



UNIVERSITÀ
DEGLI STUDI
DI PAVIA



DOCTORAL DISSERTATION

Design, modeling and simulation in engineering (38th cycle)

SUITABILITY MAPS FOR PINOT NOIR

BASED ON THE USE OF GEOGRAPHIC
INFORMATION AND ENVIRONMENTAL
DATA IN THE OLTREPÒ PAVESE REGION

This research investigates the environmental suitability of the Oltrepò Pavese region (Lombardy, Italy) for Pinot Noir cultivation using Geographic Information Systems (GIS), environmental data, and remote sensing.

By integrating bioclimatic and environmental factors within two complementary spatial modelling approaches – Multi-Criteria Decision Analysis (MCDA) and Fuzzy Logic – the study develops high-resolution suitability maps to support viticultural planning.

The proposed methodology provides a reproducible and transferable framework to support vineyard planning and territorial analysis in the context of ongoing environmental and climatic change.

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Supervisor: **Prof. Vittorio Marco Casella**



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Prof. Vittorio Marco Casella

2026

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Abstract

Viticulture represents one of the oldest agricultural practices and is closely linked to the environmental characteristics of the territory where vines are cultivated. Vine growth and grape quality are strongly influenced by a combination of climatic, topographic, and soil-related factors, including temperature, solar radiation, water availability, and soil properties. For sensitive grape varieties such as *Pinot Noir*, achieving optimal grape composition requires a careful balance among these factors, while inadequate conditions can negatively affect grape yield and wine quality.

In the context of climate change, traditional viticultural areas are undergoing significant transformations, with shifts in temperature and rainfall patterns altering vineyard suitability. This has increased the need for spatially explicit, data-driven tools to support sustainable vineyard planning and adaptation strategies at the local scale. Geographic Information Systems (GIS), combined with advanced modelling techniques, provide an effective means of integrating heterogeneous environmental data and assessing viticultural suitability at high spatial resolution.

The aim of this research is to produce high-resolution viticultural suitability maps for *Pinot Noir* in the Oltrepò Pavese area (Lombardy, Italy). The study involved the collection and processing of environmental data layers, with particular attention to thermal conditions through the computation of the Winkler Index. Vineyard suitability was subsequently assessed using two modelling techniques: (i) a GIS-based Multi-Criteria Decision Analysis (MCDA), and (ii) a Fuzzy Logic model implemented in MATLAB.

Both approaches used the same set of topographic, pedological, climatic, and land-use criteria to identify areas classified as highly suitable, moderately suitable, marginally suitable, or unsuitable for *Pinot Noir* cultivation. The comparison between the GIS-MCDA and Fuzzy Logic outputs revealed both areas of agreement and disagreement in the resulting suitability patterns. The suitability maps were further compared with the spatial distribution of existing vineyards, obtained from available reference data, to assess the consistency of the model outputs with established viticultural practices.

Overall, this research demonstrates the effectiveness of integrating GIS-based MCDA and Fuzzy Logic modelling for vineyard suitability assessment. The proposed methodology provides a valuable decision-support tool for land-use planning, precision viticulture, and sustainable vineyard management. It offers a reproducible framework that can be adapted to other grape varieties and regions facing climate-related challenges.

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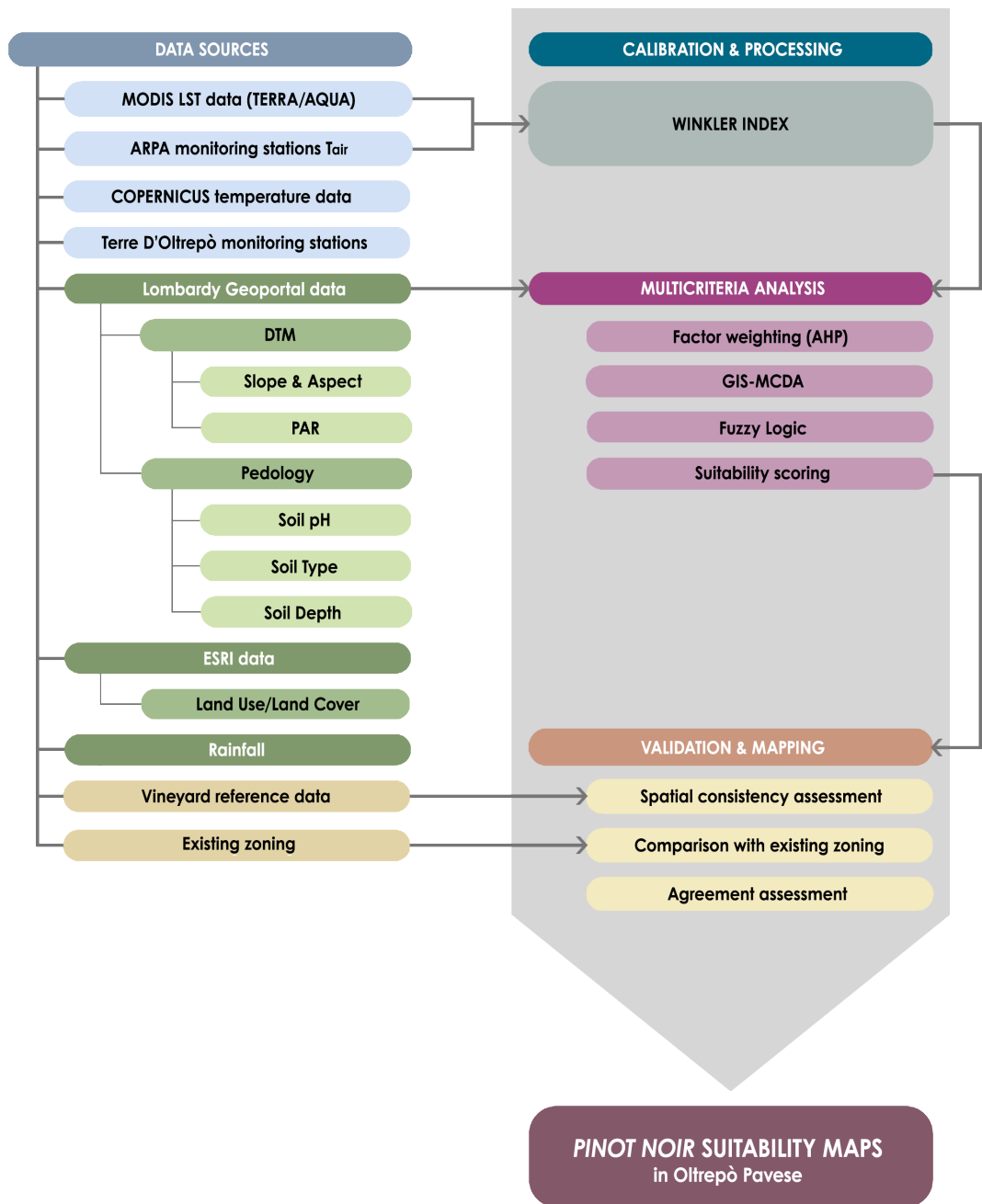
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List of Abbreviations

ARPA	<i>Agenzia Regionale per la Protezione Ambientale</i> (Regional Environmental Protection Agency)
AHP	Analytic Hierarchy Process
a.s.l.	Above Sea Level
CDS	Climate Data Store
CI	Consistency Index
CR	Consistency Ratio
DTM	Digital Terrain Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ESRI	Environmental Systems Research Institute
FAO	Food and Agriculture Organisation
FIS	Fuzzy Inference System
GEE	Google Earth Engine
GIS	Geographic Information Systems
HS	Highly Suitable
IDW	Inverse Distance Weighting
ISTAT	<i>Istituto Nazionale di Statistica</i> (Italian National Institute of Statistics)
LI	Linear Interpolation
LOOCV	Leave One Out Cross-Validation
LST	Land Surface Temperature
LULC	Land Use/Land Cover
MAD	Median Absolute Deviation
MaS	Marginally Suitable
MCDA	Multi-Criteria Decision Analysis
MODIS	Moderate Resolution Imaging Spectroradiometer
MoS	Moderately Suitable
N or NS	Not Suitable
NaN	Not a Number
NN	Nearest Neighbour
NODES	<i>Nord-Ovest Digitale E Sostenibile</i> (Digital and Sustainable North-West)
PAR	Photosynthetically Active Radiation
PNRR	<i>Piano Nazionale di Ripresa e Resilienza</i> (National Recovery and Resilience Plan)

RI	Random consistency Index
RMSE	Root Mean Square Error
S	Suitable
S1	Highly Suitable
S2	Moderately Suitable
S3	Marginally Suitable
Std	Standard Deviation
T _{air}	Air Temperature
TDO	<i>Terre D'Oltrepò</i>
UT	Territorial Unit
UTS	Soil Typological Units
VINO	VIneyard management for viNeprOduction
WI	Winkler Index
WMS	Web Map Service
WO	Weighted Overlay
WSM	Weighted Sum Model
WRB	World Reference Base

Project Overview



Oltrepò Pavese

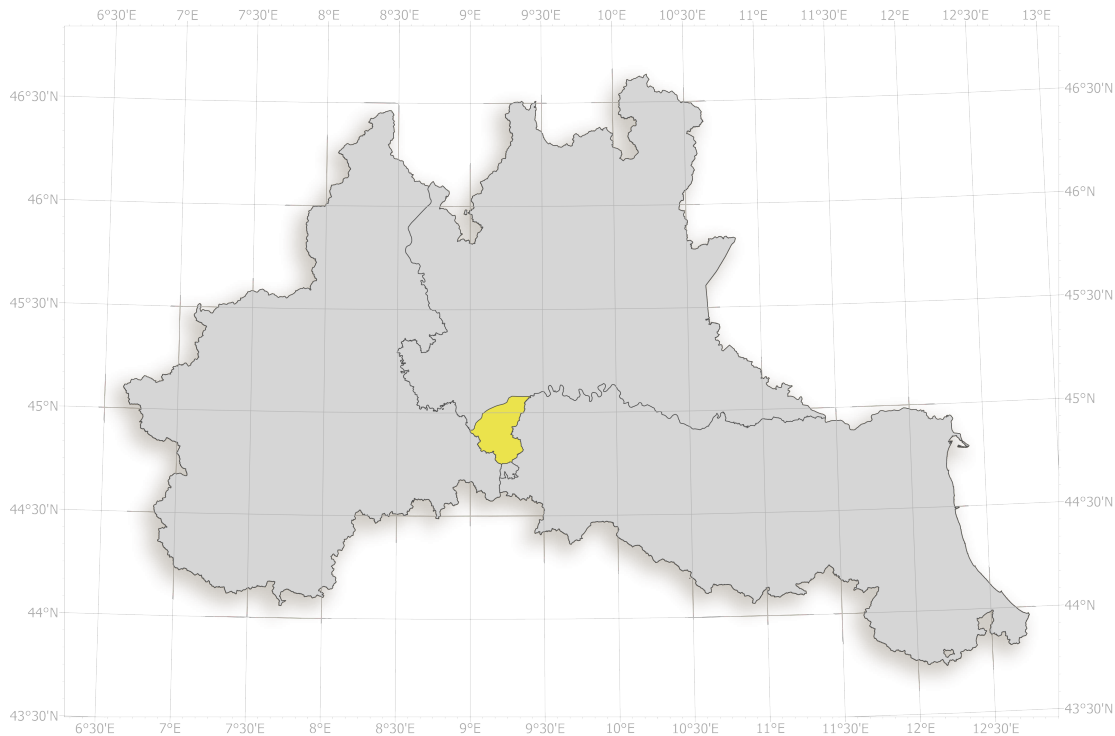


Figure 1. Location of the Oltrepò Pavese study area within the Lombardy Region. Administrative boundaries from ISTAT data [1]. Unless otherwise specified, all maps and coordinates presented in this thesis refer to the WGS84 geographic coordinate system (EPSG:4326).

Oltrepò Pavese (highlighted in yellow in Figure 1) is one of the Italian territories most closely associated with viticulture and wine production [2]. The vineyard area covers approximately 12,066 hectares (2024 data, based on the official list of cultivated grape varieties provided by the *Consorzio Tutela Vini Oltrepò Pavese*), accounting for nearly 50% of Lombardy's total viticultural area. Among the grape varieties cultivated in the area, *Pinot Noir* [3] represents a key component of local production, with an estimated surface of approximately 2,820 hectares.

Oltrepò Pavese has long been a reference point for Italian winemaking, owing to its favourable climatic conditions, pedological variability, and long-standing viticultural tradition. Located in the southern part of the Province of Pavia, the Oltrepò Pavese borders Piedmont and Emilia-Romagna Regions, with elevations ranging between about 57 m and 1,460 m above sea level [4, 5]. The territory covers nearly 100,000 hectares and is characterised by dry winters and well-ventilated summers, with marked temperature variability, conditions that have contributed to the area's suitability for vine cultivation and high-quality wine production.

1. Introduction

Viticulture represents one of the oldest agricultural activities and has always been closely linked to the environmental conditions of the territory. Like most perennial crops, grapevines are strongly influenced by environmental factors, particularly soil characteristics and climatic conditions, which determine not only yield but also grape quality. The highest potential quality is achieved when environmental limitations on photosynthesis are minimised through balanced water supply, adequate light exposure, and moderately warm temperatures. Under these conditions, grapes can reach an optimal compositional balance of sugars, acids, colour, and aromas. Conversely, thermal extremes – whether excessive cold leading to high acidity or extreme heat causing sugar spikes and low acidity – can compromise the balance and quality of the wine [6]. Environmental characterisation in viticulture increasingly relies on integrating ground-based meteorological measurements with satellite-derived data, enabling high-resolution mapping of climate parameters that affect grapevine development.

1.1. The challenge of climate change

In an era when consumers expect consistent quality attributes in wines, climate change has emerged as a significant challenge, altering traditional paradigms for vineyard site selection and management. While rising temperatures may enhance suitability in high-latitude or high-elevation regions previously constrained by cold, they simultaneously threaten the viability of traditional warm-climate viticulture. Predicting these shifts is inherently complex due to the interactions among multiple biophysical factors. Large-scale suitability assessments conducted at national or global levels are valuable for providing general trends, but they are often performed at low spatial resolution. This approach may underestimate fine-scale variability, which can be critical for maintaining viticultural viability through local adaptation strategies and microclimate exploitation under changing climatic conditions.

1.2. Data-driven viticulture and GIS

Innovative technologies and data-driven approaches increasingly support the transition toward sustainable viticulture. Modern agricultural practices are now shaped by the dual challenge of maximising productivity and ensuring long-term environmental sustainability [7].

Identifying the best location for vineyard establishment is a complex, site-specific task that requires an interdisciplinary integration of agronomy, climatology, and soil science [4]. Optimal conditions for plant development result from a combination of biophysical and chemical factors – including soil composition, temperature, humidity, and solar radiation – that significantly influence vine growth, yield, and fruit quality [8].

Land suitability mapping provides a spatially explicit approach to evaluate a territory's viticultural potential by integrating different environmental parameters. Through the use of Geographic

Information Systems (GIS), it is possible to analyse and combine these datasets to identify areas with high potential and zones where viticulture may be constrained [9]. This multi-criteria approach uses both vector and raster formats, enabling informed decision-making in vineyard planning, sustainable land management, and climate adaptation strategies.

The effectiveness of the analysis depends on the calibration and weighting of individual factors, which must take into account the accuracy and resolution of the available data [10], as well as the specific physiological requirements of the target grapevine variety.

A comprehensive land suitability analysis can employ Multi-Criteria Decision Analysis (MCDA) techniques to integrate various data layers [8] with the aim of accurately modelling the complex relationships among environmental factors. The resulting suitability maps serve as strategic tools for vineyard development, ensuring alignment between site characteristics, cultivar needs, and the intended wine style.

1.3. Case study: Pinot Noir suitability mapping

This study focuses on *Pinot Noir* (*Vitis vinifera* L.), a cultivar characterised by its high sensitivity to environmental fluctuations. For clarity, in this context, *Pinot Noir* refers to the grapevine cultivar and not the final wine product. To assess its territorial suitability, the following variables were identified:

- **Land morphology**, including elevation, slope, exposure, and solar radiation;
- **Soil properties** based on pedological data;
- **Land-use/Land-cover layers**;
- **Historical climate data**.

1.4. Research objective and study framework

Technological advancements in Geographic Information Systems (GIS) and remote sensing now allow for sophisticated, multi-parameter evaluations of viticultural potential. By integrating datasets – sourced from official regional repositories such as the Lombardy Region Geoportal [11] and ARPA (*Agenzia Regionale per la Protezione Ambientale*) [12] – with advanced digital modelling, this study proposes an innovative approach to *terroir* characterisation, specifically for climate-sensitive cultivars such as *Pinot Noir*. ARPA Lombardy acts as a regional data repository, providing high-quality meteorological observations, including air temperature and other climatic variables, from a network of monitoring stations across the study area.

The goal of this research is to obtain high-resolution (10 m) suitability maps for *Pinot Noir* by comparing two analytical approaches (Multi-Criteria Decision Analysis and Fuzzy Logic). The resulting maps are intended to support vineyard site selection and precision viticulture by identifying fine-scale spatial variability in environmental suitability within Oltrepò Pavese.

The research is structured into two phases, moving from data refinement to comparative spatial analysis.

