulent transport processes in the atmosphere and laminar processes in the sub-surface manifests itself in the land surface energy balance, which can be expressed as the following (Bastiaanssen et al., 1998a).

$$\dot{q}_n'' = \dot{q}_{sens}'' + \dot{q}_{soil}'' + \dot{q}_{lat}'' , \quad (3.5)$$

where $\dot{q}_n''$ corresponds to the net surface radiation flux ($\text{W}\cdot\text{m}^{-2}$), $\dot{q}_{sens}''$ is the sensible heat flux to the atmosphere ($\text{W}\cdot\text{m}^{-2}$), $\dot{q}_{lat}''$ is the latent heat flux ($\text{W}\cdot\text{m}^{-2}$), and $\dot{q}_{soil}''$ is the soil heat flux ($\text{W}\cdot\text{m}^{-2}$). A sketch for the energy balance at the surface is shown in Figure 3.6.

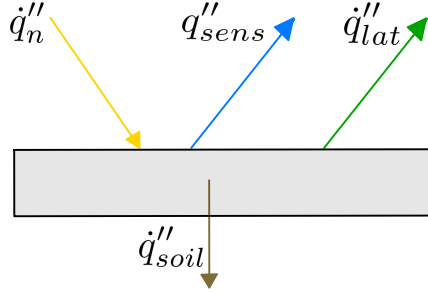


Figure 3.6: Surface energy balance.

The sensible heat flux can be determined by equation (3.6) (Bastiaanssen et al., 1998a).

$$\dot{q}_{sens}'' = \frac{\rho c_p}{r_a} (T_s - T_a) \quad (3.6)$$

where ρ and c_p are the air density ($\text{kg}\cdot\text{m}^{-3}$) and specific heat at a constant pressure ($\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$), T_s is the surface temperature ($^{\circ}\text{C}$), T_a is the near-surface air temperature ($^{\circ}\text{C}$), and r_a is the aerodynamic resistance ($\text{s}\cdot\text{m}^{-1}$), which is a momentum transfer resistance between a reference height and the surface (Hou et al., 2013; Thom & Oliver, 1977). The latter can be estimated using the following model developed by Thom & Oliver (1977).

$$r_a = 4.72 \cdot \frac{\ln^2(z/z_o)}{1 + 0.54 U_r} \quad (3.7)$$

where z is the reference height (m) at which the wind speed U_r is measured, and z_o is the surface-roughness length that reflects the roughness at the border of the land surface and the atmosphere. This parameter is mainly influenced by vegetation, water, buildings and any other land cover (Hou et al., 2013).

Soil heat flux ($\dot{q}_{soil}''$) is variable within a day, but its magnitude is small as compared to $\dot{q}_n''$ or $\dot{q}_{lat}''$ and therefore it is possible to assume the value of $\dot{q}_{soil}''$ as a constant over the day (Batra et al., 2006). Moran et al. (1989) proposed the following relationship between $\dot{q}_{soil}''$ and $\dot{q}_n''$.

$$\dot{q}_{soil}'' = \dot{q}_n'' 0.583 e^{(-2.13 \text{ NDVI})} \quad (3.8)$$

where NDVI is the Normalized Difference Vegetation Index (Rouse et al., 1974). Combining equations (3.5), (3.6) and (3.8), the NSAT can be expressed by equation (3.9).

$$T_a = T_s - \frac{r_a}{\rho c_p} \left(\dot{q}_n'' \left\{ 1 - 0.583 e^{(-2.13 \text{ NDVI})} \right\} - \dot{q}_{lat}'' \right) \quad (3.9)$$

Where T_s is the land surface temperature and is obtained from MODIS MYD11A1 product (Wan et al., 2015). NDVI is computed from both MODIS MYD13A1 vegetation indices (Didan, 2015) and MODIS MYD09GA surface reflectance (Vermote & Wolfe, 2015) products. Radiation used was the total downward shortwave radiation (DSR) from MODIS MCD18A1 product (Wang, 2017), which is an estimate of the total amount of shortwave radiation (both direct and diffuse) that reaches the earth surface. The latent heat flux ($\dot{q}_{lat}''$) is obtained from MODIS MYD16A2 net evapotranspiration product (Running et al., 2017), where the average latent heat flux layer is used. Note that the units of the $\dot{q}_{soil}''$ layer are in $\text{J}\cdot\text{m}^{-2}\cdot\text{day}^{-1}$, and hence it was converted to $\text{W}\cdot\text{m}^{-2}$ after applying the corresponding scale factor. The wind speed (U_r) is the same speed simulated in WindNinja (see Section 3.4.7.1) at the flyover time of Aqua satellite, which is within a raster layer of the MYD11A1 product. The output-height of the simulated wind speed data is at 10 meters height, and thus $z = 10$ m. Finally, z_o is computed using the roughness length results of the SEBAL model (Bastiaanssen et al., 1998a,b), where the land cover is divided into five types: water, grass, forest, farmland, and city areas, whose respective values are 0.005, 0.02, 0.5, 0.2, and 0.15 (Hou et al., 2013). These values are applied to the Chilean Land Use Inventory (LUI; CONAF, 2016) data within the region of interest (ROI) i.e. the five municipalities, and subsequently, the resultant vector (or shapefile) with z_o information is rasterized. Finally, both air density and specific heat at constant pressure were used as a constant value at standard ambient temperature and pressure (298 K), i.e. $\rho = 1.170 \text{ kg}\cdot\text{m}^{-3}$ and $c_p = 1.007 \text{ kJ}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$ (Bergman et al., 2011).

All the satellite data was resampled to the extent and resolution of the land surface temperature product (MYD11A1 ~ 1 km) with the raster package (Hijmans, 2020) in R using a bilinear interpolation for continuous variables (e.g. U_r) and nearest neighbor for categorical variables (e.g. z_o). Note that all the MODIS products are from Aqua satellite (MYD). Furthermore, radiation ($\dot{q}_n''$) DSR product comes at different times per day (multiple layers), and hence the layer used was the one that minimized the time difference against MODIS MYD11A1 land surface temperature product. NDVI from MODIS MYD13A1 and $\dot{q}_{lat}''$ from MODIS MYD16A2 are averaged rasters that come at a temporal resolution of 16 and 8 days, respectively, and hence the closest image to the land surface temperature day of study was used per day of analysis. Finally, a validation of the NSAT was carried out comparing the results against the weather station NSAT measurements at the closest time of the land surface temperature product. The weather stations used for validation are those in Figure 3.5.

3.4.7.4 NSAT by regression models

Zhang et al. (2014) developed an improved satellite-based approach for estimating vapor pressure deficit from MODIS data. To accomplish their objective they used the ambient temperature (NSAT) as one of the independent variables for their model from the basis that NSAT and land surface temperature (T_s) are two different concepts, yet its high correlation has been confirmed in numerous studies (e.g. Good et al., 2017; Kawashima et al., 2000; Mutiibwa et al., 2015). Furthermore, the authors discuss that because of the complexity and influence of solar radiation, cloud cover, wind speed, and soil moisture, evaluating NSAT from surface temperature based on surface energy balance is difficult. The model proposed by Zhang et al. (2014) is based on the assumption that the relationship between NSAT and T_s will only be influenced by NDVI and the total precipitable water content (PW), where the latter corresponds to the amount of liquid water that would be obtained if all the vapor in the atmosphere within the vertical column was compressed to the point of condensation (Dupont et al., 2008). Hence, the model proposed by Zhang et al. (2014) is the following.

$$T_s - \text{NSAT} = k_0 + k_1 \cdot \text{NDVI} + k_2 \cdot \text{PW} \quad (3.10)$$

where k_0 , k_1 and k_2 are regression coefficients determined by statistical methods. The regression analysis was carried out for MODIS Terra, MODIS Aqua, and VIIRS-SNPP information. For MODIS, T_s is obtained from MODIS MCD11A1 (MOD11A1 for Terra and MYD11A1 for Aqua) product (Wan et al., 2015) while PW is obtained from MODIS MOD05 product (Gao & Kaufman, 2015). For VIIRS-SNPP, T_s was obtained from VNP21 Land Surface Temperature and Emissivity 6-min L2 Swath 750 m (Hulley & Hook, 2018), which also contains a layer with PW data. MODIS MOD05 and VIIRS-SNPP VNP21 were downloaded from NASA’s EarthData (see Appendix A). The two products do not have an established tile system for the ROI, meaning that there might be days where only one image is necessary to cover the ROI, while there are other days in which more than one image is required to obtain the information for the whole ROI. Thus, all images were downloaded using the corner coordinates or extent of the region of interest. The following steps were carried out to study the regression models. A flowchart of the procedure is shown in Figure 3.7. The following sections report the steps that were carried out to build each model.

3.4.7.4.1 Building the regression dataset

Building the dataset stands for the retrieval of all the variables data tabulated in data frames for the posterior regression analysis. For PW and T_s , daily images of January from 2010 to 2016 for both Aqua/Terra-MODIS, and daily images of January from 2012 to 2016 for VIIRS-SNPP (since the starting operation of VIIRS-SNPP was on January 2012) were downloaded. The raster information was extracted from the pixels where the weather stations are located within the ROI.

Since NDVI is also a required variable to develop the regression model proposed by Zhang et al. (2014), three different products were used: MODIS MOD13A1 (Didan, 2015), MODIS MOD09GA (Vermote & Wolfe, 2015) and VIIRS VNP13A1 (Didan & Barreto, 2018). Both MODIS products were downloaded using MODISTsp package in R (see Appendix A), while VIIRS VNP13A1 was downloaded from NASA’s EarthData. MODIS MOD09GA corresponds to the daily surface reflectance product, and hence NDVI was computed using the following formula (Rouse et al., 1974).

$$\text{NDVI}_{\text{MOD09GA}} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}} = \frac{B2 - B1}{B2 + B1} \quad (3.11)$$

where, ρ_{NIR} and ρ_{RED} are the reflectance (ρ) bands at the near-infrared (NIR) and red regions, which correspond to MODIS bands B2 and B1, respectively. Instead, MOD13A1 and VNP13A1 are a 16-day product with pixel values already corresponding to the NDVI, and hence for each day of analysis, the closest NDVI data to the land surface temperature image day of study was used.

MODIS MOD05 product was downloaded from NASA’s EarthData, and since this atmospheric product is a non-constant 5-min swath granule, there are more data granules (or images) towards high latitudes (it is not a constant *tiled* product as M**D11A1* or any other non-atmospheric MODIS products), and therefore more observations are available in a single day. Hence, for each day of study, the MOD05 image with the lowest time difference with MODIS M**D11A1* was used. For MOD05 product, the time was extracted from the product metadata, which is in UTC (Universal Time Coordinated), and thus was transformed to local timezone (America/Santiago). For M**D11A1* product, the layer “Day_view_time” within the product was extracted and processed. This layer contains the local time at the overpass time of the satellite at a pixel level, i.e. each pixel has a numeric value of local time acquisition. The image was cropped and masked to the extent of the ROI and the mean of the pixels time was calculated. Once both times are acquired, it is then possible to obtain the MOD05 image with the lowest time difference with respect to

M*D11A1 product per day of analysis.

Finally, the weather station data for ambient temperature and other variables at the 8 weather stations within the ROI was downloaded from AGROMET (National Agroclimatic Network; <https://www.agromet.cl/> – last access in May 2022). Depending on the weather station, the data is stored every 30 minutes or 1 hour. The weather station data was extracted for the closest date-time of the M*D11A1 daily product.

Once all the previous steps are done, an algorithm that goes through all the satellite-derived products extracts the pixel value at the weather station location and stores them in a data frame. At the same time, the algorithm filters the weather station data for the closest date-time of the M*D11A1 product and stores the data within the same data frame. As a result, a table with all the variables is obtained.

3.4.7.4.2 Training datasets

After the dataset with all the required regression data is acquired, this data is filtered for dates under 2017–01–01, which corresponds to the training dataset. Multiple linear regression models as well as machine learning regression algorithms are applied to the training dataset. Each regression model was built based on the following expression.

$$\text{NSAT} \sim T_s + \text{PW} + \text{NDVI} \quad (3.12)$$

being T_s , PW and NDVI the independent variables, and NSAT the dependent variable. A brief definition of the regression models used in this study is presented below.

1. Multiple linear regression models were developed using Eq. (3.12). The data per row of the data frame correspond to extracted pixel-values at the weather stations locations, and the weather station NSAT measured values. Note that both MODIS and VIIRS NDVI products were studied for the models.
2. Machine Learning regressions. For this analysis, the independent and dependent variables are the same as in the multiple linear regression model. Three regression algorithms were used to study the NSAT, which are the following.
 - 2.1. **Decision trees** (DT). This algorithm can be used for both regression and classification problems, and corresponds to a non-parametric decision tree that uses a binary recursive partitioning scheme by splitting two child nodes repeatedly, starting with the root node, which contains the complete learning sample (Breiman et al., 1984). Each node in the tree structure characterizes a feature, with corresponding branches representing possible values connecting features and leaves representing the class that terminates a series of nodes and branches (Awad & Khanna, 2015). Using the `rpart` package (Therneau & Atkinson, 2022) in R, a decision tree model was developed for the regression model datasets.
 - 2.2. **Support vector machines** (SVM). This algorithm corresponds to a supervised learning method that analyzes data and recognizes patterns. Support vector regression (SVR) is the name of SVM for regression models, and it gives a little bit more buffer to a regression model compared to a linear regression, since it generates an *epsilon sensitive tube* whose objective is to settle the margin limits or allowed discrepancies (error) of the data (Awad & Khanna, 2015). Using the `e1071` package (Meyer et al., 2021) in R, an svm model was developed for the training dataset.

- 2.3. **Random forests (RF)**: This algorithm is a supervised learning method that uses the *ensemble learning* approach for regression. Ensemble learning method is a technique that combines predictions from multiple machine learning algorithms to make a more accurate prediction than a single model, in which “weak learners” collaborate to form “strong learners”, using a large collection of decorrelated decision trees (Awad & Khanna, 2015). Using the `randomForest` package (Liaw & Wiener, 2002) in R, a random forest regression model was developed for the training dataset.

Once all the regression models are applied, each one is saved as a *.RDS file, which is a native Rdata format to store R objects.

3.4.7.4.3 Testing datasets

The resulting dataset generated in Section 3.4.7.4.1 is filtered for rows whose dates are greater than 2017-01-01, which corresponds to the testing dataset (January 2017 data). Since LST, PW and NDVI data is within raster files (and all the rasters have the same resolution and extent), the centroids of each cell was extracted and tabulated in a data frame. Hence, each regression model obtained in the previous section is opened and applied to the latter data frame.

The statistical analysis for the results focuses on the model efficacy against weather station NSAT data, which is carried out using the Root Mean Square Error (RMSE) and the Pearson’s correlation coefficient (r), which are calculated as the following.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_{ws_i})^2} \quad (3.13)$$

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (3.14)$$

where $\hat{y}_i$ and y_{ws_i} are the estimated NSAT and measured NSAT at weather station location at the i th data frame row. On the other hand, x_i and $\bar{x}$ are the i th estimated NSAT value and its mean within all the dataset, respectively, while y_i and $\bar{y}$ are the i th NSAT measured at the weather station and its mean value within all the dataset, respectively.

3.4.7.5 Precipitation

Integrated Multi-SatellitE Retrievals (IMERG, Huffman et al., 2014) for Global Precipitation Measurement (GPM) satellite images were used to obtain daily precipitation in mm. The product used was GPM IMERG Final Precipitation L3 day $0.1^\circ \times 0.1^\circ$ (≈ 11 km) V06, which represents the final estimate of daily accumulated precipitation (Huffman et al., 2019b). The image field or layer used was the Multi-Satellite precipitation estimate with gauge calibration. The data was obtained from NASA’s EarthData hub, and was resampled in R to match the extent and resolution of the M*D11A1 (Land Surface Temperature MODIS product).

3.4.7.6 Relative humidity

Relative humidity (RH) can be defined as the ratio of the actual water vapor pressure e_a to the equilibrium vapor pressure over a plane of water e_s (often called the saturation vapor pressure; Lawrence, 2005).

$$\text{RH} = \frac{e_a}{e_s(T_a)}, \quad (3.15)$$

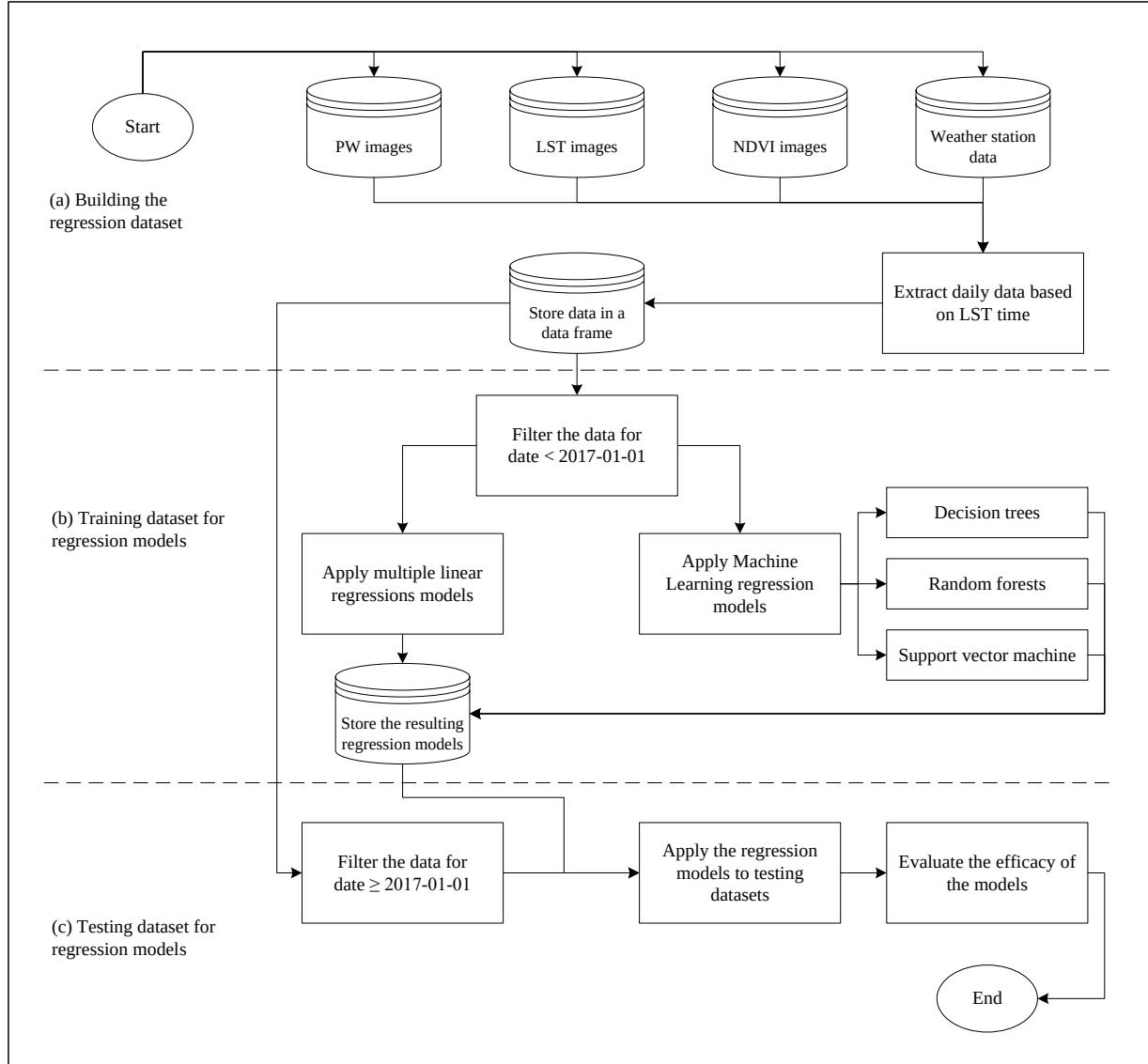


Figure 3.7: Flowchart for the NSAT estimation by regression models.

where e_a corresponds to the actual vapor pressure (kPa), e_s is the saturation vapor pressure at the air temperature (kPa), and T_a is the ambient/air temperature (or NSAT, in °C). The temperature to which an air parcel at initial temperature T_a and pressure P must be cooled isobarically to become saturated is T_{dew} , and hence the definition is normally expressed in terms of the vapor pressure as the following.

$$e_s(T_{dew}) = e(T_a) \quad (3.16)$$

To express the dew point temperature in terms of the relative humidity, an expression for the dependence of the saturation vapor pressure on the ambient temperature is required ($e_s(T_a)$). A review and evaluation of both theoretical and empirical saturation vapor pressure expressions was studied by [Gibbins \(1990\)](#). From those, one of the most widely used empirical expressions is the Magnus formula, which is the following.

$$e_s(T_a) = C_1 \exp \left[\frac{A_1 T_a}{B_1 + T_a} \right] \quad (3.17)$$

Alduchov & Eskridge (1996) evaluated this expression and recommended the following values for the coefficients: $A_1 = 17.625$, $B_1 = 243.04^\circ\text{C}$, and $C_1 = 610.94 \text{ Pa}$. These provide values for $e_s(T_a)$ with a relative error of $< 0.4\%$ over the range $-40^\circ\text{C} \leq T_a \leq 50^\circ\text{C}$ (Lawrence, 2005). If expression (3.17) is substituted in (3.16), the dew-point temperature can be expressed by the following.

$$T_{dew} = \frac{B_1 \left[\ln \left(\frac{RH}{100} \right) + \frac{A_1 T_a}{B_1 + T_a} \right]}{A_1 - \ln \left(\frac{RH}{100} \right) - \frac{A_1 T_a}{B_1 + T_a}} \quad (3.18)$$

which, according to Lawrence (2005), corresponds to a highly accurate conversion from RH to T_{dew} . However, the variable under study is RH, therefore expression (3.18) can be rewritten as shown in equation (3.19).

$$RH = 100 \cdot \exp \left[\frac{A_1 T_{dew}}{B_1 + T_{dew}} - \frac{A_1 T_a}{B_1 + T_a} \right] \quad (3.19)$$

This expression was used to compute RH, and the coefficients employed are those proposed by Alduchov & Eskridge (1996) mentioned before. T_a is the estimated NSAT (near surface air temperature, see Section 3.4.7.2), and the dew-point temperature was retrieved by the MODIS M*D07 Atmosphere Profile Product (Borbas & Menzel, 2017). This corresponds to a 5-min L2 swath at a 5 km pixel resolution. Since it is a “swath product”, it is not *tilled* as a constant image through time, and there might be more than one image per day. The working procedure to compute RH is shown in Figure 3.8.

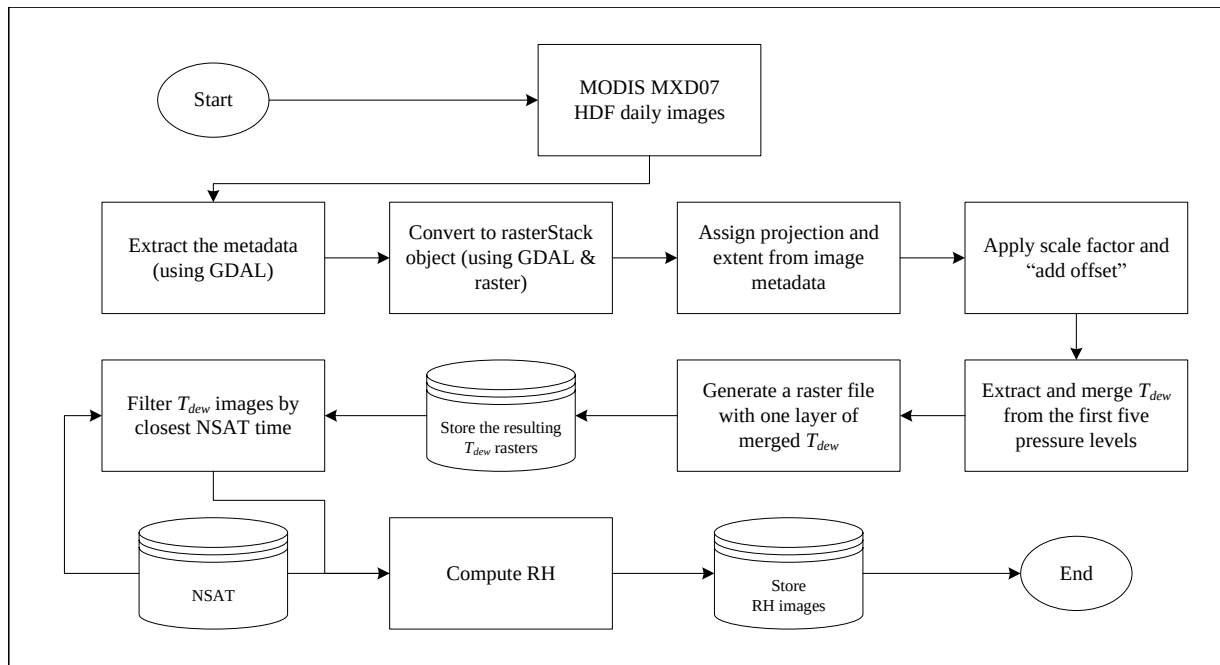


Figure 3.8: Flowchart for the relative humidity calculation.

Note that the images are in Hierarchical Data Format (*.hdf), and hence the image metadata is opened using the GDAL (rgdal) package (Bivand et al., 2022) in R. Once the metadata is known, the image is opened using the raster package (Hijmans, 2020) in R, particularly using the stack function, since the product is multi-layered, i.e. it comes with multiple T_{dew} images for different altitudes considering the standard atmosphere. The projection (geographic coordinates – WGS84) and the extent of the image was assigned to the latter rasterStack object and the scale factor (s_f) and “add offset” (a_o) values were applied using the following expression.

$$T_{dew,f} = \left[s_f \cdot (T_{dew,i} - a_o) \right] - 273.15 \quad (3.20)$$

where $T_{dew,i}$ is the raw dew-point temperature obtained from the rasterStack object. According to product information, $s_f = 0.009999999776482582$ and $a_o = -15000$. After applying both the scale factor and “add offset”, the result will be in Kelvin, and subtracting 273.15, the result is the dew-point temperature $T_{dew,f}$ in degrees Celsius. These images were stored with their acquisition time in the output filename, which is in Coordinated Universal Time (UTC), and hence was converted to local time using the chron package (James & Hornik, 2020) in R.

Finally, using the date and local time of the NSAT images, the closest T_{dew} raster was used to compute the relative humidity. For the sake of simplicity, T_{dew} images were resampled to the extent and resolution of the NSAT images using the raster package in R. Thus, with both NSAT and T_{dew} rasters with the same resolution and extent, Equation (3.19) was applied to each pixel to obtain the relative humidity.

3.4.7.7 Calculation of the Fire Weather Index

Once all the previous variables are calculated (NSAT, precipitation, RH and wind speed), the following step is to compute the FWI. For this, the cffdrs package (Wang et al., 2017a) in R was used, since it has all the FWI equations described by Van Wagner & Pickett (1985). Using the package, it is possible to set initial conditions for the FWI calculation. These conditions are within a rasterStack containing the Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), and the Drought Code (DC). For more information see Section 2.4.

For every day-iteration, the algorithm calculates the three variables, as well as the Built-Up Index (BUI), which is an indicator of the amount of fuel available for combustion (based in the DMC and DC), and the Initial Spread Index (ISI), which is a combination of wind and the FFMC that represents a rate of spread alone without the influence of fuel-based variables (Van Wagner, 1974).

The initial conditions were studied using the European Centre for Medium-Range Weather Forecasts (ECMWF) data, particularly the world-gridded data for the “Fire danger indices historical data from the Copernicus Emergency Management Service” (Di Giuseppe et al., 2020; Vitolo et al., 2020, 2019), downloaded from: <https://cds.climate.copernicus.eu/> (last access in May 2022). The product corresponds to a Global Land Reanalysis at a $0.25^\circ \times 0.25^\circ$ resolution (≈ 28 km). Average data from the last 11 days of December from 2010 to 2016 was used to compute the mean of the FFMC, DMC and DC ratings at the ROI. These were rasterized in R and stacked (converted to a multi-layer raster object) in order to use it for the FWI calculation. Additionally, the month of the year was set to 1 (January) with latitude adjustment (taken from the rasters projection). The workflow for the FWI calculation is shown in Figure 3.9.

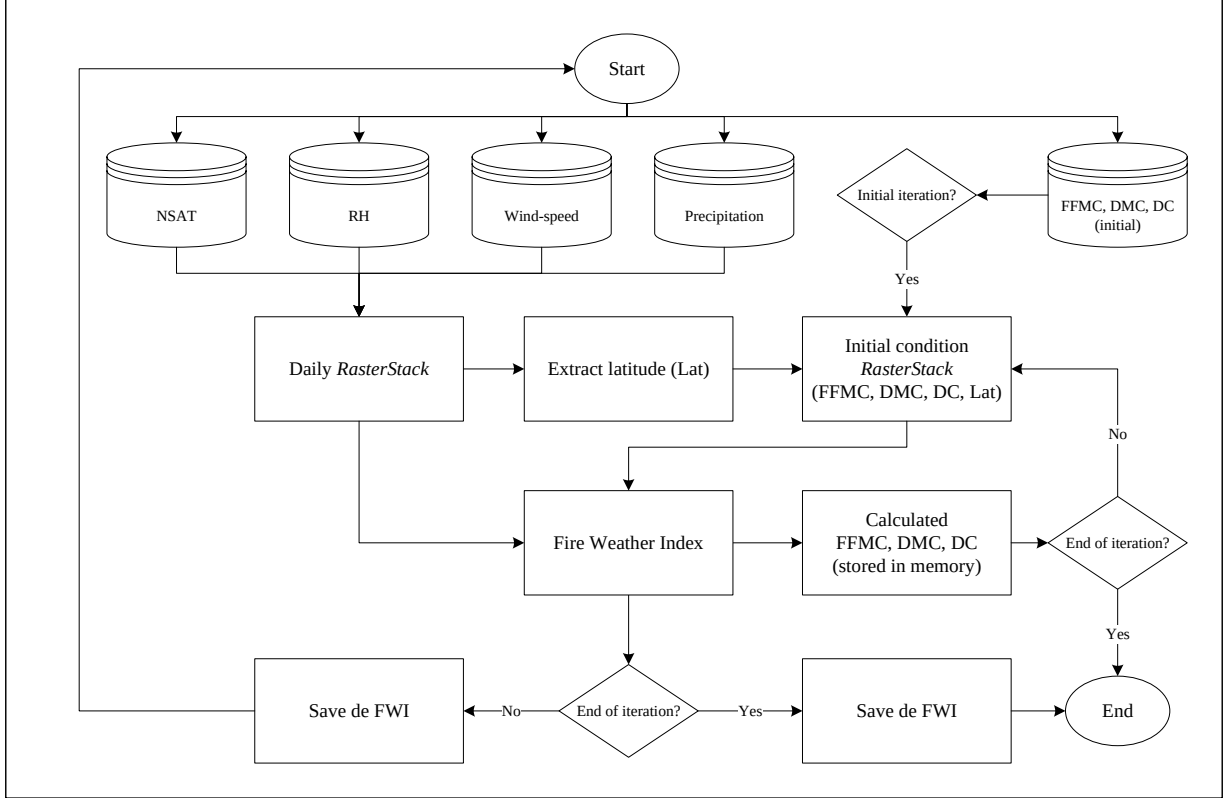


Figure 3.9: Flowchart for the Canadian Fire Weather Index (FWI) calculation using the *cffdrs* package in R.

3.4.7.8 Calculation of the approximated Fire Weather Index

In the study developed by [Avila et al. \(2022\)](#) a simple formula based on a reduction of the FWI equation-parameters is used to calculate the index under certain conditions specified in [Section 2.4](#). The equations used were the following.

$$\begin{aligned}
 \ln(B) &\approx \ln(0.1 \times 0.208 f(W)f(F)f(D)) \\
 &\approx \vdots \\
 \ln(B) &\approx 0.05039 u - 0.1386 \left(0.942 RH^{0.679} + 11e^{\frac{RH-100}{10}} + 0.18(21.1 - T_a)(1 - e^{-0.115 RH}) \right) + \\
 &\quad + \ln(1.912 \times 40)
 \end{aligned} \tag{3.21}$$

Where, $f(W)$, $f(F)$ and $f(D)$ are the wind, fine fuel moisture, and duff moisture functions, respectively, and B , u , RH and T_a are the FWI in its intermediate form, wind-speed (in $\text{km}\cdot\text{h}^{-1}$), relative humidity (in %), and air temperature (in degrees Celsius). Finally, using equation (3.21), the approximated Fire Weather Index (FWI_{app}) can be calculated using the following expression.

$$\text{FWI}_{\text{app}} = \exp\left(2.72 \cdot \{0.434 \ln(B)\}^{0.647}\right) \tag{3.22}$$

Therefore, this approximation approach for the FWI only requires the wind-speed, u , the relative humidity, RH , and the NSAT, T_a , for its calculation. There is no need for the initial parameters such as the fine fuel moisture code, duff moisture code, drought code nor the precipitation data.

4 | Results

This chapter is divided in three main sections: (i) “Vegetation”, which study the fuel conditions (pre-, per-, and post-fire) and pre-fires within the ROI, (ii) “Meteorology”, which describes the meteorological variables within the ROI, and (iii) “Las Máquinas wildfire”, which addresses the per-fire conditions, burned area, fire evolution, air quality, among others.

4.1. Vegetation

Since the fuel that feeds the combustion process of wildfires is vegetation, it is relevant to analyze the flora evolution prior to the event, as well as the consequences on it after the event.

4.1.1 Vegetation evolution

The Normalized Difference Vegetation Index (NDVI), which was one of the earliest remote sensing analytical products used to simplify the complexities of multi-spectral imagery, is now the most popular index used for vegetation assessment (Huang et al., 2021). There are multiple conclusions that can arise from the NDVI, however the most common ones are those that use the NDVI as an indicator of vegetation health and growth (Coops & Stone, 2005; McVeagh et al., 2012), which can be encompassed in the term *vigor*. The evolution of this index, as well as the Normalized Difference Water Index (NDWI; Gao, 1996), which is used as an indicator of water content within vegetation, were studied in the ROI from January 2010 to March 2022 at a temporal resolution of 16-days using the MODIS MOD13A1 product (Didan, 2015). NDVI results are shown in Figure 4.1a, while NDWI results are presented in Figure 4.1b, both at a municipality scale within the ROI.

For both the NDVI and NDWI a similar cyclical behavior within a year is observed, where its highest values are achieved in the austral winter season (June-July-August). Moreover, prior to the “Las Máquinas” wildfire (which is represented by the vertical dashed line in Figure 4.1), all of the averaged-NDVI (for each municipality) had a slight tendency to increase, excepting the Empedrado municipality, whose average NDVI has remained slightly constant. Before the event (2010–2016 data), Empedrado had the highest avg. NDVI compared to the other municipalities within the ROI, which can be seen in Table 4.1, while both pre-fire NDVI and NDWI data distribution are shown in Appendix D (cf. Figure D.1).

During the wildfire days, it is clear that the NDVI had its lowest values. Moreover, only from this set

Table 4.1: Average NDVI pre- and post-fire per municipality within the ROI. P. diff (%) stands for percentage difference of Avg. NDVI prefire and Avg. NDVI postfire.

Municipality	Avg. NDVI prefire	Avg. NDVI postfire	P. diff (%)
Cauquenes	0.593 ± 0.065	0.597 ± 0.085	0.63%
Chanco	0.702 ± 0.045	0.746 ± 0.049	6.11%
Constitución	0.713 ± 0.029	0.699 ± 0.046	-1.93%
Empedrado	0.721 ± 0.034	0.634 ± 0.058	-12.81%
San Javier	0.591 ± 0.053	0.575 ± 0.068	-2.65%

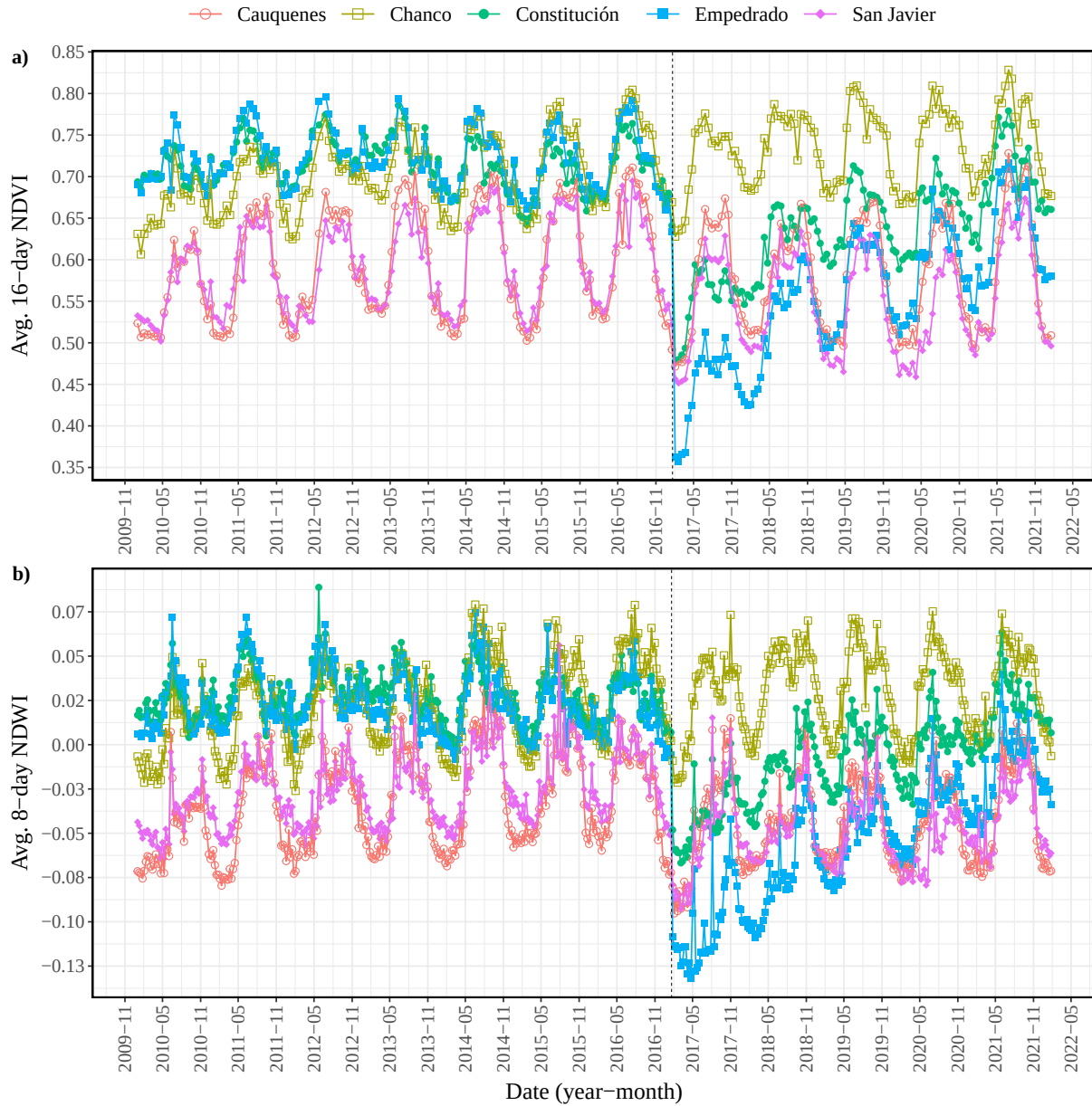


Figure 4.1: *Pre-, per- and post-fire* a) averaged NDVI evolution at a 16-day temporal resolution from MODIS MOD13A1, and b) averaged NDWI evolution at a 8-day temporal resolution from MODIS MOD09GA product. Vertical dashed line corresponds to January 20, 2017, the “Las Máquinas” wildfire start day.

of results it is possible to observe that the most affected municipality, in terms of severity to its flora, was Empedrado, followed by Constitución, Cauquenes, San Javier and Chanco, in that order. Furthermore, it is possible to notice that Chanco was slightly affected by the event from the NDVI point of view. Vegetation recovery has been slightly different for each municipality. For example, until March 2022, i.e. five years later, Empedrado has not yet reached its NDVI pre-fire values. Considering the last NDVI post-fire cycle i.e. from January 2021 to march 2022, a percentage difference of -12.81% was found between avg. NDVI pre-fire and last-cycle post-fire NDVI. The latter can be seen in [Table 4.1](#).

4.1.2 Previous fires

Previous fires are important to study the anatomy of “Las Máquinas” wildfire from the point of view of locations more fire-prone and the relationship between the event and the fuel availability, which can be related with the NDVI analysis.

The previous fires are shown for both location and size in [Figure 4.2](#), where it is interesting to observe that prior the “Las Máquinas” event, the closest wildfires to this date took place in the Constitución municipality (north of the ROI) shown in orange-to-red colors, where the village of “Santa Olga” and the town of “Constitución”¹ are located. The biggest wildfire prior the “Las Máquinas” event took place at around 15 km to the east of Santa Olga (marked as a populated area), with a size of $\approx 12,500$ ha, which has been the single largest wildfire before the “Las Máquinas” event (at least from the Global Fire Atlas database; [Andela et al., 2019a,b](#)). In addition, it is interesting to notice that there were no wildfires in the Empedrado municipality (center of the ROI) for at least 8 years before the “Las Máquinas” fire. Furthermore, no fire has occurred in the entire period under study at the Chanco municipality (at the west of the ROI), at least not within the Global Fire Atlas database, which is one MODIS pixel i.e. $\sim 460 \text{ m} \times 460 \text{ m} \approx 210,000 \text{ m}^2 \approx 21 \text{ ha}$ ([Andela et al., 2019a](#)).

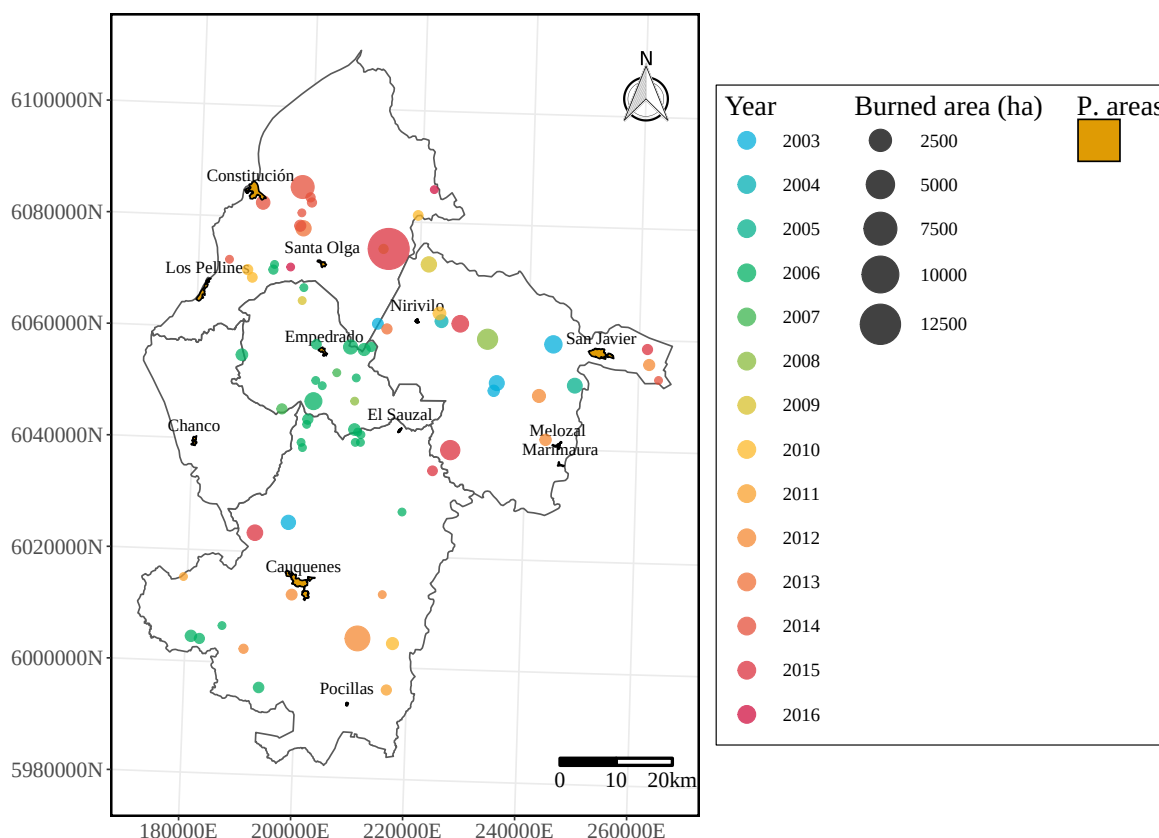


Figure 4.2: Map of previous fires (before the “Las Máquinas” wildfire) using the Global Fire Atlas database from 2003 to 2016. The map shows the fire locations per year of the event (by color) and magnitude (size), as well as the populated areas (P. areas) within the ROI i.e. the five municipalities. The map coordinate system is WGS84 UTM Zone-19 south.

¹N.B: There is a town named “Constitución” within the “Constitución” municipality.

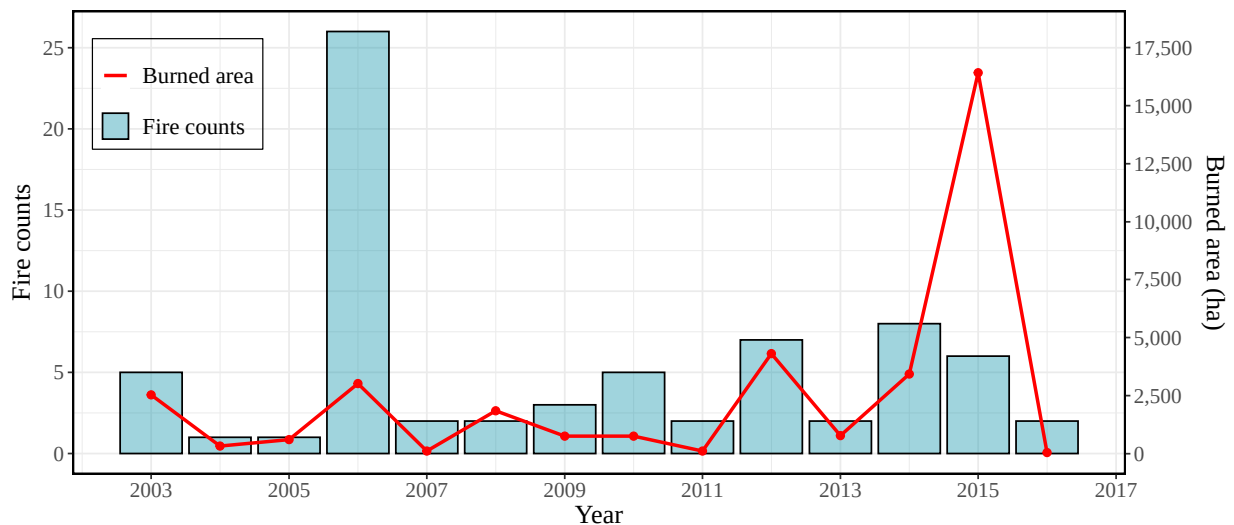


Figure 4.3: Fire counts and burned area taken from the Global Fire Atlas database from 2003 to 2016 within the ROI.

An additional observation is that in Empedrado and Chanco, the average NDVI had the highest values prior to the “Las Máquinas” wildfire (see [Section 4.1.1](#)). Particularly for Empedrado, the average NDVI right before the fire was around 0.67, which means that, on average, that particular municipality had healthy and high density vegetation. Hence, both the absence of wildfires over time and high NDVI values within Empedrado indicate a high fuel availability.

Fire counts and burned area (per year) within the ROI were also studied. The results are shown in [Figure 4.3](#). As it is possible to observe, fire counts usually remain constant through years. However, in the year 2006 there were a total of 26 fires with a total burned area of ~3,000 ha, while in 2015 there were a total of 6 fires yet the affected area was around 16,000 ha, i.e. more severe fires. The average fire counts for the 2003–2016 data was 5, while the mean burned area was 2,500 ha.

4.2. Meteorology

4.2.1 Temperature evolution

According to the Global Climate Change Vital Signs of NASA ([Shaftel et al., 2018](#)), the Earth’s global surface temperature in 2017 increased by 0.9°C relative to the average temperatures between 1951 and 1980. With a change in climate come weather anomalies that can drastically affect populations of certain areas. In extreme cases, these changes in global temperature can subject people to a greater risk of natural disasters. And in that matter, wildfires are one of the biggest threats ([Rossiello & Szema, 2019](#)). Therefore, a study of the monthly averaged maximum temperature evolution within the ROI was carried out. For this, a gridded maximum temperature product developed by the CR² (Center for Climate and Resilience Research) based on the ERA-Interim reanalysis data was used ([CR2, 2022](#)). The results are shown in [Figure 4.4](#).

Note that each data-point in [Figure 4.4](#) corresponds the mean of the product for all the pixels within the ROI, i.e. the mean of the monthly-averaged maximum temperatures at the ROI. As it is possible to observe, there is a negligible trend for the maximum monthly temperature. A mean of all the data is $20.02 \pm 4.50^\circ\text{C}$.

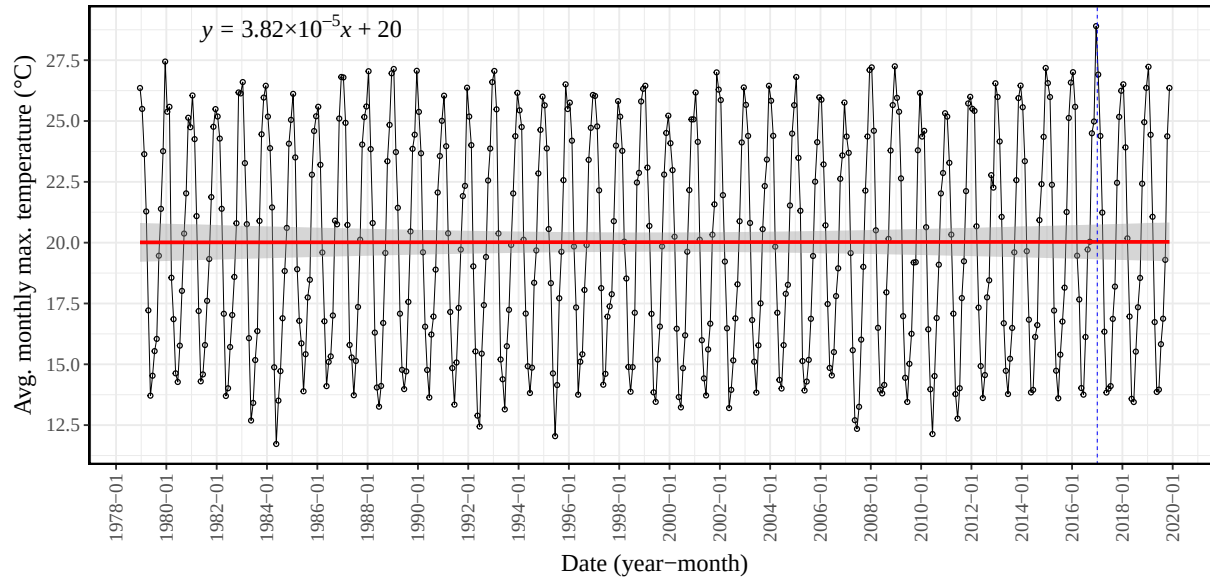


Figure 4.4: Average maximum temperature within the ROI from January 1979 to December 2019. Red line corresponds to the data trendline (linear regression), while the gray zone is the confidence interval. The blue dashed line corresponds to the “Las Máquinas” wildfire start date.

Furthermore, right before the “Las Máquinas” wildfire (the month before, i.e. December 2016), the highest maximum temperature for all the dataset was registered, with a value of 28.9°C, being the highest found since 1979 within the ROI according to the data. This result is very important, since it characterizes a weather-based risk variable for the pre-fire analysis.

This findings are consistent with the results obtained by [CONAF \(2017a\)](#), not from the maximum temperature point of view but from the “month of records” conclusion in terms of temperatures and drought.

4.2.2 Drought analysis using the SPI

The Standardized Precipitation Index (SPI) was calculated using monthly precipitation images derived from the IMERG-GPM satellites ([Huffman et al., 2019a](#)) from 2001 to 2016 (all available data). Since the objective of this work is to use remotely-sensed data, the IMERG-GPM was the best option to obtain the monthly precipitation for computing the SPI. Nevertheless, it would have been interesting to compare the SPI derived from IMERG-GPM data against measured precipitation data at the weather stations within the ROI, but unfortunately the weather stations data within the ROI are only available from 2010 onwards. Thus, calculating the SPI from 2010 to 2016 would not consider the drought impact, and hence its analysis is statistically superfluous. Therefore, the only possible comparison is with the ERA-Interim reanalysis data. However, the CR² built a monthly precipitation dataset based on the ERA-Interim reanalysis product but calibrated for Chile ([CR2, 2022](#)), which is used for this study. This data has a 0.05° pixel-resolution (≈ 5 km), while IMERG-GPM has a 0.1° pixel-resolution (≈ 11 km). Using both products, the SPI was calculated and the results are shown in [Figure 4.5](#).

As it is possible to observe from [Figure 4.5](#), [Figures 4.5a](#) and [4.5b](#) exhibit a similar behavior. However, IMERG-GPM data ([Figure 4.5a](#)) shows a more severe drought during the 2010–2011 and 2013–2014 timeframes than the SPI calculated with the CR² data, manifested in lower SPI values and a broader area. Nevertheless, both results show that there had been severe and persisting drought, and just before the

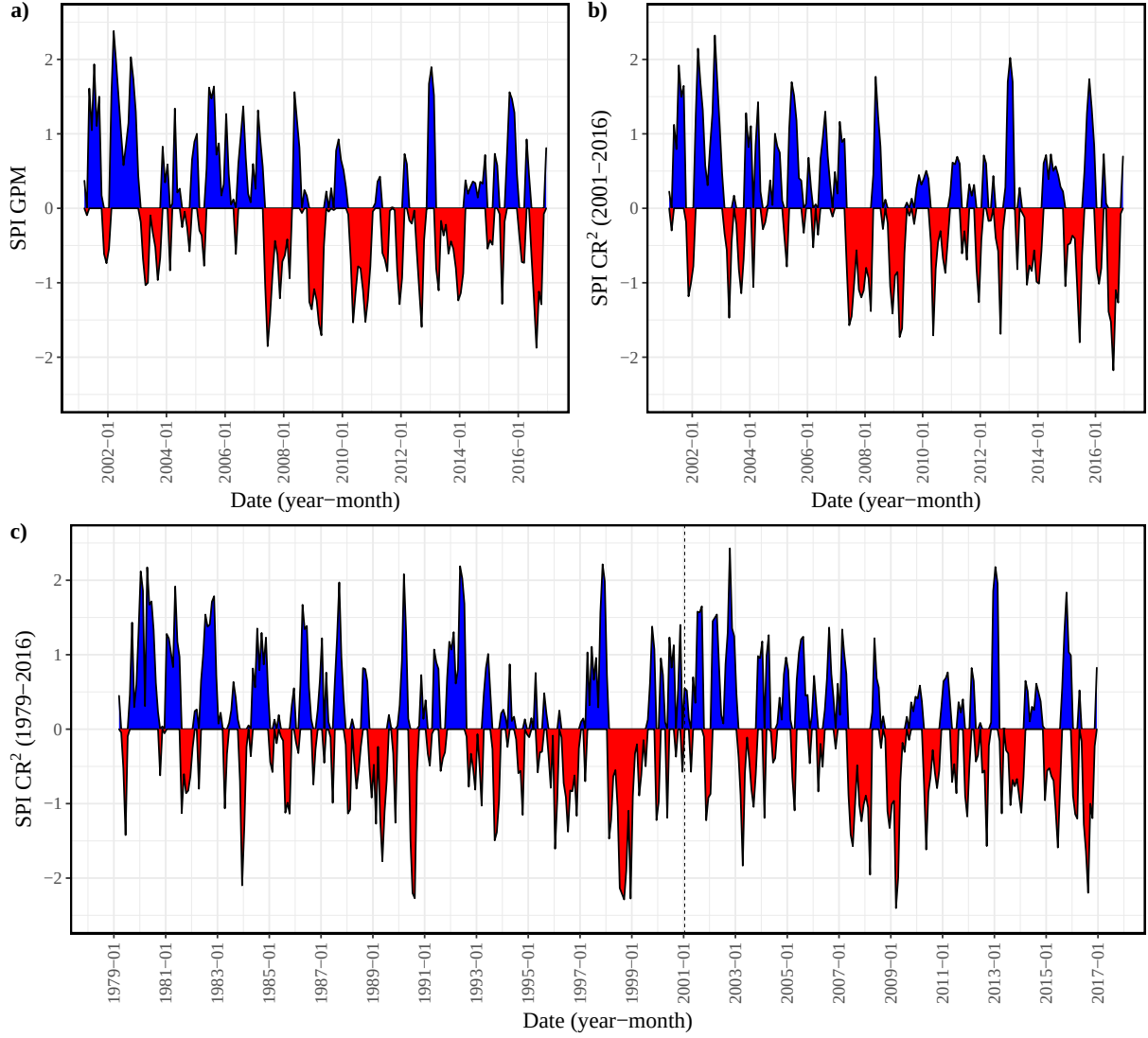


Figure 4.5: Standardized Precipitation Index using monthly precipitation for the ROI from a) IMERG-GPM satellite images from 2001 to 2016, b) CR^2 data from 2001 to 2016, and c) CR^2 data from 1979 to 2016. The vertical dashed line in c) represents January 2001, the starting date for a) and b).

wildfire (year 2016), there was a severe drought, with SPI values close to -2.0 for the IMERG-GPM data, and even under -2.0 for the CR^2 data. Furthermore, from [Figure 4.5c](#) it is possible to observe the SPI evolution since 1979, and maybe the drought had not been as severe from the SPI value point of view, however the persistence of the drought has increased since 1998 for the ROI. With the objective to study the SPI based on a more quantitative method, the area under the curve (AUC) was calculated for both datasets as the following.

$$AUC = \sum_{i=1}^n SPI_i \Delta x_i \quad (4.1)$$

where i corresponds to the date, and Δx_i to the interval between date i and $i - 1$ or $x_i - x_{i-1}$. The SPI AUC results are shown in [Figure 4.6](#). The discrete AUC corresponds to the Δx interval AUC value, i.e. the result for each i within AUC_i in Equation (4.1), while the cumulative AUC is the consecutive sum of the

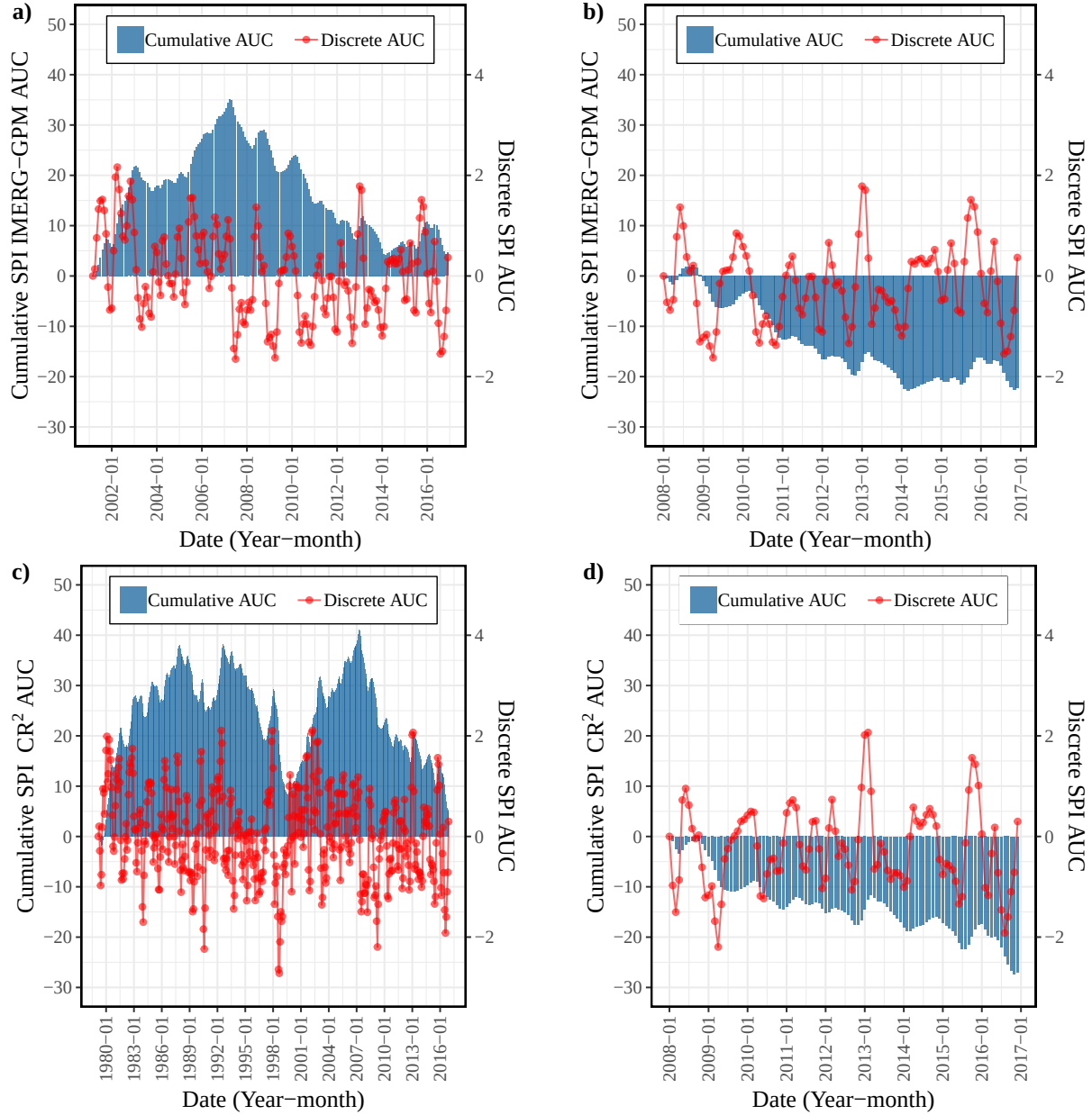


Figure 4.6: AUC of the Standardized Precipitation Index using monthly precipitation for the ROI from a) IMERG-GPM satellite images from 2001 to 2016, b) IMERG-GPM satellite images from 2008 to 2016, c) CR^2 data from 1979 to 2016, and d) CR^2 data from 2008 to 2016.

discrete AUC.

From Figure 4.6 it is possible to observe that for the IMERG-GPM data (Figure 4.6a) the SPI area under the curve has been continuously decreasing since 2009. Moreover, if only the AUC for the SPI between 2008 and 2016 is analyzed (Figure 4.6b) the results are only negative bars from year 2009 onwards (from cumulative AUC). The same results are obtained from CR^2 data (Figure 4.6c and 4.6d). Therefore, the findings suggest that there has been a persistent and severe drought within the ROI from 2009 until the event, which are the same results found by Garreaud et al. (2020) for Central Chile.

An interesting analysis to carry out is the validation of the SPI from a statistical approach. Using the monthly-obtained α and β Gamma distribution coefficients from the SPI results, it is possible to calculate the theoretical Gamma distribution function for each month.

$$X \sim \Gamma(\alpha, \beta) \equiv \text{Gamma}(\alpha, \beta) \quad (4.2)$$

$$f(x; \alpha, \beta) = \frac{e^{-x/\beta} x^{\alpha-1}}{\beta^\alpha \Gamma(\alpha)}, \quad 0 \leq x < \infty, \alpha, \beta > 0 \quad (4.3)$$

$$F(x; \alpha, \beta) = \int_0^x f(u; \alpha, \beta) du \quad (4.4)$$

where $F(x; \alpha, \beta)$ is the cumulative distribution function. Once the integral in Eq. (4.4) is evaluated for each α and β coefficients and for each month of analysis, this value can be compared to the empirical cumulative distribution function of the precipitation data of each month (which is calculated in R). Finally, knowing both the theoretical Gamma distribution and the empirical cumulative distribution, the Kolmogorov–Smirnov (Kolmogorov-Smirnov, 2008) test (K-S) is applied to both distribution functions, where the following hypotheses are studied.

$$\begin{cases} H_o : \text{Both distributions follow the same distribution (Gamma)} \\ H_a : \text{They do not follow the same distribution} \end{cases}$$

H_o and H_a are the null and alternative hypothesis for the K-S test. The latter is evaluated with the p -value, which is defined as the probability, calculated under the assumption that the null hypothesis is correct, of having outcome as extreme as the observed value in the sample (Greenland et al., 2016). If a p -value is less than 0.05 means a rejection of the null hypothesis. The results for both the IMERG-GPM and CR² data can be seen in Table 4.2.

Table 4.2: Statistical p -value results with the Kolmogorov Smirnov test for the IMERG-GPM and CR² data. The values with the asterisk symbol are those within the null hypothesis of the K-S test, meaning that both the theoretical and empirical distribution functions follow the same Gamma distribution.

Month	p -value GPM	p -value CR ² (2001-2016)	p -value CR ² (1979-2016)
January	0.0350	0.0933*	0.0001
February	0.4263*	0.0350	0.0049
March	0.7164*	0.4263*	0.1445*
April	0.2145*	0.4263*	0.0446
May	0.0933*	0.0933*	0.0109
June	0.0933*	0.2145*	0.0227
July	0.7164*	0.9999*	0.5452*
August	0.4263*	0.4263*	0.0227
September	0.0001	0.0001	0.0001
October	0.0030	0.0112	1.1×10^{-5}
November	0.0350	0.0112	3.1×10^{-6}
December	0.0933*	0.0112	8.2×10^{-7}

Two conclusions can be obtained from Table 4.2. The first one is that SPI IMERG-GPM achieved a more statistically-strong results than the CR² data, meaning that there are more months whose data distributions are actually a Gamma distribution under the employment of the K-S test, and thus resulting in a well-built SPI. Second, comparing the results of the two time-ranges analysis of the CR² SPI, the results were better for the 2001–2016 period than for the 1979–2016 timeframe, since for the latter there are less statistically significant results within each month based on the p -value.

4.3. Las Máquinas wildfire

4.3.1 Burned area

The burned area of the “Las Máquinas” wildfire was studied using combined Aqua/Terra-MODIS data (MODIS MCD64A1 product), and pre- and post-fire reflectance images of both Landsat-8 & Sentinel-2. Whereas the MODIS product comes with processed burned-pixel values, spectral indices were computed for both Landsat-8 and Sentinel-2 images to analyze the burned area. The spectral indices used were the delta Normalized Burn Ratio (dNBR; Key & Benson, 1999, 2006; Van Wagtenonk et al., 2004) and the Relativized Burn Ratio (RBR; Parks et al., 2014). Hence, the burned area relies on the threshold values used for the indices, and thus the variation of these and its associated burned area was studied. The results are shown in Figure 4.7.

According to CONAF, the burned area of the fire was 218,076 ha (calculated from the official burned area ESRI shapefile distributed by CIREN, 2017a, the Chilean Natural Resources Information Center). They calculated this area using both MODIS MCD64A1 data and in situ observations. This value corresponds to the upper-bound of the rectangle with red-filled area in Figure 4.7. On the other hand, if only MODIS MCD64A1 data is used, the burned area obtained is 193,804 ha, which corresponds to the lower-bound of rectangle in Figure 4.7. These values are useful to establish a pseudo-calibration procedure, since CONAF burned area is corrected in situ and the MODIS MCD64A1 algorithm has been widely validated among several ecosystems and, moreover, usually its burned area results are underestimated (Giglio et al., 2009; Roy & Boschetti, 2009). Hence, using this methodology, the dNBR and RBR threshold

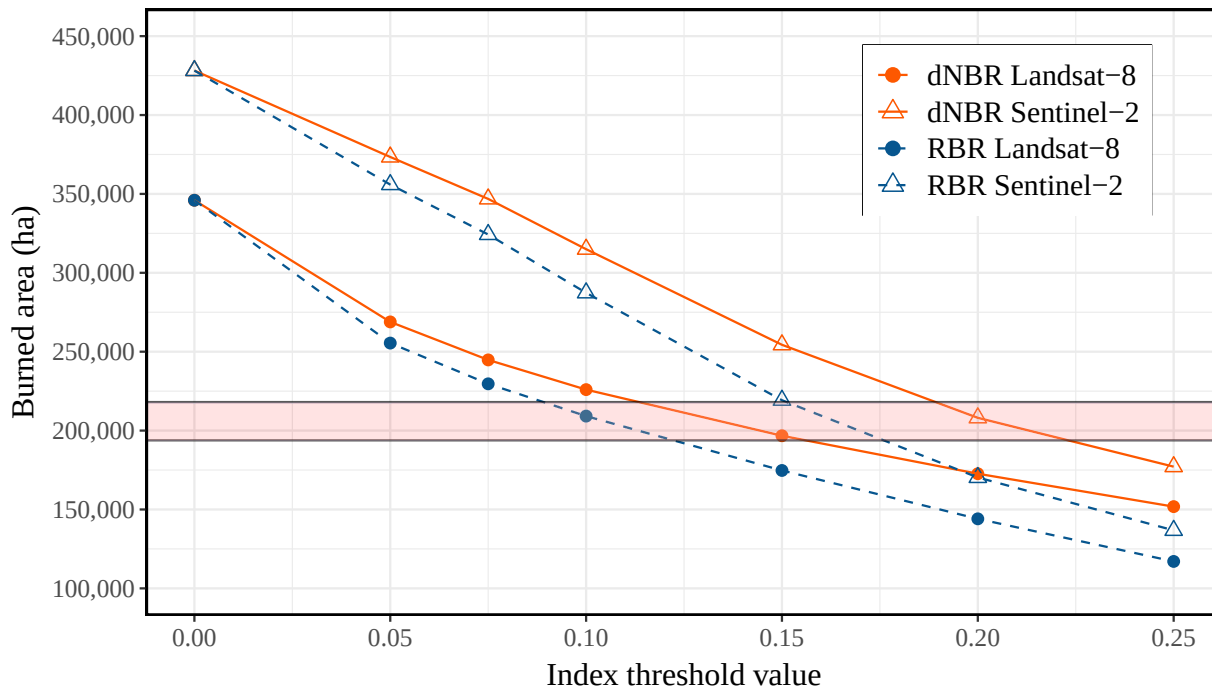


Figure 4.7: Burned area versus index threshold value for Landsat-8 and Sentinel-2 images using the dNBR and RBR spectral indices. The point shapes indicate the satellite, while the line color and type indicates the spectral index. The filled area is delimited in the top by the official burned area given by CONAF, while the bottom corresponds to the MODIS MCD64A1 calculated area.

values for Landsat-8 and Sentinel-2 data should be the following (within the red-filled area of [Figure 4.7](#)).

$$\text{dNBR Landsat-8} : \theta_{L8} \in [0.12, 0.155]$$

$$\text{dNBR Sentinel-2} : \theta_{S2} \in [0.19, 0.22]$$

$$\text{RBR Landsat-8} : \psi_{L8} \in [0.08, 0.12]$$

$$\text{RBR Sentinel-2} : \psi_{S2} \in [0.15, 0.175]$$

where θ and ψ are the dNBR and RBR threshold values, respectively. A visual result of the burned area using MODIS MCD64A1, Landsat-8 and Sentinel-2 at certain threshold values can be observed in [Figure 4.8](#). From these results, at equal threshold values for both Landsat-8 and Sentinel-2, some differences are perceivable throughout the images. For example, in both cases there are burned pixels in Chanco municipality (west of the ROI), yet no burned pixels are observed for MODIS MCD64A1 image in that municipality. Furthermore, there is no report from CONAF mentioning wildfires in Chanco. Moreover, as it was studied in the Vegetation section (see [Section 4.1.1](#)), there was no significant decrease in the average NDVI for the latter municipality. Nevertheless, Chanco's boundary with Empedrado was affected according to MODIS results ([Figure 4.8a](#)), and that might be the reason of the slight decrease in the average NDVI for that municipality. It is because of the latter that it was interesting to study the dNBR severity ([Key & Benson, 2006](#)) for both Landsat-8 and Sentinel-2 images, whose results are shown in [Figure 4.9](#). From the last figure it is possible to observe that all the dNBR pixels in Chanco municipality are within the range of low and moderate to low severity, but mainly low severity values.

Moreover, high severity dNBR values can be observed in Constitución, Empedrado and San Javier municipalities. Particularly, high severity pixels were found in the surroundings of the village of Santa Olga and Nirivilo, although in the former a much more severe situation is observed.

In addition, from [Figure 4.9](#) it is also possible to observe that Sentinel-2 categorized low severity pixels in places where Landsat-8 did not (e.g. south-east of the ROI). This might be because of 1) differences in sensors-pixel resolution, and 2) band differences used to compute the NBR for each product, since the NIR band used for Sentinel-2 is the Narrow-NIR (Band 8A), which has a bandwidth of 21 nm, while Landsat-8 NIR band (Band 5) has a bandwidth of 30 nm. Nevertheless, both SWIR and NIR bands are centered at the same wavelength. Finally, the mean and standard deviation dNBR values for Sentinel-2 and Landsat-8 were 0.22 ± 0.28 and 0.15 ± 0.28 , respectively, hence it is clear that, on average, Sentinel-2 obtained higher dNBR values.

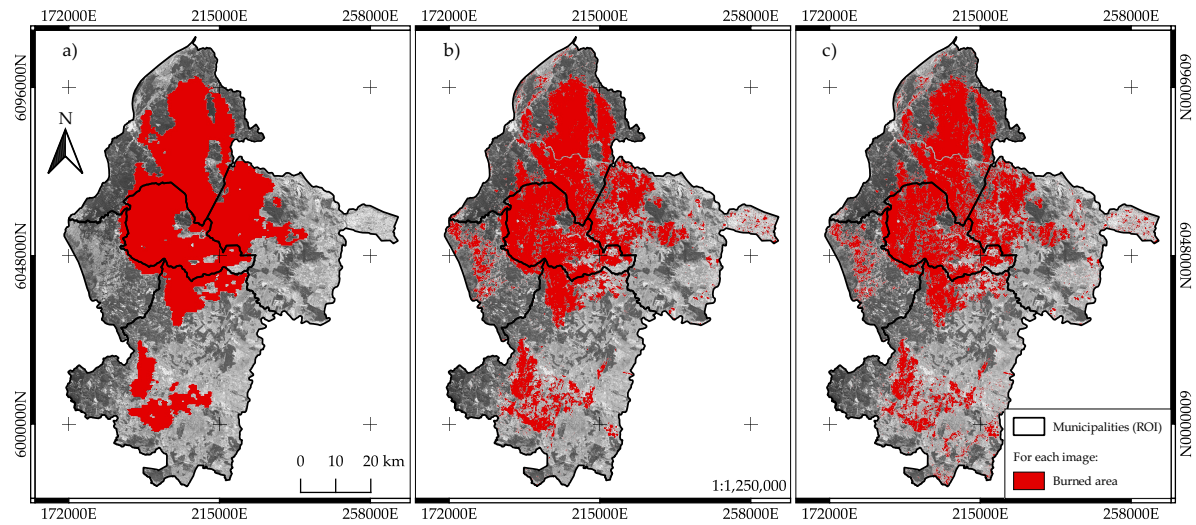


Figure 4.8: Burned area for a) MODIS MCD64A1 product, b) Landsat-8 OLI with $\theta_{L8} = 0.135$, and c) Sentinel-2 MSI with $\theta_{S2} = 0.205$. Considering the dNBR threshold values mentioned before, the Landsat-8 and Sentinel-2 burned area results were 204,440 ha and 204,450 ha, respectively. While the affected surface with MODIS MCD64A1 was 193,804 ha. Coordinate system of the map is WGS84 UTM Zone 19-South. Background image is Landsat-8 OLI pre-fire in grayscale.

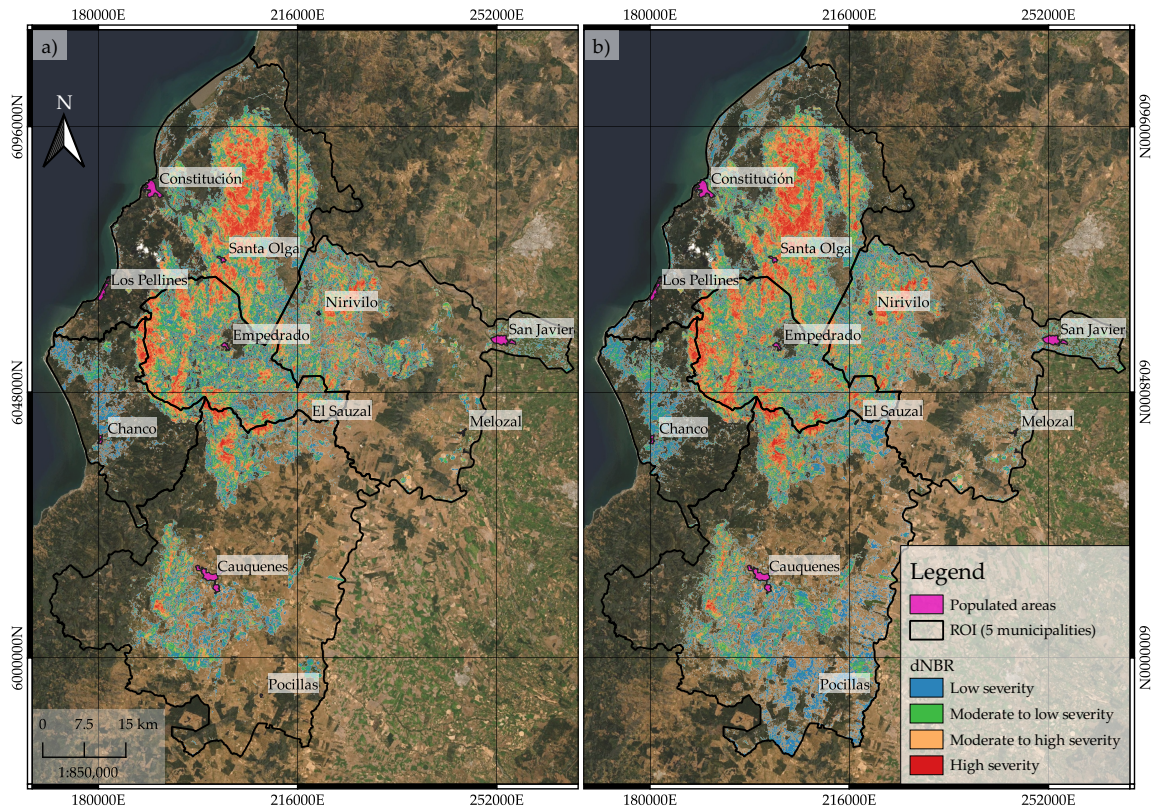


Figure 4.9: Burned area severity using the dNBR values from Key & Benson (2006). a) correspond to Landsat-8 dNBR, and b) Sentinel-2 dNBR. Map coordinate system is WGS84 UTM Zone 19-South. Background image corresponds to ESRI-satellite world imagery data.

4.3.2 Fire evolution

The evolution of the fire front was computed using MODIS-MCD64A1 product. The daily burned area evolution (only fires per day) registered by the latter product are shown in [Figure 4.10](#).

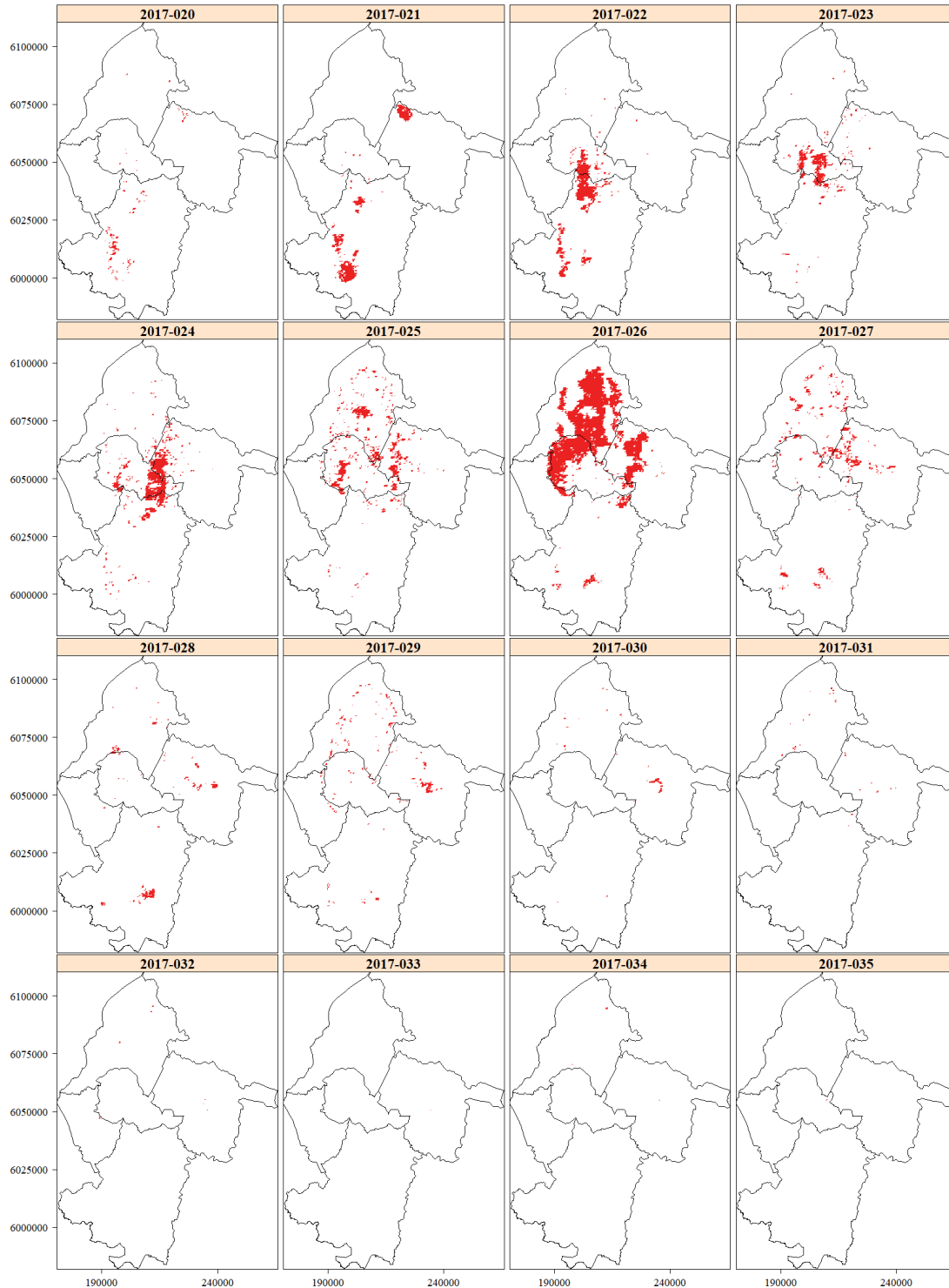


Figure 4.10: Burned area evolution calculated using MODIS MCD64A1 product between Julian days 020–035 (January 20 to February 4th, 2017) within the ROI. Each image corresponds to daily data.

Furthermore, both cumulative and daily burned area results are shown in [Figure 4.11](#). From both figures it is possible to observe that the most catastrophic days during the fire were between January 25th and 26th. In those days, according to the MODIS product, around 85,000 hectares were burned. Nevertheless, CONAF estimated a total burned area of 115,000 ha between those days ([CONAF, 2017a](#)), but no methodology was found for the estimation within the official information. However, and since their total burned area estimation was carried out from both MODIS data and in situ observations, it is possible that this methodology was applied. Since MODIS MCD64A1 product has a bias to underestimate the burned area (see [Section 4.3.1](#)), hence that surface area difference is plausible. Although note that the area estimated by CONAF is around 44% higher than MODIS MCD64A1 for those days.

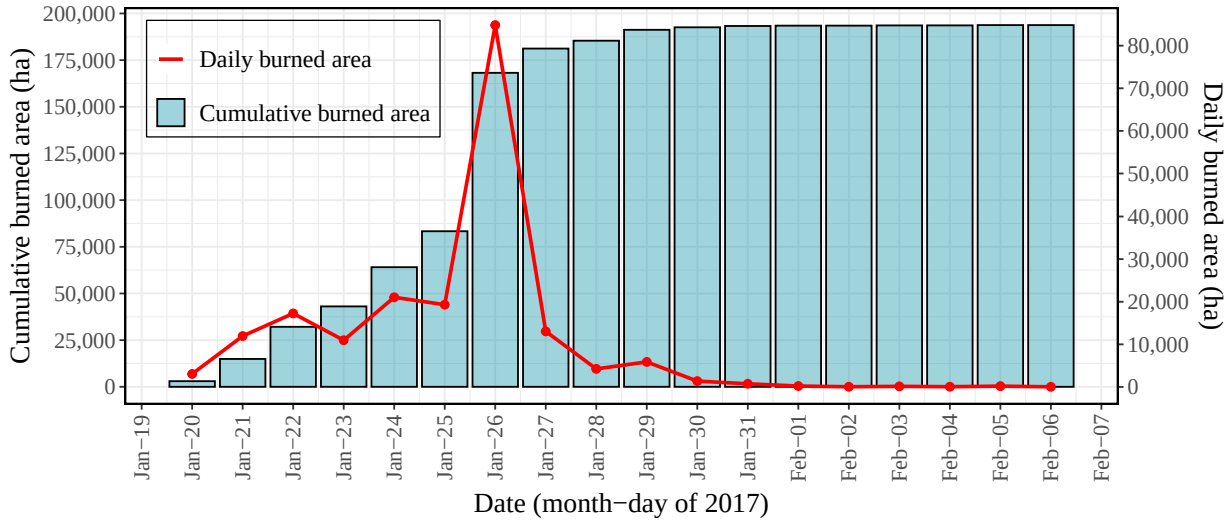


Figure 4.11: Burned area evolution calculated using MODIS MCD64A1 product between Julian days 020–035 (January 20 to February 4, 2017) within the ROI. Left Y-axis (cyan bars) corresponds to cumulative burned area, while right Y-axis (red line) is the daily burned area values.

4.3.3 Maximum fire radiative power

Maximum daily fire radiative power (FRP, in MW) was obtained from daily VIIRS-SNPP VNP14A1 images. The FRP images are shown in [Figure 4.12](#). From the last figure it is possible to observe that there are some pixel values with FRP > 1500 MW, which can be seen in DOY 021 around 4 km to the south of the Empedrado municipality (located in the center of the ROI), as well as in DOY 023 towards the south of the same municipality and finally in DOY 026 at the Constitución municipality (north of the ROI), around 5 km to the north-west of the village of Santa Olga. Note that this last value was recorded a couple of hours after the fire destroyed Santa Olga.

On the other hand, product MODIS M*DI4A1 thermal anomalies ([Giglio & Justice, 2021](#)) was studied from both Terra and Aqua satellites at a 1 km pixel resolution. However, this is an 8-day product meaning that 8-day data is stored within each image. The only image with FRP values from January 1 to February 28 were those of January 25 (for both satellite platforms), which has information from January 17 to 25. The results are shown in [Figure 4.13](#).