Phase I: High-Resolution Climatic Modelling

The first part of the thesis addresses the gap between temporal and spatial climatic data. While ARPA stations provide accurate point-based air temperature records, MODIS satellite data offer continuous spatial coverage of land surface temperature (LST).

MODIS was selected because it provides a consistent multi-year LST time series over the study period. Future work could investigate the integration of Landsat and Sentinel-3 products to evaluate the influence of different spatial and temporal resolutions.

- **Calibration:** a MATLAB-based regression approach was used to generate a high-resolution, MODIS-derived air temperature dataset.
- **Winkler Index:** the resulting air-temperature estimates enabled calculation of the Winkler Index across the study area, providing a first application of the proposed temperature-mapping framework for assessing the thermal suitability of *Pinot Noir*.

Phase II: Comparative Suitability Mapping (MCDA vs Fuzzy)

The output from **Phase I** was integrated with topographic, pedological, and climatic data to produce suitability maps using two complementary approaches.

- **GIS-based MCDA:** a multi-criteria analysis was performed using ArcGIS *Suitability Modeler*. Criteria weights were assigned using the Analytic Hierarchy Process (AHP), resulting in a discrete spatial classification.
- **MATLAB Fuzzy Logic:** a Fuzzy Inference System (FIS) was developed to model gradual transitions between suitability classes and better represent environmental variability.

Validation: to evaluate the performance of both models, the resulting suitability maps were compared with available reference data and existing zoning studies developed by Professor Attilio Scienza [13]. The multilevel assessment supported the spatial consistency of the proposed framework and the applicability of both MCDA and Fuzzy Logic approaches for viticultural suitability evaluation in complex wine-growing regions.

1.5. Principal research outcomes

The implementation of the developed methodology led to the following key results:

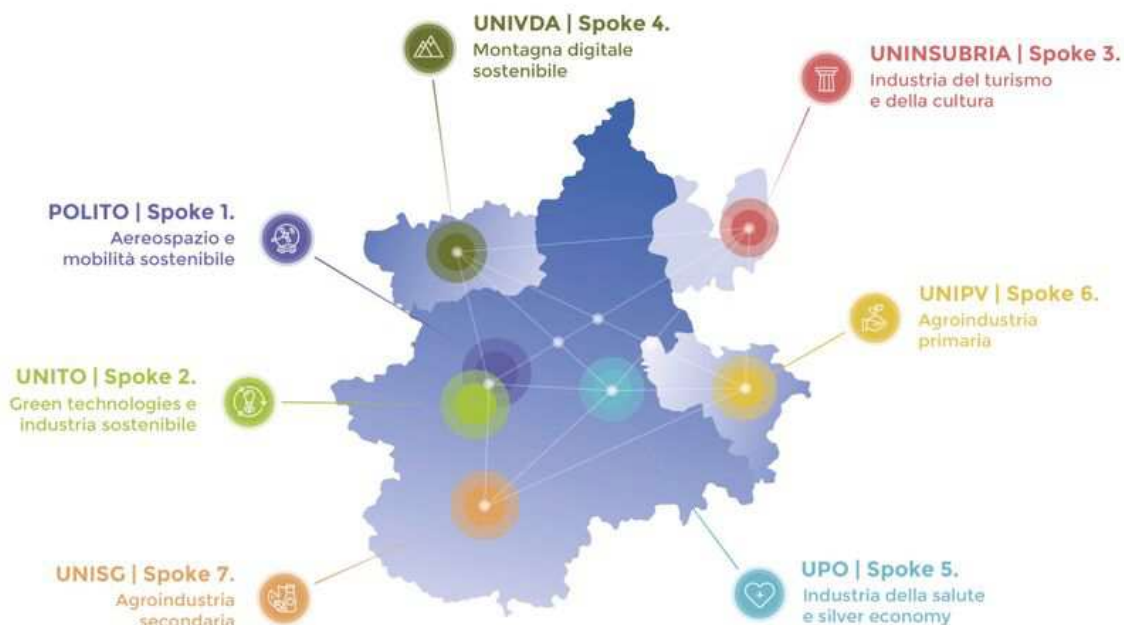
- **Generation of spatially continuous air temperature maps.** The study established a robust calibration between MODIS Land Surface Temperature (LST) and ARPA monitoring station measurements, enabling the generation of spatially continuous rasters. These layers provided a solid basis for subsequent bioclimatic index calculations.
- **Identification of the most suitable wine-growing zones.** Both GIS-MCDA and Fuzzy Logic models identified specific microregions with optimal environmental conditions. These areas represent the convergence of factors that best meet the needs of *Pinot Noir*.
- **Methodological replicability and scalability.** The integration of satellite observations, ground-based measurements, bioclimatic analysis, and spatial multicriteria modelling resulted in a structured framework for viticultural suitability assessment that can be adapted to other cultivars and study areas.

2. NODES Project

NODES (*Nord-Ovest Digitale E Sostenibile*) is a comprehensive innovation ecosystem encompassing the northwestern regions of Italy, including Valle d'Aosta, Piedmont, and the western provinces of Lombardy. Established under the Italian National Recovery and Resilience Plan (PNRR) and aligned with Horizon Europe's Cluster 4 objectives, NODES aims to strengthen the competitiveness of industries and research institutions [14].

The ecosystem comprises 24 partners, including public and private universities, research centres, competence centres, innovation clusters, incubators, and accelerators. The consortium is organised into seven thematic “Spokes”, each focusing on specific sectors (Figure 2), with the aim of contributing to the objectives of the “Digital, Industry and Space” sector.

Figure 2. NODES ecosystem.



2.1. VINO Flagship Project – Spoke 6

Within Spoke 6, dedicated to Primary Agroindustry, the VINO (*VIneyard management for viNeproduction*) flagship project directly addresses the challenges posed by climate change to viticulture in northwestern Italy. The project focuses on regions renowned for wine production, such as Oltrepò Pavese (Figure 3), Langhe, and Colli Piacentini [15]. VINO promotes collaboration among stakeholders through three main pillars: technological development, advanced modelling, and practical application.

Key initiatives include:

- **Remote Sensing and Big Data:** use of satellite imagery and data analytics to monitor vineyard health and predict environmental stressors, thereby supporting precision agriculture [16].
- **Climate Modelling:** development of predictive models to assess the effects of climatic variables on grape quality and yield [17], providing insights for adaptive vineyard-management strategies.
- **Sustainable Practices:** implementation and evaluation of sustainable viticultural techniques designed to enhance resilience to climate-related challenges. This includes soil health improvement, biodiversity conservation, and integrated pest management approaches.

The project places particular emphasis on high-resolution temperature mapping to optimise viticultural strategies, recognising that microclimatic variations significantly influence grape development, phenology, and wine quality. Tailored practices, such as precision irrigation and harvest timing, can be informed by these temperature maps to enhance grape quality.

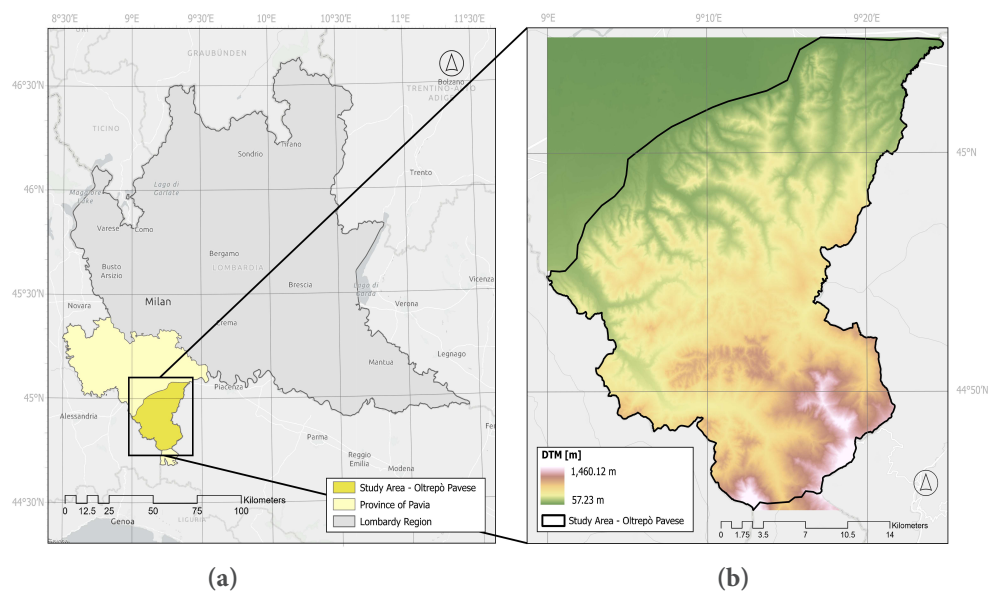


Figure 3. Geographic context of the study area: location within the province of Pavia and the Lombardy Region (a), and Digital Terrain Model (DTM) showing elevation variations across the Oltrepò Pavese (b).

Pinot Noir

Pinot Noir is one of the oldest and most elegant grape varieties, tracing its origins to Burgundy, France. The variety's name derives from its morphological characteristics: the compact, pine cone-like shape of the bunch (French: *pinot*) and the tightly arranged berries [18].

The first documented reference to *Pinot* (in the archaic form *Pinoz* or *Pynos*) dates back to the 14th century. Contemporary *Pinot Noir* evolved from its ancient forms, which were generally low-yielding. Modern types began emerging in Burgundy and Champagne during the 18th century, reflecting both natural selection and human intervention in varietal development [13].

Over the centuries, *Pinot Noir* has spread across numerous wine-growing regions, including Germany, Italy, California, Oregon, New Zealand, and Chile. Each territory gives it a distinctive character, making this grape variety a lens through which the pedoclimatic characteristics of different *terroirs* can be interpreted [19].

Although *Pinot Noir* is best suited to cool-temperate regions, it spread throughout Italy from the end of the 19th century, reaching as far south as Sicily, thanks to its reliable productivity and high sugar content. However, the variety's early ripening characteristics proved problematic in warmer southern regions, leading to a gradual decline and concentration in climatically favourable northern territories, particularly in Oltrepò Pavese and Trentino-Alto Adige [15].

Pinot Noir is considered one of the most challenging varieties to grow and vinify, while also being capable of producing some of the most refined and expressive wines [20]. Its defining characteristic lies in its sensitivity to the environment: more than many other cultivars, *Pinot Noir* directly reflects climatic conditions, soil composition, altitude and vineyard management.

Pinot Noir vines exhibit early budbreak and have a short ripening period, making them susceptible to spring frosts and pests.

Optimal performance occurs in cool-temperate climates with clay-limestone soils, whereas warmer conditions accelerate ripening and increase berry susceptibility to solar damage [21]. In cool and well-ventilated environments, *Pinot Noir* develops remarkable aromatic complexity.

Conversely, excessive heat compromises the variety's finesse, producing wines with increased alcohol levels. For this reason, it is particularly suitable to hilly areas with marked temperature ranges and well-drained soils [22].



The Oltrepò Pavese case study

In Italy, *Pinot Noir* has found an ideal habitat in some areas of the North, especially in the Oltrepò Pavese. The area's limestone hills, cool exposures, and sparkling wine tradition have given rise to two distinctive expressions: elegant red wines, and classic method sparkling wines, in which *Pinot Noir* is the principal variety and may also be used exclusively [13].

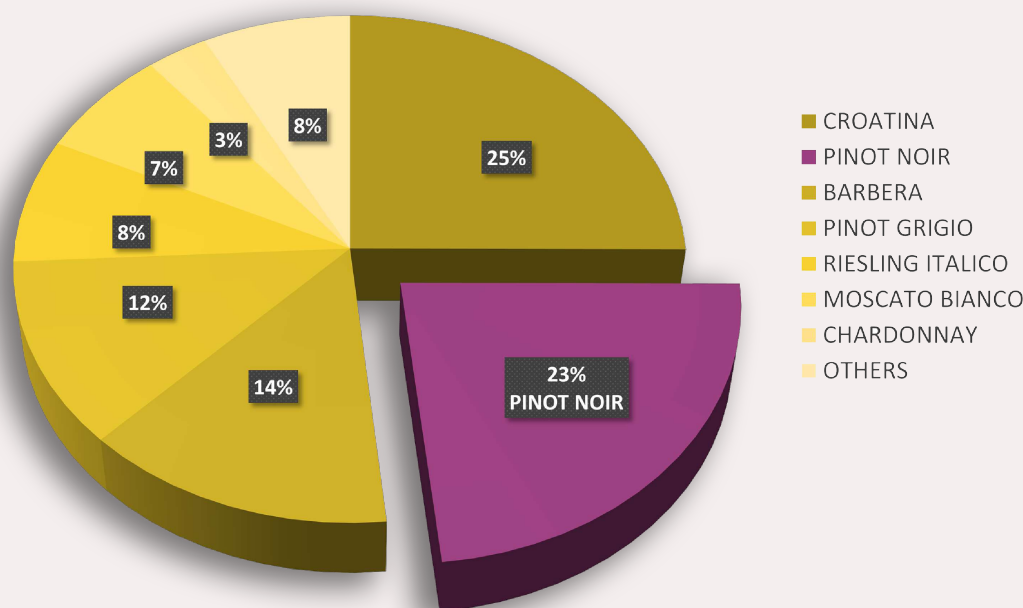


Figure 4. Percentage distribution of the main grape varieties cultivated in the Oltrepò Pavese.

Contemporary cultivation statistics for Oltrepò Pavese (Figure 4) highlight the importance of *Pinot* varieties in regional production, with approximately 2,820 hectares dedicated to *Pinot Noir* cultivation as of 2024, alongside 1,430 hectares of *Pinot Gris*.

The data, provided by the Consortium for the Protection of Oltrepò Pavese Wines (*Consorzio Tutela Vini Oltrepò Pavese*), describe the current distribution. However, they may not fully reflect the current vineyard distribution due to ongoing updates to the Lombardy regional viticultural registry.

* *What is life if the wine doesn't sparkle?* Quote from Pietro Riccadonna, founder of the Italian Wine Society of Casteggio (*Società Vinicola Italiana di Casteggio*).

3. Bioclimatic indices

In viticultural science, climate is recognised as one of the most influential factors shaping both grapevine development and wine quality. Temperature, precipitation, drought, hail, cold and heat, humidity, and aridity interact to affect the phenological cycle of the vine, from budburst to harvest. As such, the link between climatic variability and the qualitative characteristics of wine production is well established [23, 24].

In recent decades, the acceleration of climate change has significantly affected vineyard management practices. Rising average temperatures, altered precipitation regimes, and the increasing frequency of extreme weather events are reshaping the traditional boundaries of wine-growing regions [25]. In this evolving context, bioclimatic indices are used to assess thermal suitability, grapevine development, and potential harvest timing [26, 27].

Bioclimatic indices combine multiple atmospheric parameters – such as air temperature, precipitation, humidity, and solar radiation – into indicators that describe the climatic conditions of a given area. These indices not only provide a quantitative representation of climate patterns but also enable the analysis of their spatial and temporal dynamics. By synthesising complex environmental data into an interpretable metric, bioclimatic indices link climate variability with the availability and distribution of natural resources and the associated biophysical processes [28].

Historically, bioclimatic indices were introduced to characterise and compare wine-growing regions worldwide. They are often derived from thermal accumulation calculations, which typically consider daily mean air temperature above a defined physiological threshold – commonly 10 °C – below which vine vegetative growth is severely limited or completely inhibited [29]. Such thermal sums underlie several widely used indices, including the **Winkler Index** (based on Growing Degree Days), the Huglin Index, and the Cool Night Index, each of which reflects specific aspects of vine development and grape ripening potential.

By quantifying the heat availability and other climatic variables across a growing season, bioclimatic indices have made it possible to classify viticultural zones based on their suitability for different grape varieties [29]. This classification is not static; instead, it evolves in response to climate trends, making bioclimatic indices crucial tools for long-term vineyard planning, cultivar selection, and harvest scheduling.

In this study, bioclimatic indices play a central role in evaluating the suitability of the study area for *Pinot Noir* cultivation, a grape variety particularly sensitive to temperature variations and extreme weather conditions. By integrating the Winkler Index into a GIS-based framework, it is possible to generate a thematic layer that provides high-resolution information for land suitability analysis. Satellite-derived temperature data are calibrated with weather station records (point data) to produce a spatially continuous temperature map. This high-resolution map enables calculation of the Winkler Index across the entire study area with improved spatial accuracy.

Although temperature is only one of several climatic variables affecting viticulture, it remains a crucial factor. Heat accumulation, commonly expressed as Growing Degree Days, provides an effective measure of the thermal conditions of wine-growing regions. GDD values can be used to assess climatic limits to viticulture and identify the grape varieties best adapted to local conditions [30].

This approach supports the assessment of microclimatic differences within the study area, as well as precision-viticulture practices and climate-adaptation strategies.

Winkler Index in viticulture

Among the bioclimatic indices used in viticulture, the Winkler Index (hereafter WI) is one of the most widely adopted, despite its simplicity, and is commonly expressed as a thermal sum [31]. Although more complex bioclimatic indices, such as the Huglin Index, are often considered particularly suitable for hilly viticultural regions, the Winkler Index was also consistent with the available reconstructed dataset, which provides mean air temperature, whereas calculation of the Huglin Index would require reliable daily maximum temperatures.