As it is possible to observe, Aqua-MODIS registered more FRP pixels and higher maximum FRP values than Terra and VIIRS, which might be due to smoke conditions. Analyzing both the daily-burned area product (see [Figure 4.10](#)) and the daily FRP ([Figure 4.12](#)), it is possible to conclude that the maximum FRP values registered by Aqua-MODIS are from DOY 025, which is the day that Santa Olga was completely

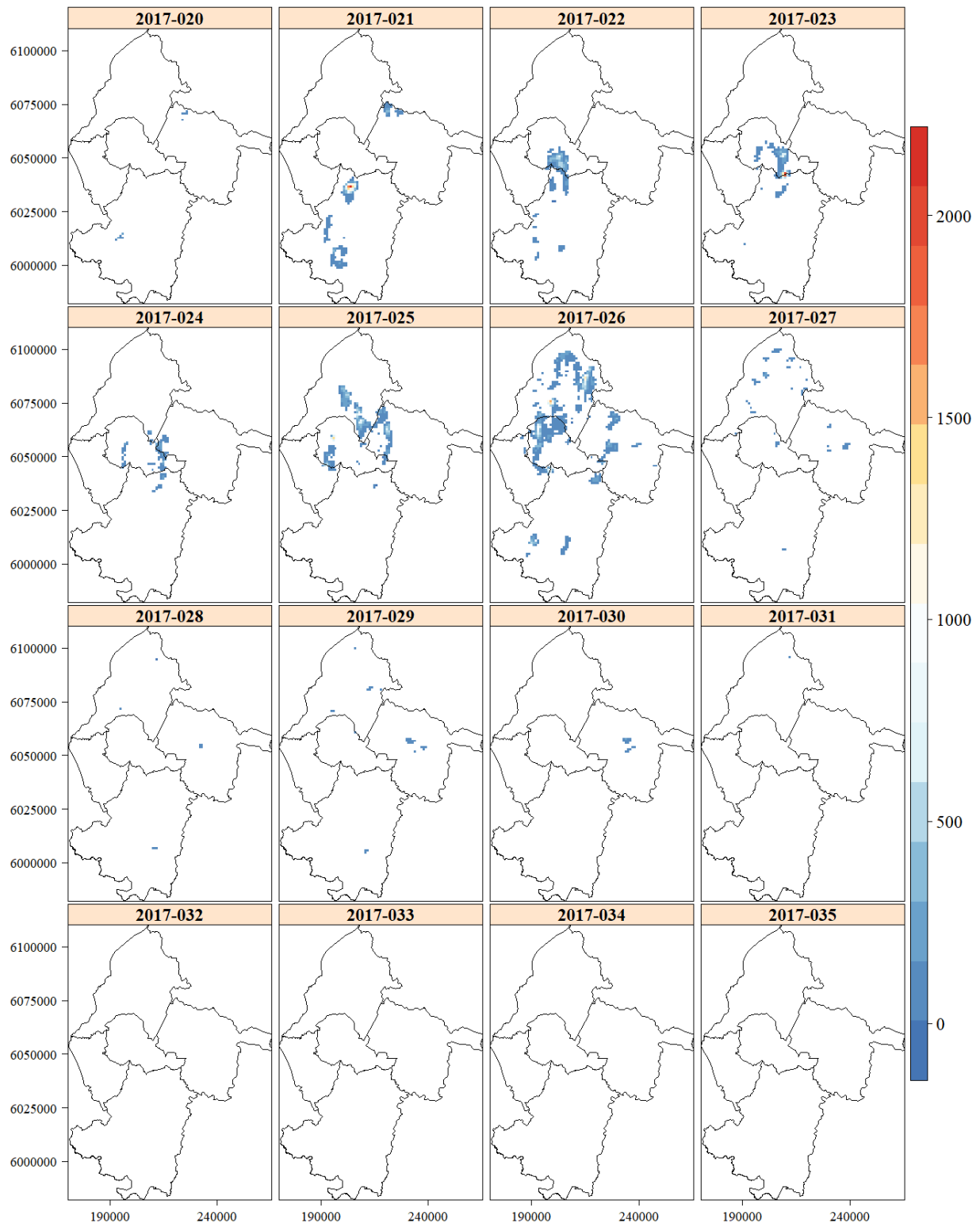


Figure 4.12: Maximum fire radiative power (FRP) obtained from VIIRS-SNPP VRP14A1 product between Julian days 020 – 035 (January 20 to February 4th, 2017) within the ROI. Each image corresponds to daily data. FRP units are in MW.

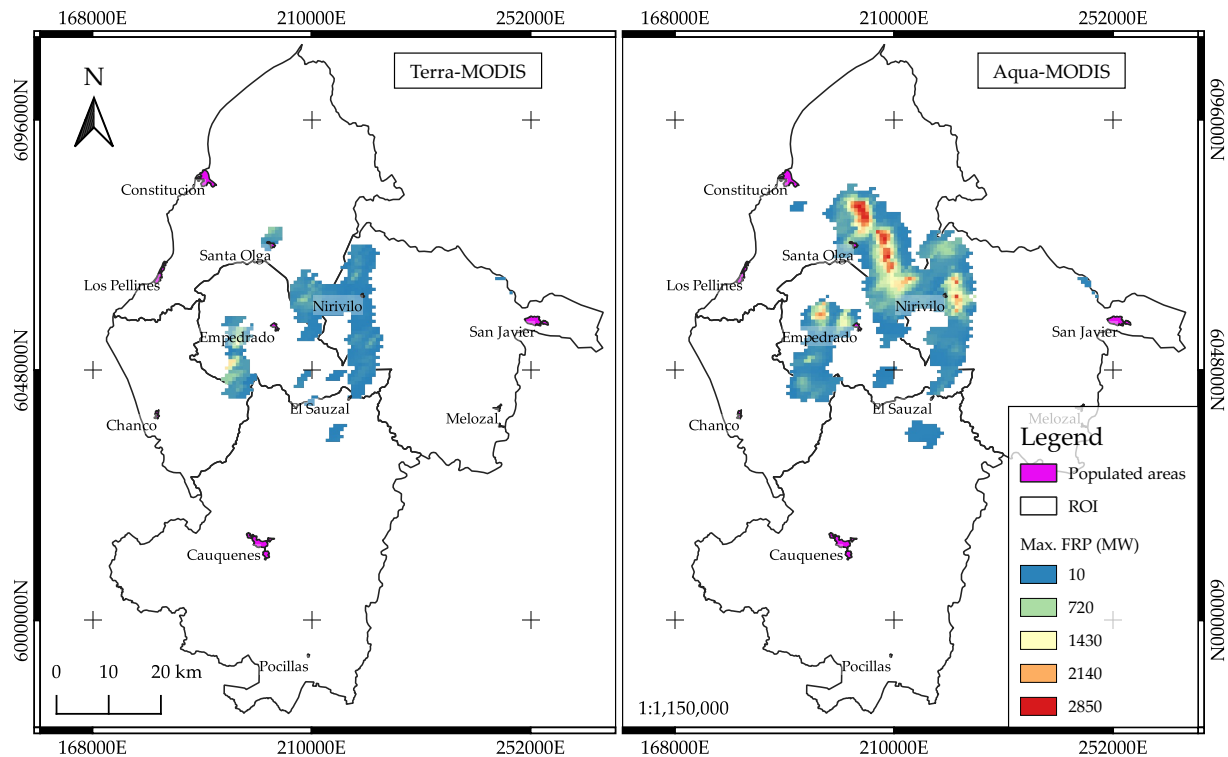


Figure 4.13: Maximum fire radiative power (FRP) obtained from M*D14A1 product for Terra-MODIS (left) and Aqua-MODIS (right) for January DOY 017–025 of 2017 within the ROI. Each image corresponds FRP values obtained through those dates. FRP units are in MW.

decimated by the wildfire. The maximum FRP values registered by Aqua-MODIS were located within a 7 km radius of Santa Olga, from the north to the east. Furthermore, if a 7 km buffer is studied from Santa Olga's location, the mean FRP value obtained is 827.3 MW of energy released by the fire and measured by Aqua-MODIS at the days when the village was destroyed.

Finally, it seemed interesting to compare these results with the fire severity derived from the dNBR analysis (see Section 4.3.1, cf. Figure 4.9). All the FRP values above 1,400 MW resulted in dNBR pixel values between 1.0 and 1.1 with dNBR calculated from both Landsat-8 and Sentinel-2 data, which means a high severity (Key & Benson, 2006). Nevertheless, it was expected that more pixels within those values were observed from VIIRS data, but as it was mentioned before, the smoke conditions within the ROI, and particularly in the Constitución municipality, might have had an impact in the retrieved data. Li et al. (2018) studied FRP from both VIIRS-SNPP and MODIS, and concluded that VIIRS fire characterization was similar to FRP derived by MODIS, yet for large boreal forest fires VIIRS FRP was approximately 47% smaller. Aqua-MODIS registered 57 pixels with FRP values above 2000 MW, which corresponded to around 2,700 ha of land releasing that amount of energy. In contrast, VIIRS-SNPP registered 3 pixels with FRP values above 2000 MW. Nevertheless, the difference is not straightforward due to the fire plume and different satellite overpass times.

4.3.4 Affected populated areas

The most affected populated areas were those within both the Empedrado and Constitución municipalities, located at the center and north of the ROI, respectively. Particularly, the most affected populated area during this wildfire was the village of “Santa Olga”, located at the south of Constitución and 3 km to the north of Empedrado (see Figure 4.14). According to the news, “January 25th of 2017 was an unforgettable day for the inhabitants of Santa Olga, the flames destroyed everything in their path, leaving four fatalities and consuming thousands of hectares” (Clarín, 2017; Cooperativa, 2017; Emol, 2021; ONEMI, 2017b).

Therefore, it is essential to analyze Santa Olga’s environment. Using Alos-Palsar DEM (CIREN, 2017b; Rosenqvist et al., 2007) at a 12.5 m pixel resolution, the slope was computed in R using the raster package. Both DEM and Slope are shown in Figure 4.15.

As it is possible to observe from the last figure, Santa Olga is located in the middle of the mountains, where the altitude varies from around 330 m (at Santa Olga’s location) to 580 m in less than 5 km to the south of the village. Moreover, it is possible to determine that Santa Olga is situated in the Wildland Urban Interface (WUI), since its surroundings are forests. Several studies have shown that there is a

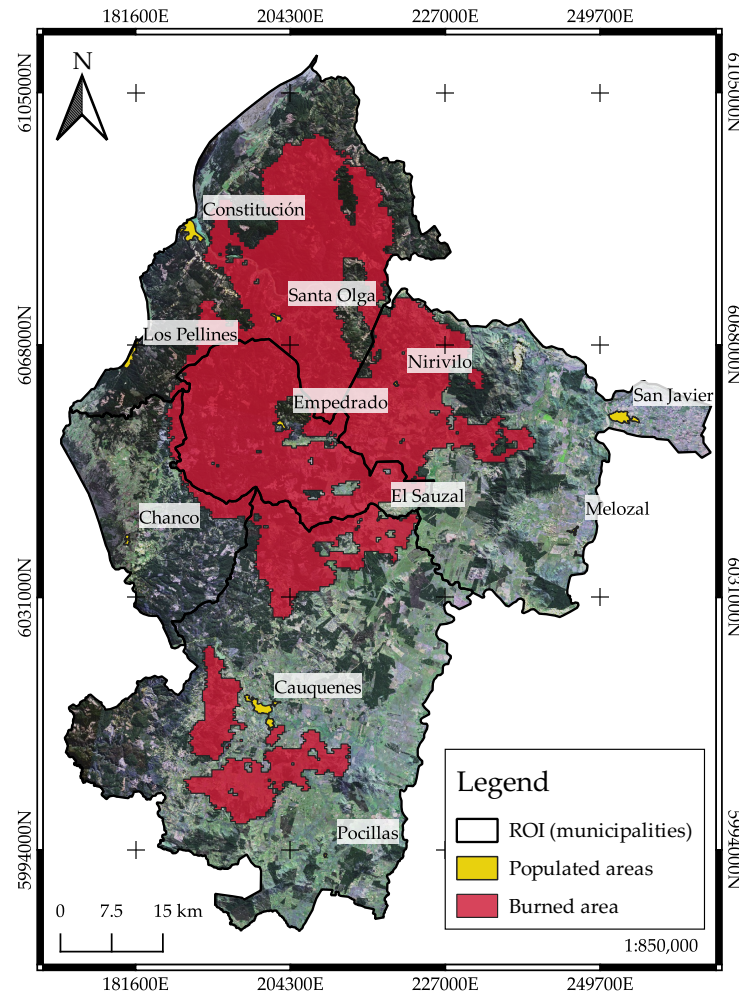


Figure 4.14: Affected populated areas within the ROI. Red pixels correspond to burned area calculated with MODIS MCD64A1 product.

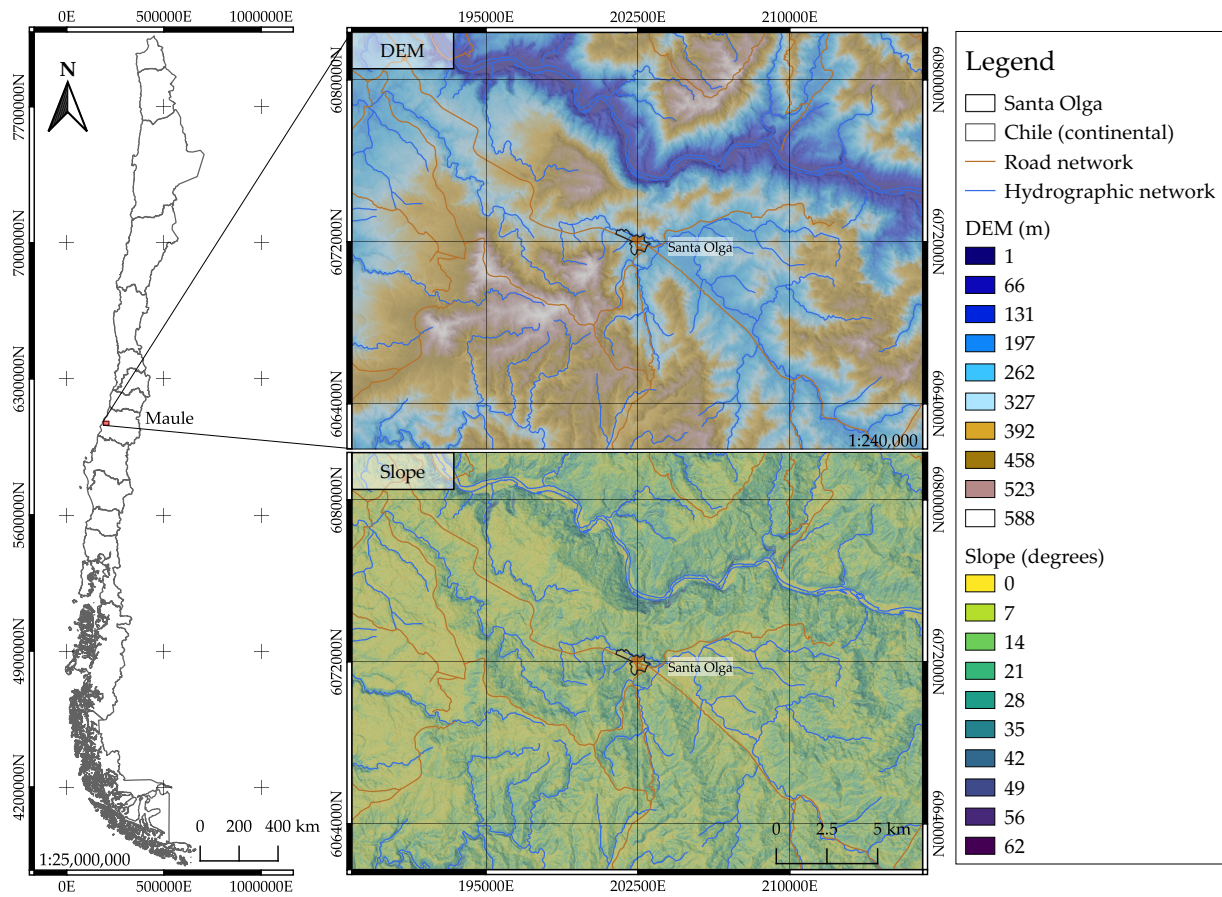


Figure 4.15: Santa Olga digital elevation model (DEM, *top*) and slope (*bottom*).

higher wildfire risk in terms of ignition probability in the WUI (Chas-Amil et al., 2013; Murray et al., 2013; Radeloff et al., 2001), however that is not the whole and only story for Santa Olga. These fires were man-made. Nevertheless, ignition is one important variable, yet fire propagation is another one, and the dependence of the last one is mainly due to weather conditions, fuel type and moisture content, and topography. At least from this perspective, Santa Olga’s location had an inherent wildfire risk. It was a month of records, highest temperatures (see Section 4.2.1), low precipitations and hence a persistent drought (see Section 4.2.2) and high vegetation density (see Section 4.1.1) for zones where there have been no fires in years, i.e. a recipe for disaster.

4.3.5 Affected species

Using both the CONAF Land Use Inventory (LUI) and the burned area mask obtained with MODIS MCD64A1 (see Section 4.3.1), it was possible to study the affected species within the ROI. The results are shown in Figure 4.16. Among these, a burned area of 129,700 ha was estimated for *Pinus radiata* (also known as *Pinus insignis*), followed by *Vachellia caven* (Roman Cassie) with 13,700 ha, *Nothofagus glauca* (also known as “Hualo”, which is endemic to Chile and a small bordering sector of Argentina) with 13,500 ha, *Lithraea caustica* (known as “Litre”, endemic to Chile) with 8,100 ha, and *Eucalyptus globulus* (known as southern blue gum) with 7,650 ha. The total burned area of all species during the fire was 182,810 hectares. Therefore, of all the affected species, only *Pinus radiata* corresponded to a 66.9% of the species burned in the “Las Máquinas” wildfire. In addition, according to the LUI, the total *Pinus radiata* surface in

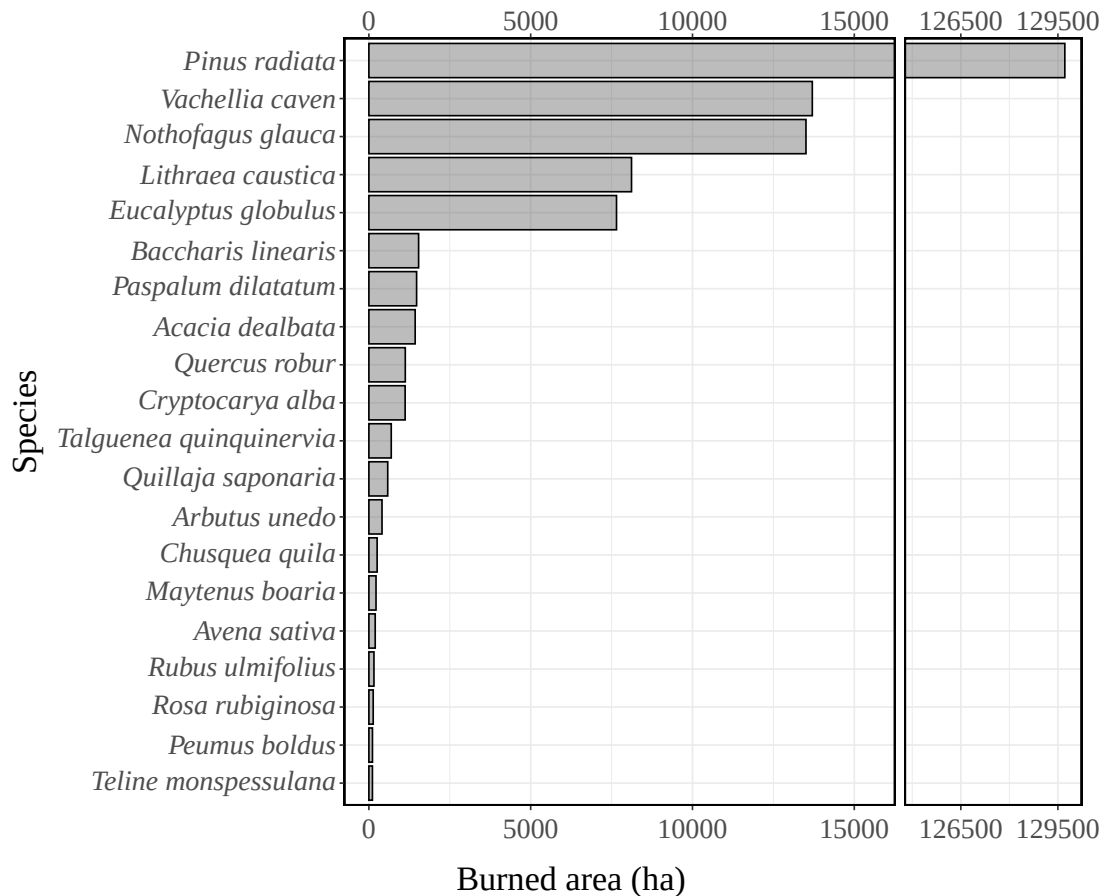


Figure 4.16: Burned area (ha) per species within the ROI with an affected area higher than 100 hectares.

the ROI before the event was 280,000 ha, of which 67% corresponded to adult plantations. Consequently, around 46% of the *Pinus radiata* surface within the ROI was lost in the wildfire.

Moreover, at the Empedrado municipality (center of the ROI) the “Los Ruiles” National Park was severely affected by the fire (see [Figure 3.1](#) –page 33– SNASPE zones). One of the species within the National Park was the *Nothofagus alesandrii*, which was declared a Natural Monument in 1995 (BCN, 1995) and classified as endangered since 2007 (Diario Oficial de la República de Chile, 2007). According to CONAF (2017b), over 90% of the national park was destroyed by the fire. In addition, the total burned area for this species was 34 hectares.

4.3.5.1 Landcover type

Using the MODIS MCD12Q1 yearly landcover type product, it was possible to study the evolution of the IGBP (International Geosphere-Biosphere Programme) values from 2001 to 2020. The results are shown in [Figure 4.17](#). Note that there are no “3” and “15” IGBP categories within the ROI, which correspond to “deciduous needleleaf forests” and “snow and ice”, respectively (see [Appendix C](#), cf. [Table C.1](#)). Notice that the main needleleaf species within the ROI before the event was *Pinus radiata* ($\approx 280,000$ ha), which is classified as *perennial* vegetation.

Additionally, it is interesting to observe that the IGBP categories that decrease after the wildfire are mainly “1”, “2”, “7” and “10”, which are “evergreen needleleaf forests”, “evergreen broadleaf forests”,

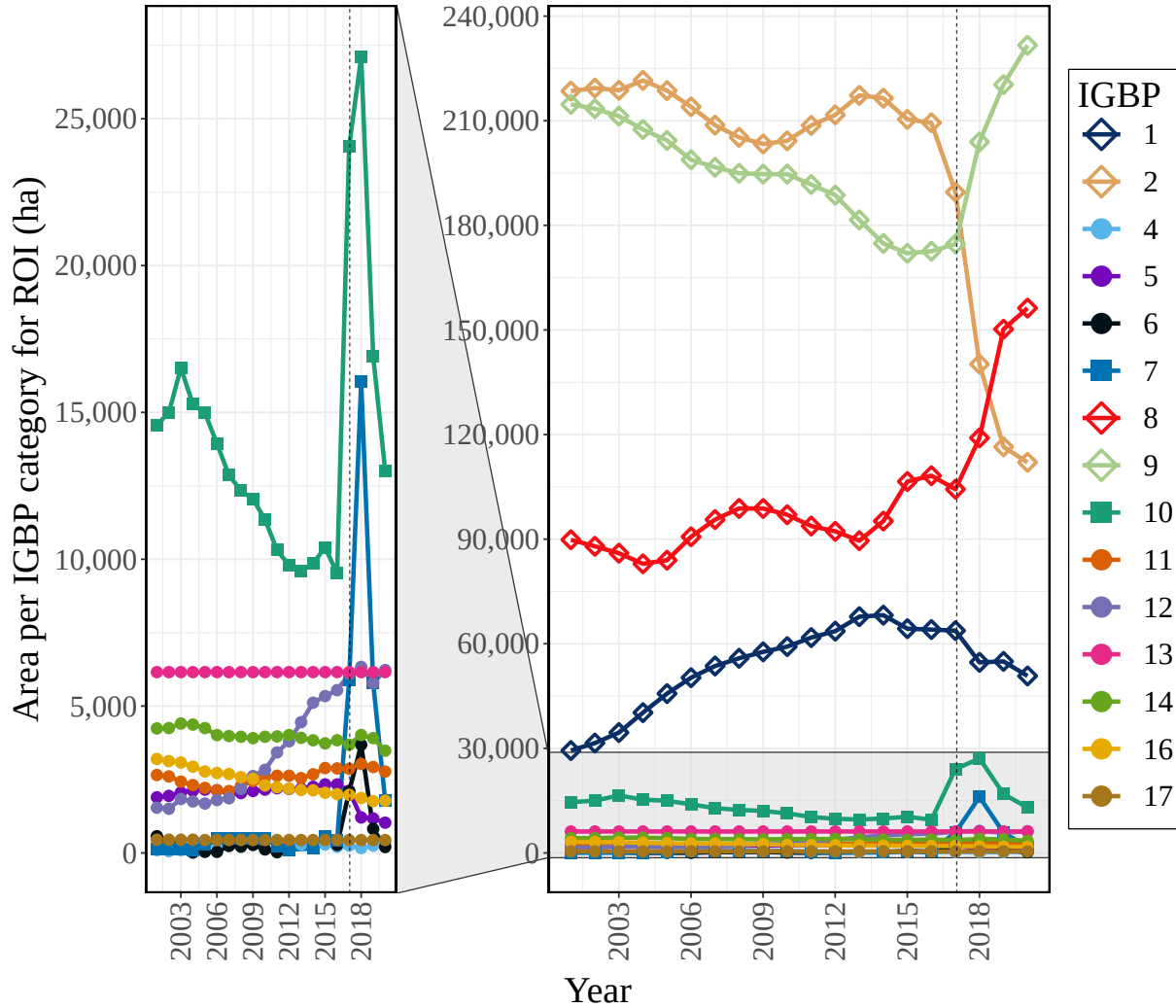


Figure 4.17: International Geosphere-Biosphere Programme (IGBP) evolution using yearly MODIS MCD12Q1 product (from 2001 to 2020). The values correspond to the frequency of each classification within the ROI (the five municipalities) multiplied by the product spatial resolution. The vertical dashed line correspond to the “Las Máquinas” wildfire event.

“open shrublands” and “grasslands”, respectively. Nonetheless, “1” and “2” categories started to decline before the event, while, at around the same period of time, categories such as “8” (“woody savannas”) and “9” (“savannas”) started to increase. Furthermore, both “7” and “9” IGBP categories increased the year after the event, but two years later its value decreased considerably. However, since the decline was not observed in the year after the event, it is not straightforward to relate or attribute its decrease to the event. What it is actually plausible for these categories is that its growth (observed at the wildfire year data) was significant with respect to the year prior to the event, and hence it is possible that the IGBP algorithm within the MODIS product categorized most burned areas as open shrublands and grasslands, or that forests become replaced by grasslands.

Furthermore, a decrease in the IGBP categories means that there is an increase in other ones. Hence, IGBP categories of 1, 2, 8 and 9 were studied in greater depth. Pre- and post-fire IGBP values mentioned before can be geographically observed in Figure 4.18. From the previous figure, it is possible to observe

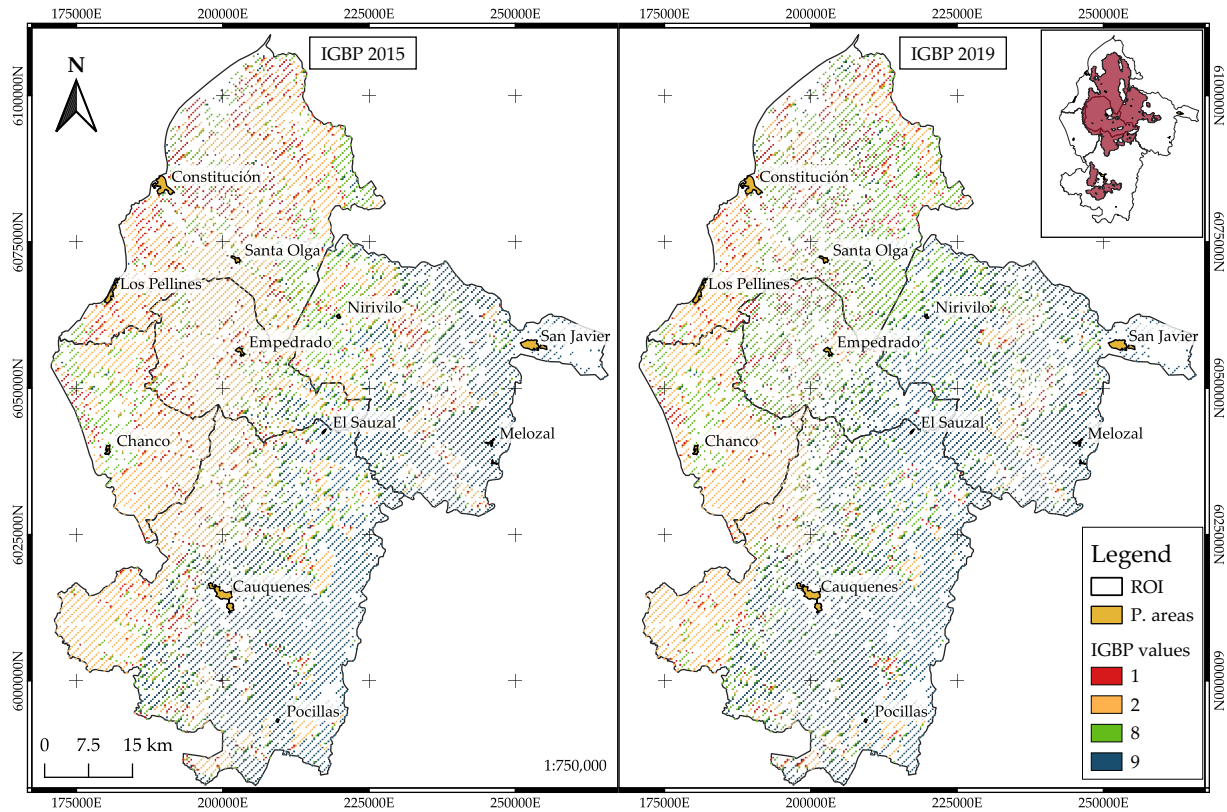


Figure 4.18: International Geosphere-Biosphere Programme (IGBP) within the ROI for years 2015 (left) and 2019 (right), and only for IGBP values of 1, 2, 8 and 9. The small map in the top-right corner is the ROI and the burned area for reference (from MODIS MCD64A1 – see [Section 4.3.1](#)). The map coordinates system is WGS84 UTM 19-South.

that the zones where the fire took place changed mainly from IGBP = 2 (evergreen broadleaf forests, yellow cells) to IGBP = 8 (woody savannas, green cells), specially within the Empedrado municipality (center-zone of the ROI). For IGBP = 1 the pre- and post-fire differences are not apparent, since its pixels are considerably more disseminated throughout the ROI. In contrast, for IGBP = 9 (savannas, blue cells), it is evident that most “2” and “8” IGBP categories turned to 9 post-fire. There is a visible separation between evergreen broadleaf forests and savannas prior the event. Moreover, after the wildfire, the savannas category gained more terrain within its previous concentrated areas (from ~200000E to the east), while woody savannas increased its area mainly in the zones where the wildfire took place.

[Figure 4.19](#) shows the land-use type for each of the last-mentioned IGBP categories within the ROI. The IGBP values used were those of MODIS MCD12Q1 of year 2015. The data for each land type was acquired from the Chilean Land Use Inventory (LUI) ([CONAF, 2016](#)), where the “land-use type” variable was extracted from the vector data within the ROI. As a result, seven vector files (or shapefiles) were obtained, where each one corresponds to a specific “land-use type” within the ROI (forests, grasslands and shrublands, agricultural land, water area, among others – see the vertical axis of [Figure 4.19](#)). Using these files, all the data of the 2015 IGBP ROI-image was extracted within each land-use type. The results in [Figure 4.19](#) evidence the following.

- For IGBP = 1 (evergreen needleleaf forests): the most frequent value corresponds to forests, nevertheless its surface area with respect to the total forests area within the ROI is around 3.5%.

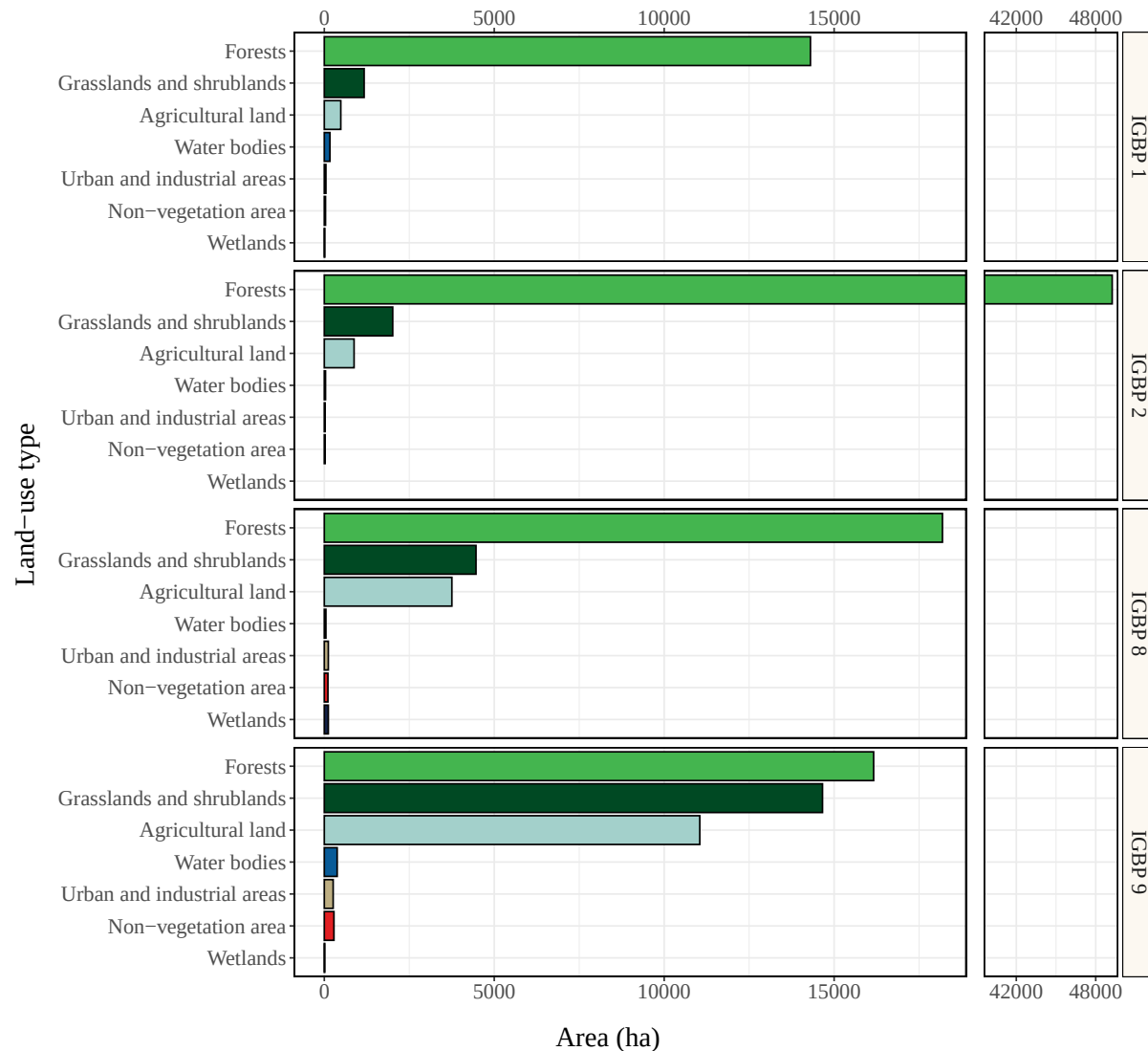


Figure 4.19: Pre-fire Land Use Inventory (LUI) – “land-use type” surface area for IGBP categories (from year 2015): 1 (evergreen needleleaf forests), 2 (evergreen broadleaf forests), 8 (woody savannas) and 9 (savannas), within the ROI.

- b) For IGBP = 2 (evergreen broadleaf forests): as in the case for an IGBP value of “1”, the forests are the most frequent land-use type. However, the total forest surface area with respect to the total forests area within the ROI is around 12.2%. There is a significant increase in the amount of grasslands and shrublands (~71% more) as well as agricultural land (~80% more) with respect to the IGBP = 1 results.
- c) For IGBP = 8 (woody savannas): the most frequent value for the woody savannas are forests, even more than for evergreen needleleaf forests (IGBP = 1). However, there is a higher amount of grasslands and shrublands as well as agricultural lands.
- d) For IGBP = 9 (savannas): there is still a high amount of forests, nevertheless it is rather clear that this category includes more surface-area corresponding to grasslands and shrublands as well as agricultural lands.

These results indicate that the forest category should be studied in depth to understand the main differences among the IGBP 1, 2, 8 and 9 classifications. This is analyzed in [Appendix E](#), and the conclusions are the following. IGBP 1 is mainly composed of plantations and native forests, categories that correspond to 72.5% and 11.9%, respectively, of the total surface area of evergreen needleleaf forests (IGBP 1) within the ROI. Similar results were found for IGBP 2. And hence, another study was carried out to examine the species within each plantations and native forests category. The findings suggest that the species which hold most of the ROI's surface area are *Pinus radiata*, *Vachellia caven* and *Eucalyptus globulus*. The first and last ones are mainly in the plantation “detailed land-use type” category, while the second can be found in several categories (e.g. in shrublands, grasslands, native forest, among others).

4.3.6 Air quality

The air quality during the event was analyzed from the smoke, aerosol optical depth, and carbon emissions perspective. For the latter, VIIRS-SNPP products such as the Deep Blue Aerosol were used.

4.3.6.1 Smoke

Using VIIRS-SNPP Deep Blue Aerosol (DBA) product, the smoke generation during the wildfire was studied. For example, in [Figure 4.20](#) an RGB image obtained with VIIRS-SNPP VNP09GA product (left) of January DOY 026 is compared to the VIIRS-SNPP Deep Blue Aerosol in the same day. Since smoke and other aerosols derived from wildfires cover a larger area, the ROI for this analysis was extended to the whole Maule region (delimited in red in [Figure 4.20](#)). The results exhibit a vast amount of pyrocumulonimbus clouds, as well as high altitude smoke and smoke. The spatial resolution of the DBA product is around 6 km and the results correspond to a bilinear interpolation applied to the gridded data.

A raster mosaic composed of three DBA images was built with the VIIRS-SNPP DBA “Aerosol Land and Ocean type” product to study the aerosol types for January DOY 026 at a 1:35,000,000 scale to

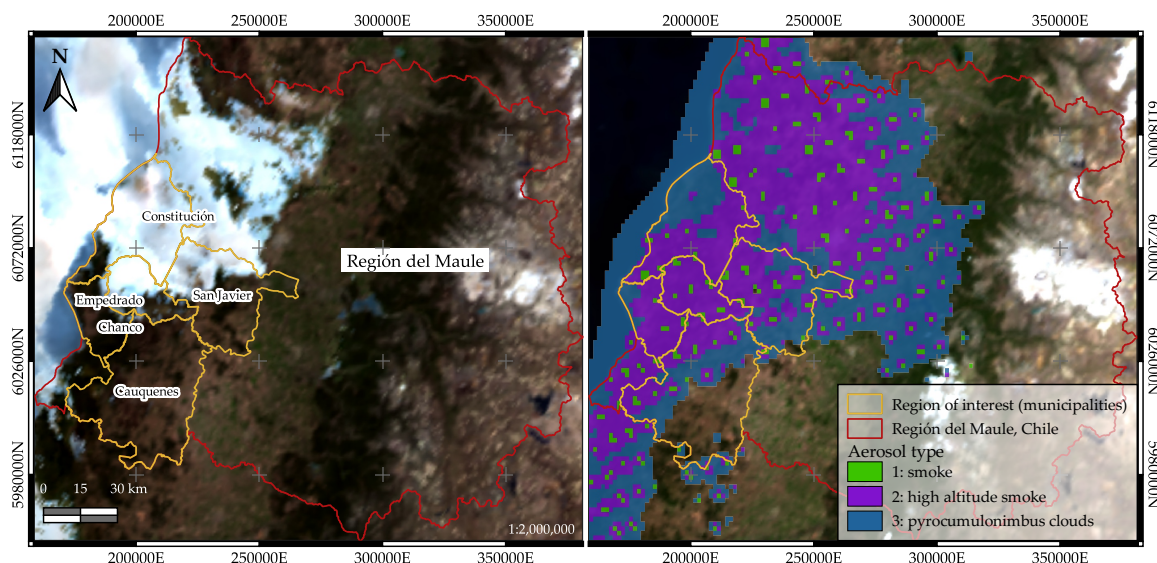


Figure 4.20: Left image corresponds to VIIRS-SNPP VNP09GA RGB composite on January 26, 2017, while right image corresponds to VIIRS-SNPP Deep Blue Aerosol - “Aerosol Type Land” product for the same day. Coordinate system for both images is WGS84 UTM-19 South. Differences in the smoke sections might be because of the acquisition times. Left image acquisition time was 14:55, while right image was taken at 16:30 (local time).

visualize the effect of the fire in continental Chile. The results can be observed in Figure 4.21. Most of the aerosol flew to the Pacific Ocean, and the majority of it was categorized as fine dominated by the DBA product within the ocean aerosol category. Note that the fire plume in Figure 4.21 came from several simultaneous fires in Central Chile, not only from the “Las Máquinas” wildfire.

The visual evolution of the three aerosol types using the “Aerosol Type Land” layer of the DBA product can be observed in Figure 4.22. As it is possible to observe, there was a vast amount of aerosols composed of pyrocumulonimbus, high altitude smoke and smoke after January DOY 025, where the two main aerosol categories found for the event were pyrocumulonimbus and high altitude smoke. Furthermore, the daily projected area of these aerosols was also studied, and the results are shown in Figure 4.23. From the last figure, it is possible to observe an increase in both high altitude smoke and pyrocumulonimbus once the event started, and its peak was between January 28 and 29, right after the two most severe days of the wildfire (see Section 4.3.1).