This index is calculated by summing the positive differences between daily mean air temperature (T_{air}) and a base temperature of 10 °C over the growing season, from 1 April to 31 October in the Northern Hemisphere [see Equation (1)]. The resulting heat accumulation is expressed in Growing Degree Days (GDD), while the Winkler Index (WI) applies these GDD values to assign a region to one of five climatic zones, ranging from the coolest to the warmest (see Table 1) [24].

$$WI = \sum_{1\text{ Apr}}^{31\text{ Oct}} \max[(T_{air} - 10^{\circ}\text{C}); 0] \quad [^{\circ}\text{C day}] \quad (1)$$

Table 1. Classification of wine-producing regions according to the Winkler Index.

Regions	Heat summation (GDD) [°C·day]	Area	Wine type
Too cold	< 850		
Region I	850 – 1390	Chablis, Champagne, Burgundy.	Light-bodied white wines. e.g., <i>Pinot Noir</i> and <i>Pinot Gris</i> .
Region II	1390 – 1667	Bordeaux, northern Rhône.	Medium-bodied red wines. e.g., <i>Chardonnay</i> , <i>Pinot Noir</i> , <i>Merlot</i> .
Region III	1667 – 1945	Sonoma Valley, southern Rhône.	Full-bodied red wines. e.g., <i>Sauvignon Blanc</i> , <i>Grenache</i>
Region IV	1945 – 2223	Napa and Barossa Valley, Tuscany.	Fortified wines. e.g., <i>Barbera</i> , <i>Porto</i> , <i>Zinfandel</i> .
Region V	2223 – 2700	Jerez, Madeira, Lodi.	Bulk wines, table and drying grapes. e.g., <i>Muscat</i> , <i>Nero d'Avola</i> .
Too hot	> 2700		

The index, based solely on temperature, was developed by Albert Winkler and Maynard Amerine in the 1940s to guide the choice of the grape variety best suited to the region's climate. The WI is a widely used indicator for characterising viticultural climate and was originally developed for Californian wine-growing regions [32].

Parts of California, particularly Napa Valley and Sonoma County, are internationally recognised wine-growing regions characterised by Mediterranean-type climates. Together with other renowned wine-producing areas, such as Piedmont in Italy, Bordeaux in France, and Georgia, they lie within the broad climatic belt suitable for viticulture shown in Figure 5. Since the WI is based on growing-season heat accumulation rather than latitude alone, it can also be applied to characterise the thermal conditions of the Oltrepò Pavese.

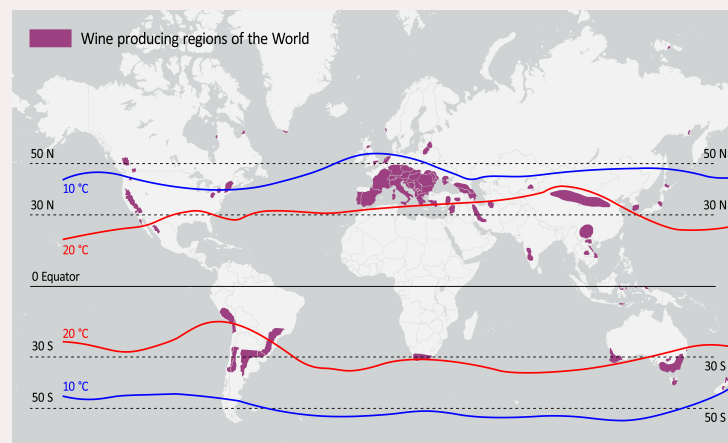


Figure 5. Map of average growing-season temperatures (Northern Hemisphere April–October, Southern Hemisphere October–April) [29].

While local climate strongly influences grape variety suitability, some cultivars are more sensitive to climate change than others. For example, *Pinot Noir* is highly climate-sensitive, whereas *Chardonnay* is generally more adaptable [33].

Figure 5 highlights the temperate zones with potential for wine-grape cultivation and production [34]. Rising temperatures in the Northern Hemisphere are leading to changes in wine characteristics: higher alcohol levels, lower acidity, and riper aromas. Earlier harvesting represents one possible short-term adaptation; in fact, many European regions are now harvesting a month earlier than they did 100 years ago, but there is a limit to how early they can be picked. If picked too early, the grapes do not have sufficient time to develop flavours and ripen tannins [33].

Long-term adaptations to climate change in viticulture include replanting with more suitable grape varieties, modifying vineyard layouts to reduce sun exposure, relocating to higher altitudes or latitudes, and applying protective measures such as kaolin particle films [35, 36] and zeolite-based products, which have been shown to mitigate heat and radiation stress, reduce berry sunburn, and limit yield losses by improving canopy microclimate and water-use efficiency [37, 38].

4. Materials

Air temperature is a key variable in this study and requires datasets combining adequate temporal resolution with spatial continuity. In the selected study area, the Lombardy Region provides reliable monitoring station observations with high temporal resolution; however, only a limited number of stations with suitable records were available within or near the study area (7 stations in 648.5 km², i.e., approximately one station per 92 km²). MODIS Land Surface Temperature (LST) products were therefore considered to provide spatially continuous information at a resolution of approximately 1 km, although they contain data gaps and have a lower temporal resolution than station observations [4]. ERA5-Land (Copernicus) data were also evaluated as a complementary temperature source.

4.1. ARPA Monitoring Stations

ARPA (*Agenzia Regionale per la Protezione Ambientale*) Lombardia [12] monitors air temperature and other meteorological variables through a network of fixed monitoring stations. The complete list of these stations is available on the Lombardy Region's open data portal in the *Meteorological Stations Map* section [39]. The network includes more than 1,230 sensors (Figure 6), for which the following metadata are available:

- Sensor ID;
- Type (water level, snow height, precipitation, temperature, relative humidity, global radiation, wind speed and direction);
- Unit of measurement;
- Altitude;
- Province;
- Start and end dates of the observations;
- Geographic coordinates.

Seven temperature monitoring stations located within or near the study area were initially identified (Figures 6–7). However, station ID 8002 was excluded from the principal calibration and validation analyses because its observations ended in September 2018; the remaining six stations provided sufficiently complete records for model development over the selected period. The dataset was obtained from ARPA Lombardia through an online data-request form [40]. Table 2 summarises the detailed metadata for each station, including sensor ID, location, altitude, temporal resolution, and data availability.

Figure 8 presents an excerpt of historical air temperature data, recorded between 2018 and 2022 at the ARPA monitoring station located in Fortunago (ID 8007).

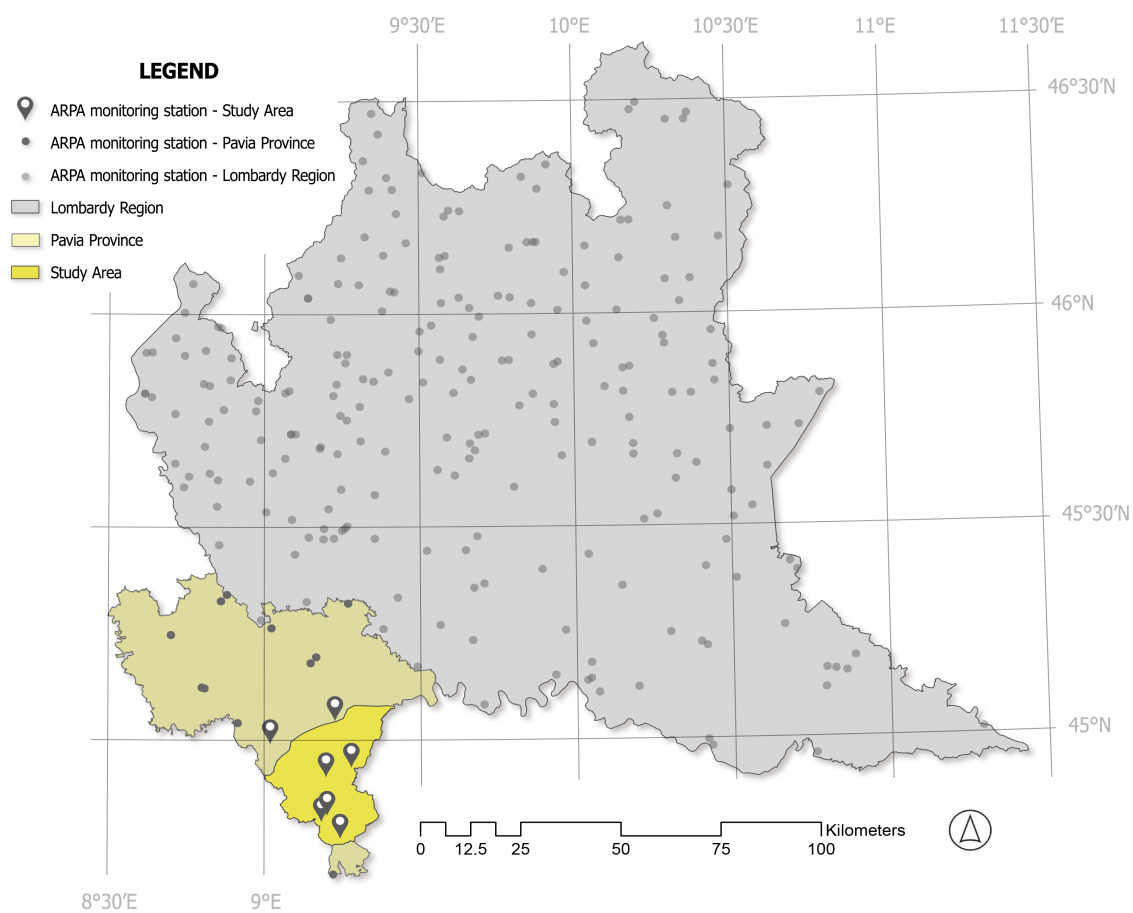


Figure 6. Distribution of ARPA meteorological monitoring stations across the Lombardy Region, highlighting the Province of Pavia and the Oltrepò Pavese Study Area.

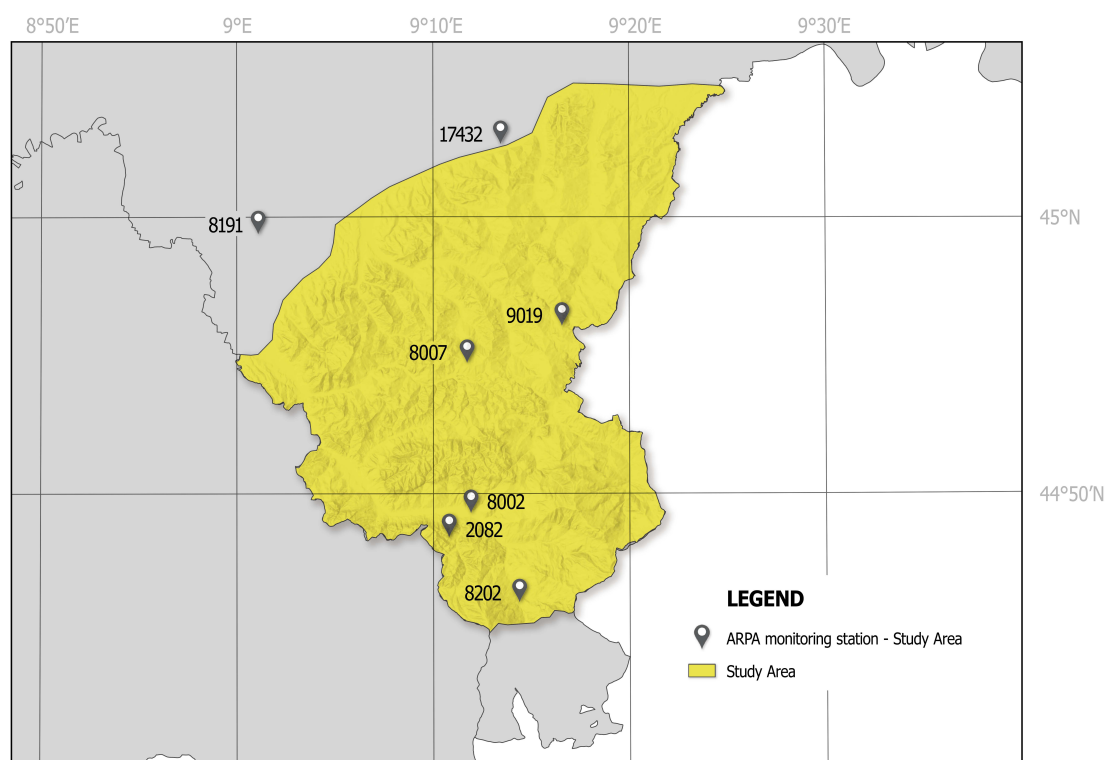


Figure 7. ARPA monitoring stations located within and around the Oltrepò Pavese Study Area, with their corresponding sensor IDs.

Table 2. ARPA monitoring stations located within or near the study area.

Sensor ID	Location	Altitude [m a.s.l.]	Unit	Temporal resolution	Data Availability
2082	Varzi Nivione	500	°C	hourly	2011/05/15 to present
8002	Varzi Via Mazzini	485	°C	hourly	1998/01/01 to 2018/09/18
8007	Fortunago	501	°C	hourly	1998/01/01 to present
8191	Voghera	95	°C	hourly	2003/03/04 to present
8202	Santa Margherita	575	°C	hourly	2003/01/01 to 2023/06/30
9019	Canevino	455	°C	hourly	2004/01/01 to present
17432	Broni	77	°C	hourly	2018/03/22 to present

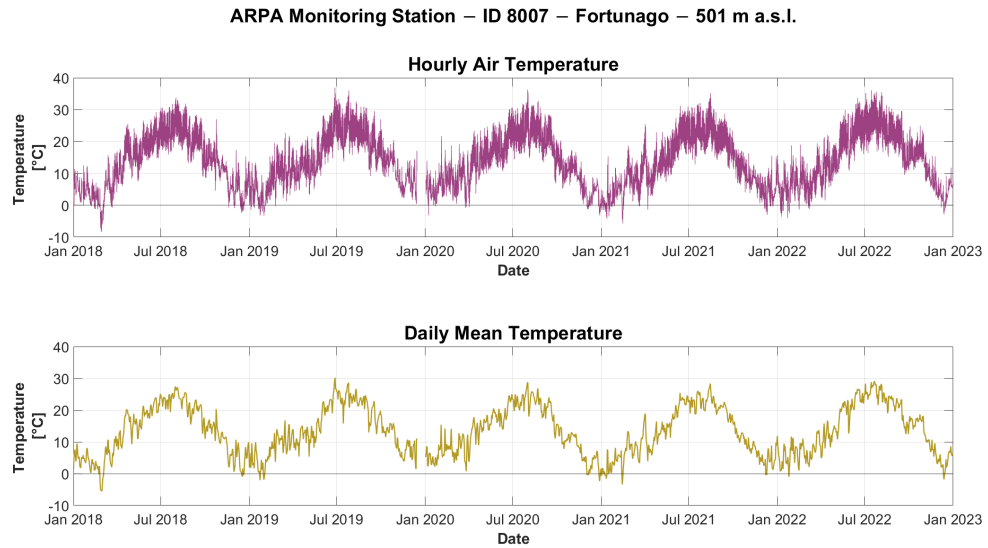


Figure 8. Excerpt from the 2018–2022 historical air-temperature time series recorded at ARPA monitoring station ID 8007 in Fortunago. **Top panel:** hourly air temperature, showing short-term variability. **Bottom panel:** daily mean air temperature, showing seasonal patterns.

4.2. MODIS Data

MODIS (Moderate Resolution Imaging Spectroradiometer) instruments are onboard NASA's TERRA and AQUA satellites, launched in 1999 and 2002, respectively. Designed for Earth observation, MODIS acquires data in 36 spectral bands, ranging from 0.4 to 14.4 μm , at multiple spatial resolutions. Together, the TERRA and AQUA MODIS instruments are capable of mapping the entire Earth's surface within one or two days. They provide information on large-scale global dynamics, including changes in cloud cover, radiant energy and various terrestrial, oceanic and atmospheric processes [41].

The AQUA and TERRA MODIS LST (MYD11A1 v6.1 and MOD11A1 v6.1) products provide daily measurements of land surface temperature and emissivity at a nominal spatial resolution of 1 km. In addition to the daytime and nighttime LST bands, the products include information on observation times, sensor zenith angles, clear-sky coverage, and surface emissivity.

However, preliminary analysis of the daily data revealed significant gaps; therefore, 8-day composite products – MYD11A2 v6.1 [42] (AQUA) and MOD11A2 v6.1 [43] (TERRA) – were adopted to obtain a more complete dataset (Figure 9).