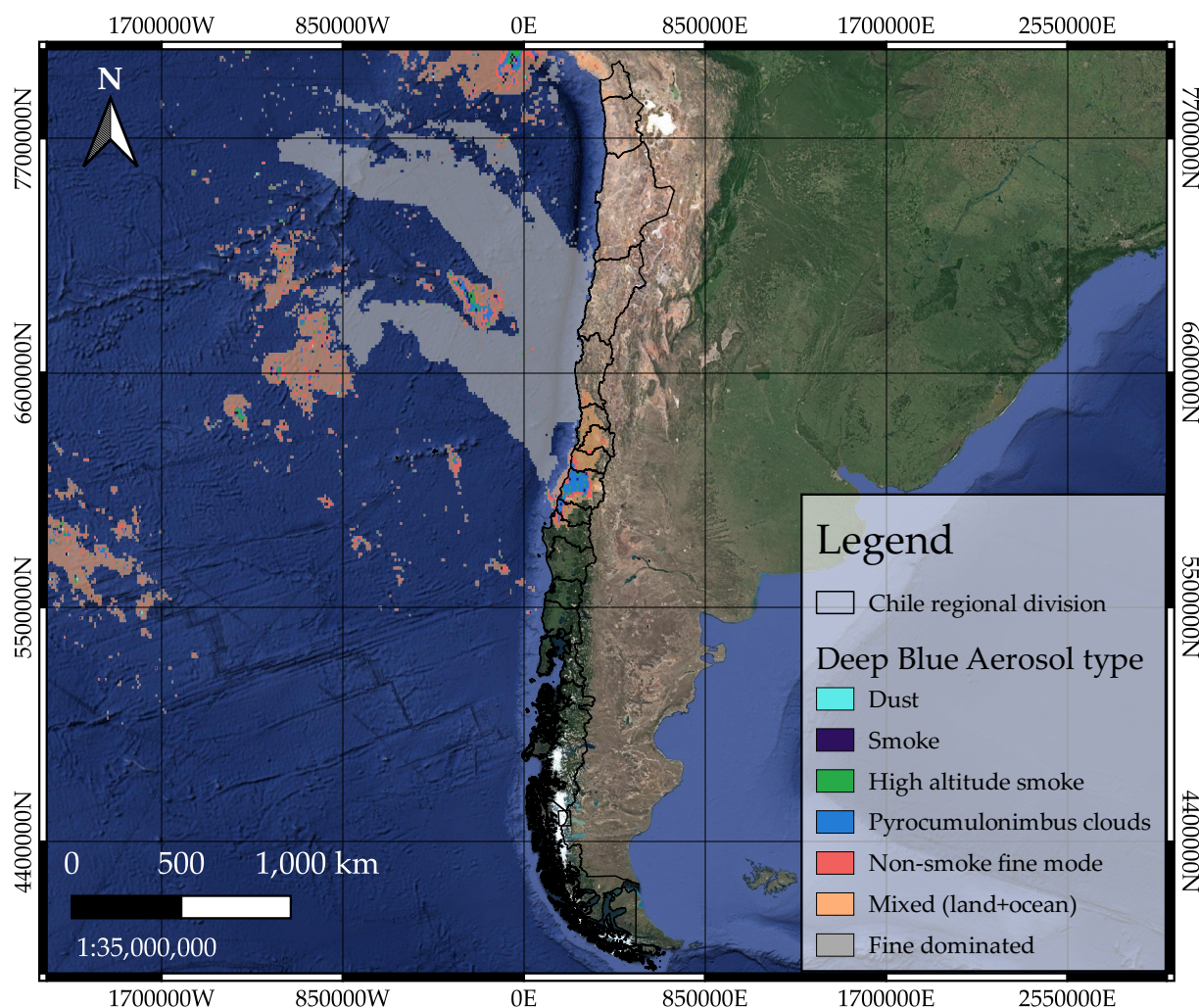


Figure 4.21: VIIRS-SNPP Deep Blue Aerosol product (“Aerosol Land and Ocean type” variable) for January 26th at continental Chile scale. The map coordinate system is WGS84 UTM-19 South. Background corresponds to Google Satellite images in QGIS (QGIS Development Team, 2009).

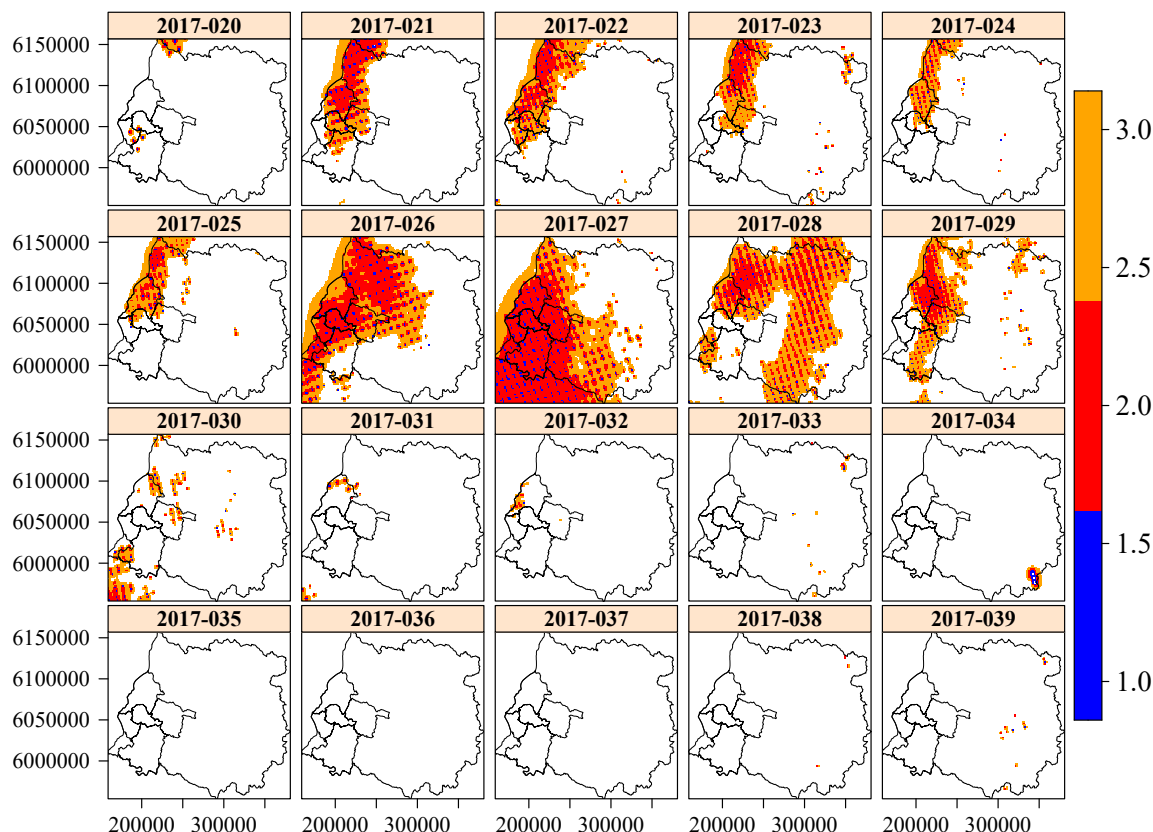


Figure 4.22: Smoke (pixel value of 1: blue), high altitude smoke (pixel value of 2: red), and pyrocumulonimbus clouds (pixel value of 3: orange) for the Región del Maule in the time-frame of the “Las Máquinas” wildfire. These images were computed from VIIRS-SNPP DBA 6-km product. The map coordinate system is WGS84 UTM 19-South.

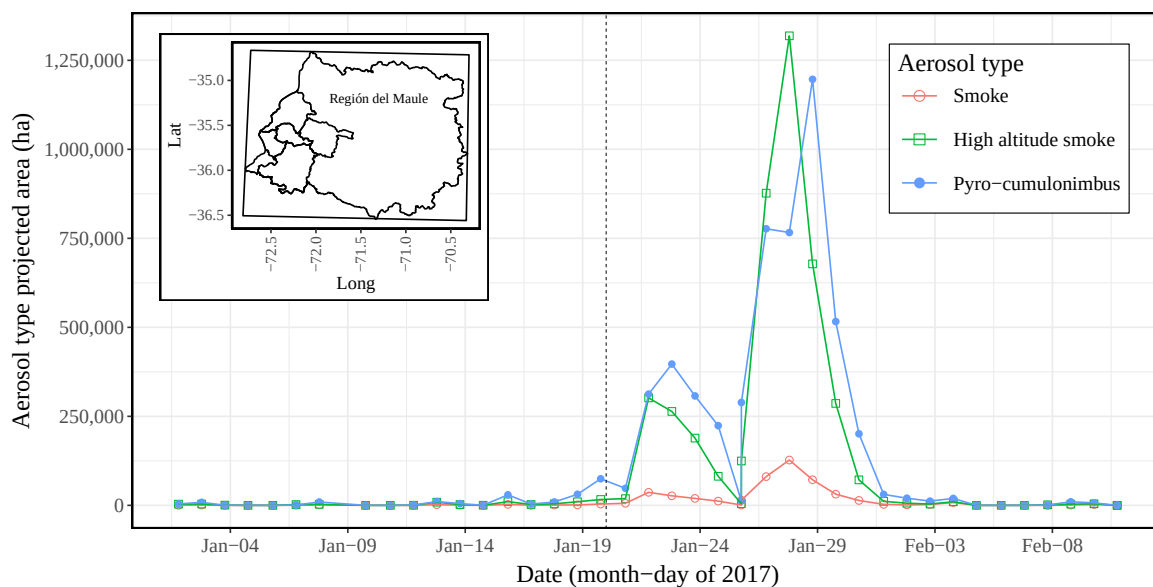


Figure 4.23: Aerosol type projected area evolution during the event. The study zone corresponds to the Maule region, Chile, whose extent can be seen in the map within the plot. Map is in WGS84 Geographic coordinate system. The vertical dashed line corresponds to the starting date of the wildfire.

4.3.6.2 Aerosol optical depth

Using another layer of the VIIRS-SNPP Deep Blue Aerosol product, the aerosol optical depth (AOD) at a reference wavelength of 550 nm was obtained and analyzed at the same extent of the smoke generation data, i.e. at the Maule region. The evolution of the AOD during the event can be observed in Figure 4.24. For an observer on the ground, an AOD of less than 0.1 is “clean”, characteristic of clear blue sky, bright sun and maximum visibility. As AOD increases to 0.5, 1.0, and greater than 3.0, aerosols become so dense that the Sun is obscured. The mean values (represented by a red diamond) are close to zero before the event (which is marked with a vertical dashed line), however three days prior to the event some higher values were detected by the VIIRS sensor, which could be due to the other fires that were taking place in the Biobío and O’Higgins regions.

It is clear that after the event, and within the most severe days (January 25 and 26) the AOD increased considerably, with mean AOD around $AOD \approx 1.0$. Moreover, the upper limit of the boxplots for those days, which correspond to the largest value within 1.5 times the interquartile range above 75th percentile, registered AOD values around 3.0, and even statistically atypical maximum points close to 5.0.

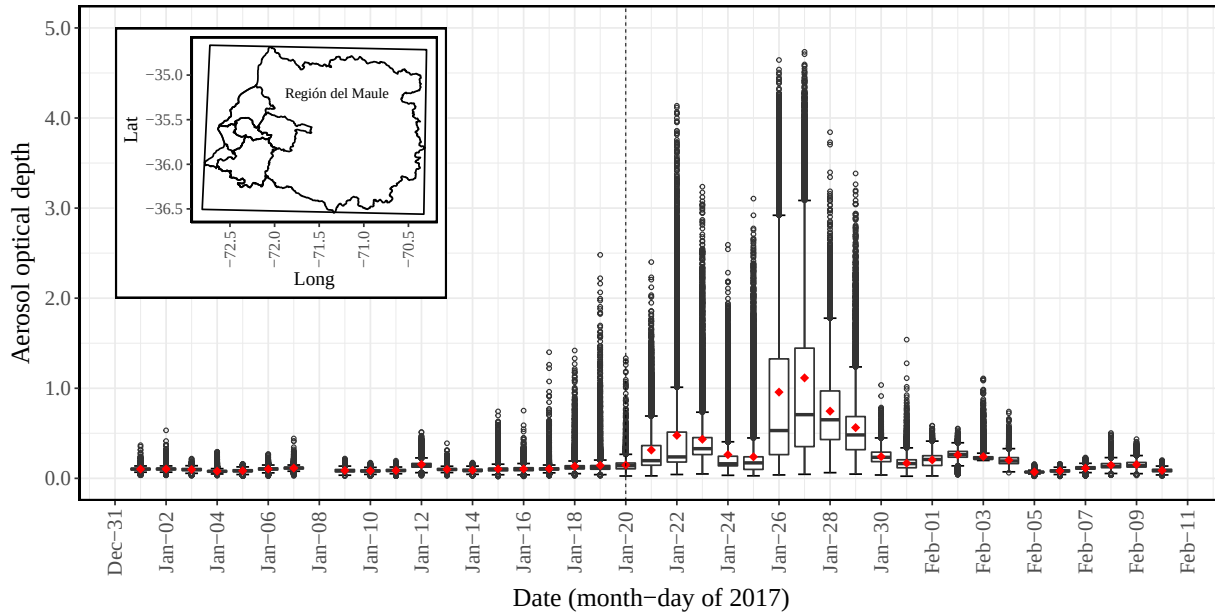


Figure 4.24: Aerosol optical thickness (or depth, AOD) evolution during the event. The study zone correspond to the Maule region, Chile, whose extent can be seen in the map within the plot. The total surface of the extent of the region of interest is 4,552,520 hectares. The five regions shown inside the Maule region map correspond to the five municipalities (or ROI) of this study. Map is in WGS84 Geographic Coordinate System. The vertical dashed-line correspond to the starting date of the wildfire.

4.3.6.3 Carbon emissions

Carbon emissions were obtained from the Global Fire Emissions Database (GFED) from gridded data at a $0.25^\circ \times 0.25^\circ$ resolution (≈ 28 km). The mean carbon emissions and its standard deviation for each year on January can be seen in Figure 4.25. In addition, the figure also displays the maximum value found within each monthly dataset (right axis). Considering the data from 2010 to 2016, the mean carbon emission was 5.27 ± 22.39 g·C·m $^{-2}$, while the mean value for January 2017 was 197.49 ± 290.90 g·C·m $^{-2}$, i.e. 3,750% higher. The maximum carbon emission value found in January 2017 corresponded to 1,270 g·C·m $^{-2}$.

Furthermore, if the pixels within the Maule region are all summed up and are multiplied by the pixel resolution, the mass of carbon is obtained. As a result, a mean of 2.5×10^5 t·C was found for January months between the years 2010 and 2016, while the amount of carbon found in January 2017 was 9.4×10^6 t·C.

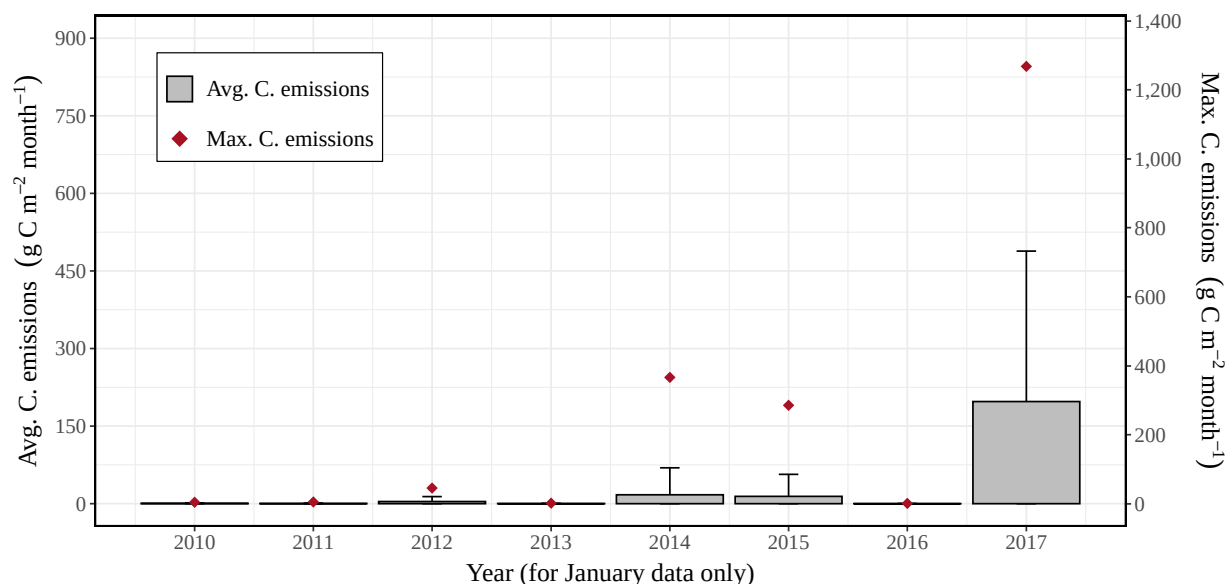


Figure 4.25: Average carbon emissions (left Y-axis, represented by bars) and maximum carbon emissions (right Y-axis, represented by red diamonds) for January month between years 2010 and 2017 based on the Global Fire Emissions Database (GFED). This results are at the Maule region scale. The error bars represent the positive standard deviation.

4.3.7 Canadian fire weather index

4.3.7.1 MODIS regression models for NSAT

The first step in building the Canadian FWI consists in calculating the NSAT using regression models. In this section this will be done for both Aqua-MODIS (MYD) and Terra-MODIS (MOD) files.

4.3.7.1.1 MODIS regression models training

Regression models were built for January data (DOY 001 to 031) from 2010 to 2016, and thus the total sample corresponded to $N = 217$. For each day, there is a total of 8 control points or weather stations, which can be seen in [Figure 3.5](#) (page 44). Therefore, the total data if there are no missing values for any variable is $N \times 8 = 1,736 = n$. However, this varies from analysis to analysis because of the methodology applied, i.e. for each regression the NDVI product varied, and thus there are missing values that arise due to different NDVI products used. For example, the regression model built with the NDVI from MOD09 product, the amount of samples was 1,291. On the other hand, the regression using NDVI from VIIRS-SNPP VNP13A1 product, the samples decreased to 991.

The regression results for Aqua-MODIS can be seen in [Figure 4.26](#). Each plot represents a regression model of the NSAT predictions using the training dataset (ordinates axis). For the linear regression models, the best result was the one using the MODIS MOD13A1 NDVI product ([Figure 4.26c](#)), which achieved the highest Pearson's correlation coefficient ($r = 0.709$) and the lowest root mean square error (RMSE = 2.883°C). This regression model was applied to $n = 1,291$ samples (since there are some variables with missing values for a certain day, mainly from the land surface temperature and precipitable water vapor products). It is important to mention that the regression models for Aqua-MODIS were studied using both MOD05 (Terra) and MYD05 (Aqua) products. The best results were achieved using the Aqua-MODIS water vapor product, and hence the PW derived from MYD05 was used to build the regression models for Aqua data. The average acquisition time of each product can be observed in [Table 4.3](#) (NDVI is not in the table since it was either computed by surface reflectance –MOD09GA– or 16-day products such as MOD13A1 or VNP13A1, which is indicated within each plot in the ordinates axis).

The regression models of [Figure 4.26d](#), [4.26e](#), and [4.26f](#) were developed using Machine Learning (ML) algorithms. Decision trees (DT, [Figure 4.26d](#)) is clearly showing results like a classification algorithm rather than a regression, which corresponds to one of its limitations. On the other hand, the support vector machine regression algorithm (SVR) exhibit a higher Pearson's correlation coefficient and lower RMSE compared to all multiple linear regression models. However, random forests results are the best ones. The findings suggest that RF regressions using T_s , PW and NDVI can statistically explain NSAT with a high Pearson's correlation coefficient ($r = 0.958$) and low root mean square error (RMSE = 1.280°C) within the ROI. These results were the same found for the regression models applied to Terra-MODIS in

Table 4.3: Satellite products average local time of data acquisition for the regression models (training dataset).

Product	Satellite	Variable name	Approx. Local time
MODIS MYD11A1	Aqua	Land surface temperature	14:00
MODIS MOD11A1	Terra	Land surface temperature	10:00
MODIS MYD05	Aqua	Precipitable water vapor for Aqua	13:20
MODIS MOD05	Terra	Precipitable water vapor for Terra	11:30

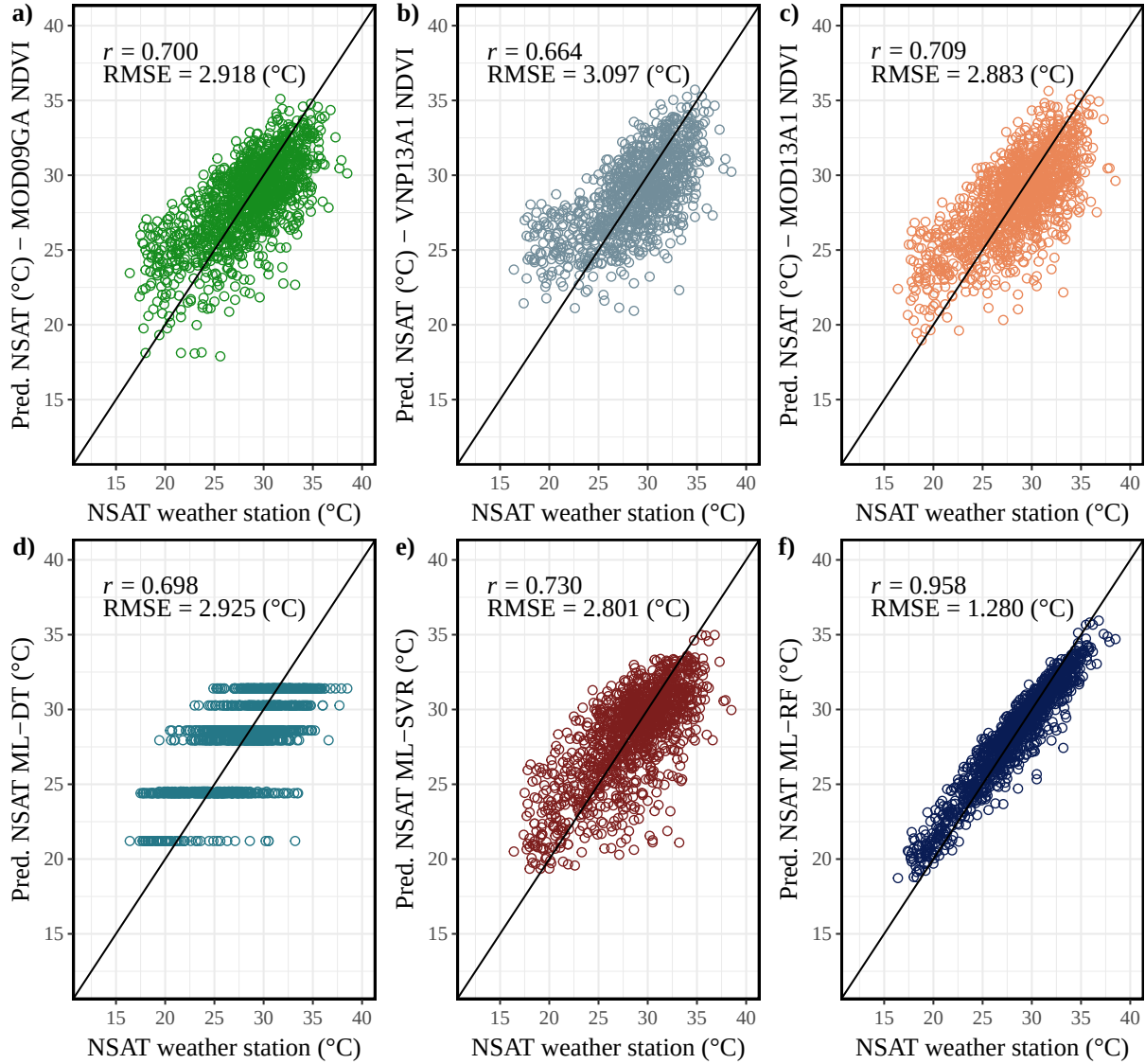


Figure 4.26: NSAT Aqua-MODIS regression models. Each ordinate axis represents the predicted NSAT applying a) Multiple linear regression using daily MODIS MOD09GA NDVI data, b) multiple linear regression using VIIRS VNP21A1 NDVI data, c) multiple linear regression using MODIS MOD13A1 NDVI data, d) machine learning (ML) decision trees (DT) regression, e) machine learning (ML) support vector regression (SVR), and f) machine learning (ML) random forests (RF) regression. For all machine learning regressions, the NDVI used was MODIS MOD13A1 product. For each plot, the diagonal black line represents $y = x$, r is the Pearson's correlation coefficient, and RMSE is the root mean square error.

Figure 4.27, where the best results were the machine learning random forests regression. Nevertheless, it is important to mention that for the Terra-MODIS data the T_s was lower (since its acquisition time is around 10:00 AM), and a greater data dispersion was observed. Moreover, a lower Pearson's correlation coefficient and higher RMSE values were found in contrast to Aqua-MODIS results.

For each random forest regression model (for both Aqua/Terra-MODIS), an “Importance matrix” is obtained. This matrix analyzes the percentage of the increase in the MSE (mean squared error), “%IncMSE”

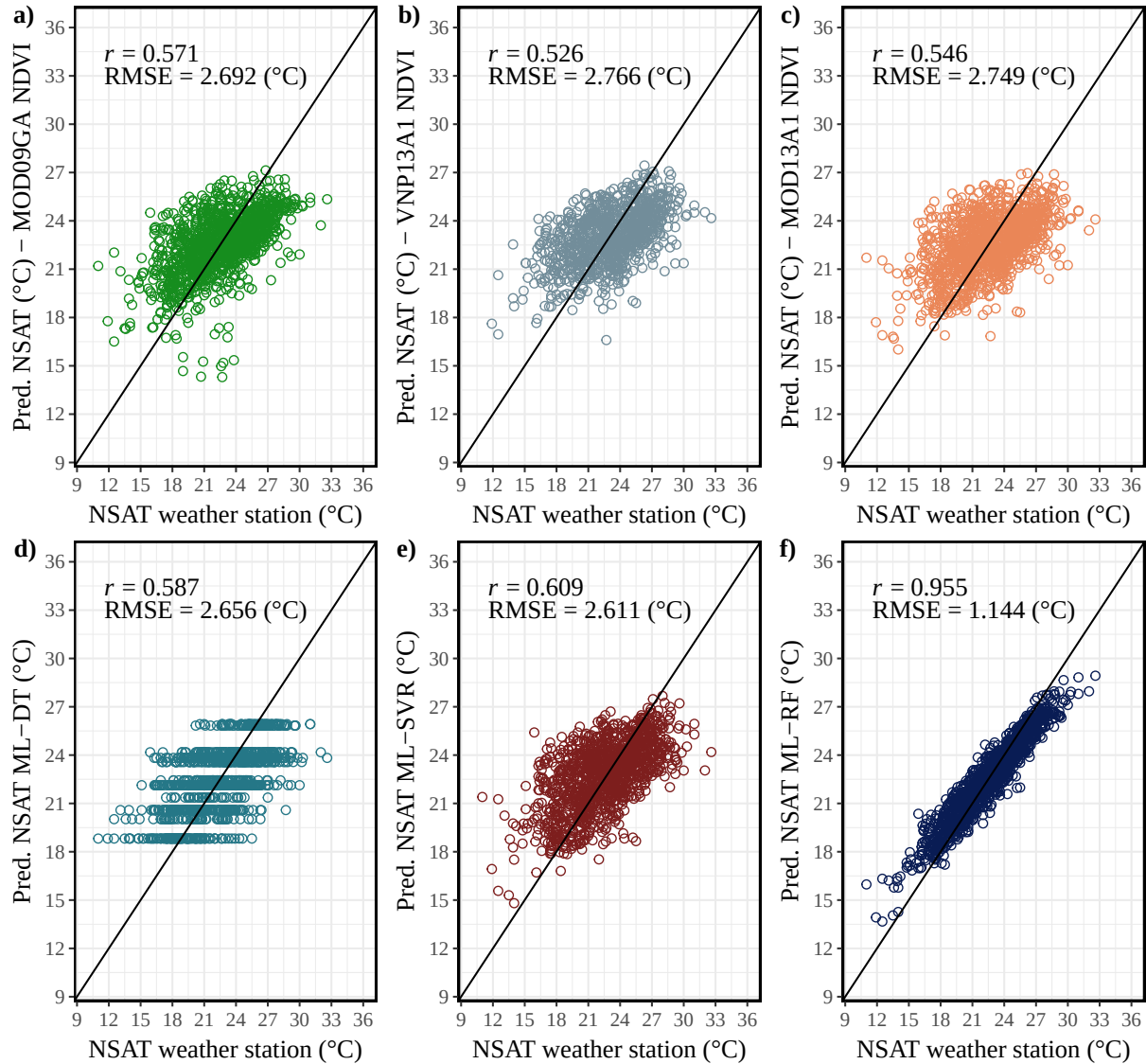


Figure 4.27: NSAT Terra-MODIS regression models. Each ordinate axis represents the predicted NSAT applying a) multiple linear regression using daily MODIS MOD09GA NDVI data, b) multiple linear regression using VIIRS VNP21A1 NDVI data, c) multiple linear regression using MODIS MOD13A1 NDVI data, d) machine learning (ML) decision trees (DT) regression, e) machine learning (ML) support vector regression (SVR), and f) machine learning (ML) random forests (RF) regression. For all machine learning regressions, the NDVI used was MODIS MOD13A1 product. For each plot, the diagonal black line represents $y = x$, r is the Pearson's correlation coefficient, and RMSE is the root mean square error.

and the increase in the node purity “IncNodePurity”, and the results can be seen in Figure 4.28. The first one is the most robust and informative measure, which corresponds to the increase in the MSE of the predictions without the variable, and therefore it is related to the mean decrease in accuracy of the model performance, i.e. the bigger the %IncMSE, the better the model will perform with *that* variable, since if it is not in the model, there will be *that* increase in the MSE of the model. On the other hand, the IncNodePurity is related to the mean decrease in the Gini index, and therefore it measures how pure the nodes are at the end of the tree *without* each variable, and hence a higher IncNodePurity variables

imply a higher mean decrease in the Gini index, indicating a variable that makes the model perform more accurately. The importance matrix results for the random forest regression models indicate that, for both cases, the most important variable is the land surface temperature (LST, or T_s), followed by the NDVI (which in this case is the 16-day MOD13A1 product) and finally the precipitable water content (or vapor), PWV. Nevertheless, LST has a grater relevance for the Aqua regression in terms of the percentage increase in the MSE, meaning that LST is a more important variable for Aqua’s random forest regression results than for Terra’s. This difference in the percentage increase in the MSE is around 10% between the two regression models.

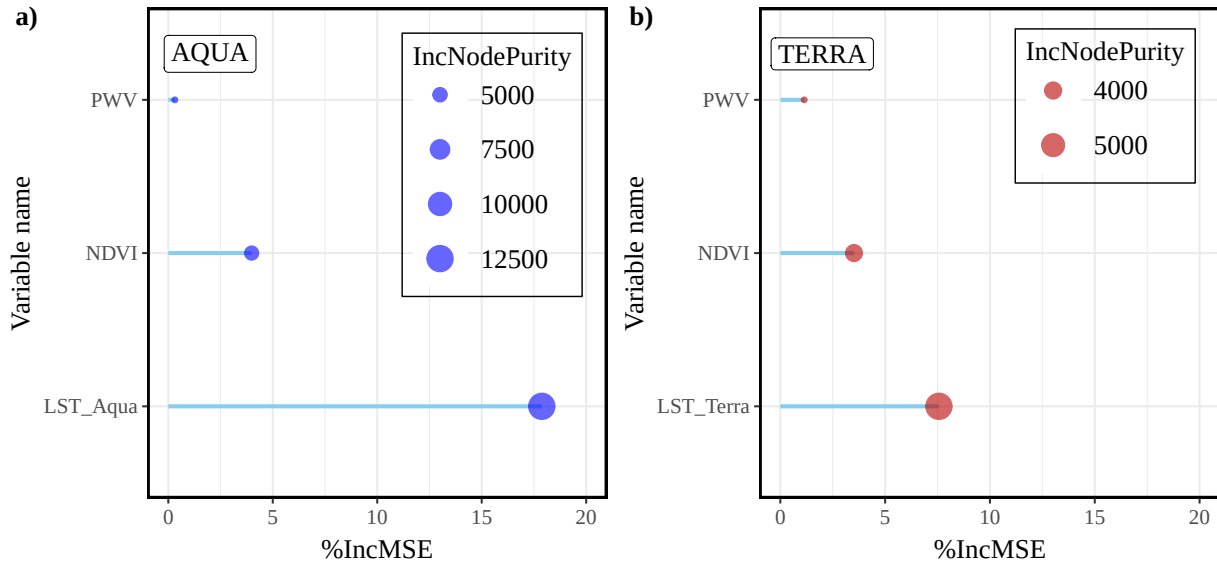


Figure 4.28: Importance matrix results for the random forests regression algorithms performed for both a) Aqua and b) Terra models. LST stands for “land surface temperature (T_s), and PWV for precipitable water vapor (or PW).

4.3.7.1.2 MODIS regression models validation

The validation of the efficacy of the models was tested for January 2017 (from DOY 001 to 031) daily data, which corresponds to the testing dataset. Since the best-performing linear regression (LR) model in the training section was the one where the MODIS MOD13A1 NDVI product was used and the best-performing machine learning regression model was the random forests (RF) model, these two were utilized to predict the near-surface air temperature for the testing dataset. Once the model was applied to the dataset, the pixel values at the weather station locations were extracted and compared to the measured weather station NSAT. The results are shown in Figure 4.29, where the model-predicted NSAT corresponds to the values in the ordinates axis.

The results were statistically better for Aqua than for Terra models. Overall, the best-performing model was the machine learning random forests regression applied to the Aqua data (Figure 4.29b), with the highest Pearson’s correlation coefficient and the second lowest RMSE. It is interesting to note that even though the Pearson’s correlation coefficient was lower for Terra-MODIS data, the RMSE in the multiple linear regression model (Figure 4.29c) was lower than the best-performing Aqua-MODIS results using the random forests regression. Furthermore, it is possible to observe different data behaviors for lower “morning” temperatures derived from Terra-MODIS measurements (~10:00 AM), compared to the “around-noon” data derived by Aqua-MODIS (~14:00 PM), indicating that the data acquisition at

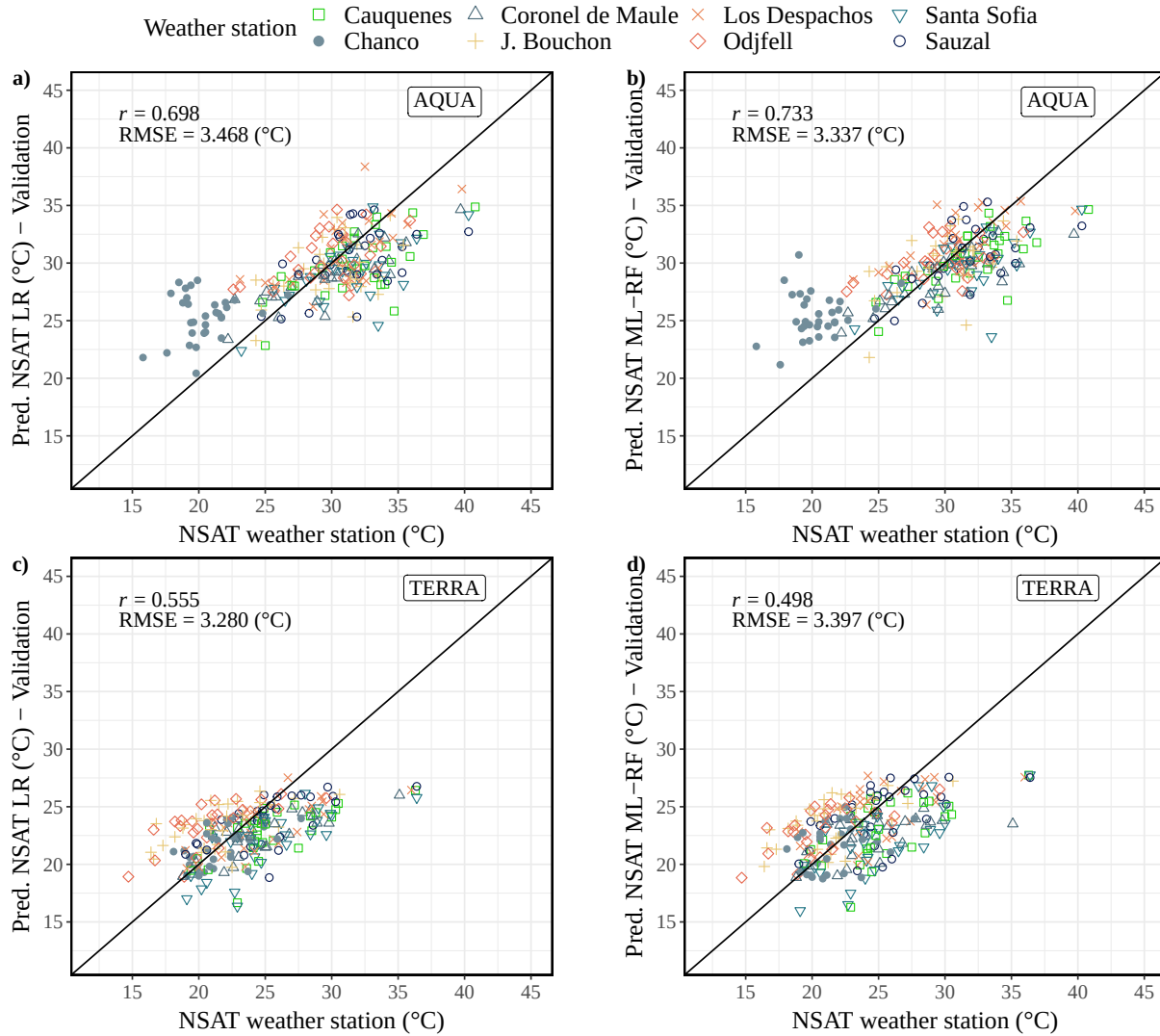


Figure 4.29: NSAT regression models applied to the testing dataset (January DOY 001 to 031, 2017). Each ordinate axis represent the predicted NSAT applying a) Multiple linear regression model for Aqua-MODIS data, b) machine learning (ML) random forests (RF) regression for Aqua-MODIS data, c) Multiple linear regression model for Terra-MODIS data, and d) machine learning (ML) random forests (RF) regression for Terra-MODIS data. For each regression, the NDVI used was the MODIS MOD13A1 product. For each plot, the diagonal black line represents $y = x$, r is de Pearson’s correlation coefficient, and RMSE is the root mean square error.

“around-noon” time performed better from an statistical point of view. Overall, it is possible to observe that the models had a slight trend to underestimate the NSAT, since most of the data-points where under the $y = x$ line, however Chanco’s weather station data was completely overestimated in the Aqua models. Note that this weather station is located around 5 km from the Pacific Ocean.

On the other hand, there where some high NSAT values registered by the weather stations for the testing dataset. The NSAT distribution, measured at weather station, is shown in Figure 4.30 for both Aqua and Terra overpass time. These values (above 38°C) were all registered in January 26th, the day the “Las Máquinas” wildfire was on its peak. The weather stations that registered over 40°C were Sauzal, Santa

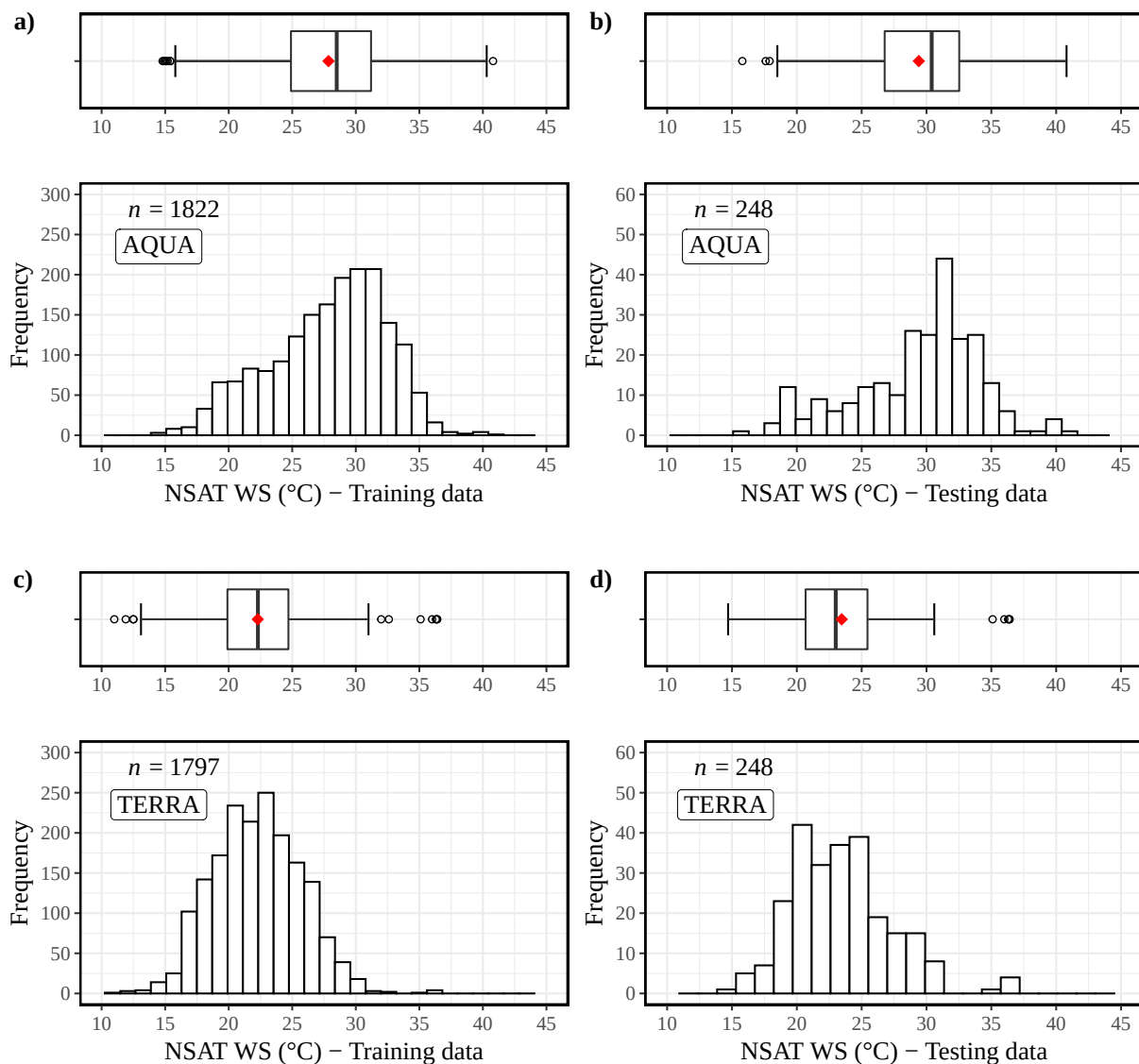


Figure 4.30: Weather station (WS) NSAT histograms and boxplots for a) Aqua-MODIS training dataset (January 2012 - 2016), b) Aqua-MODIS testing dataset (January 2017), c) Terra-MODIS training dataset (January 2012 - 2016), and d) Terra-MODIS testing dataset (January 2017).

Sofía and Cauquenes, which happen to be the closest weather stations to the event. Moreover, on the same day at around 11:00 AM the weather stations at the same locations registered NSAT values over 36°C, which abruptly escapes from mean NSAT values within the ROI. The regression models were not properly trained for such temperatures, which thus had an impact on the testing results obtained.

Finally, the best NSAT predictors for Aqua/Terra-MODIS were the machine learning random forests (Figure 4.29b) and the multiple linear regression (Figure 4.29c), respectively. Therefore, these models are used for the NSAT calculation in the estimation of the Canadian Fire Weather Index for both Aqua and Terra datasets (see Section 4.3.7.7).

4.3.7.2 VIIRS-SNPP regression models for NSAT

The same methodology used for MODIS was applied to VIIRS-SNPP data. The idea behind the use of multiple satellite-products is to cover as many hours of the day as possible for the FWI estimation, having both a high-temporal and medium-spatial resolution.

4.3.7.2.1 VIIRS regression models training

Since the same methodology as in MODIS data was applied to VIIRS-SNPP data, the same regression algorithms were studied. The results are shown in [Figure 4.31](#) for VIIRS data of January DOY 001-031 from 2012 to 2016, where the ordinates axis has the predicted NSAT values using the corresponding regression model. As in both Aqua/Terra-MODIS results, the best multiple linear regression model was the one that uses the NDVI from MODIS MOD13A1 product ([Figure 4.31c](#)), while the best machine learning regression algorithm was the random forests. Both regression models achieved the highest Pearson's correlation coefficient (r), and the lower RMSE for their category. The findings with VIIRS-SNPP data exhibit the best-performing statistical results for the predicted NSAT with the random forests regression algorithm.

Since the best performing regression model was the random forests, the importance matrix of the model was studied, whose results are shown in [Figure 4.32](#). As it is possible to observe, there is a similar behavior as in the Aqua/Terra-MODIS importance matrix (cf. [Figure 4.28](#)). The most important variable for the model is the LST (land surface temperature, T_s), i.e. if the variable is not included in the model, there will be a percentage increase of the mean squared error (MSE) around 17.4%. Moreover, the importance of both the NDVI and precipitable water vapor (PW or PWV), by means of the percentage increase in the MSE, was higher compared to the Aqua/Terra-MODIS results. The increment of the node purity for LST is around the same value as the Aqua-MODIS results, however the node purity for PWV is 54% higher than for Aqua-MODIS. This means that the VIIRS-SNPP random forests regression algorithm considers PWV a more important variable since if this one is not within the model, there will be an increase in the Gini index, i.e. a more *impure* result.

4.3.7.2.2 VIIRS regression models validation

The validation of the best-performing VIIRS-SNPP regression models were applied to January 2017 DOY 001 to 031 data, i.e. the testing dataset. The results can be seen in [Figure 4.33](#). As it is possible to observe, even though in the training phase the best-performing model was the random forest regression algorithm (ML-RF), the predicted NSAT achieved better statistical results with for the multiple linear regression model (LR). Moreover, the Pearson's correlation coefficient for the latter is close the one obtained with the random forest regression model with Aqua-MODIS data. Nevertheless, a 0.8°C difference was found in the RMSE between the VIIRS-SNPP results and the Aqua-MODIS.

This results might be due to the fact that higher NSAT values were measured by the weather stations within the VIIRS-SNPP validation dataset (satellite overpass time). For example, on January 26th, six of the eight weather stations within the ROI registered NSAT values of $41.64 \pm 1.55^{\circ}\text{C}$.

In [Figure 4.34](#) it is possible to observe both boxplots and histograms for the NSAT distribution data within the weather station for the training and testing datasets (acquired at the satellite overpass time). The interquartile range (box) of the testing (or validation) dataset is displaced towards higher temperatures. Moreover, the mean value, represented by the red diamond, is also displaced to higher temperatures for the validation dataset, in addition, a higher number of outliers are observed.

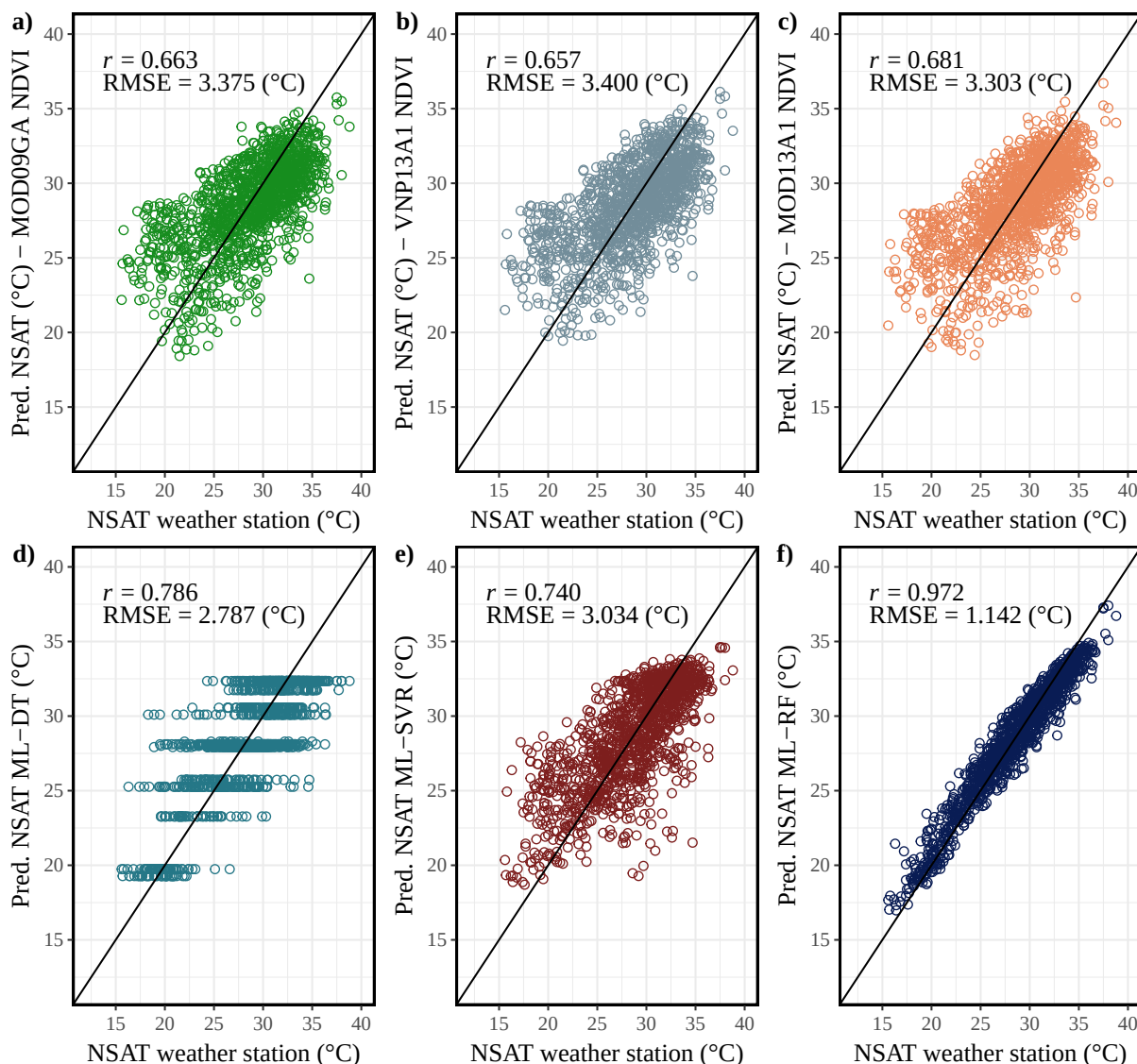


Figure 4.31: NSAT VIIRS regression models. Each ordinates axis represents the predicted NSAT applying a) Multiple linear regression model using daily MODIS MOD09GA NDVI data, b) multiple linear regression model using VIIRS VNP21A1 NDVI data, c) linear regression model using MODIS MOD13A1 NDVI data, d) machine learning (ML) decision trees (DT) regression, e) machine learning (ML) support vector regression (SVR), and f) machine learning (ML) random forests (RF) regression. For all machine learning regressions, the NDVI used was the MODIS MOD13A1. For each plot, the diagonal black line represents $y = x$, r is the Pearson's correlation coefficient, and RMSE is the root mean square error.

As in the case for both Aqua/Terra-MODIS results, the temperature increase in the the validation dataset might be the cause of the random forest regression model results, since the model was not trained for such temperatures (see Figure 4.34). Hence, the higher NSAT values found in the testing dataset were classified within the highest temperatures of the training dataset, which were lower, since the algorithm only learned up to the NSAT training data. However, as it is possible to observe from Figure 4.33b, the greatest data dispersion was found at lower temperatures. The main two differences between VIIRS-SNPP

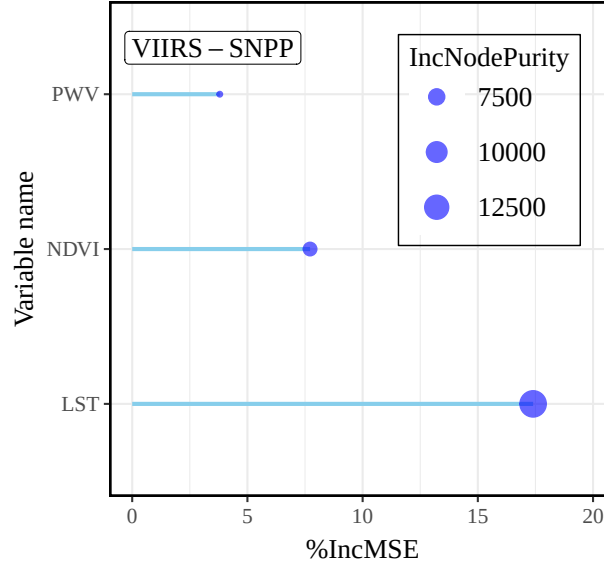


Figure 4.32: Importance matrix results for the random forests regression algorithms performed VIIRS-SNPP data. LST stands for “land surface temperature (T_s), PWV for precipitable water vapor (or PW) and NDVI for normalized difference vegetation index (MODIS MOD13A1 product).

and Aqua/TERRA-MODIS are a) the satellite overpass time, and b) the pixel resolution. Thus, it is expected that these variables are the ones affecting the results obtained.

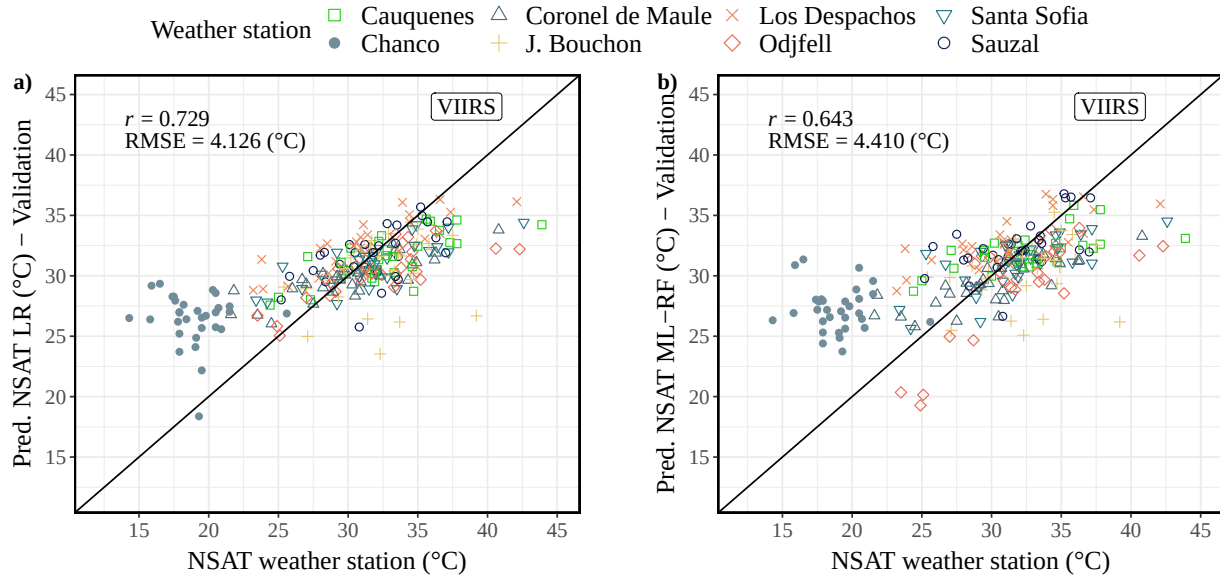


Figure 4.33: NSAT VIIRS regression models validation. Each ordinates axis represent the predicted NSAT applying a) Multiple linear regression (LR) model, and b) machine learning (ML) random forests (RF) regression. Both regression models used MODIS MOD13A1 NDVI data. For each plot, the diagonal black line represents $y = x$, r is de Pearson correlation coefficient, and RMSE is the root mean square error.

Finally, since the NSAT with the best statistical results was the one estimated with the linear regression model, this data is going be used for the Fire Weather Index determination for the VIIRS-SNPP datasets

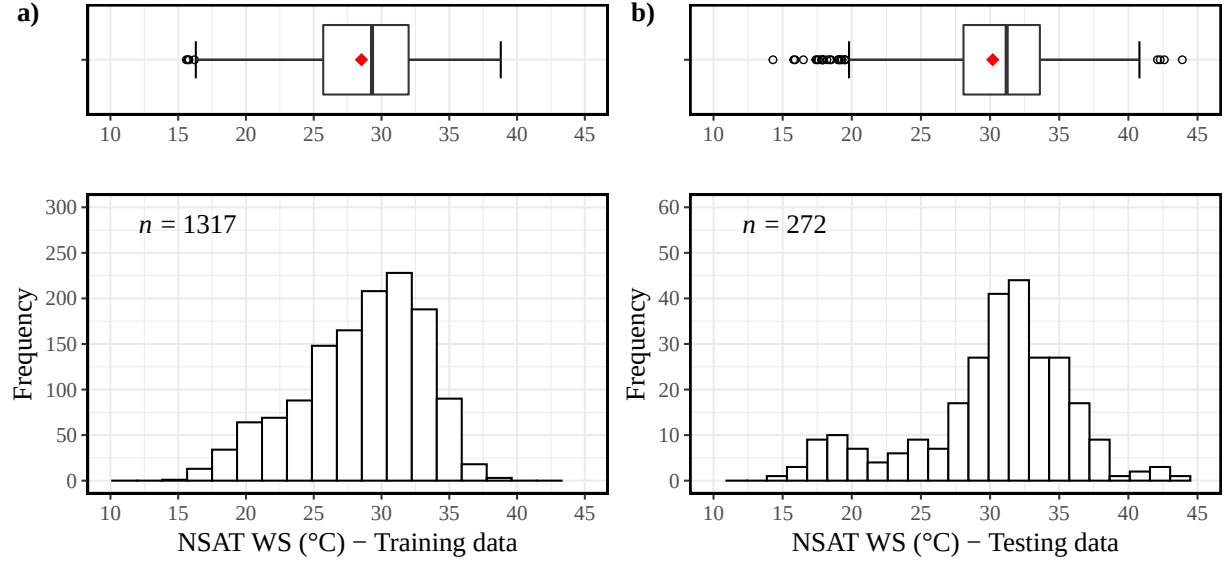


Figure 4.34: Weather station (WS) NSAT histograms and boxplots at VIIRS-SNPP overpass time for a) training dataset (January 2012–2016), and b) validation dataset (January 2017).

(see [Section 4.3.7.7](#)).

4.3.7.3 NSAT from surface energy balance

The other method used to obtain the NSAT is through an energy balance applied to the surface. The model is presented in equation (3.9) (see [Section 3.4.7.3](#) in [page 44](#)). The best results were found for Aqua-MODIS data, and are shown in [Figure 4.35](#). This means that the land surface temperature used was the one from MODIS MYD11A1, latent heat flux from MODIS MYD16A2, NDVI was used from both MYD13A1 vegetation indices and computed from MODIS MOD09GA surface reflectance product. Wind speed is the same one used in [Section 4.3.7.4](#) for Aqua-MODIS data (based in MYD11A1 land surface temperature product time).

The results in [Figure 4.35](#) exhibit RMSE above 10°C for the energy balance (EB) models, and the results of EB-2 ([Figure 4.35b](#)) are slightly better (with NDVI computed from MODIS MYD09GA surface reflectance product) than those of EB-1 ([Figure 4.35a](#), computed with NDVI from the MODIS MYD13A1 product). With the ambition to study better statistical results, a machine learning random forests regression was applied to both datasets from [Figures 4.35a](#) and [4.35b](#) following the equation below.

$$\text{NSAT}_{\text{ws}} \sim \text{NSAT}_{\text{EB}_k}, \quad (4.5)$$

where NSAT_{ws} is the NSAT measured at the weather station (dependent variable) and $\text{NSAT}_{\text{EB}_k}$ is the NSAT calculated by the energy balance using the k method ($k \in \{1, 2\}$, 1: EB-1 with NDVI from MYD13A1, and 2: EB-2 with NDVI from MYD09GA) as the independent variable. The regression model was built with 500 trees. Once the model was computed, the predicted NSAT was analyzed against the weather station data, whose results can be observed in [4.35c](#) for the EB-1 data and in [4.35d](#) for the EB-2 data. The findings exhibit a better statistical performance in terms of the Pearson's correlation coefficient (r) and the RMSE compared to the NSAT solely derived from the energy balance models. Moreover, these results are statistically better than the NSAT obtained for either MODIS or VIIRS data in [Section 4.3.7.1](#)

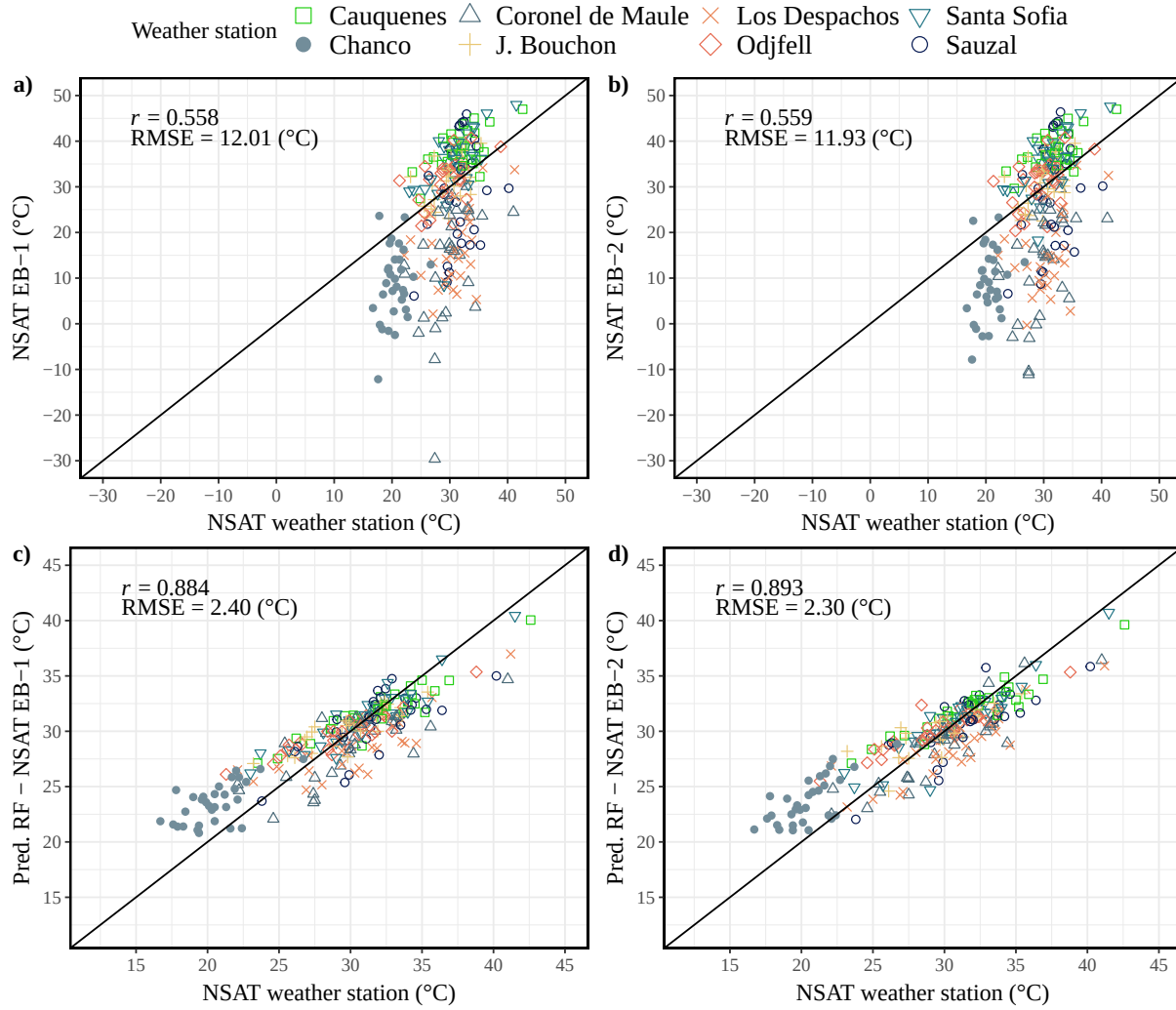


Figure 4.35: NSAT calculated with a) energy balance (EB) with NDVI obtained from MYD13A1 product (which is called EB-1), b) energy balance with NDVI calculated from MYD09GA (EB-2), c) machine learning random forest (RF) regression model prediction for EB-1, and d) machine learning random forests (RF) regression model prediction for EB-2. The random forests regression was carried out using the weather station's NSAT as the endogenous variable and the EB NSAT as exogenous variable.

and [Section 4.3.7.2](#).

Finally, the distribution and evolution of the NSAT results for each methodology studied can be seen in [Figure 4.36](#). As it is possible to observe, all satellite-derived methodologies reached their maximum NSAT values a day or two prior to the start of the fire (VIIRS, Terra, Energy balance), or in the starting day of the event (Aqua). Note that the fire start date corresponds to the vertical dashed line in [Figure 4.36b](#). In addition, the NSAT distribution exhibits a high variation for both Terra and VIIRS-SNPP data, where several outliers (or atypical values) are found, which means that there are various data points above and under the maximum 1.5 times the interquartile range (defined by the boxplot whiskers). Furthermore, it is clear that mean NSAT values for Aqua, VIIRS and Energy balance are close and under 1°C difference, which makes sense since their acquisition time is in the afternoon and ranges from 14:00 to 16:00. In contrast, the mean NSAT derived from Terra data was 23.68 ± 2.85 °C, around 6°C lower than the mean

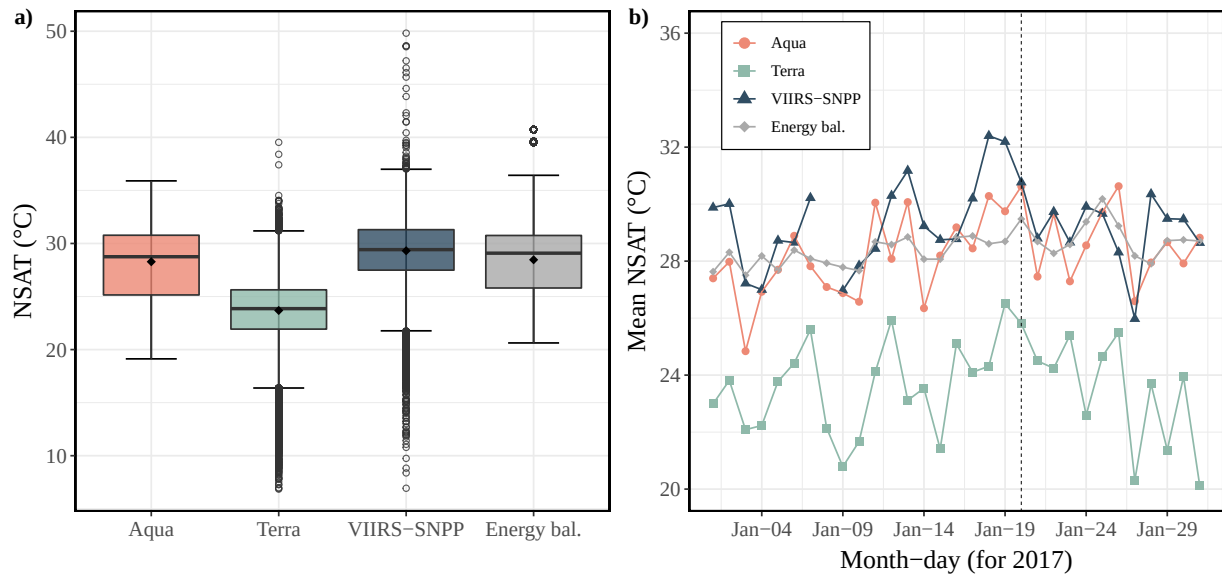


Figure 4.36: Near-surface air temperature a) distribution and b) evolution within the ROI between DOY 001–031 of 2017. The results are for Aqua-MODIS, Terra-MODIS, VIIRS-SNPP and Energy balance satellite-derived NSAT.

value obtain by the other satellites, which is explained by the fact that Terra’s overflight time is in the morning (around 10:00 AM).

4.3.7.4 Wind speed

Wind speed was simulated at a fine-resolution (around 770 m) in WindNinja software (Forthofer et al., 2014) using the mass-conservation algorithm with weather station data as the point of initialization. At first, a total of 13 weather stations were used: the ones within the ROI (see Figure 3.5 in page 44), and others outside of it. This was done because some weather stations did not have wind speed measurements or wind direction, which are required by the Wind Ninja’s algorithm to perform the wind speed simulation. From the 13 weather stations, only 9 satisfied the conditions for the simulation within the time-frame of analysis. The ones within the ROI were: *Cauquenes*, *Chanco*, *Coronel de Maule*, *Los Despachos*, *Santa Sofía* and *Sazual*, while the other ones outside of it were: *San Javier*, *Yerbas Buenas* and *Pencahue*, located at the east of the ROI.

The next step was to build a landscape file, which is a multi-band raster used by WindNinja to understand the terrain in order to perform the simulations. This file was built in FlamMap software (Finney, 2006) with topographic information (elevation, slope and aspect), as well as wildland fuels information (canopy cover and fire behavior fuel models; cf. Section 3.4.7.1 in page 43).

On the other hand, from VIIRS-SNPP Deep Blue Aerosol (DBA) 6-min swath product (Hsu et al., 2019) it is also possible to obtain the wind speed. However this gridded product comes at a 6 km spatial resolution. Using the passing time of each VIIRS-SNPP DBA daily product, the weather station data was filtered and stored at that time, which was then used for wind speed simulation in WindNinja with point initialization.

With the interest of studying the similarities and/or differences between the wind speed obtained from VIIRS-SNPP and the WindNinja’s simulated results, WindNinja’s wind speed rasterized results

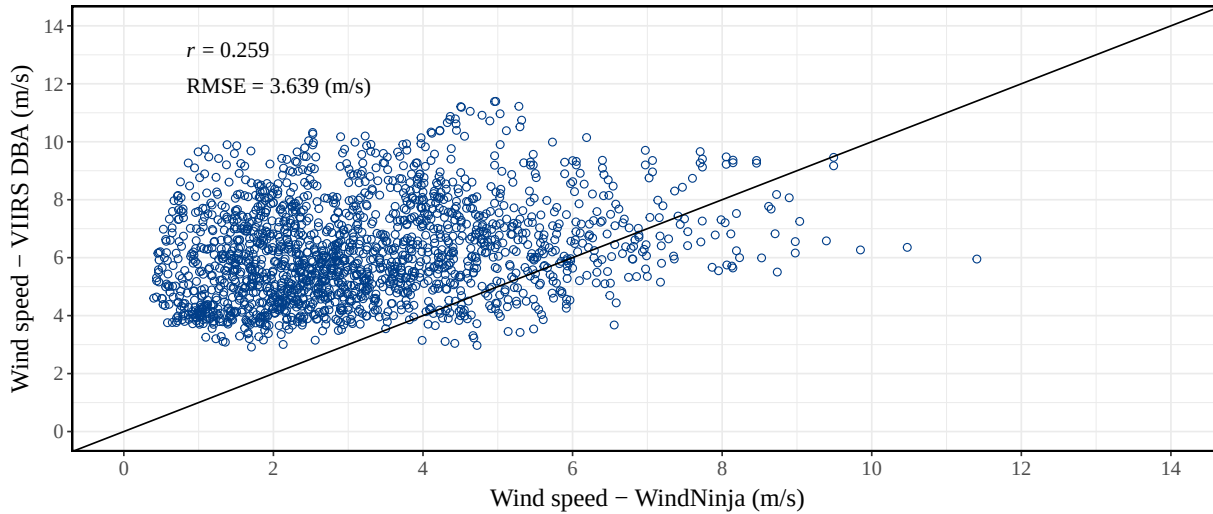


Figure 4.37: VIIRS-SNPP Deep Blue Aerosol retrieved wind-speed versus WindNinja’s simulated wind speed results. The values correspond to pixel centroids extracted from daily images from January 2017 DOY 001 to 031 from both VIIRS-SNPP DBA product and WindNinja rasterized simulation results. The diagonal black line represents $y = x$, r is the Pearson’s correlation coefficient and RMSE is the root mean square error.

were resampled using a bilinear interpolation to match both the extent and resolution of the VIIRS-SNPP DBA product, i.e. from ≈ 770 m to 6 km pixel resolution. The centroid value of each pixel and for each daily-image was extracted and stored in an R data frame simultaneously. The results are shown in Figure 4.37 for daily images of January 2017 DOY 001–031.

The results in Figure 4.37 show that VIIRS-SNPP DBA product had a bias to overestimate wind speed values derived from WindNinja’s simulation at the same pixel-centroid location, and that there is a meager linear correlation between both variables.

With the aim to study the relation between VIIRS-SNPP DBA wind speed against measured wind speed at weather stations, Figure 4.38 was built. First, the average VIIRS-SNPP DBA overpass time for the temporal range of analysis was at 15:52 PM, while the average time for the weather stations data retrieval was 15:50 (the algorithm filters the weather station data for the closest acquisition time of the VIIRS-SNPP DBA image), and the mean time difference was 15.87 ± 8.98 minutes.

The results in Figure 4.38a show that VIIRS-SNPP overestimated the wind speed for most of the weather station records within January 2017, DOY 001–031. In order to study a possible improvement of these results, both a linear regression model and machine learning random forests regression was applied to the data. The results are shown in Figure 4.38b and 4.38c. The plot in Figure 4.38b corresponds to the predicted VIIRS-SNPP wind speed (WS; ordinates axis) using the linear regression model between the weather station wind speed as the dependent variable and VIIRS-SNPP wind speed as the independent variable. The Pearson’s correlation coefficient for Figure 4.38b was the same as in Figure 4.38a, however the root mean square error decreased to the half while using the linear regression model.

From a statistical point of view, the wind speed prediction results using the machine learning random forests regression algorithm (Figure 4.38c) improved substantially compared to the wind speed results derived directly from the VIIRS DBA product, achieving the highest Pearson’s correlation coefficient and the lowest RMSE.

This last approach was achieved using the `randomForest` package in R (Liaw & Wiener, 2002),

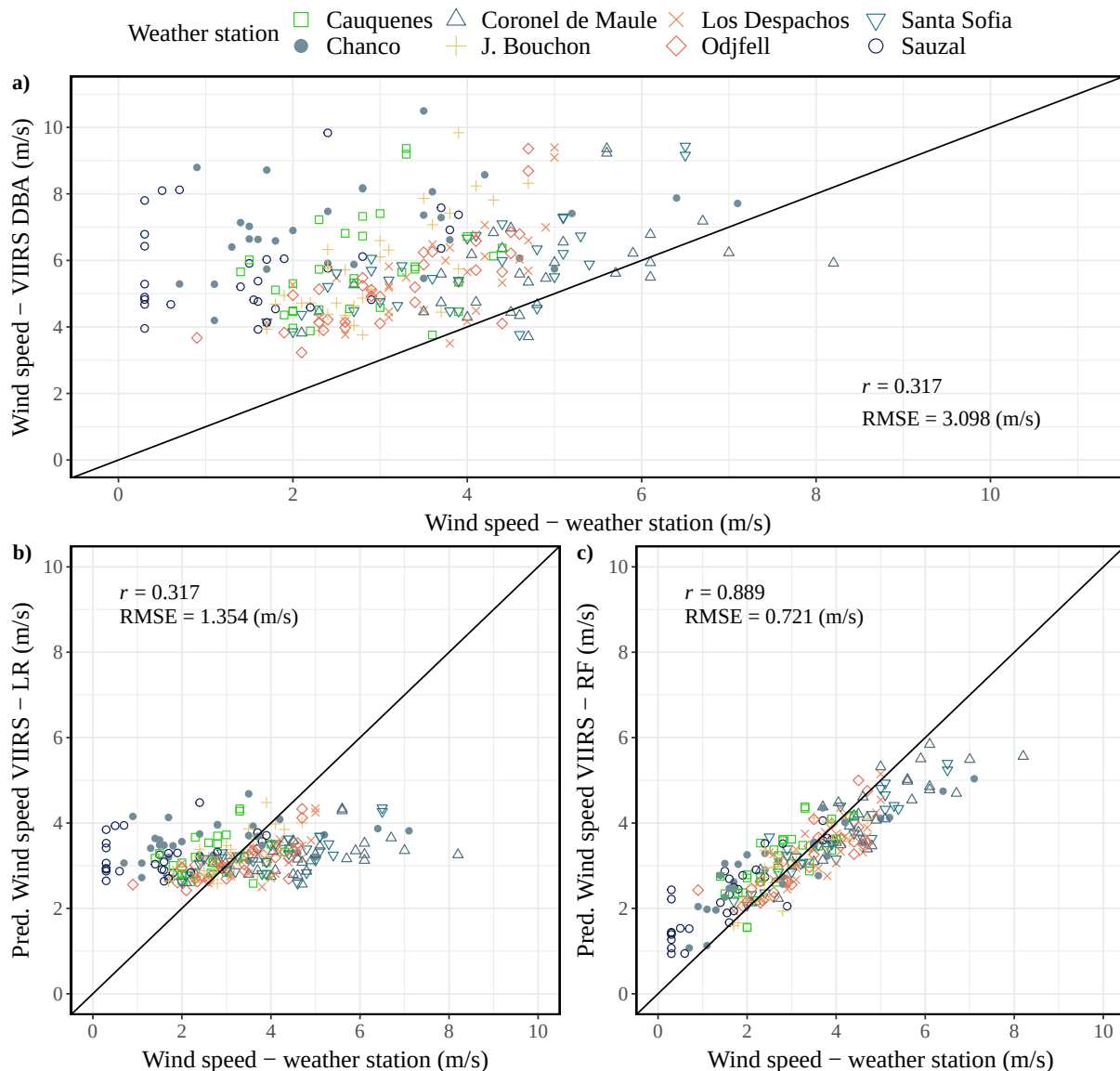


Figure 4.38: Wind speed (WS) results and analysis. a) Retrieved VIIRS-SNPP Deep Blue Aerosol (DBA) wind speed and the corresponding weather station wind speed (the data was extracted using shapefile points of each weather station), b) Predicted VIIRS wind speed using a linear regression model (LR) where the dependent variable was the weather station wind speed and the independent variable was the VIIRS-SNPP DBA wind speed, and c) Predicted VIIRS-SNPP wind speed using machine learning random forests (RF) regression, the regression variables were the same as in b). The diagonal black line represents $y = x$, r is the Pearson's correlation coefficient and RMSE is the root mean square error. Results are from January 1 to 31, 2017, for a total of $n = 245$ samples.

establishing 100 trees and a regression-solver type. More trees did not yield better results. Therefore, it is possible to conclude that applying random forests regression to the VIIRS-SNPP Deep Blue Aerosol wind speed rasters should statistically improve the accuracy of the wind speed data within the region of interest. Other machine learning algorithms were tested, including decision trees and support vector regression, however their results were not as good as those obtained with random forests.

4.3.7.5 Relative humidity

Once NSAT was calculated for each satellite-sensor, the dew-point temperature, T_{dew} , was obtained for the first five pressure levels of MODIS M*D07 (M*D means for both MYD and MOD products, i.e. Aqua and Terra, respectively) atmospheric profile 5-min L2 swath product (Borbas & Menzel, 2017), and Equation (3.19) was used to compute the relative humidity (RH). Note that the five pressure levels used are those that matches the maximum altitude of the ROI.

The time differences between the previously-estimated NSAT (acquired from land surface temperature product) and MODIS MD07 atmospheric products can be seen in Table 4.4. Note that for NSAT computed with Terra-MODIS, product Terra-MODIS MOD07 was used for T_{dew} , with a mean difference time of 97.54 minutes between both of them. For NSAT computed with Aqua-MODIS, product Aqua-MODIS MYD07 was used for T_{dew} , with a mean difference of almost 100 minutes. Finally, for NSAT estimated with VIIRS-SNPP, product Aqua-MODIS MYD07 was used for T_{dew} , since the time difference was the lowest.

Table 4.4: Local time differences between the satellite sensors used to compute NSAT and the M*D05_L2 product to calculate relative humidity. These results were based on the January 2017 DOY 001-031 data.

Satellite used for NSAT	T_{dew} product	NSAT avg. time	T_{dew} avg. time	Time difference (min)
Terra-MODIS	MOD07_L2	10:10	11:45	97.54 ± 26.25
Aqua-MODIS	MYD07_L2	14:00	15:38	99.16 ± 22.86
VIIRS-SNPP	MYD07_L2	15:20	15:42	42.24 ± 26.65

For each RH raster, the pixels-data was extracted to analyze its distribution and evolution within the ROI. The results are shown in Figure 4.39. From Figure 4.39a it is possible to observe that mean values, represented by the black diamond within each boxplot, were reasonably close. Mean values for Aqua data was $\overline{RH}_{aqua} = 39.04 \pm 17.99$ (%), while for Terra data $\overline{RH}_{terra} = 36.62 \pm 17.18$ (%), and for VIIRS-SNPP data $\overline{RH}_{viirs} = 37.46 \pm 16.73$ (%). From Figure 4.39b it is possible to observe that there is some missing data, since those images were completely covered by clouds, specially for VIIRS-SNPP passing time through January DOY 005 to 015, 2017. There is no clear trend for lower RH values after the starting date of the wildfire, represented by the vertical dashed line, however $RH \approx 30\%$ was observed within the most catastrophic days of the fire: January 25 and 26.

Furthermore, Figure 4.40 exhibits the validation analysis for the relative humidity results calculated by each satellite-sensor against measured relative humidity at the weather stations for January 2017, DOY 001 to 031. As it is possible to observe in Figure 4.40a 4.40b and 4.40c, which correspond to the RH derived from the satellite data against the measured RH at the weather stations, there is no indication of a correlation between the data. In fact, it is possible to appreciate a considerable dispersion of the data.

For example, for both Aqua-MODIS and VIIRS-SNPP results, “Chanco’s” weather station data (gray dot), was mostly underestimated and found to be isolated from the data, while for Terra-MODIS the Chanco’s results were part of the data dispersion. Since both Aqua-MODIS and VIIRS-SNPP information is acquired at the afternoon (see Table 4.4), relative humidity is mainly under 50%, however “Chanco” weather station is located at around 5.5 km from the coast of the Pacific Ocean, and hence this might be the reason for higher RH values.

In order to attempt a possible improvement of the RH derived from satellite information, a machine

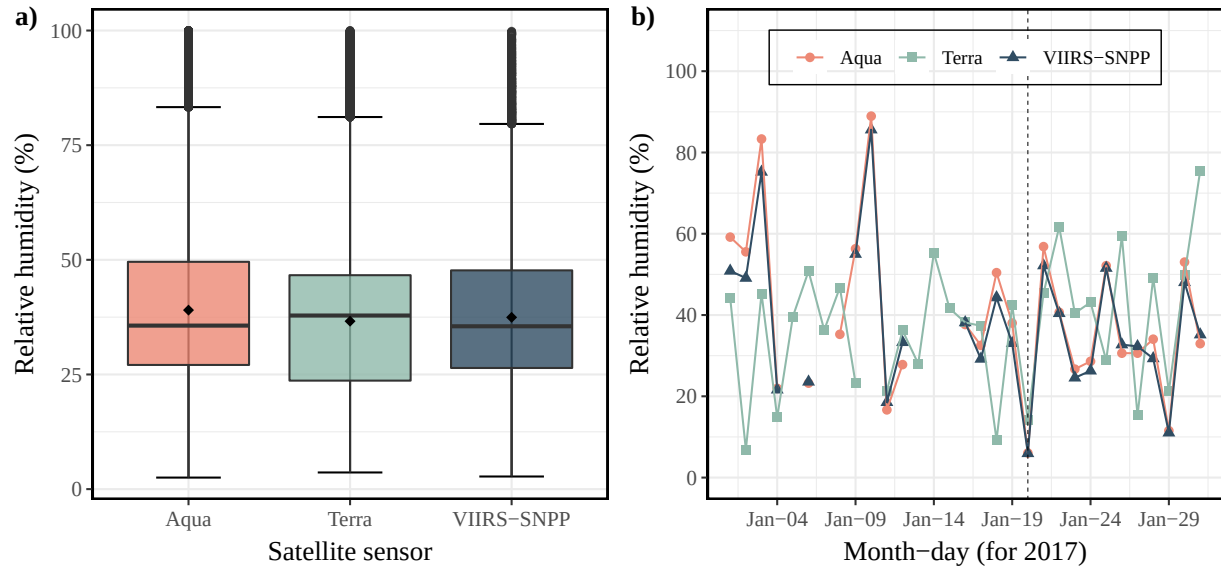


Figure 4.39: Relative humidity values for each satellite sensor during January 2017 DOY 001 to 031 within the ROI. a) relative humidity boxplots data distribution, and b) mean relative humidity evolution. In a), the diamond in each box represent the mean RH values. In b) the dashed vertical line corresponds to the “Las Máquinas” wildfire start time.

learning random forests regression was applied to the data using the RH measured at the weather station as the dependent variable and the satellite-derived RH as the independent variable. The results are shown in Figure 4.40d, 4.40e and 4.40f for Aqua-MODIS, Terra-MODIS and VIIRS-SNPP data, respectively. For each regression model, a total of 500 trees were established. From the predicted values with the random forest regression results, it is possible to observe that the regression algorithms improved the results considerably, obtaining higher Pearson’s correlation coefficient and lower RMSE values. Therefore, this regression models will be applied to the corresponding satellite-sensor RH raster data for the FWI estimation.

4.3.7.6 Precipitation

Since the dates under analysis are within the austral summer (January 2017), rainfall was close to zero. In fact, a brief analysis using the data from the weather stations for each study day and summing all precipitation, the results show a mean and standard deviation of 0.008 ± 0.055 mm. Considering all IMERG-GPM raster data per day, the mean and standard deviation was 0.311 ± 0.158 mm, which are slightly higher than the weather station data. However, the following considerations should be taken into account. The pixel resolution of the IMERG-GPM product is ≈ 11 km, and most of the high values were found near the Pacific Ocean. Comparing the pixel values with the weather station data, a $RMSE = 0.125$ mm and $r = 0.005$ was found.