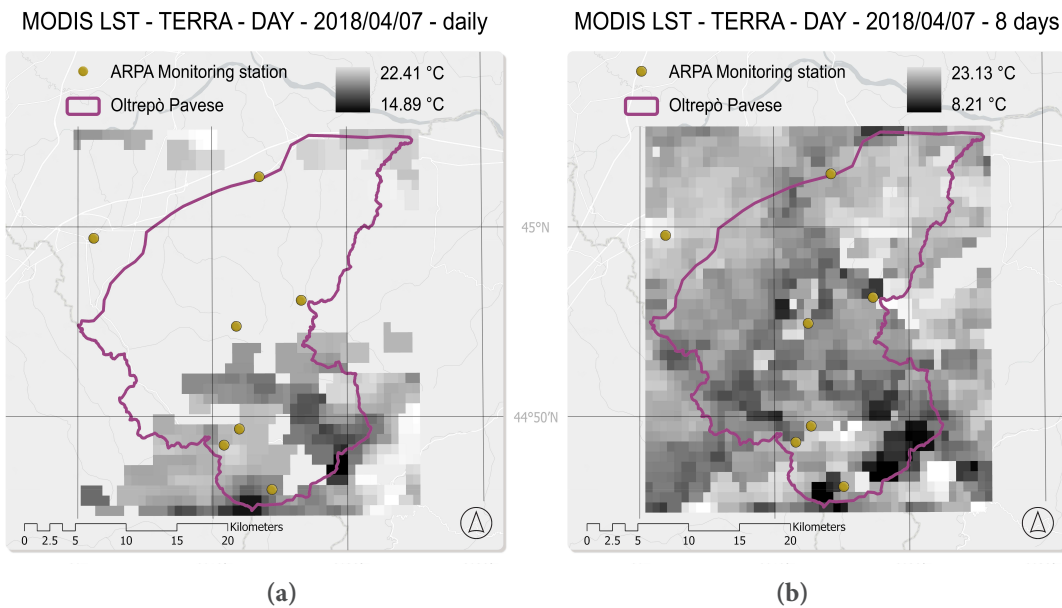


Figure 9. Comparison of daily (a) and 8-day composite (b) MODIS LST data. Extensive gaps in the daily image motivated the use of 8-day composites, which provided more spatially complete time series at a resolution of approximately 1 km. (MODIS TERRA, T_{day}, 07 April 2018).

Each pixel in the 8-day products represents the arithmetic mean of the valid clear-sky daily LST observations available within the corresponding compositing period. These products were selected because the daily LST images contained substantial gaps caused by missing or invalid observations, whereas the 8-day composites provided more complete spatial coverage and temporal stability for comparison with ARPA 8-day mean air temperatures. Within the study area and over the analysed period, local observation times ranged from approximately 09:06 to 12:08 for TERRA daytime acquisitions and from 18:30 to 23:48 for TERRA nighttime acquisitions. For AQUA, the corresponding ranges were approximately 09:42–15:12 and 00:18–05:30 local time.

Tables 3 and 4 summarise the main characteristics of the MODIS Land Surface Temperature (LST) dataset used in this study. Table 3 presents the general specifications of the MODIS TERRA and AQUA products. Table 4 details the layers and variables considered in the analysis.

Table 3. Characteristics of MODIS LST data.

Characteristic	Description
Collection	AQUA MODIS TERRA MODIS
DOI	10.5067/MODIS/MYD11A2.061 10.5067/MODIS/MOD11A2.061
Temporal resolution	8-day
Temporal extent	2002/07/04 to present 2000/02/18 to present
Spatial extent	Global
Pixel size	1,000 m
File format	GeoTIFF

Table 4. Layers and variables of MODIS LST data products MYD11A2.061 and MOD11A2.061 used in this study.

Field Name	Description	Units	Scale Factor
LST_Day_1km	Daytime Land Surface Temperature	Kelvin	0.02
Day_view_time	Local time of day observation	Hours	0.1
LST_Night_1km	Nighttime Land Surface Temperature	Kelvin	0.02
Night_view_time	Local time of night observation	Hours	0.1

MODIS LST data were accessed and downloaded using a script implemented in Google Earth Engine (GEE). This cloud-based geospatial analysis platform provides access to NASA satellite archives, allowing data to be filtered by spatial extent and time period, and then exported for further analysis. The complete GEE procedure used is provided in Script 1.

Specifically, Script 1 imports both the MODIS AQUA (MYD11A2) and MODIS TERRA (MOD11A2) image collections, providing land surface temperature (LST) data at 1 km spatial resolution and 8-day temporal resolution. The collections are filtered based on the Oltrepò Pavese study area and for the specified time interval (from 1 January 2018 to 31 December 2022). After filtering, the downloaded dataset consisted of 229 images from the AQUA satellite and 230 images from the TERRA satellite.

The following bands were selected for analysis:

- **LST_Day_1km** – Daytime Land Surface Temperature;
- **LST_Night_1km** – Nighttime Land Surface Temperature;
- **Day_view_time** – Time of satellite overpass during the day;
- **Night_view_time** – Time of satellite overpass during the night.

Subsequently, the collections were exported to Google Drive as unsigned 16-bit integer GeoTIFF files using the *Geetools batch export* function.

Script 1. Google Earth Engine script used to import, filter, and export MODIS AQUA (MYD11A2) and TERRA (MOD11A2) 8-day LST products over the Oltrepò Pavese study area for the period 2018–2022.

```
/******  
* Load and Export MODIS LST Data (AQUA + TERRA, 8-day, 1 km)  
* Study area: Oltrepò Pavese | Period: 2018 - 2022  
*****/  
  
// Define study area geometry (Oltrepò Pavese)  
var geometry = ee.Geometry.Polygon(  
  [[[8.998234, 44.750051],  
    [9.412481, 44.749306],  
    [9.414859, 45.080784],  
    [8.998224, 45.081537],  
    [8.998234, 44.750051]]]);  
  
// Date range  
var start = ee.Date('2018-01-01');  
var end = ee.Date('2023-01-01');  
  
// Import Geetools batch export module  
var batch = require('users/fitoprincipe/geetools:batch');
```

```

// Bands to select
var bands =
['LST_Day_1km', 'LST_Night_1km', 'Day_view_time', 'Night_view_time'];

//***** MODIS AQUA (MYD11A2) *****
var aqua = ee.ImageCollection('MODIS/061/MYD11A2')
  .filterBounds(geometry)
  .filterDate(start, end)
  .select(bands);

batch.Download.ImageCollection.toDrive(aqua, 'GEE_MODIS_Aqua', {
  region: geometry,
  type: 'uint16',
  crs: 'EPSG:4326',
  scale: 1000 // 1 km resolution
});

//***** MODIS TERRA (MOD11A2) *****
var terra = ee.ImageCollection('MODIS/061/MOD11A2')
  .filterBounds(geometry)
  .filterDate(start, end)
  .select(bands);

batch.Download.ImageCollection.toDrive(terra, 'GEE_MODIS_TERRA', {
  region: geometry,
  type: 'uint16',
  crs: 'EPSG:4326',
  scale: 1000 // 1 km resolution
});

```

4.3. Copernicus – ERA5-Land dataset

The ERA5-Land dataset is a global, high-resolution climate reanalysis product developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) as part of the Copernicus Climate Data Store (CDS) [44]. For the present case study, the 2-meter air temperature variable was extracted over the Oltrepò Pavese study area using a geographic bounding box expressed in WGS84 coordinates (EPSG:4326) extending from 44.74° N to 45.10° N and from 8.99° E to 9.45° E. The 2-meter air temperature variable represents modelled near-surface air temperature at a standard height of 2 m above the land surface. As a reanalysis variable, it is not a direct observation, although it is widely used in meteorological and climate studies. However, ERA5-Land and MODIS provide temperature information with different spatial resolutions and different physical meanings. ERA5-Land 2-meter air temperature is a reanalysis product available on a regular grid

of approximately $0.1^\circ \times 0.1^\circ$, corresponding to about 9 km. Each ERA5-Land grid cell therefore covers an area considerably larger than the spatial scale of local thermal variability in the Oltrepò Pavese. As a result, the spatial pattern appears smoother and less detailed, especially in a hilly area where elevation, slope, aspect, and land cover can strongly affect local thermal conditions.

By contrast, TERRA MODIS daytime LST is a satellite-derived land surface temperature product with a spatial resolution of approximately 1 km. It describes the radiometric temperature of the land surface under clear-sky conditions and does not directly correspond to 2-meter air temperature. Nevertheless, its finer grid captures local thermal heterogeneity more clearly than ERA5-Land. Therefore, the comparison shown in Figure 10 is not intended as a direct pixel-by-pixel validation, but as an illustration of the differences in spatial detail and physical meaning between a coarse-resolution reanalysis air temperature product and a finer-resolution satellite-derived land surface temperature product.

Tables 5 and 6 provide an overview of the ERA5-Land reanalysis dataset, which was used as an additional temperature source.

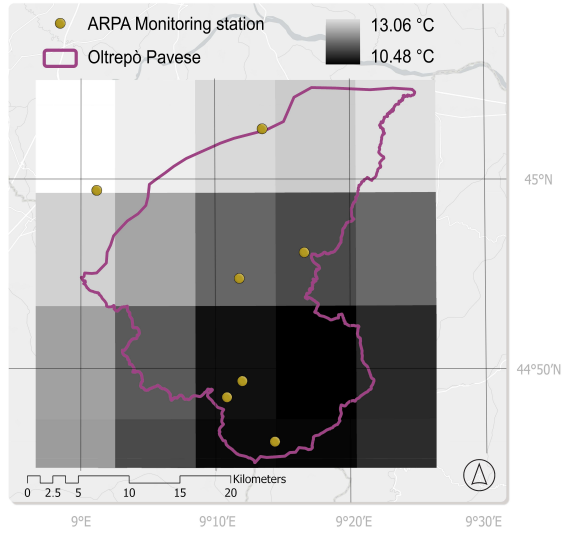
Table 5. Characteristics of ERA5-Land data (Copernicus).

Characteristic	Description
Temporal coverage	January 1950 to present
Spatial extent	Global
Spatial resolution	$0.1^\circ \times 0.1^\circ$ (~9 km grid)
Temporal resolution	Daily (derived from hourly values)
File format	NetCDF

Table 6. ERA5-Land variable related to 2-m air temperature.

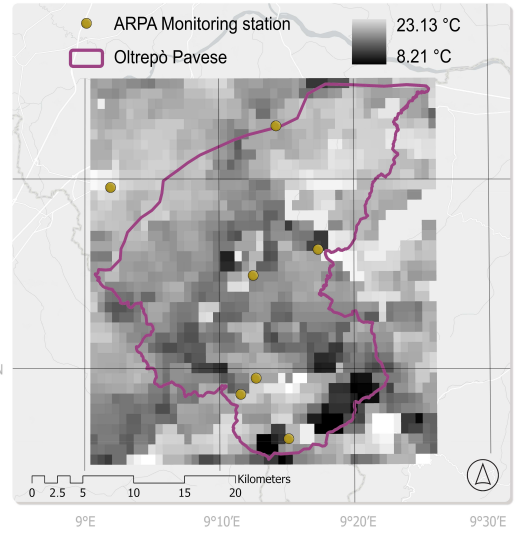
Field Name	Description	Units	Scale Factor
2-m temperature	Air temperature represented at 2 m above the modelled land surface	Kelvin	-

COPERNICUS - Tair - 2m - 2018/04/07 - daily



(a)

MODIS LST - TERRA - DAY - 2018/04/07 - 8 days



(b)

Figure 10. Daily ERA5-Land 2-meter air temperature (Copernicus, ~9 km resolution) (a) and MODIS LST TERRA daytime (8-day composite, ~1 km resolution) (b) for 7 April 2018 over the Oltrepò Pavese. The figure highlights the different spatial resolutions and physical meanings of the two datasets: ERA5-Land represents near-surface air temperature on a coarse reanalysis grid, whereas MODIS represents land surface temperature at a finer spatial resolution.

5. MODIS LST vs ARPA air temperature

The downloaded MODIS images were processed using a series of scripts developed in MATLAB (version 24.2, R2024b). The workflow included data harmonisation, interpolation of missing values, time-series generation, integration with ARPA observations, and statistical modelling. A regression model was subsequently calibrated using MODIS LST as the predictor and ARPA air temperature as the response variable, allowing spatially continuous air-temperature rasters to be derived from the satellite observations.

The workflow was organised into the sequential tasks shown in Figure 11.

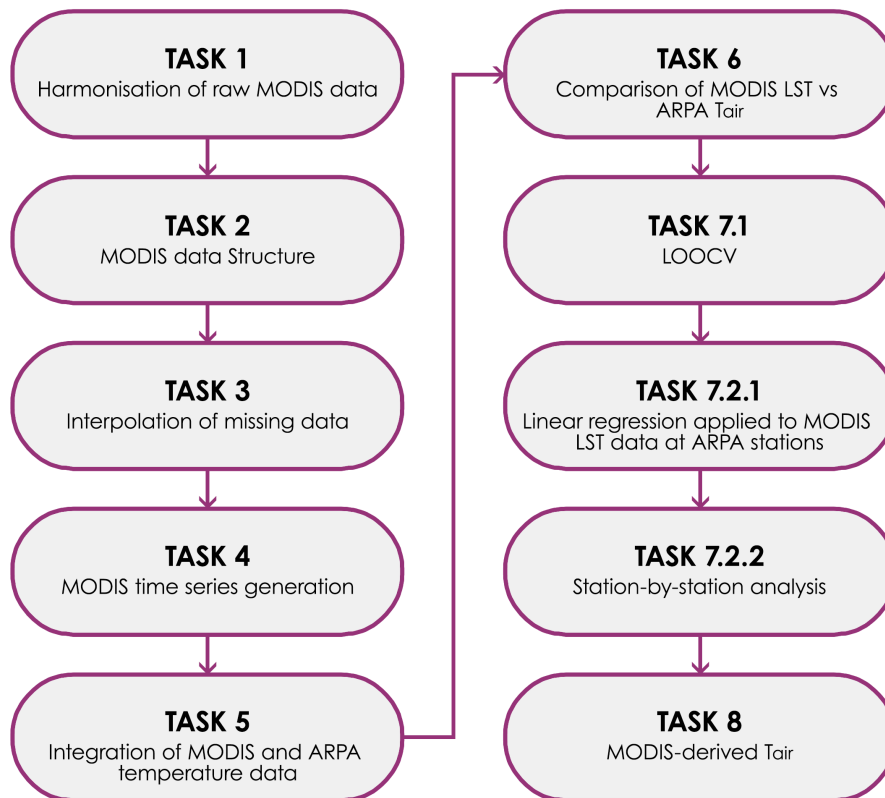


Figure 11. Workflow adopted to derive 8-day mean air temperature (T_{air}) from MODIS Land Surface Temperature (LST) observations.

5.1. TASK 1 – Harmonisation of raw MODIS data

The MODIS raster files downloaded from Google Earth Engine in GeoTIFF format were processed using two dedicated MATLAB functions: Script 2 was used for the AQUA MYD11A2 product, whereas Script 3 was used for the TERRA MOD11A2 product.

Both scripts replace zero-valued pixels, corresponding to invalid values in the exported products, with NaN, convert the daytime and nighttime LST bands from scaled Kelvin values to degrees Celsius, and harmonise the acquisition-time bands.

The raw LST values are converted to degrees Celsius using the MODIS scale factor of 0.02 and subtracting 273.15, as shown in Equation (2). Equation (3) provides a numerical example.

$$\text{Converted Pixel value} = (\text{Pixel value} \cdot 0.02) - 273.15 \quad [^{\circ}\text{C}] \quad (2)$$

$$\text{e.g. } \text{Converted Pixel value} = (14,136 \cdot 0.02) - 273.15 = 9.57 \quad [^{\circ}\text{C}] \quad (3)$$

The bands related to acquisition time are stored as integer values representing decimal hours scaled by a factor of 0.1. Therefore, each raw pixel value is divided by 10 to obtain the local acquisition time in decimal hours, as shown in Equation (4). Equation (5) provides a numerical example.

$$\text{Harmonized Pixel time} = (\text{Pixel time} \cdot 0.1) = H.dd \xrightarrow{\text{conversion}} H:mm \quad (4)$$

$$\text{e.g. } \text{Harmonized Pixel time} = (128 \cdot 0.1) = 12.8 \xrightarrow{\text{conversion}} 12h\ 48' \quad (5)$$

The harmonised arrays are saved both as MATLAB .mat files and as georeferenced GeoTIFF files.