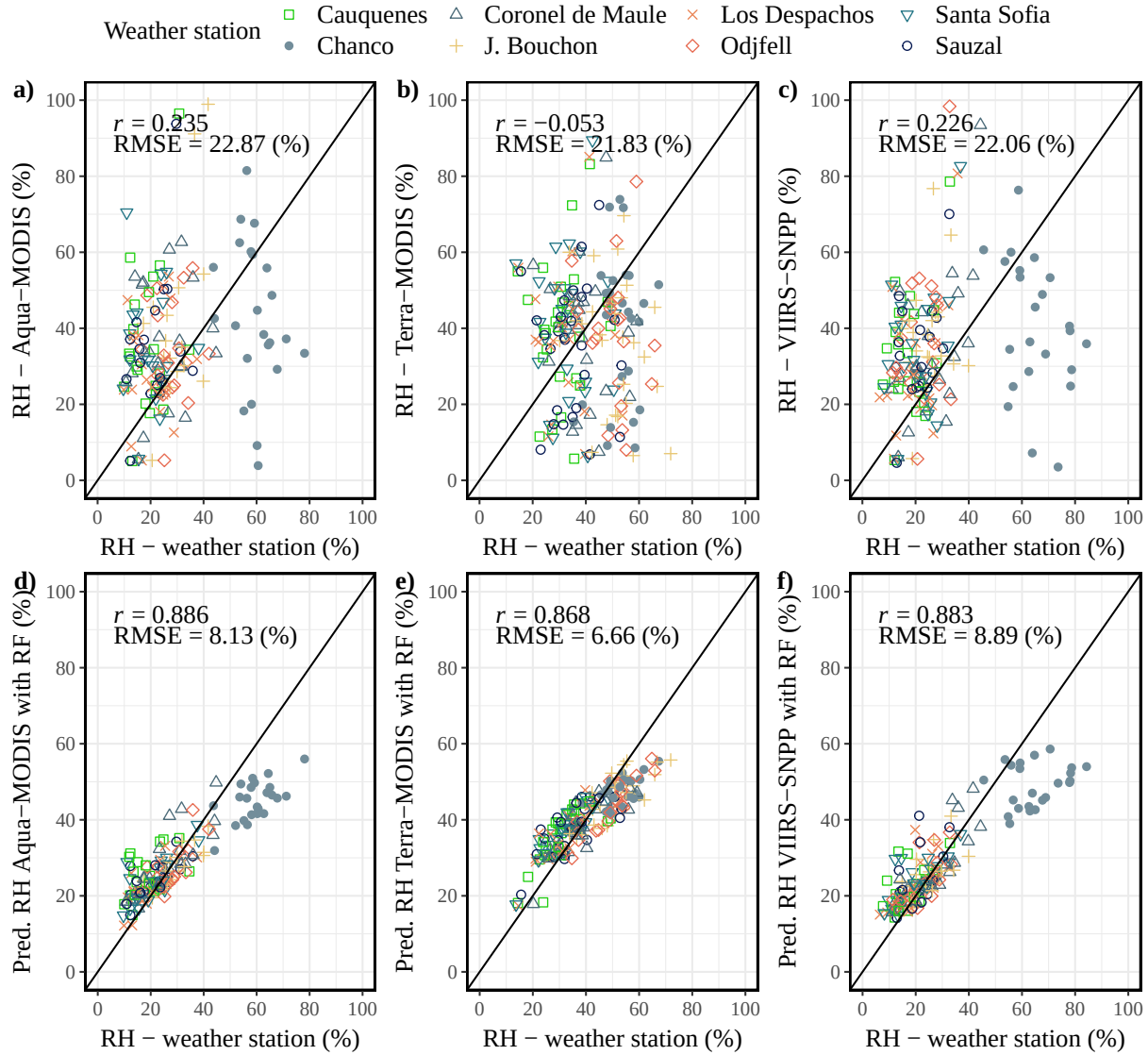


Figure 4.40: Validation of satellite-sensor RH results against weather station RH data for a) Aqua-MODIS, b) Terra-MODIS, c) VIIRS-SNPP, d) Predicted Aqua-MODIS RH data with Random Forests (RF) regression, e) Predicted Terra-MODIS with Random Forests(RF) regression, and f) Predicted VIIRS-SNPP RH data with Random Forests (RF) regression. For each plot, the diagonal black line represents $y = x$, r is the Pearson's correlation coefficient and RMSE is the root mean square error.

4.3.7.7 Fire Weather Index from remote sensing data

Once NSAT, relative humidity (RH), precipitation (PP), and wind-speed (U_r) are estimated for each satellite sensor, the following step is to determine the initial conditions for the FWI calculation, i.e. the `rasterStack` containing the FFMFC, DMC and DC. These variables were obtained using the Copernicus/ECMWF fire danger indices historical data for the last 11 days of December from 2010 to 2016 (see [Section 3.4.7.7](#)). The mean of these was computed and the resulting rasters are shown in [Figure 4.41](#).

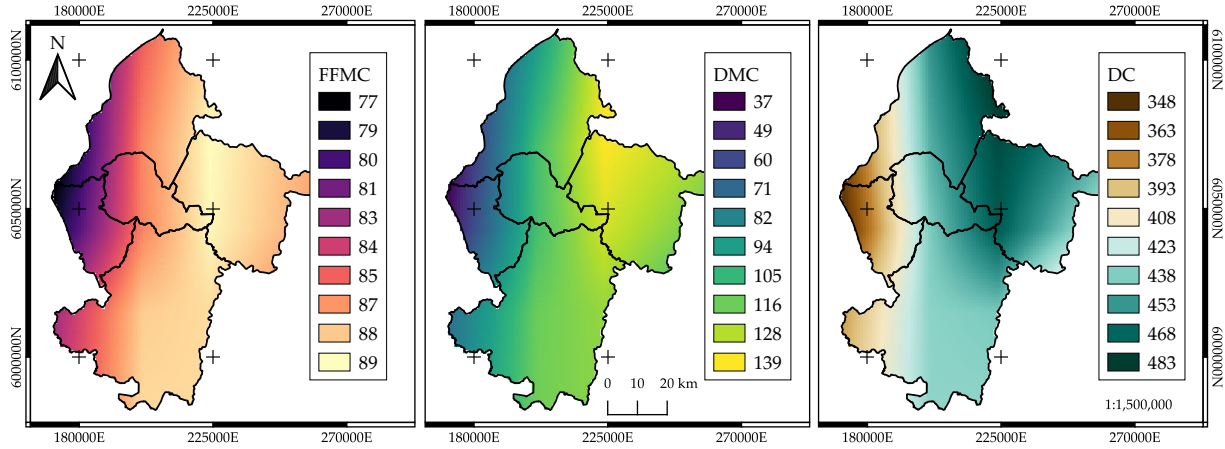


Figure 4.41: Initial conditions of the FFMFC, DMC and DC for the Fire Weather Index calculation.

However, it is necessary to mention that the actual pixel resolution of the FFMFC, DMC and DC is $0.25^\circ \times 0.25^\circ$ (≈ 28 km). Therefore, the first step was to resample the FFMFC, DMC and DC rasters to the extent and resolution of the corresponding input data for each FWI computation e.g. the variables were resampled to NSAT images estimated with Aqua-MODIS data in order to compute the FWI from Aqua-MODIS information (the resolution of Aqua-MODIS is the same as in Terra-MODIS, but different for VIIRS-SNPP), which are the results shown in [Figure 4.41](#). Is due to the resampling procedure that a noticeable gradient is observed through each image. All the variables displayed equal behavior, i.e. higher values towards the East of the ROI.

The FFMFC, DMC and DC are placed together in a `rasterStack` object, and in conjunction with NSAT, precipitation, RH and wind speed, the Canadian Fire Weather Index was calculated. It is worth mentioning that there were days in which the images had missing values (NA, *not available* pixels), and if that was the case, the estimated FFMFC, DMC and DC obtains NA as a result. Therefore, if the previous happened, the algorithm was designed to compare both the calculated and previous FFMFC, DMC and DC, and if there is any NA within the former, it will be filled with the previous pixel values for the corresponding variable.

The Fire Weather Index results are shown in [Figure 4.42](#) for all the datasets. Note that each row corresponds to a satellite-sensor product, and the second column for each row corresponds to the approximated FWI (FWI_{app} , cf. [Section 3.4.7.8](#)). The FWI estimated with Aqua/Terra-MODIS data, VIIRS-SNPP-WN (WindNinja), and Energy Balance used the wind speed simulated by WindNinja, while FWI VIIRS-DBA (Deep Blue Aerosol, [Figure 4.42g](#) and [4.42h](#)) were calculated using the wind speed derived from the DBA product (see [Section 4.3.7.4](#)). As it is possible to observe, all the datasets, excepting the FWI VIIRS-DBA results, exhibit an increase in the FWI during the wildfire, achieving, in some cases, maximum atypical values of $FWI > 100$. In addition, the FWI_{app} results are considerably close to the CFFDRS FWI (calculated with precipitation, FFMFC, DMC and DC; first column in [Figure 4.42](#)), although exhibiting some overestimation. In addition, FWI maps were generated throughout January DOY 023 to 028, the results are shown in [Figure 4.43](#).

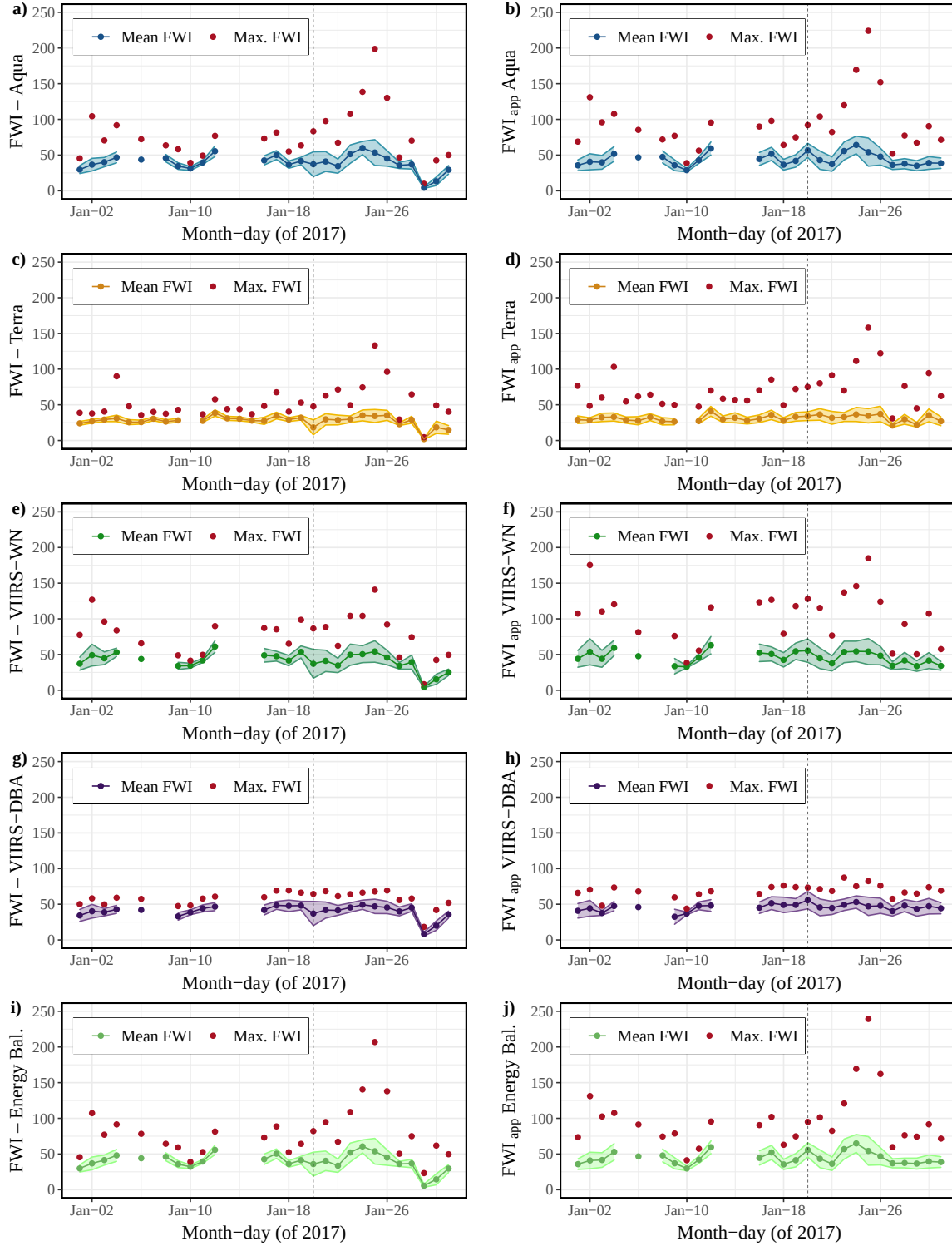


Figure 4.42: Results of the FWI using its mean values, standard deviation (colored areas), and maximum value at the ROI for a) Aqua-MODIS data, b) Aqua-MODIS & FWI_{app} , c) Terra-MODIS data, d) Terra-MODIS & FWI_{app} , e) VIIRS-WN (WindNinja wind speed) data, f) VIIRS-WN & FWI_{app} , g) VIIRS-DBA (deep blue aerosol wind speed) data, h) VIIRS-DBA & FWI_{app} , i) Energy balance data, and j) Energy balance & FWI_{app} . The vertical dash line corresponds to DOY 020, the starting day of the event.

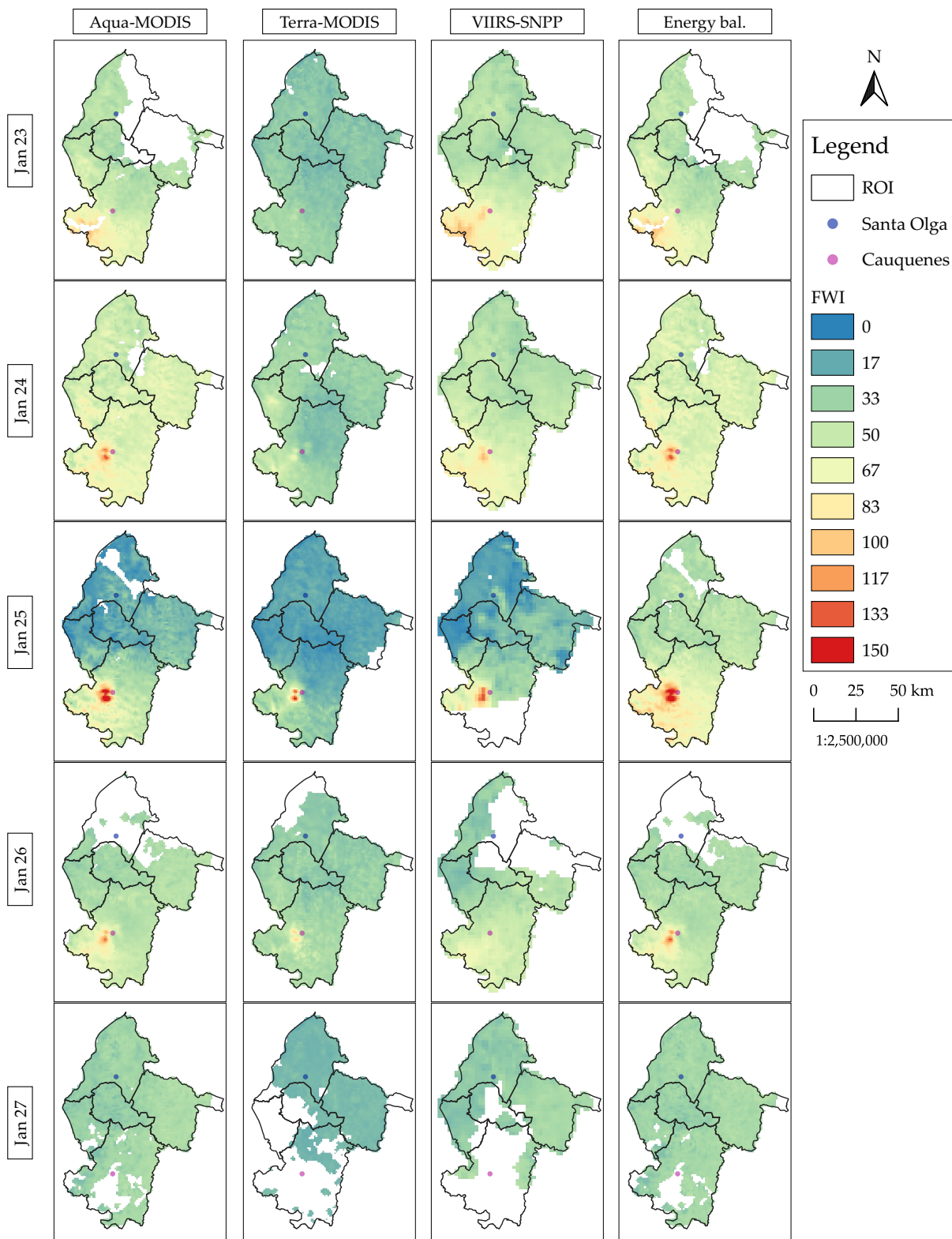


Figure 4.43: Fire weather index estimated with Aqua, Terra, VIIRS-SNPP and Energy balance. Note that the maximum FWI values for the color palette was set to 150, since above that value only a few pixels were found, which corresponded to fire locations. This was done to observe larger differences between the FWI values from 50 to 100.

In addition, it is possible to observe significant differences between Aqua's and Terra's FWI results. For Aqua (Figure 4.42a), the mean FWI was 39.08 ± 11.93 and the mean of the maximums FWI was 76.40 ± 37.84 , while for Terra (Figure 4.42c) the mean FWI was 27.50 ± 7.04 and the mean of the maximums FWI was 52.09 ± 23.71 . Moreover, the standard deviation values are lower for Terra's FWI, which means that the FWI values are more consistent over time. These findings could be due to the overpass time of each satellite, since the average flyover time of Terra is around 10:00 AM, while the average flyover time of Aqua is around 14:00 PM. This corresponds to the reason why the FWI was also studied from VIIRS-SNPP data, since the overpass time of this satellite is later than Aqua's, and is around 15:40 for the land surface temperature and precipitable water vapor products (see Table 4.4). Using the simulated wind speed obtained from WindNinja (Figure 4.42e) for VIIRS-SNPP data, the mean FWI was 40.90 ± 12.49 , while the mean of the maximums FWI was 76.58 ± 29.33 , resulting in the highest FWI values found within these three satellite products.

On the other hand, the VIIRS-SNPP FWI results using wind speed derived from the Deep Blue Aerosol product (Figure 4.42g) exhibited the lowest maximums FWI results for the "afternoon" datasets, i.e. all FWI results but Terra-MODIS. Furthermore, since the same variables, except for the wind speed, were used to calculate the FWI from the VIIRS-SNPP data, it is possible to conclude that the latter variable was the responsible for the results obtained, where a mean FWI of 40.13 ± 9.18 and a mean of maximums FWI 57.63 ± 11.24 were found.

Further, the FWI derived from the NSAT based on the surface energy balance methodology (Figure 4.42i) obtained the highest maximums FWI values. The mean FWI was 39.38 ± 11.84 and the mean of the maximums FWI was 79.74 ± 37.96 , which are considerable close to VIIRS-SNPP results, although exhibiting higher standard deviations.

In addition, if the trend of the mean FWI prior to the fire is analyzed (from January 1st to 19th), all the datasets exhibit a positive slope. For example, the slope for Aqua's (Figure 4.42a) mean FWI tendency was 0.34 (see Table 4.5). Hence, the positive slope from the trend analysis for the FWI for such values might be an indicator for wildfire risk. Nevertheless, further studies are required to conclude its efficacy through this FWI approach.

Finally, the FWI map (Figure 4.43) shows a similar behavior throughout the days within each satellite-

Table 4.5: FWI mean values tendency analysis for the pre-event results (from January 001 to 019). Maximum FWI was settled to 150 in order to not affect the scale, since the amount of cells with that or higher values are under two pixels within the ROI.

FWI dataset	Slope	Intercept
Aqua	0.34	37.69
Aqua-app	0.16	41.52
Terra	0.29	26.4
Terra-app	0.13	29.22
VIIRS WN	0.31	42.64
VIIRS WN-app	0.15	46.63
VIIRS DBA	0.61	36.43
VIIRS DBA-app	0.49	39.81
Energy Bal.	0.29	38.61
Energy Bal.-app	0.09	42.52

derived FWI estimation. However, Aqua, VIIRS-SNPP and the Energy balance methodology exhibited higher FWI than Terra, which was expected since NSAT was much lower for the Terra because of its flyover time. It is interesting to notice that on January 23, all the south of the ROI (within the Cauquenes municipality) manifested FWI > 67, which represents an extreme risk. Moreover, the orange-to-red pixels displaying high FWI values are actually not quite useful since these corresponds to wildfires in the south of the ROI. Additionally, on January 24th, a the day prior to the catastrophic events that took place in Santa Olga, the FWI derived from Aqua and the surface energy balance methodology exhibited FWI values around 50-67 in Constitución and near Santa Olga (blue dot). This behavior was partly repeated on January 25th only for the FWI derived from the energy balance methodology. On the night of that day, the fire propagated to the north of the ROI from Empedrado to Constitución, burning the village of Santa Olga. This is why there is no data in the northern ROI for January 26th, as the fire plume obstructed the satellite sensors.

4.3.7.8 Fire Weather Index at weather station

Using the weather stations data within the ROI, the FWI was calculated using both the CFFDRS methodology/equations (Van Wagner & Pickett, 1985), using the *cffdrs* package in R (Wang et al., 2017a), and the approximated Fire Weather Index (FWI_{app}). The results are shown in Figure 4.44.

Each peak value in Figure 4.44 corresponds to 12:00 – 14:00 hours data. As it is possible to observe, higher FWI values were achieved during the event, specially in weather stations such as *Santa Sofia*, *Odjfell*, *Los Despachos* and *Coronel de Maule*, all located towards the south of the ROI at the Cauquenes municipality. Note that the highest values were found for January 25th and 26th. Furthermore, from the burned area results (see Figure 4.10 in page 65), the area burned in the southern ROI during January 25th and 26th was increasing about 6 km north of the *Odjfell* weather station, 10 km southeast of the *Santa Sofia* weather station, and 8 km east of the *Los Despachos* weather station.

It seemed interesting to study the FWI differences derived from the CFFDRS equations (Van Wagner & Pickett, 1985) and the approximated FWI (Avila et al., 2022), whose results are shown in Appendix F (cf. Figure F.1). The results exhibit a statistically strong relation between them, and hence this confirms that the FWI approximation in the austral summer at the ROI is a suitable approach if variables such as the FFMC, DMC and DC are not available.

4.3.7.9 Fire Weather Index validation

Using both the FWI derived from remotely-sensed data (see Section 4.3.7.7) and the fire weather index derived from weather stations data (see Section 4.3.7.8), a validation was carried out comparing the FWI pixel values at which the weather stations are located and at the closest overpass time of the corresponding satellite product. The results are shown in Figure 4.45.

Overall, from a statistical point of view, the best-performing FWI product was the approximated FWI using Terra-MODIS dataset, with the highest Pearson's correlation coefficient and lowest RMSE, followed by the Terra-MODIS FWI calculated with the FWI equations.

Another interesting result is to analyze the FWI derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-5 reanalysis (Vitolo et al., 2020, 2019). This is a $0.25^\circ \times 0.25^\circ$ product (≈ 28 km), and hence around 20 pixels cover the entire ROI. Then, the FWI values corresponding to the pixel at the location of the weather stations are extracted. Since the product is simulated at 12:00, the FWI derived from the weather station data at that time was used. The results can be observed in

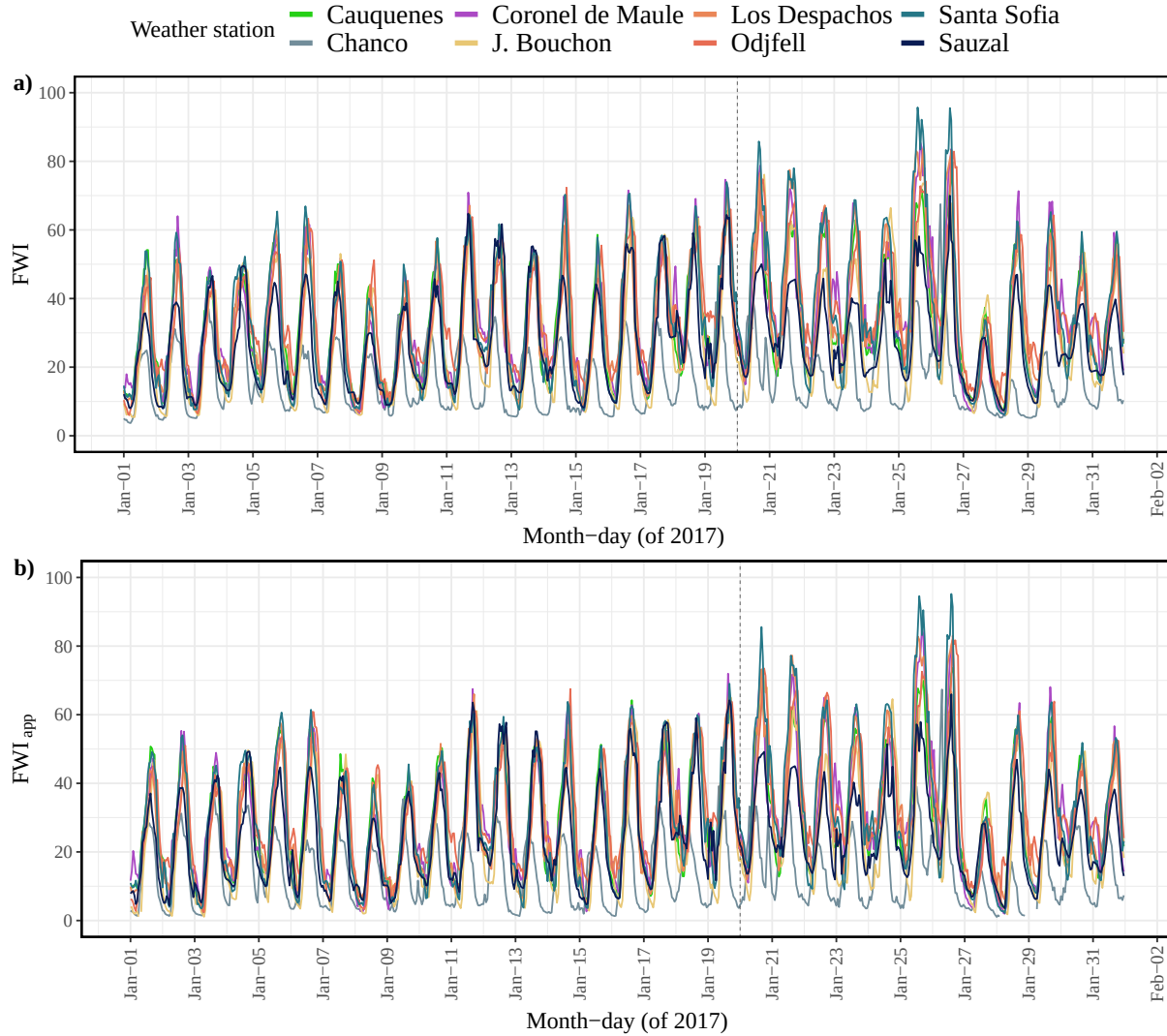


Figure 4.44: Results of the FWI at the weather stations within the ROI with a) the *cffdrs* package i.e. with an initial condition of FPMC, DMC, DC, latitude and batch processing through time, and b) with the approximation method (see equation (3.22) in Section 3.4.7.8). The black vertical dashed-line corresponds to DOY 020, the starting day of the event.

Figure 4.46. The findings show that even for such high spatial resolution, accurate FWI values can be obtained. Nevertheless, this is a reanalysis product and therefore is only available every ≈ 2 months. Furthermore, the FWI derived from ERA-5 exhibits a similar behavior to the FWI derived from Aqua, Terra, and VIIRS data. It would be interesting to study its differences, but since the products time of acquisition is not the same, the analysis becomes irrelevant.

It is interesting to observe that, overall, the results are at least not strongly overestimated or underestimated, which means that the approach of the FWI estimated using remotely-sensed data and simulated wind speed is not overstated considering that this data can be used on a daily-basis at a ≈ 1 km pixel resolution and for free, which is useful in developing countries such as Chile to monitor wildfire risk from a fire weather point of view.

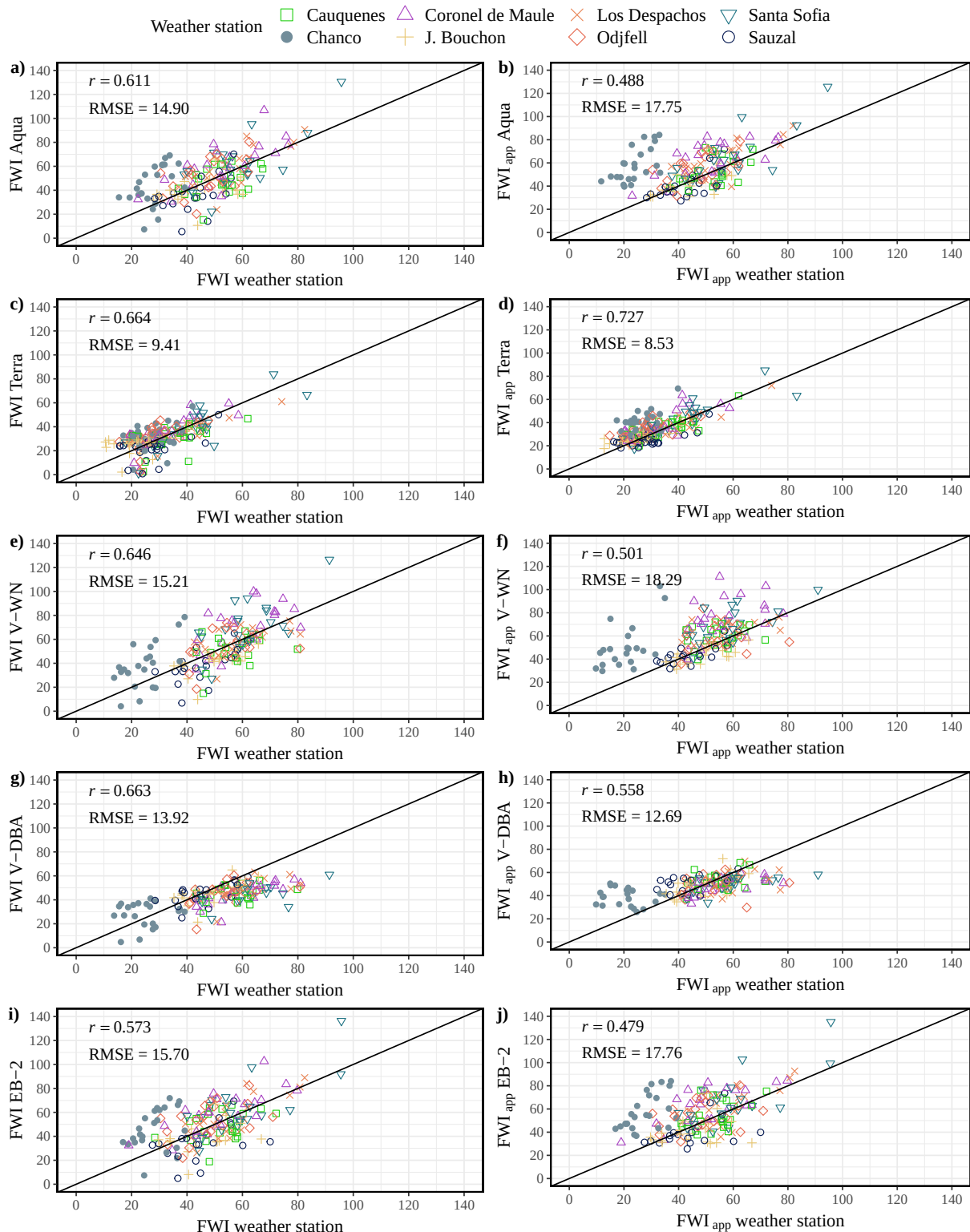


Figure 4.45: Fire weather index calculated at weather station (abscissa) versus a) FWI from Aqua-MODIS, b) FWI approx. from Aqua-MODIS, c) FWI from Terra-MODIS, d) FWI approx. from Terra-MODIS, e) FWI from VIIRS-SNPP with WindNinja's (WN) wind-speed, f) FWI approx. from VIIRS-SNPP with WindNinja's wind-speed, g) FWI from VIIRS-SNPP with Deep Blue Aerosol (DBA) wind speed, and h) FWI approx. from VIIRS-SNPP with DBA wind-speed. The diagonal black line corresponds to $y = x$.

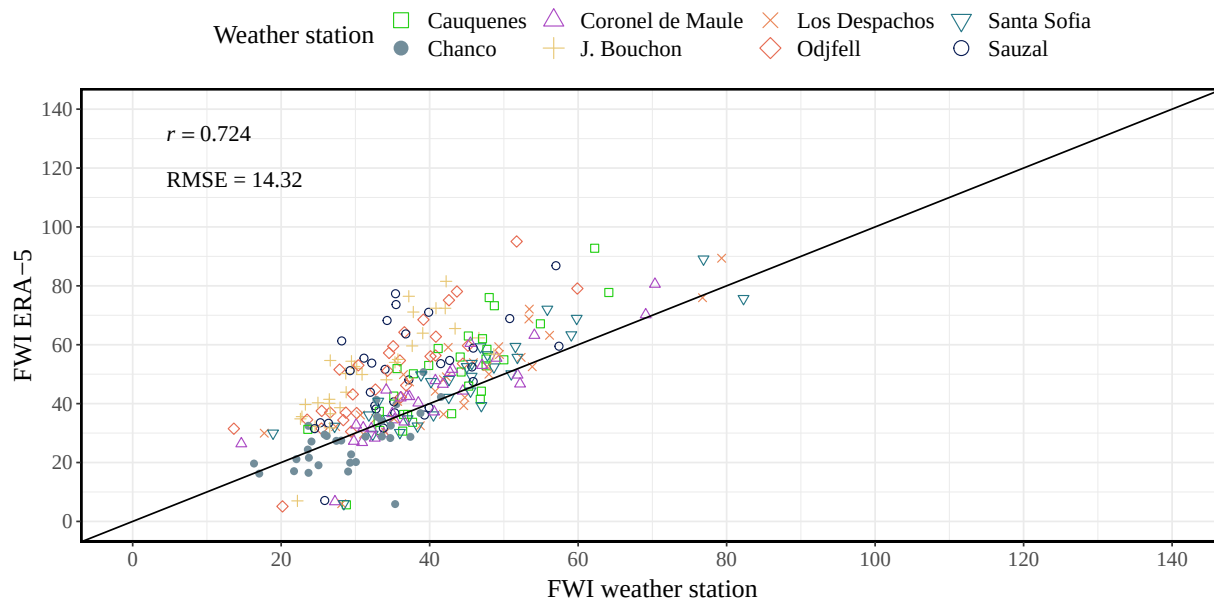


Figure 4.46: Fire weather index derived from ECMWF ERA-5 reanalysis data against FWI calculated at the weather stations. All the data is at 12:00 PM from January DOY 001 to 031, 2017.

4.3.7.10 FWI discussion

Bowman et al. (2019) studied the FWI for all the fires that took place within the austral summer of 2016–2017 in Central Chile using ERA-5 reanalysis data. The FWI results obtained in their study shows a similar behavior during the days of analysis in this study (Bowman et al., 2019, cf. Fig. 4). The maximum mean FWI was obtained during January 24th to 26th, 2017, whose value was around 60, and are the same mean FWI results obtained in this study on January 24th by the FWI derived from both Aqua and surface energy balance.

On the other hand, the FWI validation through weather station data shows that the capability of this methodology is not strongly overestimating nor underestimating the FWI, nevertheless more calibration points (weather stations) are required to conclude its efficiency for Central Chile.

The FWI evolution shows an upward trend before the event (from January 1st to 19th, 2017), and hence this might be a good indicator of the fire weather conditions within the ROI. However, the Fire Weather Index only shows a meteorological-based wildfire risk, which must be accompanied with other variables such as the fuel moisture content, or any other fuel-related variable.

A timeline of the event with the burned area, FWI and NSAT evolution is shown in Figure 4.47. Note that the burned area of MODIS MCD64A1 for a given day corresponds to the last 24 hours, and hence the values on January 26th includes the fires in Santa Olga the night of January 25th. Additionally, the maximum FWI values do not correspond to Santa Olga or close to its proximity, but have been detected at the south of the ROI in fires near Cauquenes. Nevertheless, the FWI map (see Figure 4.43) exhibits high FWI values (above 50) in Constitución municipality prior to the event from VIIRS-SNPP, Aqua-MODIS and the Energy balance, which are classified as extreme values.

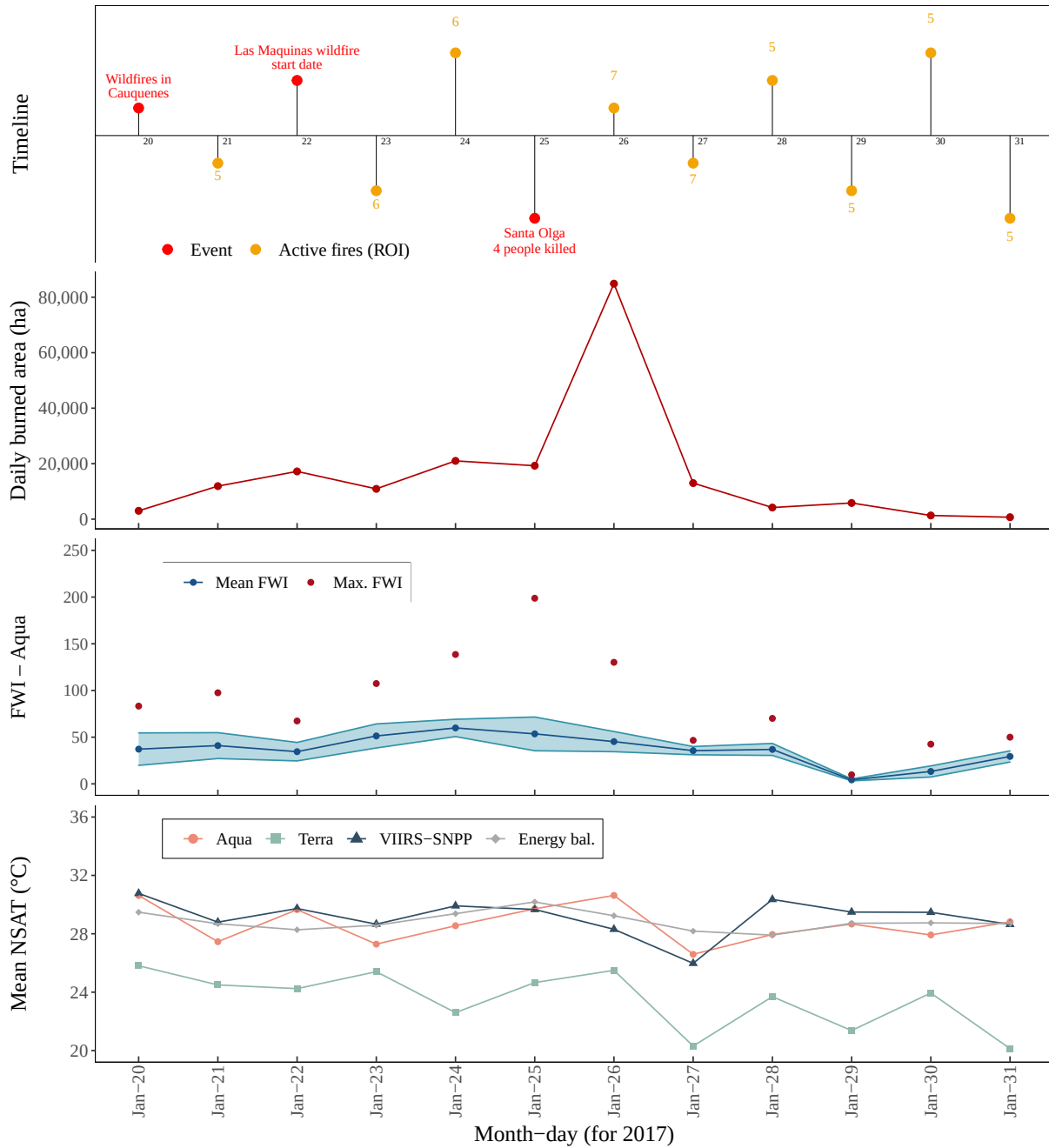


Figure 4.47: Event timeline, daily burned area, FWI, and NSAT evolution. Note that the timeline events were taken from [ONEMI \(2017b\)](#), and the active fires are within the Maule region.

Finally, the methodology proposed in this study exhibits the possibility to acquire the FWI within the same day, since MODIS and VIIRS-SNPP data is available within the day.

Conclusion

A framework to study the anatomy of the “Las Máquinas” wildfire was conducted using Earth Observation tools derived from multiple satellite-sensor products at a medium spatial resolution. The findings suggest that this methodology is useful for developing countries like Chile, where the acquisition of variables related to wildfire risk, such as the Canadian Fire Weather Index, can be obtained on a daily basis for free, and to provide insights on catastrophic events, which could be useful for forensic and public policy purposes.

Prior to the event, abundant and healthy vegetation was found within the ROI, with NDVI values above 0.5 for all the municipalities. The days before the event, Empedrado registered NDVI values around 0.67, and 16 days later (until the following satellite-sensor product was acquired) its mean NDVI decreased substantially to around 0.36 due to the fire, which makes it the most affected municipality based on the flora damage point of view. The affected species were mainly *Pinus radiata*, *Vachellia caven* and *Nothofagus glauca*, whose total burned area was 129,700, 13,700 and 13,500 ha, respectively. Moreover, the national park “Los Ruiles” within the Empedrado municipality had mainly *Nothofagus alessandrii* trees, an endangered species, and according to [CONAF \(2017b\)](#) the fire destroyed over the 90% of its surface.

In addition, some affected municipalities like Empedrado and Chanco had not experienced wildfires for several years according to the Global Fire Atlas database. This, together with high NDVI values indicate a high fuel availability at least for those municipalities. Moreover, average maximum temperatures obtained with ERA-Interim reanalysis and calibrated data by the CR² exhibited mean values (for the whole ROI) of around 29°C the month prior to the event, being the highest value registered by the product since 1979 for the region of interest. Additionally, the SPI shows from both IMERG and CR² data that there had been a severe and persistent drought since 2009. Therefore, the high fuel availability, high temperatures and severe drought manifest a high wildfire risk, which is even higher if the WUI component is added.

The severity of the fire derived from the dNBR analysis from both Landsat-8 and Sentinel-2 data exhibits high severity pixels within the Constitución and Empedrado municipalities. Furthermore, the most affected zones were those near the village of Santa Olga, which was completely decimated by the fires on the night of January 25th, where the burned area between that day and the next was about 85,000 ha according to the MODIS MCD64A1 product. Additionally, the FRP derived from both VIIRS-SNPP and MODIS data recorded energy release values over 2,000 MW within a 7-km radius of Santa Olga. The location of this village corresponds to an accurate description of the Wildland-Urban Interface, as it is surrounded by forests and its topography varies considerably nearby.

Air quality during the event was studied using the VIIRS-SNPP Deep Blue Aerosol (DBA) product, and the results showed a high presence of both high-altitude smoke and pyrocumulonimbus. To the author’s best knowledge, there is no report mentioning the formation of pyrocumulonimbus during the fire, which is interesting and gives the opportunity to do more research about it. In addition, Aerosol Optical Depth (AOD) was also acquired from the DBA product, and the results show an average AOD around 1.0 for January 25th and 26th, which also displayed maximum AOD values over 4.5, meaning that there were pixels in which the sunlight was completely blocked due to high amounts of particles in the atmosphere derived from the fire. Furthermore, carbon emissions were studied using the Global Fire Emissions database, and a high amount of carbon particles were found during the fire in January, with a mean of 197.49 g·C·m⁻², versus average values of 5.27 g·C·m⁻² in the previous seven years for the same month.

The Canadian Fire Weather Index (FWI) is a numeric rating of fire intensity used in the Canadian Fire

Danger Rating System, and in this study was calculated at a landscape-scale using daily remotely-sensed images at a medium resolution derived from both MODIS and VIIRS information. Near-surface air temperature is required for the computation of the FWI, and was calculated using multiple linear regression models, machine learning regression algorithms, and by applying a surface energy balance.

Overall, the best-performing regression models used to obtain the NSAT were those that applied machine learning and, in particular, random forests regression to the training dataset (e.g. $r = 0.955$ and $RMSE = 1.144^{\circ}\text{C}$ for Aqua data; cf. Figure 4.26). However, when the models were applied to the testing dataset, the pixels-validation against measured NSAT at the weather stations showed lower Pearson's correlation coefficients and higher RMSE results. When analyzing the data, the main difference found between the training and testing datasets was that the latter recorded higher temperatures, which affected the machine learning random forests regression algorithm, as the *machine* was not trained for such temperatures. For the MODIS-derived datasets, the best performing regression algorithm was the one applied to the Aqua data with random forests, where a Pearson's correlation coefficient of $r = 0.73$ and $RMSE = 3.34^{\circ}\text{C}$ were obtained. But for the morning data, i.e. derived from Terra-MODIS, the multiple linear regression model achieved better statistical results than the random forests. The largest errors in NSAT estimation were found towards the Pacific Ocean coast, particularly at *Chanco* weather station, where generally the NSAT values were overestimated or underestimated by the regression models, which may be due to the high variability of ambient temperature in a short period of time at the coast. Therefore, further studies are required to conclude on the effectiveness of NSAT estimates at the coast using the proposed methodology.

On the other hand, the NSAT calculated using the surface energy balance obtained the worst statistical results, displaying RMSE values over 11°C . However, after applying a random forests regression to the results using the weather station NSAT as the dependent variable, the results improved considerably, displaying $r = 0.893$ and $RMSE = 2.3^{\circ}\text{C}$ for the energy balance model using the NDVI derived from the daily surface reflectance product, i.e. EB-2 using MODIS MYD09GA, thus resulting in the best performing model to explain the near-surface air temperature.

As there was no correlation between the calculated relative humidity (RH) and the RH measured at the weather stations, the calculated RH also went through a pseudo-calibration procedure using the weather station RH as the dependent variable. This calibration was carried out using machine learning random forests regression, resulting in r values over 0.86 and RMSE under 9% of the RH.

In general, the Canadian FWI results showed the same behavior, although variations were found between the maximum FWI values for each of the satellite-sensor data used to compute the FWI. For example, the estimated FWI using the Aqua data achieved a maximum FWI of 200, while the approximate FWI using the same data resulted in a value of 225 on the same day. Moreover, the mean FWI values obtained are similar to those reported by Bowman et al. (2019) (cf. Fig. 4), who used ERA-Interim reanalysis data for all the fires that took place in Central and Southern Chile, and was around 60 between January 24th and 28th. The FWI index evolution did not show critical FWI values (over 100) near Santa Olga. However, extreme FWI values ranging from 50 to 83 were found on January 24th in Constitución near Santa Olga, i.e. one day before the catastrophe. In addition, the FWI evolution from January 1st to 19th showed an upward trend of the FWI, which can be interpreted as an increasing wildfire-risk within the ROI.

A validation of the FWI estimated from remotely-sensed data was carried out by comparing it with the FWI measured at weather stations. The results show that the use and application of a remote sensing methodology to calculate the FWI is feasible, since the results are neither strongly overestimated nor underestimated, however it would be interesting to study this approach for more wildfires in other Mediterranean regions, and to have even more control points (weather stations), since, as could be seen in the present work, there was a lack of them in the ROI.

Bibliography

- Albini, F. (1976). *Estimating wildfire behaviour and effects*. General Technical Report INT-30, USDA Forest Service, Intermountain Forest and Range Experiment Station.
- Alduchov, O. A. & Eskridge, R. E. (1996). Improved Magnus form approximation of saturation vapor pressure. *Journal of Applied Meteorology and Climatology*, 35(4), 601–609.
- Andela, N., Morton, D. C., Giglio, L., Paugam, R., Chen, Y., Hantson, S., Van Der Werf, G. R., & Randerson, J. T. (2019a). The global fire atlas of individual fire size, duration, speed and direction. *Earth System Science Data*, 11(2), 529–552.
- Andela, N., Morton, D. C., Giglio, L., & Randerson, J. (2019b). Global fire atlas with characteristics of individual fires, 2003-2016. ORNL DAAC, Oak Ridge, Tennessee, USA.
- Anderson, H. E. (1982). *Aids to determining fuel models for estimating fire behavior*. General Technical Report INT-122, USDA Forest Service, Intermountain Forest and Range Experiment Station Ogden, UT 844401.
- Arevalo-Ramirez, T., Villacrés, J., Fuentes, A., Reszka, P., & Cheein, F. A. A. (2020). Moisture content estimation of *Pinus radiata* and *Eucalyptus globulus* from reconstructed leaf reflectance in the SWIR region. *Biosystems Engineering*, 193, 187–205.
- Avila, J. I., Valdivia, J., Alves, D., Auat-Cheein, F., Fuentes, A., & Reszka, P. (2022). A modified Canadian Fire Weather Index for use in Central and Southern Chile. Manuscript submitted for publication.
- Awad, M. & Khanna, R. (2015). *Efficient learning machines: theories, concepts, and applications for engineers and system designers*. Springer nature.
- Balch, J. K., Bradley, B. A., Abatzoglou, J. T., Nagy, R. C., Fusco, E. J., & Mahood, A. L. (2017). Human-started wildfires expand the fire niche across the United States. *Proceedings of the National Academy of Sciences*, 114(11), 2946–2951.
- Balocchi, F., Flores, N., Neary, D., White, D. A., Silberstein, R., & de Arellano, P. R. (2020). The effect of the ‘Las Maquinas’ wildfire of 2017 on the hydrologic balance of a high conservation value Hualo (*Nothofagus glauca* (Phil.) Krasser) forest in central Chile. *Forest Ecology and Management*, 477, 118482.
- Bastiaanssen, W. G., Menenti, M., Feddes, R., & Holtslag, A. (1998a). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. *Journal of Hydrology*, 212, 198–212.
- Bastiaanssen, W. G., Pelgrum, H., Wang, J., Ma, Y., Moreno, J. F., Roerink, G. J., & van der Wal, T. (1998b). A remote sensing surface energy balance algorithm for land (SEBAL). 2. Validation. *Journal of Hydrology*, 212, 213–229.
- Batra, N., Islam, S., Venturini, V., Bisht, G., & Jiang, L. (2006). Estimation and comparison of evapotranspiration from MODIS and AVHRR sensors for clear sky days over the Southern Great Plains. *Remote Sensing of Environment*, 103(1), 1–15.

- BCN (1995). Decreto 13: Declara Monumento Natural Las Especies Forestales Queule, Pitao, Belloto del sur, Belloto del Norte y Ruil. Biblioteca del Congreso Nacional, BCN Legistalción chilena. Ministerio de Agricultura.
- Beguería, S. & Vicente-Serrano, S. M. (2017). *SPEI: Calculation of the Standardised Precipitation-Evapotranspiration Index*. R package version 1.7.
- Bergman, T. L., Incropera, F. P., DeWitt, D. P., & Lavine, A. S. (2011). *Fundamentals of heat and mass transfer*. John Wiley & Sons, 7th edition.
- BioBio (2017). Michelle Bachelet confirma 43 detenidos en 36 incendios forestales. Accessed in May 2022 from: <https://www.biobiochile.cl/noticias/nacional/chile/2017/01/29/michelle-bachelet-confirma-43-detenidos-en-36-incendios-forestales.shtml>.
- Bivand, R., Keitt, T., & Rowlingson, B. (2022). *rgdal: Bindings for the 'Geospatial' Data Abstraction Library*. R package version 1.5-30.
- Boisier, J. P., Rondanelli, R., Garreaud, R. D., & Muñoz, F. (2016). Anthropogenic and natural contributions to the Southeast Pacific precipitation decline and recent megadrought in central Chile. *Geophysical Research Letters*, 43(1), 413–421.
- Borbas, E. & Menzel, P. (2017). MODIS atmosphere L2 atmosphere profile product. NASA MODIS Adaptive Processing System. Goddard Space Flight Center Greenbelt, MD, USA.
- Bowman, D. M., Moreira-Muñoz, A., Kolden, C. A., Chávez, R. O., Muñoz, A. A., Salinas, F., González-Reyes, Á., Rocco, R., de la Barrera, F., Williamson, G. J., Borchers, N., Cifuentes, L. A., Abatzoglou, J. T., & Johnston, F. H. (2019). Human–environmental drivers and impacts of the globally extreme 2017 chilean fires. *Ambio*, 48(4), 350–362.
- Bradshaw, L. S., Deeming, J. E., Burgan, R. E., & Cohen, J. D. (1983). *The 1978 National Fire-Danger Rating System: Technical Documentation*. General Technical Report INT-169, USDA Forest Service. Intermountain Forest and Range Experiment Station, Ogden, UT.
- Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and regression trees*. Chapman & Hall/CRC.
- Burgan, R. E. (1979). *Estimating Live Fuel Moisture for the 1978 National Fire Danger Rating System*. Research Paper INT-226, USDA Forest Service.
- Burgan, R. E. (1988). *Revisions to the 1978 National Fire-Danger Rating System*. Research Paper SE-273, USDA Forest Service, Southeastern Forest Experiment Station.
- Burgan, R. E., Klaver, R. W., & Klaver, J. M. (1998). Fuel models and fire potential from satellite and surface observations. *International Journal of Wildland Fire*, 8(3), 159–170.
- Busetto, L. & Ranghetti, L. (2016). MODISstp: An R package for automatic preprocessing of MODIS Land Products time series. *Computers & Geosciences*, 97, 40–48.
- Butler, B., Cohen, J., Latham, D., Schuette, R., Sopko, P., Shannon, K., Jimenez, D., & Bradshaw, L. (2004). Measurements of radiant emissive power and temperatures in crown fires. *Canadian Journal of Forest Research*, 34(8), 1577–1587.
- Campbell, J. B. & Wynne, R. H. (2011). *Introduction to Remote Sensing*. New York, United States: The Guilford Press, 5th edition.

- Cardil, A., Rodrigues, M., Ramirez, J., de Miguel, S., Silva, C. A., Mariani, M., & Ascoli, D. (2021). Coupled effects of climate teleconnections on drought, Santa Ana winds and wildfires in southern California. *Science of The Total Environment*, 765, 142788.
- Carmagnani, M. A., Drake, P. W., Caviedes, C. N., & Johnson, J. J. (2022). Chile. encyclopedia britannica. Accessed in May 2022, from: <https://www.britannica.com/place/Chile>.
- Castillo, M., Plaza, Á., & Garfias, R. (2020). A recent review of fire behavior and fire effects on native vegetation in Central Chile. *Global Ecology and Conservation*, 24, e01210.
- Castillo, M., Saavedra, J., & Brull, B. B. (2019). Severidad del fuego en los mega incendios forestales ocurridos en Chile, en 2017. Acciones para mejorar el sistema de protección. *Territorium*, I(26), 5–18.
- Ceccato, P., Flasse, S., & Grégoire, J.-M. (2002a). Designing a spectral index to estimate vegetation water content from remote sensing data: Part 2. Validation and applications. *Remote Sensing of Environment*, 82(2-3), 198–207.
- Ceccato, P., Gobron, N., Flasse, S., Pinty, B., & Tarantola, S. (2002b). Designing a spectral index to estimate vegetation water content from remote sensing data: Part 1: Theoretical approach. *Remote Sensing of Environment*, 82(2-3), 188–197.
- Chas-Amil, M., Touza, J., & García-Martínez, E. (2013). Forest fires in the wildland–urban interface: a spatial analysis of forest fragmentation and human impacts. *Applied Geography*, 43, 127–137.
- Chuvieco, E. (2010). *Teledetección Ambiental: La observación de la Tierra desde el espacio*. Barcelona, España: Ariel Ciencia. 3° edición en esta presentación, actualizada: Octubre de 2010.
- Chuvieco, E., Riaño, D., Aguado, I., & Cocero, D. (2002). Estimation of fuel moisture content from multitemporal analysis of Landsat Thematic Mapper reflectance data: applications in fire danger assessment. *International Journal of Remote Sensing*, 23(11), 2145–2162.
- CIREN (2017a). Metadata: Área mega-incendio 2017. Centro de Información de Recursos Naturales. Cubierta cartográfica de megaincendio 2017 de CONAF. Accessed in April 2022 from: http://erosionmaule.ciren.cl/layers/geonode:AREA_MEGAINCENDIO_2017/metadata_detail.
- CIREN (2017b). DEM Alos Palsar Región del Maule. Centro de Información de Recursos Naturales. Accessed in January 2022 from Infraestructura de Datos Espaciales (IDE): <https://bit.ly/3fKi2SY>.
- Clarín (2017). Devastación en el sur del país. Incendios en Chile: ya son seis los muertos y el fuego sigue fuera de control. Accessed in May 2022 from: https://www.clarin.com/mundo/incendios-chile-muertos-fuego-sigue-control_0_rJX21TlVl.html.
- Climate Adapt (2020). Fire Weather Index - Monthly Mean, 1979-2020. Climate Adapt, sharing adaptation knowledge for a climate-resilient Europe. Accessed in May 2022 from <https://climate-adapt.eea.europa.eu/metadata/indicators/fire-weather-index-monthly-mean-1979-2019#:~:text=The%20fire%20weather%20index%20can,is%20between%2021.3%20and%2038.0>.
- Cocero, D., Riaño, D., Meza, E., & Chuvieco, E. (2004). Cartografía del tipo y estado de los combustibles. In E. Chuvieco & M. P. Martín Isabel (Eds.), *Nuevas tecnologías para la estimación del riesgo de incendios forestales*, volume 4 chapter III, (pp. 33–62). España: Consejo Superior de Investigaciones Científicas, Instituto de Economía y Geografía, csic edition.

- Cohen, J. D. & Deeming, J. E. (1985). *The National Fire Danger Rating System: basic equations*. General Technical Report PSW-82, USDA Forest Service, Pacific Southwest Forest and Range Experiment Station.
- CONAF (2016). Catastro de uso de suelo y vegetación. Comisión Nacional Forestal. Accessed in March 2022 from Infraestructura de Datos Espaciales (IDE): <https://bit.ly/3bw4K9b>.
- CONAF (2017a). Descripción y efectos: Tormenta de fuego 18 de enero al 5 de febrero de 2017. Comisión Nacional Forestal. Accessed in February 2022 from: <https://bit.ly/2r0owV5>.
- CONAF (2017b). Análisis de la Afectación y Severidad de los Incendios Forestales ocurridos en enero y febrero de 2017 sobre los usos de suelo y los ecosistemas naturales presentes entre las regiones de Coquimbo y La Araucanía de Chile. Comisión Nacional Forestal. Informe técnico. 56 p. Santiago, Chile.
- CONAF (2022a). Estadísticas - Causas según Daño de Incendios forestales 1987 - 2021. Accessed in April 2022 from: <https://www.conaf.cl/incendios-forestales/incendios-forestales-en-chile/estadisticas-historicas/>.
- CONAF (2022b). Estadísticas - Resumen nacional ocurrencia (número) y daño (superficie afectada) por incendios forestales 1964-2021. Accessed in April 2022 from <https://www.conaf.cl/incendios-forestales/incendios-forestales-en-chile/estadisticas-historicas/>.
- Contreras, T. E., Figueroa, J. A., Abarca, L., & Castro, S. A. (2011). Fire regimen and spread of plants naturalized in central Chile. *Revista Chilena de Historia Natural*, 84(3), 307–323.
- Cooperativa (2017). Confirman muerte de una persona en Santa Olga. Accessed in May 2022, from: <https://www.cooperativa.cl/noticias/pais/desastres-naturales/inundaciones/confirman-muerte-de-una-persona-en-santa-olga/2017-01-26/114458.html>.
- Coops, N. C. & Stone, C. (2005). A comparison of field-based and modelled reflectance spectra from damaged pinus radiata foliage. *Australian Journal of Botany*, 53(5), 417–429.
- CR2 (2022). Productos grillados. Center for Climate and Resilience Research. Obtained in March 2022 from: <https://www.cr2.cl/datos-productos-grillados/>.
- Danson, F. M. & Bowyer, P. (2004). Estimating live fuel moisture content from remotely sensed reflectance. *Remote Sensing of Environment*, 92(3), 309–321.
- Datt, B. (1999). Visible/near infrared reflectance and chlorophyll content in Eucalyptus leaves. *International Journal of Remote Sensing*, 20(14), 2741–2759.
- Dennison, P. E., Moritz, M. A., & Taylor, R. S. (2008). Evaluating predictive models of critical live fuel moisture in the Santa Monica Mountains, California. *International Journal of Wildland Fire*, 17(1), 18–27.
- Di Giuseppe, F., Vitolo, C., Krzeminski, B., Barnard, C., Maciel, P., & San-Miguel, J. (2020). Fire Weather Index: the skill provided by the European Centre for Medium-Range Weather Forecasts ensemble prediction system. *Natural Hazards and Earth System Sciences*, 20(8), 2365–2378.
- Diario Oficial de la República de Chile (2007). Oficializa primera clasificación de especies silvestre según su estado de conservación. Ministerio Secretaría General de la Presidencia. DS 151, Número 38.722.

- Didan, K. (2015). MOD13A1 MODIS/Terra+ Aqua Vegetation Indices 16-day L3 Global 500m SIN Grid V006 – NDVI. NASA EOSDIS Land Processes DAAC. Accessed in January 2022 from: <https://doi.org/10.5067/MODIS/MYD13A1.006>.
- Didan, K. & Barreto, A. (2018). VIIRS/NPP Vegetation Indices 16-Day L3 Global 500m SIN Grid V001. NASA EOSDIS Land Processes DAAC. Accessed in May 2022 from <https://doi.org/10.5067/VIIRS/VNP13A1.001>.
- Dos Santos, P., Matias, H., Deus, E., Águas, A., & Silva, J. S. (2015). Fire effects on capsules and encapsulated seeds from *Eucalyptus globulus* in Portugal. *Plant Ecology*, 216(12), 1611–1621.
- Dupont, J.-C., Haeffelin, M., Drobinski, P., & Besnard, T. (2008). Parametric model to estimate clear-sky longwave irradiance at the surface on the basis of vertical distribution of humidity and temperature. *Journal of Geophysical Research: Atmospheres*, 113(D7).
- Edwards, D. C. & McKee, T. B. (1997). *Characteristics of 20th century drought in the United States at multiple scales*. Climatology Report No. 97-2, Colorado State University, Department of Atmospheric Science, Fort Collins.
- El-Gammal, M., Ali, R., & Samra, R. (2014). NDVI threshold classification for detecting vegetation cover in Damietta governorate, Egypt. *Journal of American Science*, 10(8), 108–113.
- Emol (2021). Santa Olga: A cuatro años del incendio, obras de reconstrucción alcanzan un 98%. Accessed in May 2022 from: <https://www.emol.com/noticias/Nacional/2021/01/27/1010569/Reconstruccion-de-Santa-Olga.html#:~:text=El%2025%20de%20enero%20de,y%20consumiendo%20160%20mil%20h%C3%A9ctareas>.
- ESA (2022a). MultiSpectral Instrument (MSI) Overview. The European Space Agency. Accessed in May 2022 from: <https://sentinels.copernicus.eu/web/sentinel/technical-guides/sentinel-2-msi/msi-instrument>.
- ESA (2022b). Low Earth Orbit. The European Space Agency. Accessed in May 2022 from: https://www.esa.int/ESA_Multimedia/Images/2020/03/Low_Earth_orbit.
- FAO (2007). *Fire management – global assessment 2006: A thematic study prepared in the framework of the Global Forest Resources Assessment 2005*. Forestry Paper 151, Food and Agriculture Organization of the United Nations, Rome, Italy.
- Fasullo, J., Otto-Bliesner, B., & Stevenson, S. (2018). ENSO's changing influence on temperature, precipitation, and wildfire in a warming climate. *Geophysical Research Letters*, 45(17), 9216–9225.
- Fernandes, P. M., Davies, G. M., Ascoli, D., Fernández, C., Moreira, F., Rigolot, E., Stoof, C. R., Vega, J. A., & Molina, D. (2013). Prescribed burning in southern Europe: developing fire management in a dynamic landscape. *Frontiers in Ecology and the Environment*, 11(s1), e4–e14.
- Feron, S., Cordero, R. R., Damiani, A., Llanillo, P., Jorquera, J., Sepulveda, E., Asencio, V., Laroze, D., Labbe, F., Carrasco, J., et al. (2019). Observations and projections of heat waves in South America. *Scientific reports*, 9(1), 1–15.
- Filonchik, M., Yan, H., Zhang, Z., Yang, S., Li, W., & Li, Y. (2019). Combined use of satellite and surface observations to study aerosol optical depth in different regions of China. *Scientific reports*, 9(1), 1–15.

- Finney, M. A. (2006). An overview of FlamMap fire modeling capabilities. In P. L. Andrews & B. W. Butler (Eds.), *Fuels Management—How to Measure Success: Conference Proceedings*. 28-30 March 2006; Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.
- FIRMS (2022). Active fire data for near-real time monitoring and applications. NASA's Fire Information for Resource Management System. Accessed in May 2022 from: <https://firms.modaps.eosdis.nasa.gov/>.
- Flores-Aqueveque, V., Rojas, M., Aguirre, C., Arias, P. A., & González, C. (2020). South Pacific subtropical high from the late Holocene to the end of the 21st century: insights from climate proxies and general circulation models. *Climate of the Past*.
- Forthofer, J. M., Butler, B. W., & Wagenbrenner, N. S. (2014). A comparison of three approaches for simulating fine-scale surface winds in support of wildland fire management. Part I. Model formulation and comparison against measurements. *International Journal of Wildland Fire*, 23(7), 969–981.
- Franzese, J. & Raffaele, E. (2017). Fire as a driver of pine invasions in the Southern Hemisphere: a review. *Biological Invasions*, 19(8), 2237–2246.
- Friedl, M. & Sulla-Menashe, D. (2019). MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC. Obtained in March 2022 from: <https://doi.org/10.5067/MODIS/MCD12Q1.006>.
- Gao, B. & Kaufman, Y. (2015). MODIS atmosphere L2 water vapor product. NASA MODIS adaptive processing system, Goddard Space Flight Center, USA.
- Gao, B.-C. (1996). NDWI: A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, 58(3), 257–266.
- Garcia-Chevesich, P. A., Martínez, E., García, A., Castillo, M., Garfias, R., Neary, D., Pizarro, R., Valdes, R., Gonzalez, L., Venegas-Quinones, H. L., & Magni, C. (2019). Formation of post-fire water repellent layers on *Nothofagus glauca* (Hualo) forests, after the historical “Las Maquinas” wildfire in South-Central Chile. *American Journal of Environmental Sciences*, 15(1), 1–6.
- Garreaud, R. D., Alvarez-Garretón, C., Barichivich, J., Pablo Boisier, J., Christie, D., Galleguillos, M., LeQuesne, C., McPhee, J., & Zambrano-Bigiarini, M. (2017). The 2010-2015 megadrought in central Chile: impacts on regional hydroclimate and vegetation. *Hydrology and Earth System Sciences*.
- Garreaud, R. D., Boisier, J. P., Rondanelli, R., Montecinos, A., Sepúlveda, H. H., & Veloso-Aguila, D. (2020). The central Chile mega drought (2010–2018): a climate dynamics perspective. *International Journal of Climatology*, 40(1), 421–439.
- Gibbins, C. (1990). A survey and comparison of relationships for the determination of the saturation vapour pressure over plane surfaces of pure water and of pure ice. *Annales Geophysicae*, 8(8), 859–885.
- Giglio, L. & Justice, C. (2021). MODIS/Terra+ Aqua Thermal Anomalies/Fire Daily L3 Global 1km SIN Grid V061. NASA EOSDIS Land Processes DAAC.
- Giglio, L., Justice, C., Boschetti, L., & Roy, D. (2015). MCD64A1 MODIS/Terra+ Aqua Burned Area Monthly L3 Global 500 m SIN Grid V006 Burned Monthly 500m. NASA EOSDIS Land Processes DAAC: Sioux Falls, SD, USA.

- Giglio, L., Loboda, T., Roy, D. P., Quayle, B., & Justice, C. O. (2009). An active-fire based burned area mapping algorithm for the MODIS sensor. *Remote sensing of environment*, 113(2), 408–420.
- Giglio, L., Randerson, J. T., & Van Der Werf, G. R. (2013). Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4). *Journal of Geophysical Research: Biogeosciences*, 118(1), 317–328.
- Gitelson, A. A., Gritz, Y., & Merzlyak, M. N. (2003). Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *Journal of Plant Physiology*, 160(3), 271 – 282.
- Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment*, 58(3), 289–298.
- Gitelson, A. A., Keydan, G. P., & Merzlyak, M. N. (2006). Three-band model for noninvasive estimation of chlorophyll, carotenoids, and anthocyanin contents in higher plant leaves. *Geophysical Research Letters*, 33(11).
- Gitelson, A. A. & Merzlyak, M. N. (1994). Quantitative estimation of chlorophyll-a using reflectance spectra: experiments with autumn chestnut and maple leaves. *Journal of Photochemistry and Photobiology B: Biology*, 22(3), 247–252.
- Gitelson, A. A., Merzlyak, M. N., & Chivkunova, O. B. (2001). Optical properties and nondestructive estimation of anthocyanin content in plant leaves. *Photochem. Photobiol.*, 74(1), 38–45.
- Gómez-González, S., Torres-Díaz, C., Valencia, G., Torres-Morales, P., Cavieres, L. A., & Pausas, J. G. (2011). Anthropogenic fires increase alien and native annual species in the Chilean coastal matorral. *Diversity and Distributions*, 17(1), 58–67.
- González, M., Sapiains, R., Gómez-González, S., Garreaud, R., Miranda, A., Galleguillos, M., Jacques, M., Pauchard, A., Hoyos, J., Cordero, L., Vásquez, F., Lara, A., Aldunce, P., Delgado, V., Arriagada-Ugarte, A., Sepúlveda, A., Farías, L., García, R., Rondanelli, R., Ponce, R., Vargas, F., Rojas, M., Boisier, J., Carrasco, C., Little, C., Osses, M., Zamorano, C., Díaz-Hormazábal, I., Ceballos, A., Guerra, E., Moncada, M., & Castillo, I. (2020). Incendios forestales en Chile: causas, impactos y resiliencia. Center for Climate and Resilience Research (CR)2, Universidad de Chile, Universidad de Concepción y Universidad Austral de Chile.
- Good, E. J., Ghent, D. J., Bulgin, C. E., & Remedios, J. J. (2017). A spatiotemporal analysis of the relationship between near-surface air temperature and satellite land surface temperatures using 17 years of data from the ATSR series. *Journal of Geophysical Research: Atmospheres*, 122(17), 9185–9210.
- Greenland, S., Senn, S. J., Rothman, K. J., Carlin, J. B., Poole, C., Goodman, S. N., & Altman, D. G. (2016). Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. *European Journal of Epidemiology*, 31(4), 337–350.
- Guttman, N. B. (1999). Accepting the standardized precipitation index: a calculation algorithm 1. *Journal of the American Water Resources Association*, 35(2), 311–322.
- Hammer, R. B., Radeloff, V. C., Fried, J. S., & Stewart, S. I. (2007). Wildland–urban interface housing growth during the 1990s in California, Oregon, and Washington. *International Journal of Wildland Fire*, 16(3), 255–265.

- Hardisky, M. A., Klemas, V., & Smart, R. M. (1983). The influence of soil salinity, growth form, and leaf moisture on the spectral reflectance of *Spartina alterniflora* canopies. *Photogrammetric Engineering & Remote Sensing*, 49, 77–83.
- He, L., Wang, L., Li, Z., Jiang, D., Sun, L., Liu, D., Liu, L., Yao, R., Zhou, Z., & Wei, J. (2021). VIIRS environmental data record and Deep Blue Aerosol products: validation, comparison, and spatiotemporal variations from 2013 to 2018 in China. *Atmospheric Environment*, 250, 118265.
- Hijmans, R. J. (2020). *raster: Geographic Data Analysis and Modeling*. R package version 3.0-12.
- Hoover, K. & Hanson, L. A. (2022). Wildfire statistics. In Focus. Congressional Research Service, Updated June 1, 2022. Version.
- Hou, P., Chen, Y., Qiao, W., Cao, G., Jiang, W., & Li, J. (2013). Near-surface air temperature retrieval from satellite images and influence by wetlands in urban region. *Theoretical and Applied Climatology*, 111(1-2), 109–118.
- Hsu, N. C., Jeong, M.-J., Bettenhausen, C., Sayer, A., Hansell, R., Seftor, C., Huang, J., & Tsay, S.-C. (2013). Enhanced Deep Blue aerosol retrieval algorithm: The second generation. *Journal of Geophysical Research: Atmospheres*, 118(16), 9296–9315.
- Hsu, N. C., Lee, J., Sayer, A., Kim, W., Bettenhausen, C., & Tsay, S.-C. (2019). VIIRS Deep Blue Aerosol products over land: Extending the EOS long-term aerosol data records. *Journal of Geophysical Research: Atmospheres*, 124(7), 4026–4053.
- Hsu, N. C., Tsay, S.-C., King, M. D., & Herman, J. R. (2004). Aerosol properties over bright-reflecting source regions. *IEEE Transactions on Geoscience and Remote Sensing*, 42(3), 557–569.
- Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, 32(1), 1–6.
- Huete, A. R., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83(1-2), 195–213.
- Huffman, G., Bolvin, D., Braithwaite, D., Hsu, K., Joyce, R., & Xie, P. (2014). Integrated multi-satellite retrievals for GPM (IMERG). Version 4.4. NASA's Precipitation Processing Center. Accessed in May 2020 from: <ftp://arthurhou.pps.eosdis.nasa.gov/gpmdata/>.
- Huffman, G., Stocker, E., Bolvin, D., Nelkin, E., & Tan, J. (2019a). GPM IMERG Final Precipitation L3 1 month 0.1 degree x 0.1 degree V06. Edited by Greenbelt, MD. Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed in May 2020 from: <https://doi.org/10.5067/GPM/IMERG/3B-MONTH/06>.
- Huffman, G., Stocker, E., Bolvin, D., Nelkin, E., & Tan, J. (2019b). GPM IMERG Final Precipitation L3 1 day 0.1 degree x 0.1 degree V06. Edited by Andrey Savtchenko, Greenbelt, MD, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed in May 2020 from: <https://doi.org/10.5067/GPM/IMERGDF/DAY/06>.
- Hulley, G. & Hook, S. (2018). VIIRS/NPP Land Surface Temperature and Emissivity 6-Min L2 Swath 750m V001. NASA EOSDIS Land Processes DAAC. Accessed in May 2022 from: <https://doi.org/10.5067/VIIRS/VNP21.001>.

- Hunt Jr, E. R. & Rock, B. N. (1989). Detection of changes in leaf water content using Near- and Middle-Infrared reflectances. *Remote Sensing of Environment*, 30(1), 43–54.
- James, D. & Hornik, K. (2020). *chron: Chronological Objects which Can Handle Dates and Times*. R package version 2.3-56. S original by David James, R port by Kurt Hornik.
- Justice, C., Townshend, J., Vermote, E., Masuoka, E., Wolfe, R., Saleous, N., Roy, D., & Morisette, J. (2002). An overview of MODIS Land data processing and product status. *Remote Sensing of Environment*, 83(1-2), 3–15.
- Kawashima, S., Ishida, T., Minomura, M., & Miwa, T. (2000). Relations between surface temperature and air temperature on a local scale during winter nights. *Journal of Applied Meteorology and Climatology*, 39(9), 1570–1579.
- Keane, R. E., Burgan, R., & van Wagtendonk, J. (2001). Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modeling. *International Journal of Wildland Fire*, 10(4), 301–319.
- Key, C. H. & Benson, N. C. (1999). The Normalized Burn Ratio, a Landsat TM radiometric index of burn severity incorporating multi-temporal differencing. U.S. Geological Survey, Northern Rocky Mountain Science Center.
- Key, C. H. & Benson, N. C. (2006). *Landscape assessment (LA) – Sampling and analysis methods*. Technical Report RMRS-GTR-164-CD, USDA Forest Service.
- Klein, D., Richter, R., Strobl, C., & Schlöpfer, D. (2019). Solar influence on fire radiative power retrieved with the bispectral method. *IEEE Transactions on Geoscience and Remote Sensing*, 57(7), 4521–4528.
- Kolmogorov-Smirnov (2008). *Kolmogorov–Smirnov Test*, (pp. 283–287). Springer New York: New York.
- Konika Minolta (2019). What is the difference between radiometers, spectrometers, and spectroradiometers? Accessed in December 2021 from: <https://sensing.konicaminolta.us/blog/what-is-the-difference-between-radiometers-spectrometers-and-spectroradiometers/>.
- Lawrence, M. G. (2005). The relationship between relative humidity and the dewpoint temperature in moist air: a simple conversion and applications. *Bulletin of the American Meteorological Society*, 86(2), 225–234.
- Lawson, B. D. & Armitage, O. (2008). Weather guide for the Canadian forest fire danger rating system. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta. 84 pp.
- Li, F., Zhang, X., Kondragunta, S., & Csiszar, I. (2018). Comparison of fire radiative power estimates from VIIRS and MODIS observations. *Journal of Geophysical Research: Atmospheres*, 123(9), 4545–4563.
- Liacos, L. (1986). Le pâturage et le feu prescrit, des outils efficaces dans l'aménagement des forêts méditerranéennes du groupe pin d'alep. *CIHEAM–Options Mediterraneennes*, 86(1), 179–199.
- Liaw, A. & Wiener, M. (2002). Classification and regression by randomforest. *R News*, 2(3), 18–22.
- Lintz, J. & Simonett, D. S. (1976). *Remote sensing of environment*. Reading, Mass. Addison-Wesley Publishing Co., Inc.

- McAllister, S., Grenfell, I., Hadlow, A., Jolly, W. M., Finney, M., & Cohen, J. (2012). Piloted ignition of live forest fuels. *Fire Safety Journal*, 51, 133–142.
- McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432.
- McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, volume 73 (pp. 179–183). Anaheim, California.
- McVeagh, P., Yule, I., & Grafton, M. (2012). Pasture yield mapping from your groundspread truck. In L. D. Currie & C. L. Christensen (Eds.), *Advanced Nutrient Management: Gains from the Past – Goals for the Future* (pp. 24–29).: Occasional Report No. 25. Fertilizer and Lime Research Centre, Massey University, Palmerston North, New Zealand.
- McWethy, D. B., Pauchard, A., García, R. A., Holz, A., González, M. E., Veblen, T. T., Stahl, J., & Currey, B. (2018). Landscape drivers of recent fire activity (2001–2017) in South-Central Chile. *PloS One*, 13(8).
- Medrano, C. (2017). Alcalde de Constitución: Localidad de “Santa Olga se quemó entera”. Last access in May 2022.
- Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., & Leisch, F. (2021). *e1071: Misc Functions of the Department of Statistics, Probability Theory Group (Formerly: E1071), TU Wien*. R package version 1.7-9.
- Miller, R. K., Field, C. B., & Mach, K. J. (2020). Barriers and enablers for prescribed burns for wildfire management in California. *Nature Sustainability*, 3(2), 101–109.
- Mindykowski, P., Fuentes, A., Consalvi, J., & Porterie, B. (2011). Piloted ignition of wildland fuels. *Fire Safety Journal*, 46(1), 34–40.
- Miranda, A., Altamirano, A., Cayuela, L., Lara, A., & González, M. (2017). Native forest loss in the chilean biodiversity hotspot: revealing the evidence. *Regional Environmental Change*, 17(1), 285–297.
- Mishra, S. & Mishra, D. R. (2012). Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. *Remote Sensing of Environment*, 117(0), 394–406.
- Moran, M. S., Jackson, R. D., Raymond, L. H., Gay, L. W., & Slater, P. N. (1989). Mapping surface energy balance components by combining Landsat Thematic Mapper and ground-based meteorological data. *Remote Sensing of Environment*, 30(1), 77–87.
- Murray, B. R., Hardstaff, L. K., & Phillips, M. L. (2013). Differences in leaf flammability, leaf traits and flammability-trait relationships between native and exotic plant species of dry sclerophyll forest. *PloS one*, 8(11), e79205.
- Mutiibwa, D., Strachan, S., & Albright, T. (2015). Land surface temperature and surface air temperature in complex terrain. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(10), 4762–4774.
- Naresh Kumar, M., Murthy, C., Sessa Sai, M., & Roy, P. (2009). On the use of Standardized Precipitation Index (SPI) for drought intensity assessment. *Meteorological Applications*, 16(3), 381–389.

- NASA (2021). Data processing levels. NASA EarthData. Accessed in May 2022 from <https://www.earthdata.nasa.gov/engage/open-data-services-and-software/data-information-policy/data-levels>.
- NASA (2022a). MODIS: Specifications. National Aeronautics and Space Administration. Accessed in May 2022 from <http://modis.gsfc.nasa.gov/about/specifications.php>.
- NASA (2022b). Visible Infrared Imaging Radiometer Suite (VIIRS). NASA's EarthData, Level-1 and Atmosphere Archive & Distribution System - Distributed Active Archive Center (LAADS - DAAC). Accessed in May 2022 from: <https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/viirs/>.
- NASA (2022c). Landsat 8. NASA Landsat Science. Accessed in May 2022 from: [https://landsat.gsfc.nasa.gov/satellites/landsat-8/#:~:text=The%20Landsat%20satellite%20payload,and%2015%20meters%20\(panchromatic\)](https://landsat.gsfc.nasa.gov/satellites/landsat-8/#:~:text=The%20Landsat%20satellite%20payload,and%2015%20meters%20(panchromatic)).
- NASA LAADS (2018). The Deep Blue aerosol project: Aerosol retrievals from S-NPP VIIRS. Data product user guide and file specification document. This guide is specific to Version-1 of the VIIRS Deep Blue Aerosol data products. Accessed in March 2022, from: https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/viirs/viirs_deep_blue_user_guide_v1.0.pdf.
- NEO (2022). Aerosol optical depth. NASA Earth Observations (NEO). Accessed in March 2022 from: https://earthobservatory.nasa.gov/global-maps/MODAL2_M_AER_OD#:~:text=An%20optical%20thickness%20of%20less,places%20and%20times%20of%20year.
- NRC (2021). Canadian Forest Fire Weather Index (FWI) System. Natural Resources Canada, Government of Canada. Accessed in May 2022 from: <http://cwfis.cfs.nrcan.gc.ca/background/summary/fwi>.
- NWCG (2022). Glossary of wildland fire, PMS 205. Accessed in May 2022 from: https://datainventory.doi.gov/explorer/tbl/glossary.editor#nwcgorg:ORG_FMB.
- ONEMI (2017a). Resumen nacional de incendios forestales del 2017-01-31 a las 6:15 AM. Oficina Nacional de Emergencia del Ministerio del Interior, Gobierno de Chile. Accessed in May 2022 from <https://www.onemi.gov.cl/alerta/resumen-nacional-de-incendios-forestales-3/>.
- ONEMI (2017b). Monitoreo para la Región del Maule por incendios forestales. Oficina Nacional de Emergencia del Ministerio del Interior, Gobierno de Chile. Accessed in May 2022 from <https://www.onemi.gov.cl/alerta/monitoreo-para-la-region-del-maule-por-incendios-forestales/>.
- Parks, S. A., Dillon, G. K., & Miller, C. (2014). A new metric for quantifying burn severity: The Relativized Burn Ratio. *Remote Sensing*, 6(3), 1827–1844.
- Paton, D., Buergelt, P. T., Tedim, F., & McCaffrey, S. (2015). Wildfires: International perspectives on their social—ecological implications. In *Wildfire hazards, risks and disasters* (pp. 1–14). Elsevier.
- Pauchard, A., Garcia, R. A., Pena, E., González, C., Cavieres, L. A., & Bustamante, R. O. (2008). Positive feedbacks between plant invasions and fire regimes: Teline monspessulana (L.) K. Koch (Fabaceae) in Central Chile. *Biological Invasions*, 10(4), 547–553.
- Pebesma, E. (2018). Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, 10(1), 439–446.
- Pebesma, E. J. (2004). Multivariable geostatistics in s: the gstat package. *Computers & geosciences*, 30(7), 683–691.

- Peterson, S. H., Roberts, D. A., & Dennison, P. E. (2008). Mapping live fuel moisture with {MODIS} data: A multiple regression approach. *Remote Sens. Environ.*, 112(12), 4272 – 4284.
- Peñuelas, J. & Filella, I. (1998). Visible and near-infrared reflectance techniques for diagnosing plant physiological status. *Trends in Plant Science*, 3(4), 151–156.
- Peñuelas, J., Piñol, J., Ogaya, R., & Filella, I. (1997). Estimation of plant water concentration by the reflectance Water Index WI (R900/R970). *International Journal of Remote Sensing*, 18(13), 2869–2875.
- Pierce, D. (2021). *ncdf4: Interface to Unidata netCDF (Version 4 or Earlier) Format Data Files*. R package version 1.19.
- Pörtner, H.-O., Roberts, D., Poloczanska, E., Mintenbeck, K., Tignor, M., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., & Okem, A. (2022). IPCC, 2022: Summary for Policymakers. In H.-O. Pörtner, D. Roberts, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama (Eds.), *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*: Cambridge University Press. In Press.
- QGIS Development Team (2009). *QGIS Geographic Information System*. Open Source Geospatial Foundation.
- R Core Team (2021). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.
- R Core Team (2022). *foreign: Read Data Stored by 'Minitab', 'S', 'SAS', 'SPSS', 'Stata', 'Systat', 'Weka', 'dBase'*. R package version 0.8-82.
- Radeloff, V. C., Hammer, R. B., Voss, P. R., Hagen, A. E., Field, D. R., & Mladenoff, D. J. (2001). Human demographic trends and landscape level forest management in the northwest Wisconsin pine barrens. *Forest Science*, 47(2), 229–241.
- Ramos, A. P. M., Osco, L. P., Furuya, D. E. G., Gonçalves, W. N., Santana, D. C., Teodoro, L. P. R., da Silva Junior, C. A., Capristo-Silva, G. F., Li, J., Baio, F. H. R., et al. (2020). A random forest ranking approach to predict yield in maize with uav-based vegetation spectral indices. *Computers and Electronics in Agriculture*, 178, 105791.
- Ranghetti, L., Boschetti, M., Nutini, F., & Busetto, L. (2020). sen2r: An R toolbox for automatically downloading and preprocessing Sentinel-2 satellite data. *Computers & Geosciences*, 139, 104473.
- Reszka, P., Cruz, J., Valdivia, J., González, F., Rivera, J., Carvajal, C., & Fuentes, A. (2020). Ignition delay times of live and dead *Pinus radiata* needles. *Fire Safety Journal*, 112, 102948.
- Reyes, O. & Casal, M. (2001). The influence of seed age on germinative response to the effects of fire in *Pinus pinaster*, *Pinus radiata* and *Eucalyptus globulus*. *Annals of Forest Science*, 58(4), 439–447.
- Rosenqvist, A., Shimada, M., Ito, N., & Watanabe, M. (2007). ALOS PALSAR: A pathfinder mission for global-scale monitoring of the environment. *IEEE Transactions on Geoscience and Remote Sensing*, 45(11), 3307–3316.
- Rossiello, M. R. & Szema, A. (2019). Health effects of climate change-induced wildfires and heatwaves. *Cureus*, 11(5).