Script 2. MATLAB function for harmonising MODIS AQUA (MYD11A2) 8-day LST data.

```
function armonizza_dati_MODIS_AQUA()
```

Set input/output directories

```
dir_file_GE_AQUA="MODIS_5anni_GE_AQUA";  
dir_file_armonizzate="MODIS_5anni_armonizzati";  
cur_file_name_aqua="..\\"+dir_file_GE_AQUA+"\*.tif";  
lista_file_aqua=dir(cur_file_name_aqua);
```

AQUA - Main loop to process each file: for each file in the specified folder, read, transform and save it

```
for i=1:numel(lista_file_aqua)  
    cur_file_name="..\\"+dir_file_GE_AQUA+"\\"+string(lista_file_aqua(i).name);  
    [cur_image,cur_georef]=readgeoraster(cur_file_name);  
    cur_image2=double(cur_image);  
    Transform bands 1 and 2 (daytime and nighttime temperature)  
    cur_image2(:,:,1)=trasforma_temperatura(cur_image2(:,:,1));  
    cur_image2(:,:,2)=trasforma_temperatura(cur_image2(:,:,2));  
    Transform bands 3 and 4 (acquisition time for day/night)  
    cur_image2(:,:,3)=trasforma_tempo(cur_image2(:,:,3));  
    cur_image2(:,:,4)=trasforma_tempo(cur_image2(:,:,4));  
    cur_file_name=erase(string(lista_file_aqua(i).name),".tif");  
    cur_file_name="..\\"+dir_file_armonizzate+"\\"+cur_file_name+"_A";  
    Save processed data to a .mat file  
    save(cur_file_name,"cur_image2","cur_georef")  
    Save also as GeoTIFF  
    geotiffwrite(cur_file_name,cur_image2,cur_georef)  
end  
end
```

Support function: convert raw temperature values to degrees Celsius

```
function cur_band=trasforma_temperatura(cur_band)  
cur_band(cur_band==0)=nan;  
cur_band=cur_band.*0.02 - 273.15;  
end
```

Support function: convert raw acquisition times to hours

```
function cur_band=trasforma_tempo(cur_band)  
cur_band(cur_band==0)=nan;  
cur_band=cur_band./10;  
end
```


Script 3. MATLAB function for harmonising MODIS TERRA (MOD11A2) 8-day LST data.

```
function armonizza_dati_MODIS_TERRA()
```

Set input/output directories

```
dir_file_GE_TERRA="MODIS_5anni_GE_TERRA";  
dir_file_armonizzate="MODIS_5anni_armonizzati";  
cur_file_name_terra="..\\"+dir_file_GE_TERRA+"\*.tif";  
lista_file_terra=dir(cur_file_name_terra);
```

TERRA - Main loop to process each file: for each file in the specified folder, read, transform and save it

```
for i=1:numel(lista_file_terra)  
    cur_file_name="..\\"+dir_file_GE_TERRA+"\\"+string(lista_file_terra(i).name);  
    [cur_image,cur_georef]=readgeoraster(cur_file_name);  
    cur_image2=double(cur_image);  
    Transform bands 1 and 2 (daytime and nighttime temperature)  
    cur_image2(:,:,1)=trasforma_temperatura(cur_image2(:,:,1));  
    cur_image2(:,:,2)=trasforma_temperatura(cur_image2(:,:,2));  
    Transform bands 3 and 4 (acquisition time for day/night)  
    cur_image2(:,:,3)=trasforma_tempo(cur_image2(:,:,3));  
    cur_image2(:,:,4)=trasforma_tempo(cur_image2(:,:,4));  
    cur_file_name=erase(string(lista_file_terra(i).name),".tif");  
    cur_file_name="..\\"+dir_file_armonizzate+"\\"+cur_file_name+"_T";  
    Save processed data to a .mat file  
    save(cur_file_name,"cur_image2","cur_georef")  
    Save also as GeoTIFF  
    geotiffwrite(cur_file_name,cur_image2,cur_georef)  
end  
end
```

Support function: convert raw temperature values to degrees Celsius

```
function cur_band=trasforma_temperatura(cur_band)  
cur_band(cur_band==0)=nan;  
cur_band=cur_band.*0.02 - 273.15;  
end
```

Support function: convert raw acquisition times to hours

```
function cur_band=trasforma_tempo(cur_band)  
cur_band(cur_band==0)=nan;  
cur_band=cur_band./10;  
end
```

5.2. TASK 2 – MODIS data Structure

This task organises the harmonised MODIS data into a single MATLAB structure containing the daytime and nighttime LST layers and the corresponding acquisition times for both AQUA and TERRA products. For each acquisition date, the script checks whether observations from both satellites are available. If a file is missing for a given date and sensor, a placeholder raster filled with NaN values is generated to preserve the temporal alignment of the dataset.

After processing all dates, the script compiles the collected data into a struct array containing the acquisition date, georeferencing information, and the harmonised bands for both sensors. The complete procedure is reported in Script 4.

Script 4. MATLAB function for structuring harmonised MODIS AQUA and TERRA LST data into a temporally aligned dataset.

```
function struct_dati_MODIS()



---


Set the directory where harmonised .mat files are stored
dir_file_armonizzate = "MODIS_5anni_armonizzati";
cur_file_name = "..\" + dir_file_armonizzate + "\\*.mat";
lista_file=dir(cur_file_name);



---


Create a table 'modis_list' with four columns: folder path, filename, acquisition date and satellite ('A' for AQUA, 'T' for TERRA)
modis_list = table('Size', [numel(lista_file), 4], ...
'VariableTypes',{'categorical','categorical','datetime', ...
'categorical'},'VariableNames', {'path','name','date','sat'});

Fill the table with data extracted from filenames
for i = 1:numel(lista_file)
    path = lista_file (i).folder;
    name = lista_file (i).name;
    parts = strsplit(name, '_');
    date = datetime([parts{1}, '/',parts{2}, '/', parts{3}], 'Format',
'yyyy/MM/dd');
    sat = erase(parts{end}, ".mat");
    modis_list.path(i) = path;
    modis_list.name(i) = name;
    modis_list.date(i) = date;
    modis_list.sat(i) = sat;
end

Determine raster dimensions from the first image
load(string(modis_list.path(1)) + "\" + string(modis_list.name(1)));
[m, n, k] = size(cur_image2);
```

Initialize empty stacks for each variable (If any data is missing, the stack will contain NaNs for that date)

```
date = unique(modis_list.date);
```

```
stack_georef_info = [];  
stack_temp_day_terra = [];  
stack_temp_night_terra = [];  
stack_time_day_terra = [];  
stack_time_night_terra = [];  
stack_temp_day_aqua = [];  
stack_temp_night_aqua = [];  
stack_time_day_aqua = [];  
stack_time_night_aqua = [];
```

```
stack_georef_info = cat(3, stack_georef_info, cur_georef(:, :, 1));
```

Loop over each unique date to build complete stacks

```
for i = 1:numel(date)  
    TERRA data for the current date  
    ii = find(modis_list.date == date(i) & modis_list.sat == "T");  
    if length(ii) == 1  
        load(string(modis_list.path(ii)) + "\" + ...  
            string(modis_list.name(ii)));  
        stack_temp_day_terra = cat(3, stack_temp_day_terra, ...  
            cur_image2(:, :, 1));  
        stack_temp_night_terra = cat(3, stack_temp_night_terra, ...  
            cur_image2(:, :, 2));  
        stack_time_day_terra = cat(3, stack_time_day_terra, ...  
            cur_image2(:, :, 3));  
        stack_time_night_terra = cat(3, stack_time_night_terra, ...  
            cur_image2(:, :, 4));  
  
    elseif length(ii) > 1  
        error("Multiple TERRA files found for the same date")  
  
    else  
        stack_temp_day_terra = cat(3, stack_temp_day_terra, nan(m,n));  
        stack_temp_night_terra = cat(3, stack_temp_night_terra, ...  
            nan(m,n));  
        stack_time_day_terra = cat(3, stack_time_day_terra, nan(m,n));  
        stack_time_night_terra = cat(3, stack_time_night_terra, ...  
            nan(m,n));  
    end  
end
```

```

AQUA data for the current date
ii = find(modis_list.date == date(i) & modis_list.sat == "A");
if length(ii) == 1
    load(string(modis_list.path(ii)) + '\ ' + ...
    string(modis_list.name(ii)));
    stack_temp_day_aqua = cat(3, stack_temp_day_aqua, ...
    cur_image2(:, :, 1));
    stack_temp_night_aqua = cat(3, stack_temp_night_aqua, ...
    cur_image2(:, :, 2));
    stack_time_day_aqua = cat(3, stack_time_day_aqua, ...
    cur_image2(:, :, 3));
    stack_time_night_aqua = cat(3, stack_time_night_aqua, ...
    cur_image2(:, :, 4));

elseif length(ii) > 1
    error("Multiple AQUA files found for the same date")

else
    stack_temp_day_aqua = cat(3, stack_temp_day_aqua, nan(m,n));
    stack_temp_night_aqua = cat(3, stack_temp_night_aqua, ...
    nan(m,n));
    stack_time_day_aqua = cat(3, stack_time_day_aqua, nan(m,n));
    stack_time_night_aqua = cat(3, stack_time_night_aqua, ...
    nan(m,n));
end
end

Create and save the final struct: the struct contains all the harmonised data for both AQUA and TERRA
modis.date = date;
modis.georef = stack_georef_info;
AQUA bands
modis.day_aqua = stack_temp_day_aqua;
modis.night_aqua = stack_temp_night_aqua;
modis.timeD_aqua = stack_time_day_aqua;
modis.timeN_aqua = stack_time_night_aqua;
TERRA bands
modis.day_terra = stack_temp_day_terra;
modis.night_terra = stack_temp_night_terra;
modis.timeD_terra = stack_time_day_terra;
modis.timeN_terra = stack_time_night_terra;
save whole_modis.mat modis
end

```

5.3. TASK 3 – Interpolation of missing data

To handle missing data (NaN values) in the structure created, the gap-filling procedure (provided in Script 5) was implemented in two stages:

- **Horizontal interpolation** – For each 2D layer in the time series, missing values are filled using a 5×5 -pixel moving window, applying a local average approach.
- **Vertical interpolation** – After processing each layer, remaining missing values are filled along the temporal dimension for each pixel using a centred three-date moving average, considering the previous and the following acquisition dates.

Figure 12 shows an extract of the structure created, consisting of one raster image per acquisition date, with each pixel representing the Land Surface Temperature (LST) value. The white pixels in the figure represent NaN values, indicating areas where the data are unavailable or undefined.

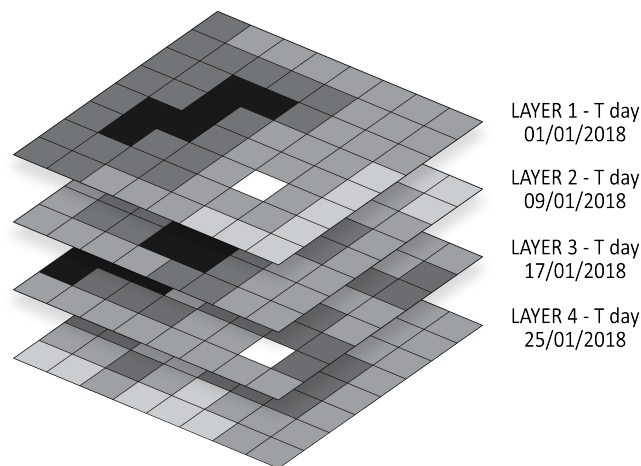


Figure 12. Extract of the stacked structure of MODIS raster images. Grey pixels represent a specific LST value, and white pixels indicate missing values (NaN).

To better explain the horizontal gap-filling operation, assume the red pixel in Figure 13 has a NaN value. To estimate its temperature, we performed spatial interpolation by averaging the pixels within a 5×5 moving window, centred on the aforementioned red pixel. It is, in effect, a spatial interpolation over an area of about $5 \times 5 \text{ km}^2$.

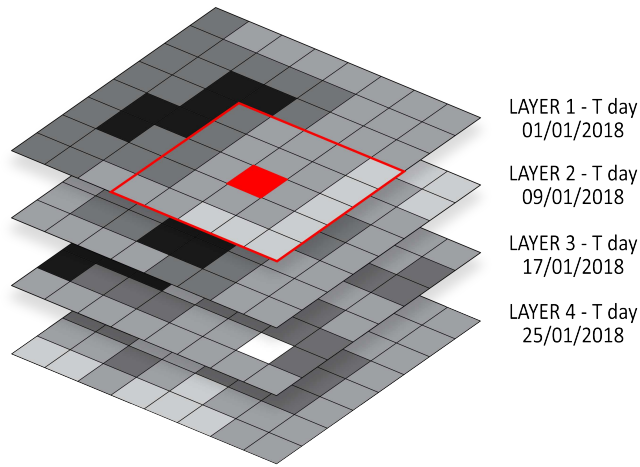


Figure 13. Example of horizontal gap-filling for missing values. To estimate the value of the missing pixel (in red), the surrounding pixels within a 5×5 window centred on the target pixel were averaged.

After the horizontal gap-filling, some missing values remained in the raster images. A vertical gap-filling procedure was therefore applied along the temporal dimension. For each missing pixel, the value was estimated using a centred moving average over three consecutive MODIS composite dates, corresponding to the previous, current, and following 8-day images. Since the central value is missing, the estimate is computed from the available non-missing values within this temporal window, as illustrated in Figure 14.

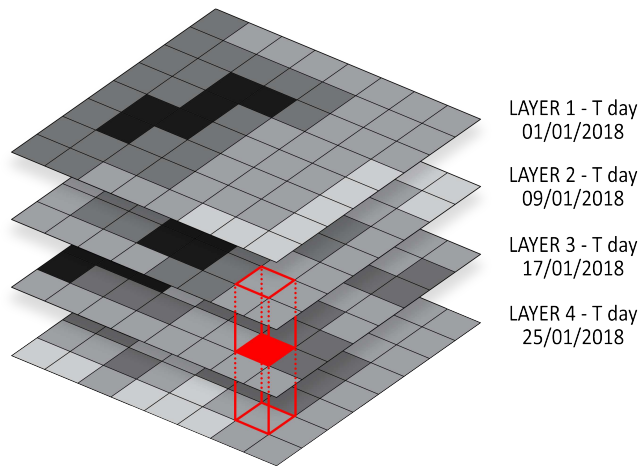


Figure 14. Example of vertical gap-filling: the residual NaN pixel, shown in red, is estimated from the corresponding pixel values in adjacent MODIS dates.

The adopted gap-filling procedure should be interpreted as a simplified, conservative preprocessing step rather than a full spatial interpolation model. Its objective was to fill small residual voids in regularly gridded MODIS LST images before extracting time series and performing the subsequent calibration with ARPA air temperature data.

For the spatial interpolation, a 5×5 moving window was adopted. Since each MODIS LST pixel represents approximately 1 km, the selected neighbourhood covers an area of about $5 \text{ km} \times 5 \text{ km}$ centred on the missing pixel. This window size represents a compromise between effective gap filling and the preservation of local spatial variability. Preliminary tests showed that a 3×3 window was often insufficient to fill larger gaps, whereas a 7×7 window introduced excessive smoothing of the thermal field. Over distances of approximately 5 km, the 8-day composite LST field was assumed to vary gradually, although local topographic and land-cover effects may still occur, particularly considering that the MODIS products are 8-day composites. Moreover, the raw LST images frequently contain isolated anomalous pixels caused by residual cloud contamination, atmospheric effects, or sensor-related artefacts. Under these conditions, the local moving average provides a simple and robust approach for reducing the influence of such outliers while simultaneously filling missing values.

For the temporal interpolation, a centred moving window including the closest available MODIS composite before and after the missing observation was adopted. Given the 8-day temporal resolution of the MODIS products, this corresponds to the minimum symmetric temporal interval (± 8 days) that can be used for interpolation. Using longer temporal windows would increase the risk of smoothing short-term temperature variability and reducing the temporal representativeness of the reconstructed values.

The principal limitation of this approach is that it may attenuate local spatial extremes and short-term temporal fluctuations. Consequently, the reconstructed values should be regarded as approximate estimates intended to improve the continuity of the MODIS time series, rather than as direct observations. Future developments could investigate more advanced interpolation techniques, such as inverse distance weighting (IDW) or kriging, capable of producing more robust temperature surfaces while maintaining the spatial and temporal characteristics of the original data.

Script 5. MATLAB function for spatial and temporal gap-filling of missing values in the MODIS dataset.

```
function fill_missing_values()



---


Load the struct containing the satellite data (AQUA and TERRA)
load whole_modis.mat



---


Parameters
curpar_window={5,5};
curpar_lenght=3;
curpar_lin=1;
method= 'movmean';



---


Horizontal and vertical interpolation of all fields in the struct
exclude_fields = ["georef", "date"];
fns = (setdiff(string(fieldnames(modis)),exclude_fields,"stable"))';
for currentField=fns
    fieldValue = modis.(currentField);

    Fill NaN in each layer - horizontal interpolation
    for i = 1:length(fieldValue)
        modis.(currentField)(:,:,i)= ...
            fillmissing2 (fieldValue(:,:,i), method,curpar_window);
    end

    Fill NaN between layers - vertical interpolation
    [row, col, ~] = size(fieldValue);
    for r = 1:row
        for c = 1:col
            modis.(currentField)(r,c,:)=fillmissing(squeeze(fieldValue
                (r,c,:)),method,curpar_lenght);
        end
    end
end

save whole_modis_fill.mat modis
end
```

5.4. TASK 4 – MODIS time series generation

This task loads the preprocessed MODIS products and extracts spatially interpolated LST values at the coordinates of the selected ARPA monitoring stations. Time series were generated for AQUA and TERRA daytime and nighttime observations, as implemented in Script 6. The 8-day composite products yielded more complete time series than the corresponding daily products, particularly for AQUA.

The extracted series are shown in Figures 15–21 and display consistent seasonal patterns in both daytime and nighttime observations.

Script 6. MATLAB function for extracting MODIS LST time series at ARPA monitoring station locations.

```
function interpolate_coord_ARPA()  
  
    Load MODIS structure and define the directory path and file names  
    load whole_modis_fill.mat  
    dir_arpa="dati_arpa_5anni";  
    dir_save="codici_matlab_VM";  
    file_coord_stazioni='StazioniMeteoPV_2.mat';  
  
    Define ARPA station IDs  
    ID_stazioni_in = [2082; 8002; 8007; 8191; 8202; 9019; 17432];  
  
    Monitoring stations data  
    wholepath_coord_stazioni="..\\"+dir_arpa+"\\"+file_coord_stazioni;  
    load(wholepath_coord_stazioni);  
    for i=1:length(ID_stazioni_in)  
        ii=find(MappaStazioniMeteorologiche.IdSensore==ID_stazioni_in(i));  
        fila=[MappaStazioniMeteorologiche.lat(ii), ...  
            MappaStazioniMeteorologiche.lng(ii)];  
        Dati_meteo=dati_MODIS_coord_ARPA(fila,ID_stazioni_in(i),modis);  
        if i==1  
            Dati_meteo_MODIS=Dati_meteo;  
        else  
            Dati_meteo_MODIS=[Dati_meteo_MODIS;Dati_meteo];  
        end  
    end  
  
    Save results to MAT file  
    filename = 'Dati_meteo_MODIS.mat';  
    filename= " ..\\"+dir_save+"\\"+filename;  
    save(filename, 'Dati_meteo_MODIS');  
    end
```

Bilinear spatial interpolation was used to estimate the MODIS value at each station coordinate.

```
function Dati_meteo=dati_MODIS_coord_ARPA(fila,ID_stazione,modis)
```

```
Dati_meteo = table('Size',[length(modis.date),12],'VariableTypes', ...  
["categorical","double","double","datetime","double","double", ...  
"double","double","double","double","double","double"], ...  
"VariableNames",["ID","fi","la","data_modis","temp_day_modis_A", ...  
"temp_night_modis_A","temp_day_modis_T","temp_night_modis_T", ...  
"time_day_A","time_night_A","time_day_T","time_night_T"]);
```

```
for i = 1:length(modis.date)  
    Dati_meteo.ID(i)=categorical(ID_stazione);  
    Dati_meteo.fi(i)=fila(1);  
    Dati_meteo.la(i)=fila(2);  
    Dati_meteo.data_modis(i)=modis.date(i);  
    cur_georef=modis.georef(1);  
    Dati_meteo.temp_day_modis_A(i)=geointerp(modis.day_aqua(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
    Dati_meteo.temp_night_modis_A(i)=geointerp(modis.night_aqua(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
    Dati_meteo.temp_day_modis_T(i)=geointerp(modis.day_terra(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
    Dati_meteo.temp_night_modis_T(i)=geointerp(modis.night_terra(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
    Dati_meteo.time_day_A(i)=geointerp(modis.timeD_aqua(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
    Dati_meteo.time_night_A(i)=geointerp(modis.timeN_aqua(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
    Dati_meteo.time_day_T(i)=geointerp(modis.timeD_terra(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
    Dati_meteo.time_night_T(i)=geointerp(modis.timeN_terra(:,:,i), ...  
    cur_georef,fila(1),fila(2));  
end
```

Generate time series plots of MODIS temperatures

```
color_day1 = [178, 34, 34] / 255;  
color_day2 = [233, 150, 122] / 255;  
color_night1 = [46, 111, 145] / 255;  
color_night2 = [116, 169, 193] / 255;
```

```

figure;
hold on;
plot(Dati_meteo.data_modis, Dati_meteo.temp_day_modis_A,'Color', ...
color_day1, 'LineWidth', 1.5);
plot(Dati_meteo.data_modis,Dati_meteo.temp_night_modis_A,'Color', ...
color_night1, 'LineWidth', 1.5);
plot(Dati_meteo.data_modis, Dati_meteo.temp_day_modis_T,'Color', ...
color_day2, 'LineWidth', 1.5);
plot(Dati_meteo.data_modis,Dati_meteo.temp_night_modis_T,'Color', ...
color_night2, 'LineWidth', 1.5);
hold off;

set(gca, 'FontSize', 18);
title(['MODIS Time Series - Coordinates of ID', num2str(ID_stazione), ...
'ARPA Monitoring Station'],'FontSize', 24)
legend('Daytime Temperature MODIS AQUA', 'Nighttime Temperature MODIS
AQUA', 'Daytime Temperature MODIS TERRA', 'Nighttime Temperature MODIS
TERRA', 'Location', 'best', 'FontSize', 16)
xlabel('Date', 'FontSize', 19, 'FontWeight', 'bold');
ylabel('Temperature [°C]', 'FontSize', 19, 'FontWeight', 'bold');
ylim([-10, 50]);
yticks(-10:10:50);
grid on
end

```

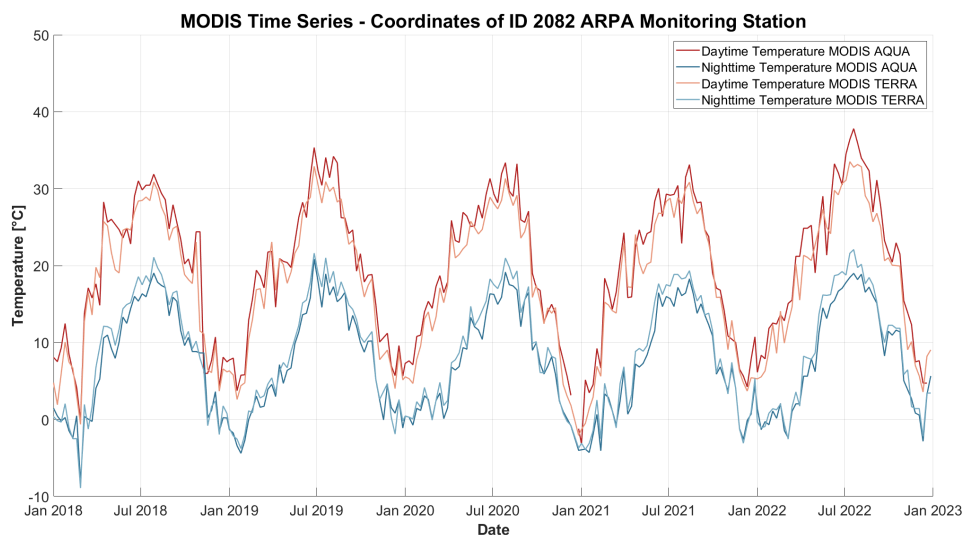


Figure 15. AQUA and TERRA daytime and nighttime MODIS LST time series extracted at ARPA station ID 2082 (Varzi Nivione, 500 m a.s.l.) for the period 2018–2022.

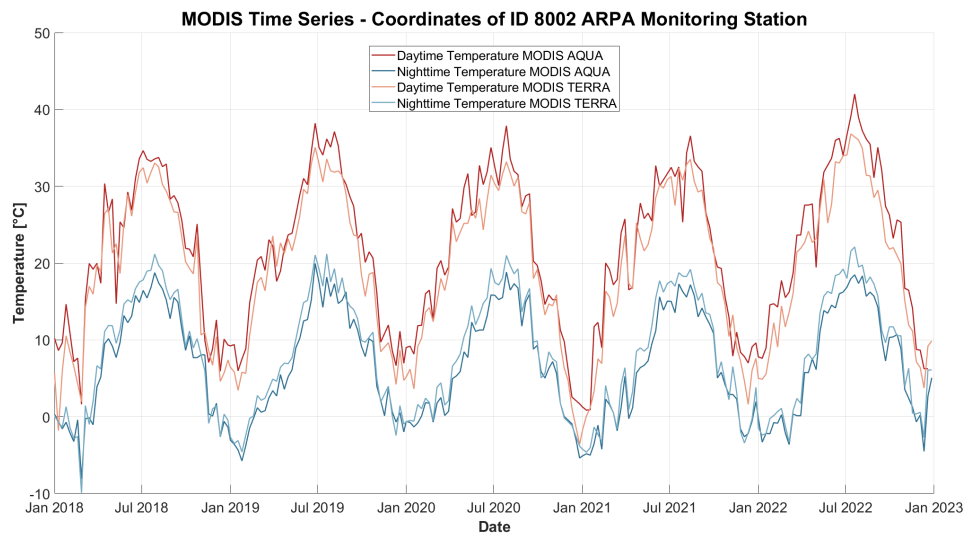


Figure 16. AQUA and TERRA daytime and nighttime MODIS LST time series extracted at ARPA station ID 8002 (Varzi via Mazzini, 485 m a.s.l.) for the period 2018–2022.

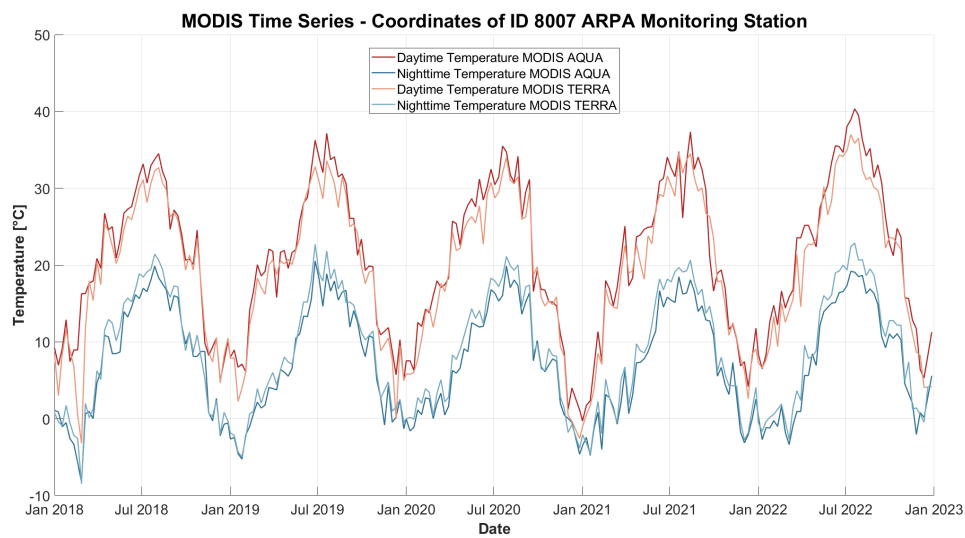


Figure 17. AQUA and TERRA daytime and nighttime MODIS LST time series extracted at ARPA station ID 8007 (Fortunago, 501 m a.s.l.) for the period 2018–2022.

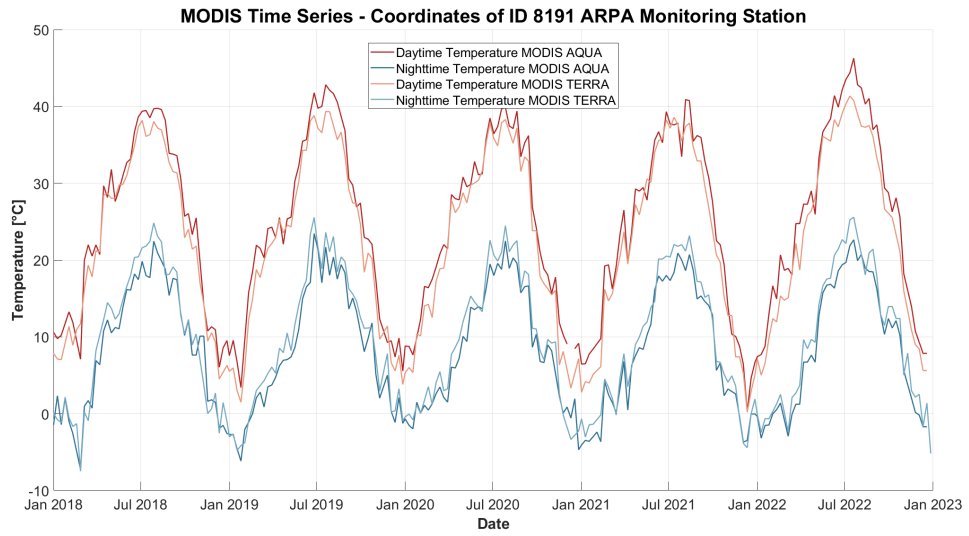


Figure 18. AQUA and TERRA daytime and nighttime MODIS LST time series extracted at ARPA station ID 8191 (Voghera via Cambiaso, 95 m a.s.l.) for the period 2018–2022.

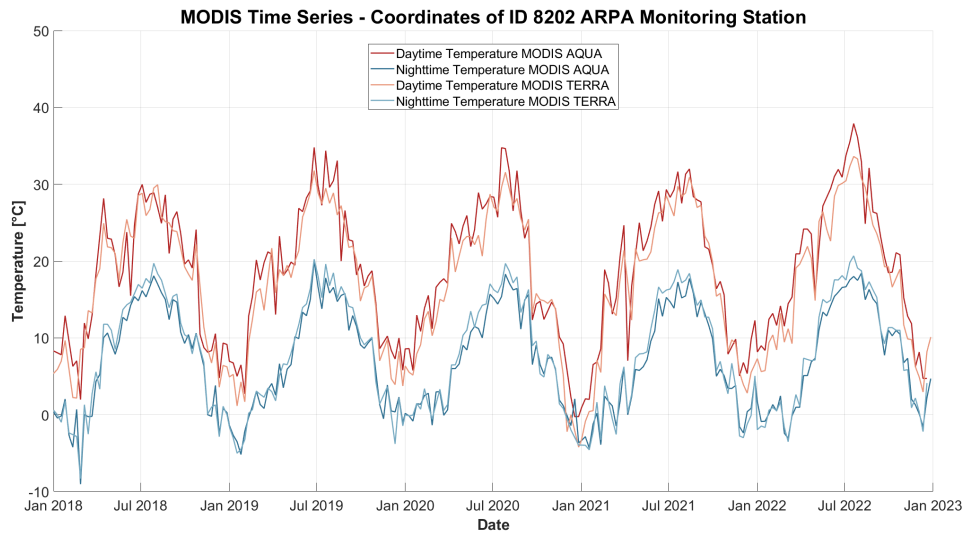


Figure 19. AQUA and TERRA daytime and nighttime MODIS LST time series extracted at ARPA station ID 8202 (Santa Margherita di Staffora Casanova, 575 m a.s.l.) for the period 2018–2022.

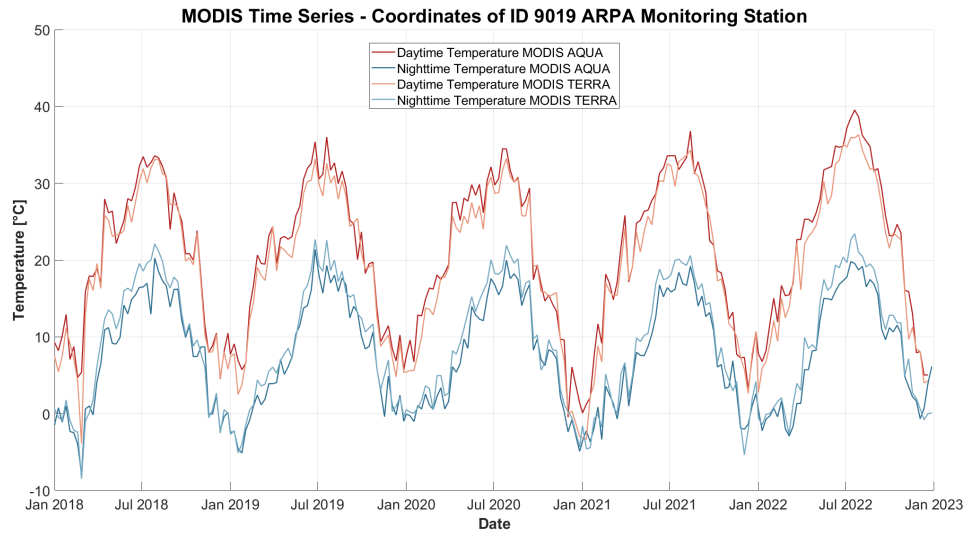


Figure 20. AQUA and TERRA daytime and nighttime MODIS LST time series extracted at ARPA station ID 9019 (Canevino, 455 m a.s.l.) for the period 2018–2022.

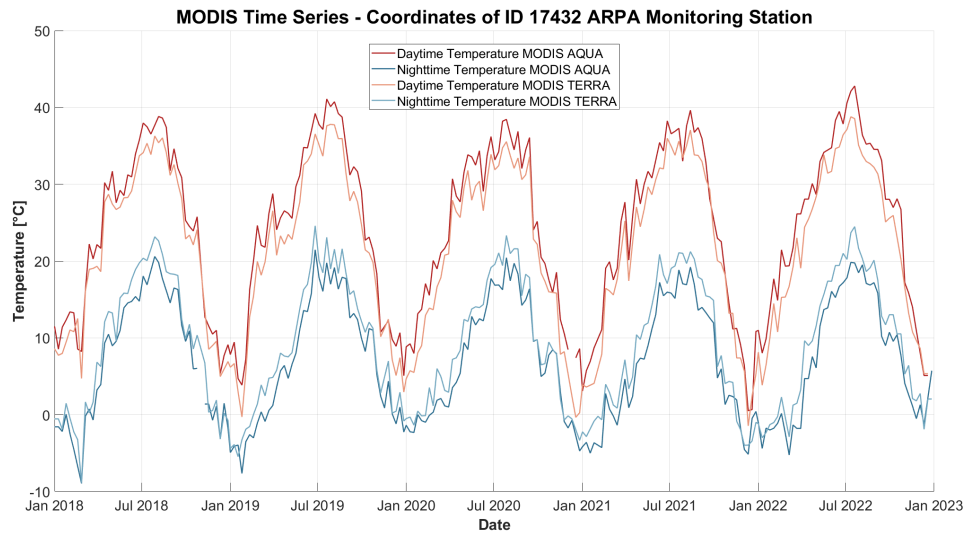


Figure 21. AQUA and TERRA daytime and nighttime MODIS LST time series extracted at ARPA station ID 17432 (Broni, 77 m a.s.l.) for the period 2018–2022.