- Rouse, J. W., Haas, R. H., Schell, J. A., Deering, D. W., & Harlan, J. C. (1973). *Monitoring the vernal advancement and retrogradation (greenwave effect) of natural vegetation*. Technical Report E74-10676, Texas A&M University, Remote Sensing Center, College Station, Texas, United States. Prepared for Goddard Space Flight Center.
- Rouse, J. W., Haas, R. H., Schell, J. A., Deering, D. W., & Harlan, J. C. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA special publication*, 351, 309.
- Roy, D. P. & Boschetti, L. (2009). Southern Africa validation of the MODIS, L3JRC, and GlobCarbon burned-area products. *IEEE Transactions on Geoscience and Remote Sensing*, 47(4), 1032–1044.
- Running, S., Mu, Q., & Zhao, M. (2017). MOD16A2 MODIS/Terra+ Aqua Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006 Latent Heat Flux. NASA EOSDIS Land Processes DAAC. Accessed in January 2022 from: <https://doi.org/10.5067/MODIS/MOD16A2.006>.
- Salas, E. A. L. & Henebry, G. M. (2013). A new approach for the analysis of hyperspectral data: Theory and sensitivity analysis of the Moment Distance Method. *Remote Sensing*, 6(1), 20–41.
- Salas, F. J. & Chuvieco, E. (1995). Aplicación de imágenes Landsat-TM a la cartografía de modelos combustibles. *Revista de Teledetección*, (pp. 5: 18–28).
- Salas, F. J. & Cocero, D. (2004). El concepto de peligro de incendio. Sistemas actuales de estimación del peligro. In E. Chuvieco & M. P. Martín Isabel (Eds.), *Nuevas tecnologías para la estimación del riesgo de incendios forestales* chapter II.4, (pp. 23–32). España: CSIC.
- Sayer, A., Hsu, N., Lee, J., Bettenhausen, C., Kim, W., & Smirnov, A. (2018). Satellite Ocean Aerosol Retrieval (SOAR) algorithm extension to S-NPP VIIRS as part of the “Deep Blue” aerosol project. *Journal of Geophysical Research: Atmospheres*, 123(1), 380–400.
- Schroeder, W. & Giglio, L. (2018). VIIRS/NPP Thermal Anomalies/Fire Daily L3 Global 1km SIN Grid V001. NASA EOSDIS Land Processes DAAC. Accessed in March 2022 from <https://doi.org/10.5067/VIIRS/VNP14A1.001>.
- Scott, J. H. & Burgan, R. E. (2005). *Standard fire behavior fuel models: A comprehensive set for use with Rothmel’s surface fire spread model*. General Technical Report RMRS-GTR-153, USDA Forest Service. Rocky Mountain Research Station.
- Scott, J. H. & Reinhardt, E. D. (2001). *Assessing crown fire potential by linking models of surface and crown fire behavior*. Research Paper RMRS-RP-29, USDA Forest Service. Rocky Mountain Research Station.
- Shaftel, H., Jackson, R., Callery, S., & Bailey, D. (2018). Global climate change: Vital signs of the planet. NASA’s Jet Propulsion Laboratory. California Institute of Technology. Accessed in May 2022 from: <https://climate.nasa.gov/causes/>.
- Shen, H., Tao, S., Chen, Y., Odman, M. T., Zou, Y., Huang, Y., Chen, H., Zhong, Q., Zhang, Y., Chen, Y., et al. (2019). Global fire forecasts using both large-scale climate indices and local meteorological parameters. *Global Biogeochemical Cycles*, 33(8), 1129–1145.
- Simeoni, A. (2016). Wildland fires. In *SFPE handbook of fire protection engineering* (pp. 3283–3302). Springer.

- Smakhtin, V. U. & Hughes, D. A. (2007). Automated estimation and analyses of meteorological drought characteristics from monthly rainfall data. *Environmental Modelling & Software*, 22(6), 880–890.
- Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F., & Stahl, K. (2015). Candidate distributions for climatological drought indices (spi and spei). *International Journal of Climatology*, 35(13), 4027–4040.
- Suarez, L., Restrepo-Coupe, N., Hueni, A., & Chisholm, L. A. (2015). Vegetation spectroscopy. In A. Held, S. Phinn, M. Soto-Berelov, & S. Jones (Eds.), *AusCover Good Practice Guidelines: A technical handbook supporting calibration and validation activities of remotely sensed data product* (pp. 221–233). Version 1.1. TERN AusCover.
- Sulla-Menashe, D. & Friedl, M. A. (2018). User guide to collection 6 MODIS land cover (MCD12Q1 and MCD12C1) product. Vol. 1, USGS: Reston, VA, USA.
- Sundström, A.-M., Arola, A., Kolmonen, P., Xue, Y., de Leeuw, G., & Kulmala, M. (2015). On the use of a satellite remote-sensing-based approach for determining aerosol direct radiative effect over land: a case study over China. *Atmospheric Chemistry and Physics*, 15(1), 505–518.
- The World Bank (2022). GDP (current US\$) - Chile. Accessed in May 2022 from: <https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=CL>.
- Therneau, T. & Atkinson, B. (2022). *rpart: Recursive Partitioning and Regression Trees*. R package version 4.1.16.
- Thom, A. S. & Oliver, H. R. (1977). On Penman's equation for estimating regional evaporation. *Quarterly Journal of the Royal Meteorological Society*, 103(436), 345–357.
- Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8(2), 127–150.
- Úbeda, X. & Sarricolea, P. (2016). Wildfires in chile: A review. *Global and Planetary Change*, 146, 152–161.
- UNEP (2022). Spreading like Wildfire – The Rising Threat of Extraordinary Landscape Fires. A rapid response assessment. United Nations Environment Programme. Nairobi.
- Urban, J. L. & Fernandez-Pello, A. C. (2020). Ignition. *Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires*, (pp. 649–657).
- Urrutia-Jalabert, R., González, M. E., González-Reyes, Á., Lara, A., & Garreaud, R. (2018). Climate variability and forest fires in central and South-Central Chile. *Ecosphere*, 9(4), e02171.
- USGS (2022a). Landsat 8. United States Geological Survey. Accessed in May 2022 from <https://www.usgs.gov/landsat-missions/landsat-8>.
- USGS (2022b). MODIS overview. United States Geological Survey. Accessed in May 2022 from: <https://lpdaac.usgs.gov/data/get-started-data/collection-overview/missions/modis-overview/>.
- USGS (2022c). VIIRS overview. United States Geological Survey. Accessed in May 2022 from: <https://lpdaac.usgs.gov/data/get-started-data/collection-overview/missions/s-npp-nasa-viirs-overview/>.

- Valdivia, J. (2017). Teledetección satelital y espectrometría de campo como herramientas para la estimación del contenido de humedad de la especie pinus radiata en la V región de Valparaíso. Memoria para optar al título de Ingeniero en Aviación Comercial, Universidad Técnica Federico Santa María – Academia de Ciencias Aeronáuticas, Santiago, Chile.
- Van Der Werf, G. R., Randerson, J. T., Giglio, L., Van Leeuwen, T. T., Chen, Y., Rogers, B. M., Mu, M., Van Marle, M. J., Morton, D. C., Collatz, G. J., & Yokelson, R. J. (2017). Global fire emissions estimates during 1997–2016. *Earth System Science Data*, 9(2), 697–720.
- Van Wagner, C. E. (1974). *Structure of the canadian forest fire weather index*. Publication No. 1333, Canadian Department of Environment. Canadian Forestry Service, Ottawa.
- Van Wagner, C. E. (1987). *Development and structure of the Canadian forest Fire Weather Index system*. Forestry Technical Report 35, Canadian Department of Environment. Canadian Forestry Service, Ottawa.
- Van Wagner, C. E. & Pickett, T. L. (1985). *Equations and FORTRAN program for the Canadian Forest Fire Weather Index system*. Forestry Technical Report 33, Canadian Department of Environment. Canadian Forestry Service, Ottawa.
- Van Wagendonk, J. W., Root, R. R., & Key, C. H. (2004). Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. *Remote Sensing of Environment*, 92(3), 397–408.
- vanRossum, G. (1995). Python reference manual. *Department of Computer Science [CS]*, (R 9525).
- Vaughan, P. (2001). *Estimación de contenido de humedad de la vegetación mediante espectroradiometría*. PhD thesis, Universidad de Alcalá, Alcalá de Henares, España.
- Verdon, D. C., Kiem, A. S., & Franks, S. W. (2004). Multi-decadal variability of forest fire risk—eastern Australia. *International Journal of Wildland Fire*, 13(2), 165–171.
- Vermote, E. & Wolfe, R. (2015). MOD09GA MODIS/Terra+ Aqua Surface Reflectance Daily L2G Global 1km and 500m SIN Grid V006 Land Surface Reflectance B1-B7. NASA EOSDIS Land Processes DAAC. Accessed in May 2022 from: <https://doi.org/10.5067/MODIS/MOD09GA.006>.
- Vitolo, C., Di Giuseppe, F., Barnard, C., Coughlan, R., San-Miguel-Ayanz, J., Libertá, G., & Krzeminski, B. (2020). ERA5-based global meteorological wildfire danger maps. *Scientific data*, 7(1), 1–11.
- Vitolo, C., Di Giuseppe, F., Krzeminski, B., & San-Miguel-Ayanz, J. (2019). A 1980–2018 global fire danger re-analysis dataset for the Canadian Fire Weather Indices. *Scientific data*, 6(1), 1–10.
- Wallemacq, P. & House, R. (2018). Economic losses, poverty & disasters: 1998-2017. Collaboration between: Centre for Research on the Epidemiology of Disasters (CRED) & United Nations Office for Disaster Risk Reduction (UNDRR).
- Wan, Z., Hook, S., & Hulley, G. (2015). MOD11A1 MODIS/Terra+ Aqua Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V006 Day Land Surface Temperature. NASA EOSDIS Land Processes DAAC. Accessed in May 2022 from: <https://doi.org/10.5067/MODIS/MOD11A1.006>.
- Wang, C., Qi, J., Moran, S., & Marsett, R. (2004). Soil moisture estimation in a semiarid rangeland using ERS-2 and TM imagery. *Remote Sensing of Environment*, 90(2), 178–189.
- Wang, D. (2017). MODIS/Terra+ Aqua Surface Radiation Daily/3-Hour L3 Global 5km SIN Grid V006 – DSR. NASA EOSDIS Land Processes DAAC. Accessed in May 2022 from <https://doi.org/10.5067/MODIS/MYD13A1.006>.

- Wang, L., Hunt Jr, E. R., Qu, J. J., Hao, X., & Daughtry, C. S. T. (2013). Remote sensing of fuel moisture content from ratios of narrow-band vegetation water and dry-matter indices. *Remote Sens. Environ.*, 129(0), 103–110.
- Wang, L. & Qu, J. J. (2007). NMDI: A normalized multi-band drought index for monitoring soil and vegetation moisture with satellite remote sensing. *Geophys. Res. Lett.*, 34(20).
- Wang, X., Wotton, B. M., Cantin, A., Parisien, M.-A., Anderson, K., Moore, B., & Flannigan, M. D. (2017a). cffdrs: An R package for the Canadian Forest Fire Danger Rating System. *Ecological Processes*, 6(1), 5.
- Wang, X., Zhang, F., & Ding, J. (2017b). Evaluation of water quality based on a machine learning algorithm and water quality index for the ebinur lake watershed, china. *Scientific reports*, 7(1), 1–18.
- Wang, Y., Anderson, K. R., Suddaby, R. M., et al. (2015). Updated source code for calculating fire danger indices in the Canadian Forest Fire Weather Index System. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, Alberta. Information Report NOR-X-424. 26 pp.
- Wei, J., Li, Z., Guo, J., Sun, L., Huang, W., Xue, W., Fan, T., & Cribb, M. (2019). Satellite-derived 1-km-resolution pm1 concentrations from 2014 to 2018 across china. *Environmental Science & Technology*, 53(22), 13265–13274.
- Wotton, B. M., Alexander, M. E., & Taylor, S. W. (2009). Updates and revisions to the 1992 Canadian forest fire behavior prediction system. Natural Resources Canada, Canadian Forest Service, Great Lakes Forestry Centre, Sault Ste. Marie, Ontario. Information Report GLC-X-10. 45 pp.
- Wu, C., Venevsky, S., Sitch, S., Mercado, L. M., Huntingford, C., & Staver, A. C. (2021). Historical and future global burned area with changing climate and human demography. *One Earth*, 4(4), 517–530.
- Yebra, M., Chuvieco, E., & Riaño, D. (2008). Estimation of live fuel moisture content from MODIS images for fire risk assessment. *Agr. Forest Meteorol.*, 148(4), 523–536.
- Yebra, M., Dennison, P. E., Chuvieco, E., Riaño, D., Zylstra, P., Hunt Jr, E. R., Danson, F. M., Qi, Y., & Jurdao, S. (2013). A global review of remote sensing of live fuel moisture content for fire danger assessment: moving towards operational products. *Remote Sens. Environ.*, 136(0), 455–468.
- Zhang, H., Wu, B., Yan, N., Zhu, W., & Feng, X. (2014). An improved satellite-based approach for estimating vapor pressure deficit from MODIS data. *Journal of Geophysical Research: Atmospheres*, 119(21), 12–256.

Appendix

A. Download satellite images

There are multiple sources or data-hubs from where to download satellite images. In this section the ones used for this study will be mentioned and briefly described.

A.1 Download via NASA's EarthData

This server might be the most used and known data-hub to download satellite images. The steps to download an image are the following.

1. Visit EarthData website and create an account in the following link: <https://urs.earthdata.nasa.gov/> (accessed in May 2022).
2. Once your account is created, go to: <https://search.earthdata.nasa.gov/search> and login to your account at the top right corner.
3. At the top left section of the webpage are several tools to filter for your data. You can set the time frame of analysis, spatial extent of your region of interest, etc. In the search bar write the desired product name. A list of the matching collections will appear if the product being searched exists or has images within the time frame and extent of your region of interest. Click on the product to see the granules. If only some of them are needed, the “download single granule data” option can be used. If more data is needed, click download all. This will redirect you to another page, where a summary of the data selected, amount of images and estimated size will be displayed. Select “download all”, and a new page will come forth. Click on save the data, and a *.txt file will be downloaded.
4. Find the downloaded *.txt file and change format to *.dat (generic data file) by changing the “.txt” to “.dat”.
5. The following steps will use Cygwin64 Terminal² software to download multiple images from the *.dat file.
6. If Cygwin64 is being stalled for the first time, place its directory in the main disk (usually C:\). Once installed in C:\ go C:\cygwin64\home\User directory and place the *.dat file there. Open Cygwin64 Terminal and run the following codes.

- i. Write the following and click enter.

```
1 touch .netrc
```

- ii. Using wget, type the following code and click enter.

```
1 wget --load-cookies .urs_cookies --auth-no-challenge=on --keep-session-  
  cookies --user=your_username --ask-password --content-disposition --no-  
  check-certificate -i your_downloaded_file.dat
```

Note that you have to replace `your_username` for your EarthData username and `your_downloaded_file.dat` for your *.dat filename. Once done, the GUI will ask for your EarthData password. If everything was correctly done, the images will start downloading and will be stored in the same directory where the *.dat was placed.

²Download link: <https://www.cygwin.com/>

A.2 Download MODIS products in R

Assuming R (R Core Team, 2021) is installed and running in your system (in this case an example for Windows machine is described), the steps to download a MODIS product are almost straightforward.

1. Install the MODIS_{tsp} package (Busetto & Ranghetti, 2016) in R using the following code.

```
1 install.packages("remotes")
2 library(remotes)
3 install_github("ropensci/MODIStsp")
```

2. Once installed, type and run in R:

```
1 MODIStsp::MODIStsp()
```

3. This will open a Graphics User Interface of MODIS_{tsp} in the web-browser.
4. In “Product and layers”, select both the MODIS product and layer you want to use (you can also select the product version and platform i.e. Terra or Aqua).
5. In “Spatial/Temporal options”, select the date range for your images and the MODIS tiles. If you select more than one tile, it will automatically perform a mosaic of the images. You can also add a shapefile (in geographic coordinates) of your region of interest. In these options it is also possible to select the output product coordinate system. I suggest using WGS84 Geographic coordinates system, i.e. EPSG:4326. For this study, EPSG:32719 was used, which corresponds to WGS84 UTM Zone 19-South coordinate system. Select “user defined” projection, and under projection name write 4326. You can even resample the data by selecting an specific spatial resolution. Note that a resampling occurs when reprojecting the image from Sinusoidal (MODIS original projection) to Geographic coordinates, and thus a resampling method is required. Choose near for nearest neighbor (if the product has a qualitative variable e.g. land cover products) or bilinear for a bilinear interpolation (if the product has a continuous variable e.g. NDVI products).
6. Finally, in the “Output Format and Folders”, select the download method as http, place your NASA’s EarthData username and password. In the output options, you can select the output format, save the data as a rasterStack, among others. If you are downloading an specific product, you can select “Yes” in the “Apply Scale/Offset” so your downloaded product has the corresponding values, i.e. it will apply the scale factor to the data. Select an output folder where the processed images will be stored and an output folder for the original *.HDF files and click “Run MODIS_{tsp}”.

A.3 Download Landsat-8 and Sentinel-2 images

Both Landsat-8 and Sentinel-2 images can be downloaded in the United States Geological Survey (USGS) EarthExplorer hub. The steps are the following.

1. Go to EarthExplorer and create an account in the following link: <https://ers.cr.usgs.gov/login> (accessed in May 2022)
2. Once your account is created, go to: <https://earthexplorer.usgs.gov/> and login to your account at the top right corner.

3. At the left of the EarthExplorer GUI, fill the search criteria. You can either use Path/Row or GNIS as geocoding method. If Path/Row is used (Worldwide Reference System, WRS-2), you will need to provide the path/row values of your region of interest, or in “KML/Shapefile Upload” you can upload a shapefile of your region of interest in geographic coordinates.
4. Select a date range, cloud cover, etc.
5. Go to the “Data Sets” tab and search for either Landsat-8 or Sentinel-2 datasets.
6. If Landsat-8 images is what you are looking for, under Landsat go to Landsat Collection 2 Level-2 and from there select Landsat 8-9 OLI/TIRS C2 L2. This product correspond to images that have undergo several correction procedures such as terrain correction, atmospheric correction, among others.
7. If Sentinel-2 images are those required, click on Sentinel and select Sentinel-2. This images correspond to level-1 product, which are not atmospherically corrected and thus pixel values are at the top-of-atmosphere (TOA). The correction can be done in R using the `sen2r` package (Ranghetti et al., 2020), or in The Sentinel-2 Toolbox³ developed by the European Space Agency (open access).

B. Work with raster data in R

There are quite a few ways to work with satellite images or rasters. These ways refer to several software based on Geographic Information Systems (GIS), which can be free and open-source to paid. The most used ones are QGIS (free and open-source, QGIS Development Team, 2009), ENVI (paid), ArcGIS (paid), etc. In addition, there has been a wide open-source libraries or packages development within Python (vanRossum, 1995) and R (R Core Team, 2021) languages for GIS.

In this work, all image processing was carried out in the free and open-source R language. The basis of the latter rely in its easiness of use within geographic information system, powerful data analysis, and not to mention its wide helpful and supportive community. For the reader, R version used was 4.1.X in Windows 10, 64-bit.

The following sections will focus on the use of R and some of its libraries for geographic information system or raster data analysis.

B.1 Geo-processing

There are several geo-processes while working with satellite images. Most of them are carried out using the `raster` package (Hijmans, 2020). Note that in R it is possible to specify a function from certain library using, for example, `raster::thefunction()`, where `raster` is the library and `thefunction()` is, for the sake of redundancy, the function of *that* library being used.

An example of some geo-processes are the following.

- a) Opening a raster file. For this, there are several libraries. For GeoTIFF images (*.tif extension), use the `raster` library. For NetCDF (*.nc or *.nc4 extension) and HDF5 (*.h5 extension) use the `ncdf` library (Pierce, 2021). Assign a variable to each image. An example where an image is opened and stored in the `x` variable is shown below.

³Download the software from: <https://sentinel.esa.int/web/sentinel/toolboxes/sentinel-2>

```
1 x <- raster::raster('your_image.tif')
```

- b) Raster math. Suppose that a raster is stored in the `x` variable, and corresponds to a “land surface temperature” product. However, the units of the pixels within the image are in Kelvin, and you want to use it in degrees Celsius. Hence, the following code can be used to achieve the latter.

```
1 y <- x - 273.15
```

Which means that the new variable “`y`” will be a new raster image or `Raster*` object with the same extent, resolution and number of cells than `x`, but 273.15 will be subtracted to each pixel and hence the units of “`y`” will be in degrees Celsius. This is also applicable to multiple rasters and for all mathematical expressions (sum, multiplication, division, etc). For example, if you want to compute the mean between two rasters `r1` and `r2`, it is possible to use R base stats and run the following code.

```
1 r <- mean(r1,r2, na.rm = TRUE)
```

Otherwise, it is possible to generate a `rasterStack` object from the two rasters and calculate the mean with the `raster` library.

```
1 s <- raster::stack(r1,r2)
2 r <- raster::calc(s, fun = mean , na.rm = TRUE)
```

N.B. the `na.rm = T` means that NA values (missing values) will not be considered while computing the mean.

- c) Reprojection. Usually when a satellite image is downloaded, it comes with a certain projection (e.g. WGS84 Geographic in latitude and longitude). Most analysis using pixel dimension would need a reprojection to work with metric pixel values, and thus reprojecting the images is required. Typically, the image is reprojected to UTM (Universal Transverse Mercator) coordinate system. In this study the WGS84 UTM Zone 19-South was used, and hence pixels were geo-transformed to meters. The reprojection of an image affects both its area, shape, distance and scale, and thus mathematical processes such as interpolation are carried out. Suppose you have a raster in geographic coordinates assigned to the `r` variable and want to reproject it to UTM Zone 19-South, the following code should be used.

```
1 utm_19s <- "+proj=utm+zone=19+south+ellps=WGS84+towgs84=0,0,0,0,0,0,0,0,0,0+
  units=m+no_defs"
2 r2 <- raster::projectRaster(r , crs = utm_19s)
```

where `utm_19s` is the desired coordinate system (WGS84 UTM Zone 19-South), and `r2` is the reprojected raster of `r`. Note that it is also possible to specify the interpolation method, which can be nearest neighbor or bilinear.

- d) Crop and mask. A satellite image will typically cover more surface than your region of interest. This is when `crop` and `mask` functions are useful. To crop and mask a raster, an extent surface is needed. For this, usually a vector-polygon data is used (frequently called *shapefiles* due to its most-common format – `*.shp`). This shapefile can be opened using the `rgdal` library (Bivand et al., 2022) using:

```
1 shp <- rgdal::readOGR("C:/data/my_shapefile.shp")
```

where the only parameter is the directory and name of the file. Suppose that the raster variable name is assigned to the `r` variable. The crop and mask can be done using the following.

```
1 crop <- raster::crop(x = r, y = extent(shp))
2 mask <- raster::mask(x = crop, mask = shp)
```

This functions crops the `r` raster to the extent of the shapefile (`shp`), and afterwards it uses the shapefile geometry to mask the data, i.e. it converts to NA (or no-data value) everything outside of it.

- e) Resample. If multiple images are used for certain raster analysis, the same resolution and extent is usually required, otherwise interpolation should be performed, or a conversion of the raster data to a data frame (which is a table or a two-dimensional array-like structure). Suppose you have two rasters `r1` and `r2` with the same projection, but `r1` has different dimensions (and thus different pixel or spatial resolution) than `r2`. Say you want `r2` to have the same dimensions as `r1`, the following code should be used for resampling `r2`.

```
1 r2.1 <- raster::resample(r2,r1,method='bilinear')
```

As a result, `r2.1` is a raster with `r2` values interpolated to the extent and dimensions of `r1`. Note that `method` stands for the interpolation method. If a continuous variable within the raster data is studied, then a bilinear interpolation is recommended, while if the raster data is categorical, a nearest-neighbor (which is `'ngb'`) interpolation should be performed.

- f) Extraction. This was substantially used in this work to extract pixel values at certain weather station points. Therefore, a shapefile of points or polygons is needed. Say the shapefile “`shp`” has the points in the same projection than raster `r` of land surface temperature (LST). If you want to obtain the corresponding LST pixel value at a specific weather station location, the following code can be used.

```
1 my_shp <- rgdal::readOGR("C:/data/my_weather_station_points.shp")
2 r.ext <- raster::extract(x = r, y = my_shp, method = "bilinear")
```

`r.ext` will be a numeric R vector with a length equal to the amount of weather stations or points within the shapefile. The method selected can be `'simple'` or `'bilinear'`. The first one retrieves the corresponding pixel value where the point is located, while the second one returns an interpolated value within four nearest raster cells. It is also possible to set a `buffer` which will make a radius around each point and will extract the cell values.

C. International Geosphere-Biosphere Programme classification

Table C.1: MCD12Q1 International Geosphere-Biosphere Programme (IGBP) legend and class descriptions. Obtained from: [Sulla-Menashe & Friedl \(2018\)](#).

Name	Value	Description
Evergreen Needleleaf Forests	1	Dominated by evergreen conifer trees(canopy>2m).Tree cover>60%.
Evergreen Broadleaf Forests	2	Dominated by evergreen broadleaf and palmate trees(canopy>2m). Tree cover>60%.
Deciduous Needleleaf Forests	3	Dominated by deciduous needleleaf(larch) trees (canopy>2m).Tree cover>60%.
Deciduous Broadleaf Forests	4	Dominated by deciduous broadleaf trees(canopy>2m).Tree cover>60%.
Mixed Forests	5	Dominated by neither deciduous nor evergreen (40-60%of each) tree type (canopy>2m). Tree cover>60%.
Closed Shrublands	6	Dominated by woody perennials(1-2m height), >60% cover.
Open Shrublands	7	Dominated by woody perennials(1-2m height), 10-60% cover.
Woody Savannas	8	Tree cover 30-60% (canopy>2m).
Savannas	9	Tree cover 10-30% (canopy>2m).
Grasslands	10	Dominated by herbaceous annuals(<2m).
Permanent Wetlands	11	Permanently inundated lands with 30-60% water cover and >10% vegetated cover.
Croplands	12	At least 60%of area is cultivated cropland.
Urban and Built-up Lands	13	At least 30%impervious surface area including building materials, asphalt, and vehicles.
Cropland/Natural Vegetation Mosaics	14	Mosaics of small-scale cultivation 40-60% with natural tree, shrub, or herbaceous vegetation.
Permanent Snow and Ice	15	At least 60%of area is covered by snow and ice for at least 10 months of the year.
Barren	16	At least 60%of area is non-vegetated barren (sand, rock, soil) areas with less than 10% vegetation.
Water Bodies	17	At least 60%of area is covered by permanent water bodies.
Unclassified	255	Has not received a map label because of missing inputs.

D. NDVI and NDWI pre-fire data distribution

Figure D.1 shows the data distribution for both NDVI and NDWI within each municipality in the ROI prior to the event, i.e. from 2010 to 2016 data.

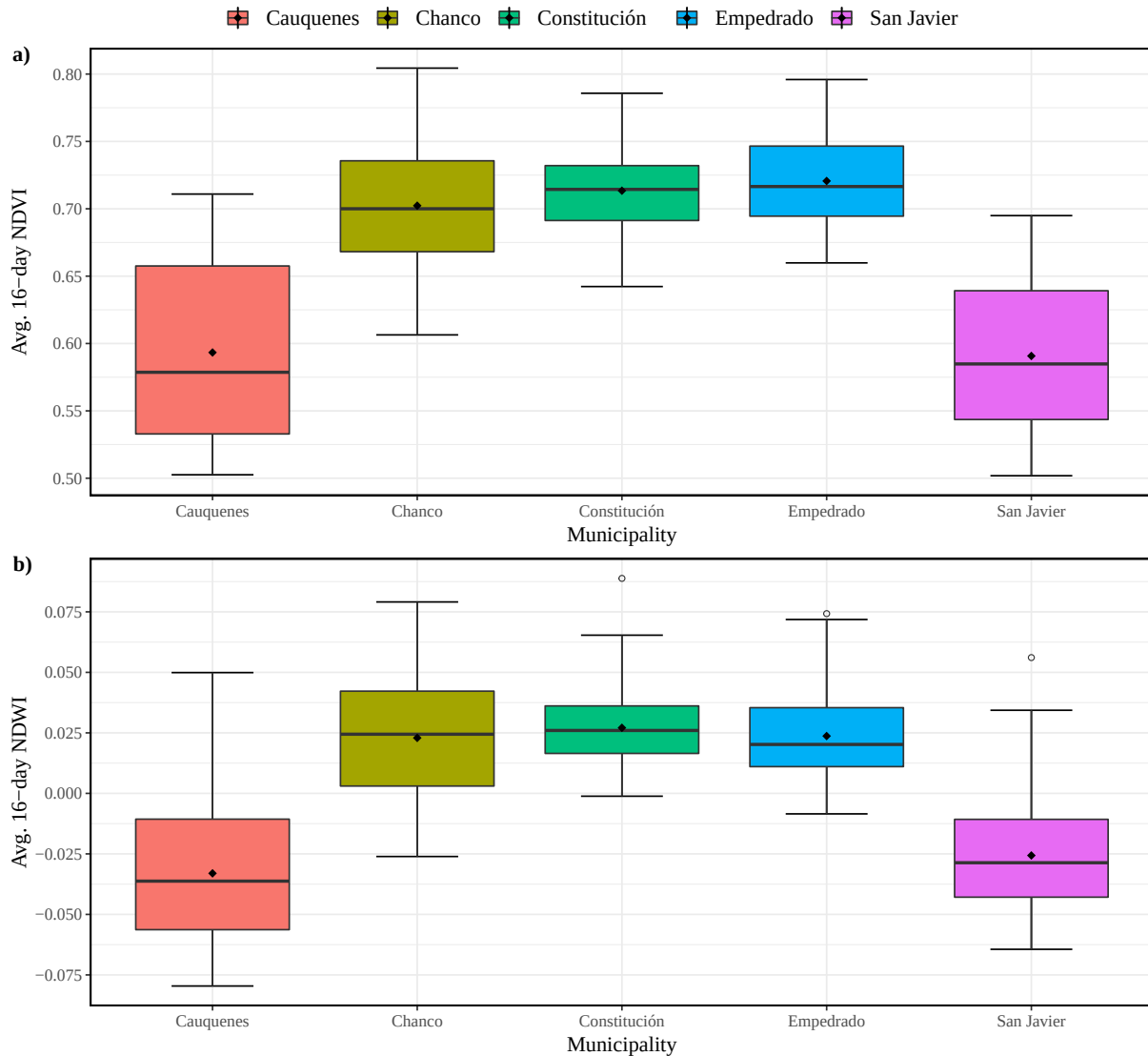


Figure D.1: Pre-fire a) averaged NDVI and b) averaged NDWI values for 2010 – 2016 data. The rhombus within each boxplot represents the mean data values.

E. IGBP detail for land-use categories

Forest category within the land-use type must be expanded in order to understand the IGBP values of 1, 2, 8 and 9. Therefore, the Land Use Inventory was used to extract another variable within its dataset: the “detailed land-use type”, which carries a more specific description of the land type including a total of 39 categories, along with, for example, plantations, native forests, rivers, grasslands, among others. The results are shown in Figure E.1.

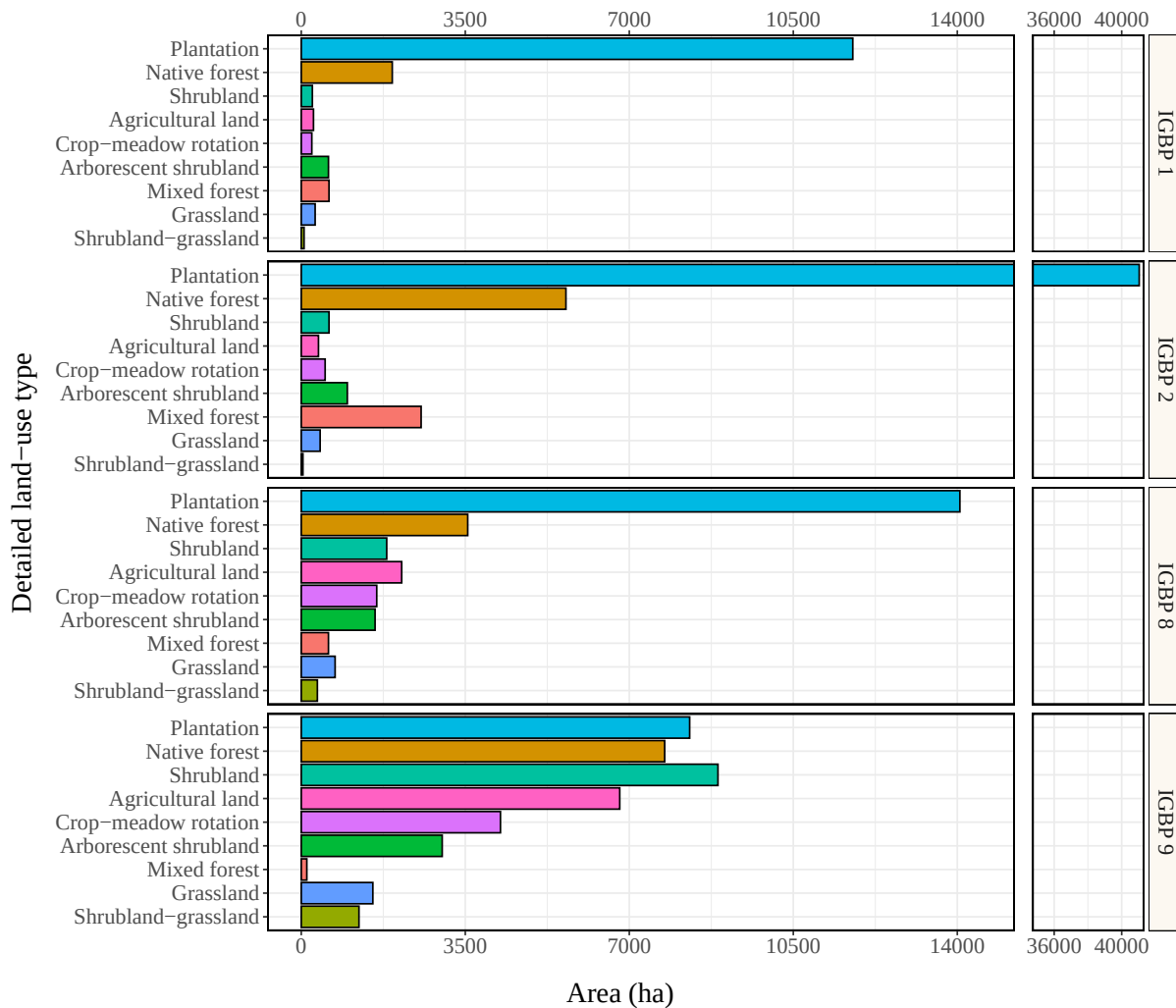


Figure E.1: Pre-fire Land Use Inventory (LUI) – “detailed land-use type” surface area for IGBP categories 1, 2, 8 and 9 (from year 2015), within the ROI. Of the 39 categories found for the ROI, only 16 were within pixel values of the IGBP 2015 image, and 9 of them met the imposed condition of a minimum surface area of 650 ha (for each IGBP category).

From [Figure E.1](#) it is possible to observe that for IGBP = 1 (evergreen needleleaf forests) category, the main classification variables for the detailed land-use type from the LUI are plantations and native forests. The sum of the latter variables is around 13,700 ha, which is close to the 14,300 ha of the “Forests” land-use type category in [Figure 4.19](#) for IGBP = 1. This behavior can also be evidenced for IGBP = 2 (evergreen broadleaf forests) and IGBP = 8 (woody savannas). Nevertheless, for IGBP = 2 there is an increase in the “mixed forest” land-use type category, and for the IGBP = 8 there is less mixed forests and more shrublands, agricultural lands, crop-meadow rotation and arborescent shrublands. For savannas (IGBP = 9) there is a mixture of all the variables mentioned before, however the presence of plantations is at around the same surface-area of agricultural land, native forests, and agricultural lands.

Therefore, it is possible to conclude the following. IGBP = 1 is mainly composed of plantations and native forests, categories that correspond to 72.5% and 11.9%, respectively, of the total surface area of evergreen needleleaf forests within the ROI, while mixed forest is 3.6% of the total surface area. For

IGBP = 2, the surface area of plantations, native forests and mixed forests correspond to 78.6%, 10.8% and 4.9%, respectively, of the total surface area of evergreen broadleaf forests within the ROI. Hence, the aspect-ratio of IGBP 1 and 2 for the three variables mentioned before, are considerably close.

Hence, at this point, the question that arises is about the different species for each detailed land-use type. As in the affected species analysis (cf. [Section 4.3.5](#)), the rasterized-*species* data was extracted using the detailed land-use type studied before to extract the species within each land-use type. The results are shown in [Figure E.2](#).

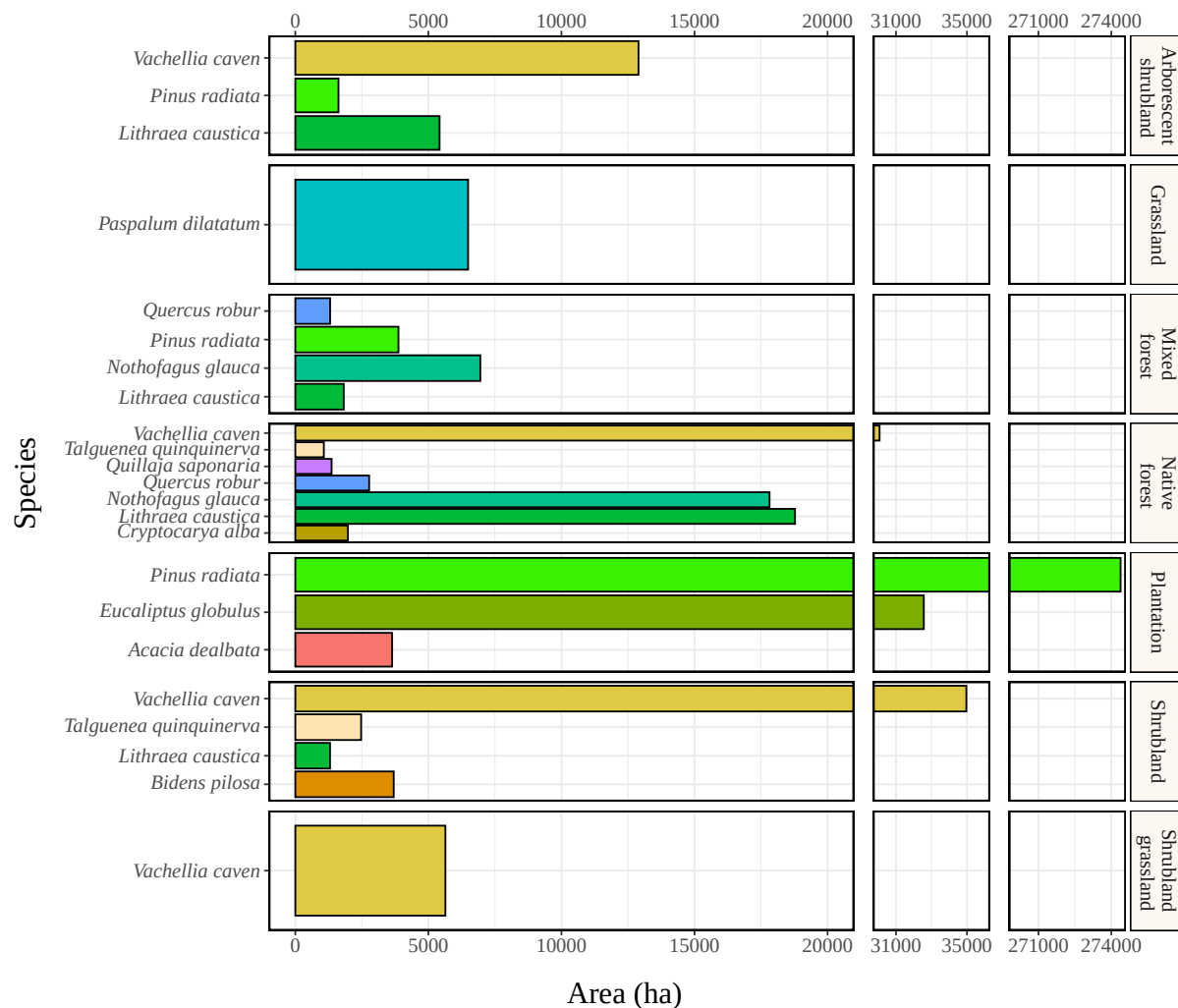


Figure E.2: Pre-fire LUI “species” surface-area for several “detailed soil-use types” within the ROI. Of the 9 categories for the “detailed soil-use type” (y-axis of [Figure E.1](#)) found for the ROI, only 7 of them met the settled condition of a minimum surface-area of 100 ha. The same criteria was applied to the species i.e. a minimum surface-area of 100 ha.

The findings suggest that the species that hold the most surface-area within the ROI are: *Pinus radiata*, *Vachellia caven* and *Eucalyptus globulus*. The first and last ones are mainly in the Plantation “detailed land-use type” category, while the second can be found in several categories. The evergreen needleleaf forests (IGBP = 1) was mainly composed by plantations and native forest, however their surface area for the plantation category should be considerably wider, since the main species within the plantation category

corresponds to needleleaf vegetation, i.e. *Pinus radiata*. Furthermore, it seems that the algorithm for IGBP is considering pixels with vegetation such as *Vachellia caven* to the Native Forest category, which would explain the surface-area of that category within IGBP = 1. Nevertheless, if the latter is true, its surface-area should be larger.

On the other hand, for evergreen broadleaf vegetation (IGBP = 2) the amount of plantations and native forests has a larger surface-area with respect to IGBP = 1. At least for the Native Forests category, this is consistent with the results shown in Figure E.2, since the species within that category are mainly broadleaf vegetation.

For woody savannas (IGBP = 8), a more detailed analysis is required to conclude on the results, since it seems clear that plantations surface-area within the latter should be larger, yet its definition states that are lands with canopy cover between 30% and 60%, while IGBP = 1 and 2 are $> 60\%$, hence those values should not be the same. Nevertheless, the amount of agricultural lands, shrublands, crop-meadow rotation and arborescent shrubland surface-area is larger than for IGBP 1 and 2, which is reasonable since the main species within the latter “detailed land-use type” corresponds to *Vachellia caven* (also known by Roman Cassie), a small tree or shrub.

Finally, savannas (IGBP = 9), whose definition is basically the same as “woody savannas”, with the difference that its canopy cover is between 10% and 30%, has even more shrublands, agricultural lands, crop-meadow rotation and arborescent shrublands than woody savannas.

F. Other Fire Weather Index results

The relation between the CFFDRS FWI and the approximated Fire Weather Index (FWI_{app}) is shown in Figure F.1.

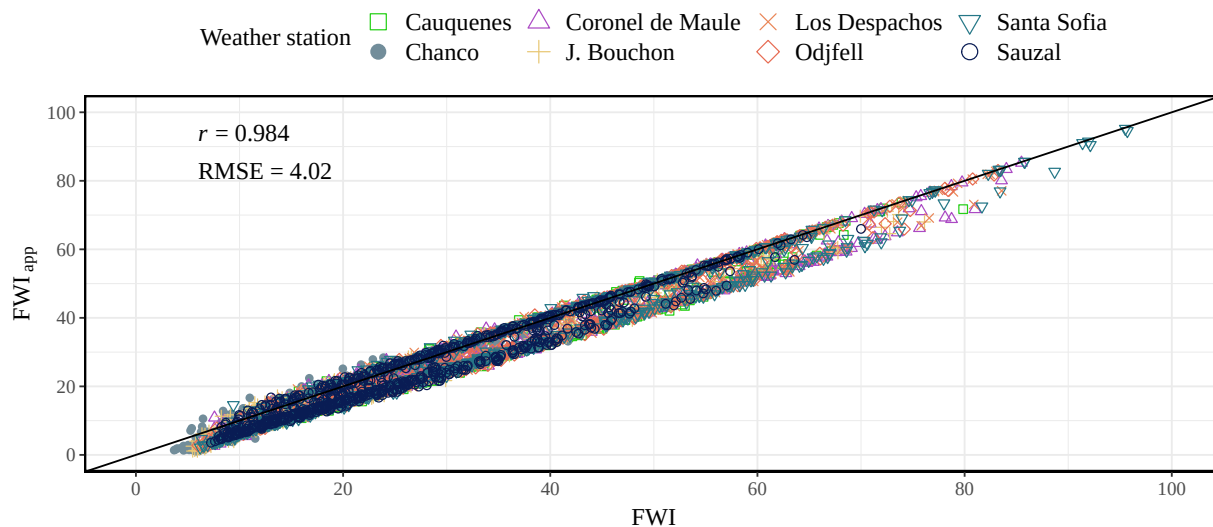


Figure F.1: Comparison of the FWI calculated using the *cffdrs* package versus the approximated FWI using weather station data.