5.5. TASK 5 – Integration of MODIS and ARPA temperature data

The MODIS products used in this study provide Land Surface Temperature as 8-day composite images. To ensure temporal consistency between satellite and ground-based observations, the ARPA air temperature measurements were aggregated over the same temporal intervals.

First, the original hourly ARPA observations were converted into daily mean air temperatures. For each MODIS acquisition date, the corresponding 8-day composite period was identified, spanning from the acquisition date T_1 to $T_2 = T_1 + 7$ days. For each monitoring station, all daily mean ARPA temperatures falling within the same period were extracted and averaged to obtain a single air-temperature value associated with each MODIS composite.

This procedure was repeated for all monitoring stations and MODIS acquisition dates, generating a dataset in which MODIS LST and ARPA air temperature observations were temporally aligned.

The workflow, reported in Script 7, consists of three main functions:

1. DateMODIS

- Scans the directory containing harmonised MODIS files;
- Extracts the acquisition dates and defines the corresponding start and end dates of each 8-day composite period;
- Saves the resulting table in the specified directory.

2. DailyMean_ARPA_filled

- Loads the temperature dataset from the ARPA monitoring stations;
- Replaces missing data (-999) with NaN;
- Interpolates missing hourly observations using a five-sample moving window;
- Aggregates the original hourly temperatures into daily means;
- Saves the daily mean temperature for each monitoring station.

3. MODIS_ARPA

- Loads the pre-processed MODIS and ARPA datasets;
- Calculates the arithmetic mean of the daily ARPA temperatures for each monitoring station falling within each MODIS 8-day composite period;
- Compiles all results into a single table (*whole_modis_arpa*), aligning MODIS and ARPA temperatures by date and station ID;
- Saves the merged dataset.

Script 7. MATLAB function for integrating MODIS LST and ARPA air temperature datasets at the 8-day temporal resolution.

```
function DateMODIS()
```

```
dir_file_armonizzate="MODIS_5anni_armonizzati";
cur_file_name= "..\"+dir_file_armonizzate + "\*_T.mat";
lista_file=dir(cur_file_name);
```

Initialise an empty table to store MODIS acquisition dates

```
DateSatellite = table('Size',[length(lista_file),3], ...
'VariableTypes',['datetime','datetime','datetime'], ...
'VariableNames',['DateSatellite','T1','T2']);
for i = 1:length(lista_file)
    fileName = string(lista_file(i).name);
    dateStr = extractBefore(fileName, '.mat');
    dateParts = strsplit(dateStr, '_');
    year = str2double(dateParts{1});
    month = str2double(dateParts{2});
    day = str2double(dateParts{3});
    currentDate = datetime(year, month, day);
    T1 = currentDate;
    T2 = currentDate + days(7);
    DateSatellite.DateSatellite(i) = currentDate;
    DateSatellite.T1(i) = T1;
    DateSatellite.T2(i) = T2;
```

```
end
```

```
filename = 'DateSatellite.mat';
save(filename, 'DateSatellite');
end
```

```
function DailyMean_ARPA_filled()
```

```
dir_arpas="dati_arpa_5anni";
wholepath_stazioni=".." + dir_arpas + "\*Tmedia*.mat";
meteoFileNames={dir(wholepath_stazioni).name}';
```

Loads ARPA monitoring stations data, replace -999 with NaN, interpolates missing values and computes daily mean temperatures, saving the results

```
for i=1:numel(meteoFileNames)
    cur_file_name=".." + dir_arpas + "\" + string(meteoFileNames(i));
    load(cur_file_name);
    Tmedia.Tmedia(Tmedia.Tmedia == -999) = NaN;
    curpar_lenght=5;
```

```

        method='movmean';
        cur_TT1 = table2timetable(Tmedia,'RowTimes','DataOra');
        cur_TT1.Tmedia_interp = fillmissing (cur_TT1.Tmedia, method, ...
        curpar_lenght);
        Compute daily mean temperature
        cur_TT2 = retime(cur_TT1,'daily','mean');
        ID_ARPA=num2str(Tmedia.IdSensore(1));
        filename = ['DailyMean_ARPA_' ID_ARPA '.mat'];
        filename= "..\"+dir_arpa+"\ "+filename
        save(filename, 'cur_TT2');
    end
end

```

```

function MODIS_ARPA()

```

```

    load Dati_meteo_MODIS.mat
    load DateSatellite.mat
    dir_arpa="dati_arpa_5anni";
    dir_save="codici_matlab_VM";

```

```

    wholepath_stazioni=".." + dir_arpa + "\*DailyMean*.mat";
    meteoFileNames={dir(wholepath_stazioni).name}';
    Dati_meteo_MODIS.Tmedia_ARPA = NaN(height(Dati_meteo_MODIS), 1);
    whole_modis_arpa=[];

    for i=1:numel(meteoFileNames)
        cur_file_name=".." + dir_arpa + "\ "+string(meteoFileNames(i));
        load(cur_file_name);
        cur_ID=categorical(cur_TT2.IdSensore(1));
        A=Dati_meteo_MODIS(Dati_meteo_MODIS.ID==cur_ID,:);
        Filters temperatures based on specified dates
        for j =1:height(DateSatellite)
            start_date=DateSatellite.T1(j);
            end_date=DateSatellite.T2(j)+hours(23);
            selected_temperatures=cur_TT2.Tmedia_interp(cur_TT2.DataOra ...
            ≥ start_date & cur_TT2.DataOra ≤ end_date);
            media=nanmean(selected_temperatures);
            A(j,:).Tmedia_ARPA=media;
        end
        whole_modis_arpa=[whole_modis_arpa;A];
    end
    filename=".." + dir_save + "\ "+'Dati_meteo_MODIS_ARPA.mat';
    save(filename, 'whole_modis_arpa');
end

```


5.6. TASK 6 – Comparison of MODIS LST vs ARPA T_{air}

The integrated MODIS–ARPA dataset was used to compare AQUA and TERRA daytime and nighttime LST values with the corresponding 8-day mean ARPA T_{air} observations. The resulting time-series plots (Figures 22–28) provided a preliminary visual assessment of the relationship between satellite-derived LST and air temperature (T_{air}) prior to model calibration.

ARPA observations were aggregated into a single 8-day mean air temperature rather than separate daytime and nighttime means. This choice was consistent with the objective of estimating the thermal variable required to calculate the Winkler Index, which is based on daily mean air temperature and accumulated growing degree days. The calibration target was therefore defined as the 8-day mean T_{air} corresponding to each MODIS compositing period. Conversely, MODIS daytime and nighttime LST values were retained as separate predictors because they describe complementary components of the surface thermal regime. Their combined use was expected to improve the estimation of mean air temperature. The plotting procedure is provided in Script 8.

Script 8. MATLAB function for plotting and comparing MODIS LST and 8-day mean ARPA air temperature at each monitoring station.

```
function PLOT_Temperature_MODIS_ARPA()  
  
load Dati_meteo_MODIS_ARPA.mat  
  
elenco_stazioni=unique(whole_modis_arpa.ID);  
Metadata for ARPA monitoring stations  
ID_MonitoringStations=[17432 2082 8002 8007 8191 8202 9019]';  
location={'Broni'; 'Varzi Nivione'; 'Varzi via Mazzini'; 'Fortunago'; ...  
          'Voghera via Cambiaso'; 'Santa Margherita di Staffora Casanova'; ...  
          'Canevino'};  
quota=[77 500 485 501 95 575 455]';  
DATI_MS_ARPA= table(ID_MonitoringStations, location, quota);  
  
color_day1 = [178, 34, 34] / 255;  
color_day2 = [233, 150, 122] / 255;  
color_night1 = [46, 111, 145] / 255;  
color_night2 = [116, 169, 193] / 255;  
color_arpa = [0.6 0.6 0.6];  
for i=1:length(elenco_stazioni)  
    figure  
    TEMPERATURE DAY AQUA  
    ii=whole_modis_arpa.ID==elenco_stazioni(i);  
    plot(whole_modis_arpa.data_modis(ii), ...  
         whole_modis_arpa.temp_day_modis_A(ii), 'Color', color_day1, ...
```

```

'LineWidth', 1.5)
hold on
TEMPERATURE NIGHT AQUA
plot(whole_modis_arpa.data_modis(ii), ...
whole_modis_arpa.temp_night_modis_A(ii), 'Color', color_night1,
'LineWidth', 1.5)
TEMPERATURE DAY TERRA
plot(whole_modis_arpa.data_modis(ii), ...
whole_modis_arpa.temp_day_modis_T(ii), 'Color', color_day2,
'LineWidth', 1.5)
TEMPERATURE NIGHT TERRA
plot(whole_modis_arpa.data_modis(ii), ...
whole_modis_arpa.temp_night_modis_T(ii), 'Color', color_night2,
'LineWidth', 1.5)
plot(whole_modis_arpa.data_modis(ii), ...
whole_modis_arpa.Tmedia_ARPA(ii), 'Color', color_arpa, 'LineStyle',
'--', LineWidth=2)
hold off
set(gca, 'FontSize', 18);
title(['ARPA Monitoring Station - ID', ...
num2str(DATI_MS_ARPA.ID_MonitoringStations(i)), ...
'- ', DATI_MS_ARPA.location{i}, '- Height a.s.l.', ...
num2str(DATI_MS_ARPA.quota(i)), 'm - Air Temperature'], ...
'FontSize', 24)
legend('Daytime Temperature MODIS AQUA', 'Nighttime Temperature MODIS
AQUA', 'Daytime Temperature MODIS TERRA', 'Nighttime Temperature MODIS
TERRA', 'ARPA Tair 8-day average', 'Location', 'best', 'FontSize', 16)
xlabel('Date', 'FontSize', 19, 'FontWeight', 'bold');
ylabel('Temperature [°C]', 'FontSize', 19, 'FontWeight', 'bold');
ylim([-10, 50]);
yticks(-10:10:50);
grid on
end
end

```

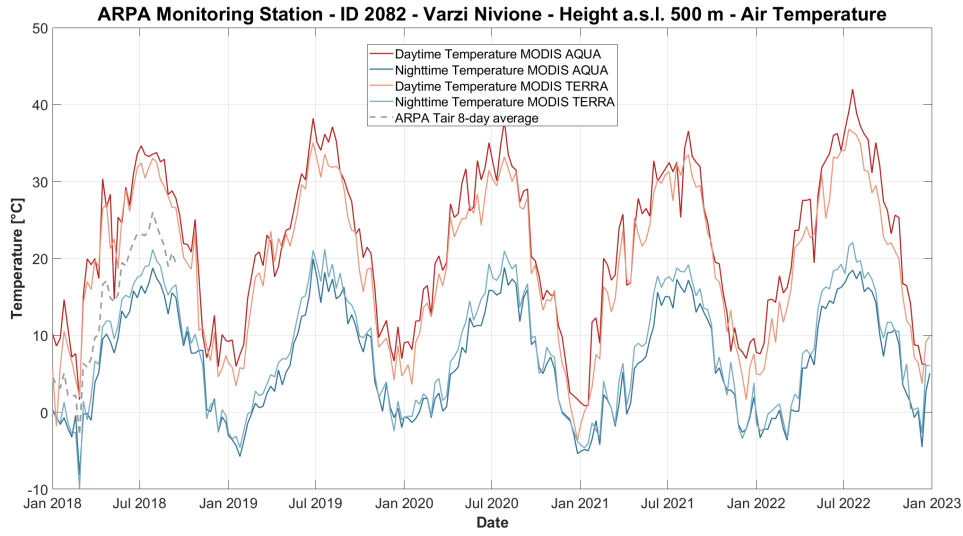


Figure 22. Comparison of AQUA and TERRA daytime and nighttime MODIS LST with the corresponding 8-day mean ARPA air temperature at station ID 2082. The series represent different physical quantities and are shown here to assess their temporal correspondence before regression calibration.

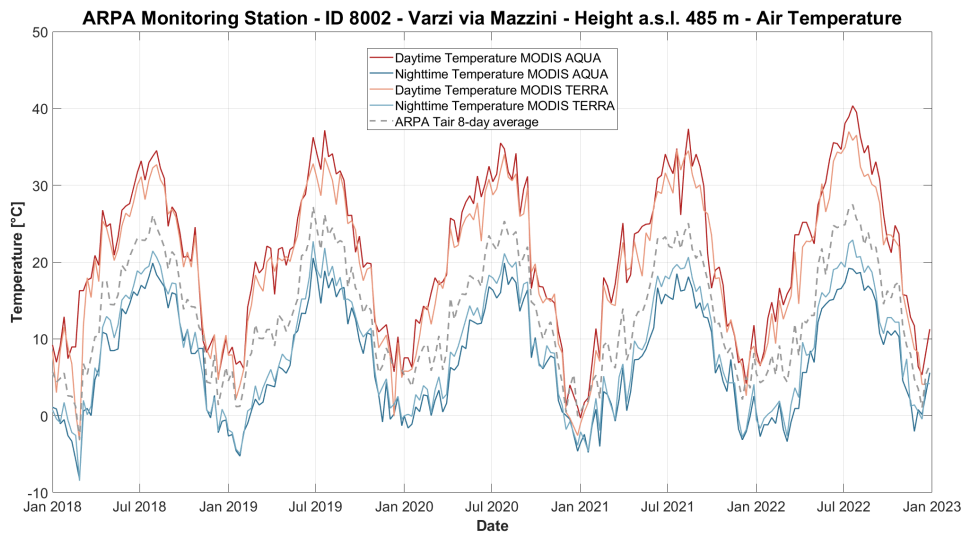


Figure 23. Comparison of AQUA and TERRA daytime and nighttime MODIS LST with the corresponding 8-day mean ARPA air temperature at station ID 8002. The series represent different physical quantities and are shown here to assess their temporal correspondence before regression calibration.

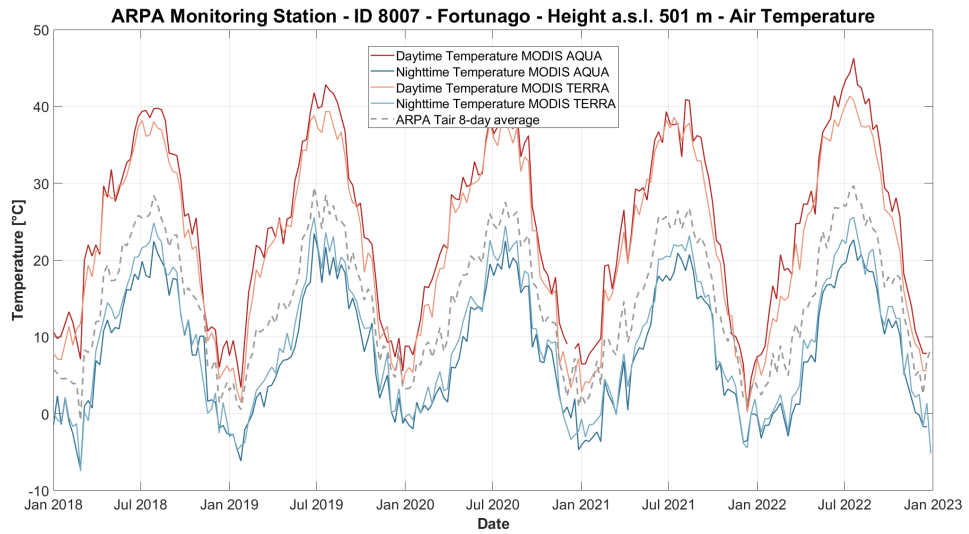


Figure 24. Comparison of AQUA and TERRA daytime and nighttime MODIS LST with the corresponding 8-day mean ARPA air temperature at station ID 8007. The series represent different physical quantities and are shown here to assess their temporal correspondence before regression calibration.

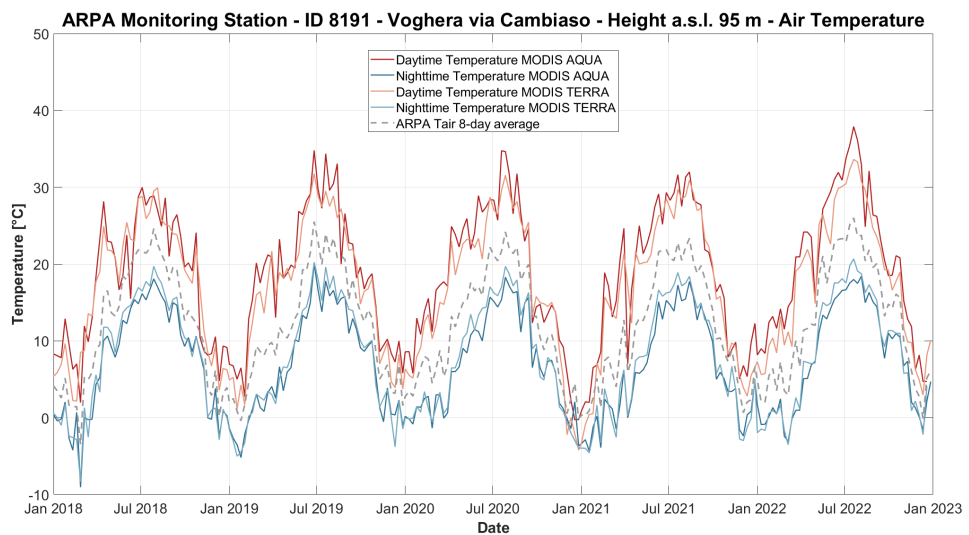


Figure 25. Comparison of AQUA and TERRA daytime and nighttime MODIS LST with the corresponding 8-day mean ARPA air temperature at station ID 8191. The series represent different physical quantities and are shown here to assess their temporal correspondence before regression calibration.

ARPA Monitoring Station - ID 8202 - Santa Margherita di Staffora Casanova - Height a.s.l. 575 m - Air Temperature

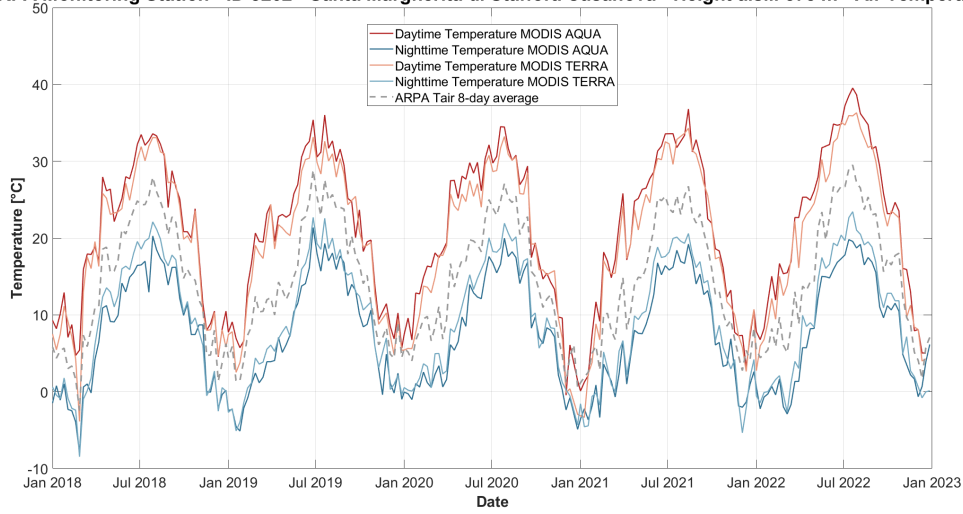


Figure 26. Comparison of AQUA and TERRA daytime and nighttime MODIS LST with the corresponding 8-day mean ARPA air temperature at station ID 8202. The series represent different physical quantities and are shown here to assess their temporal correspondence before regression calibration.

ARPA Monitoring Station - ID 9019 - Canevino - Height a.s.l. 455 m - Air Temperature

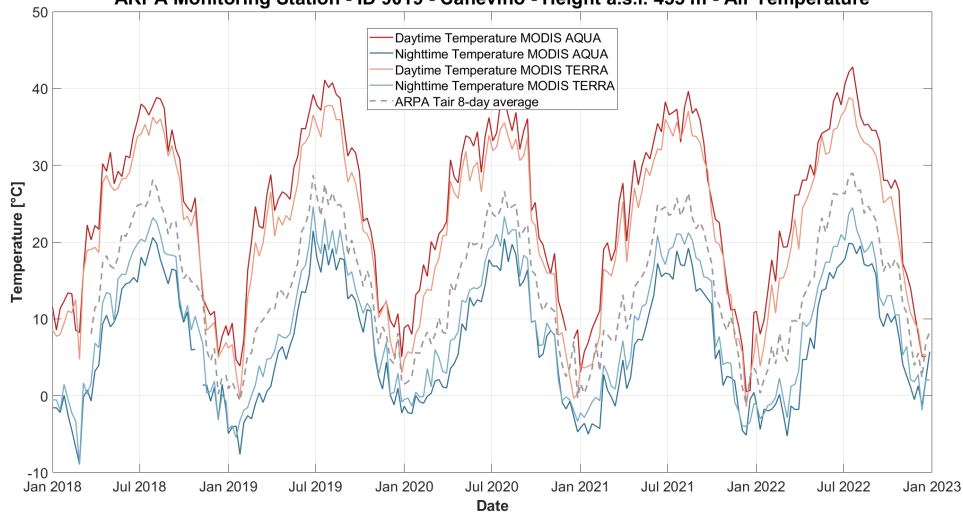


Figure 27. Comparison of AQUA and TERRA daytime and nighttime MODIS LST with the corresponding 8-day mean ARPA air temperature at station ID 9019. The series represent different physical quantities and are shown here to assess their temporal correspondence before regression calibration.

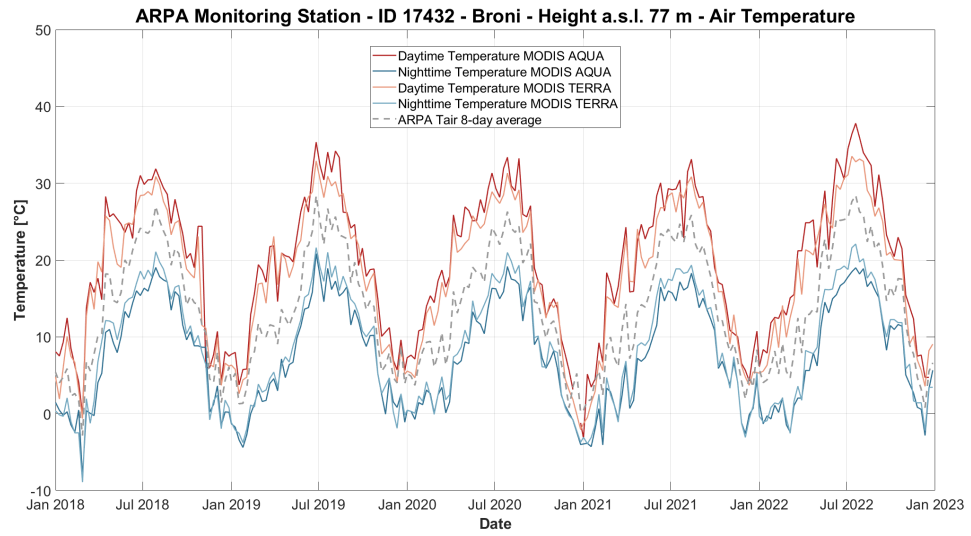


Figure 28. Comparison of AQUA and TERRA daytime and nighttime MODIS LST with the corresponding 8-day mean ARPA air temperature at station ID 17432. The series represent different physical quantities and are shown here to assess their temporal correspondence before regression calibration.

5.7. TASK 7.1 – LOOCV

The following Script 9 implements Leave-One-Out Cross-Validation (LOOCV) on the previously collected and organised dataset. The goal is to evaluate the robustness and spatial transferability of the linear regression models used to estimate air temperature (T_{air}) from MODIS LST observations.

The workflow consists of the following steps:

1. Loading of the dataset.
2. Excluding monitoring station ID 8002, due to incomplete temporal coverage.
3. Performing LOOCV – a robust linear regression model is calibrated and validated by excluding one monitoring station at a time.
4. Evaluating model performance through regression coefficients, intercept, RMSE, R^2 , and p-values.
5. Analysing the variability of model parameters by plotting the coefficients and intercept obtained in each LOOCV iteration.
6. Applying the calibrated models to estimate temperatures and quantify prediction errors for each excluded station.

During each LOOCV iteration, the excluded station is used exclusively for validation, while all observations from the remaining stations constitute the calibration dataset.

The response variable is the 8-day mean air temperature (T_{air}) derived from ARPA monitoring stations. For each MODIS composite period, the target value corresponds to the arithmetic mean of the daily average ARPA air temperatures over the same 8-day interval. The predictor variables are the four MODIS LST measurements extracted at each ARPA station location: AQUA daytime LST, AQUA nighttime LST, TERRA daytime LST, and TERRA nighttime LST. They were retained as separate predictors because daytime and nighttime observations describe different thermal conditions. Daytime LST mainly reflects surface heating due to solar radiation, whereas nighttime LST is more closely related to surface cooling. Since grapevine development depends on the overall thermal regime, both daytime and nighttime information were included in the regression model.

The regression dataset consists of paired MODIS–ARPA observations. Each record contains the four MODIS LST variables and the corresponding 8-day mean ARPA air temperature for a given monitoring station and composite period. Therefore, the regression model is calibrated using observations collected at different stations and different dates, exploiting both the spatial variability among monitoring stations and the temporal variability over the 2018–2022 study period.

Linear regression was selected because it is one of the most widely adopted approaches for estimating air temperature from MODIS land surface temperature in the remote sensing literature [9, 45, 46]. In addition, several alternative regression models were tested during the preliminary analysis. Since none of these models produced a substantial improvement in prediction accuracy, linear regression was retained as the final modelling approach owing to its simplicity, robustness, and ease of interpretation.

The general form of the linear regression model is given by Equation (6).

$$\hat{Y} = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \beta_3 \cdot X_3 + \dots + \beta_n \cdot X_n \quad (6)$$

Where β_0 is the intercept (model output when all predictors are zero), $\beta_1, \beta_2, \dots, \beta_n$ are regression coefficients for predictors $X_1, X_2, \dots, X_n$.

For this application, the predicted variable is the 8-day mean ARPA air temperature, and the regression model is expressed as Equation (7):

$$\hat{T}_{air} = Intercept + c_1 \cdot T_{dA} + c_2 \cdot T_{nA} + c_3 \cdot T_{dT} + c_4 \cdot T_{nT} \quad (7)$$

Where T_{dA} and T_{nA} are MODIS LST daytime and nighttime temperatures from the AQUA satellite, and T_{dT} and T_{nT} are MODIS LST daytime and nighttime temperatures from the TERRA satellite.

Script 9. MATLAB function for Leave-One-Out Cross-Validation of the MODIS-based air-temperature regression model.

```
function CROSS_VALIDATION ()

load('Dati_meteo_MODIS_ARPA.mat');

Exclude station 8002 since it only has data for 2018
L=whole_modis_arpa.ID=="8002";
whole_modis_arpa(L, :) = [];

Prepare results table
results=table('Size',[0,6], 'VariableTypes',{'categorical','cell', ...
'double', 'double', 'double', 'cell'}, 'VariableNames',{'StationID', ...
'Coefficients', 'RMSE', 'R2', 'PValue', 'PredictorNames'});

Define color map for the station's id for plotting
colorIDs = [2082, 8002, 8007, 8191, 8202, 9019, 17432];
colorValues = [0 0.4470 0.7410;
0.8500 0.3250 0.0980;
0.9290 0.6940 0.1250;
0.4940 0.1840 0.5560;
0.4660 0.6740 0.1880;
0.3010 0.7450 0.9330;
0.6350 0.0780 0.1840];
Colors = containers.Map(colorIDs, num2cell(colorValues, 2));
```

```
station_ids = unique(whole_modis_arpa.ID);
```

Preallocate storage

```
actual_values = [];  
predicted_values = [];  
coeff_table = table();
```

Perform Leave-One-Out Cross-Validation (LOOCV)

```
for i = 1:length(station_ids)  
    station_to_exclude = station_ids(i);  
    Create training and test sets  
    rows_to_exclude = whole_modis_arpa.ID == station_to_exclude;  
    training_data = whole_modis_arpa(~rows_to_exclude, :);  
    test_data = whole_modis_arpa(rows_to_exclude, :);  
    Predictor and response  
    predictors = training_data(:, [5:8]);  
    response = training_data.Tmedia_ARPA;  
    Train linear regression model (robust)  
    mdl = fitlm(predictors, response, 'RobustOpts', 'on')  
    Extract coefficients  
    coeffs = mdl.Coefficients.Estimate';  
    numCoeffs = length(coeffs) - 1;  
    coeffVarNames = strcat('Coeff', string(1:numCoeffs));  
    coeff_cells = num2cell(coeffs(2:end));  
    station_row=table(station_to_exclude,coeffs(1),coeff_cells{:}, ...  
    'VariableNames', ['Station_ID', 'Intercept', coeffVarNames]);  
    coeff_table = [coeff_table; station_row];  
    Predict values for the excluded station  
    test_predictors = test_data(:, [5:8]);  
    predicted_value = predict(mdl, test_predictors);  
    actual_values = [actual_values; test_data.Tmedia_ARPA];  
    predicted_values = [predicted_values; predicted_value];  
    Calculate RMSE for validation of excluded station  
    rmse_test = sqrt(nanmean((actual_values - predicted_values).^2));  
    fprintf('LOOCV RMSE: %.4f\n', rmse_test);  
    Extract model metrics on training data  
    rmse = mdl.RMSE;  
    r2 = mdl.Rsquared.Ordinary;  
    p_values = mdl.Coefficients.pValue';  
    predictor_names = mdl.CoefficientNames;  
    results=[results;{station_to_exclude,coeffs,rmse,r2,p_values, ...  
    predictor_names}];  
    save('LOOCV_results.mat', 'results');  
    save("CROSS_VALIDATION_indices.mat", "coeff_table");
```

```

    curname = strcat(string(station_to_exclude), "mdl.mat");
    save(curname,"mdl");
    disp(coeff_table);
end

```

PLOT GRAPH OF COEFFICIENTS AND INTERCEPT - 6 MODELS OF LINEAR REGRESSION

Extract coefficients and intercepts from the table

```

station_ids = coeff_table.Station_ID;
intercepts = coeff_table.Intercept;
coefficients = coeff_table{:, 3:end};
numCoeffs = size(coefficients, 2);

```

```

figure;
hold on;
xaxis = 1:length(station_ids);
markers = {'o', 's', 'd', '^'};
coeffLabels = {'Tday_A', 'Tnight_A', 'Tday_T', 'Tnight_T'};
legendEntries = {};
legendHandles = [];

```

Plot coefficients (left axis)

```

yyaxis left
for i = 1:length(station_ids)
    station_to_plot = station_ids(i);
    colorIdx = find(categorical(colorIDs) == station_to_plot, 1);
    if ~isempty(colorIdx)
        color = colorValues(colorIdx, :);
    else
        color = [0 0 0];
    end
    for j = 1:numCoeffs
        scatter(xaxis(i), coefficients(i, j), 200, color, ...
            markers{j}, 'filled');
    end
end

```

Add coefficient entries to legend

```

for j = 1:numCoeffs
    legendHandles = [legendHandles, scatter(NaN, NaN, 200, 'k', ...
        markers{j}, 'filled')];
    legendEntries = [legendEntries, coeffLabels{j}];
end
ylabel('Coefficients', 'FontSize', 24);

```

```

Plot intercept (right axis)
yyaxis right
for i = 1:length(station_ids)
    scatter(xaxis(i),intercepts(i),200,'k','DisplayName','Intercept');
end
Add intercept to legend
legendHandles = [legendHandles, scatter(NaN, NaN, 200, 'k')];
legendEntries = [legendEntries, {'Intercept'}];
ylabel('Intercept', 'FontSize', 24);

Final settings
set(gca, 'XTick', xaxis, 'XTickLabel', station_ids,'FontSize', 24);
xlabel('Excluded Station ID','FontSize', 24);
title('Coefficients and Intercepts for Each Excluded Station', ...
'FontSize', 26);
axis padded
grid on;
legend(legendHandles,legendEntries,'Location', 'Best', 'FontSize', 20)
hold off;
end

```

Coefficients remain relatively stable across analyses, indicating robustness of the model. MODIS nighttime LST predictors (Coeff 2 and Coeff 4) show a more substantial influence on the model than their daytime counterparts (Table 7).

Table 7. Regression coefficients obtained from the Leave-One-Out Cross-Validation (LOOCV) procedure.

Station ID excluded	Intercept	Coeff 1 (T_{day_A})	Coeff 2 (T_{night_A})	Coeff 3 (T_{day_T})	Coeff 4 (T_{night_T})
2082	2.6817	0.10237	0.35096	0.15005	0.35454
8007	2.8422	0.09628	0.38720	0.14443	0.34819
8191	2.6038	0.10874	0.39984	0.14662	0.33053
8202	3.0514	0.12310	0.42991	0.11321	0.30052
9019	2.7011	0.10533	0.38626	0.14136	0.33276
17432	2.8228	0.11665	0.35900	0.12520	0.36957

Performance is consistently high, with R^2 values above 0.98 and RMSE values around 1 °C for both training and validation datasets (Table 8). These results demonstrate that the models are accurate and robust, maintaining predictive capability even when a station is excluded from calibration.

Table 8. Performance metrics of the MODIS LST-based linear models evaluated using LOOCV.

Station ID excluded	R-squared	Training RMSE [°C]	Test RMSE [°C]
2082	0.9821	1.0704	1.1833
8007	0.9808	1.1127	1.1274
8191	0.9805	1.0990	1.1325
8202	0.9809	1.1048	1.1303
9019	0.9824	1.0529	1.1695
17432	0.9795	1.1253	1.1531

Slight variations in coefficients and RMSE among stations suggest minor local differences, but overall, the models are robust and reliable across all monitored locations.

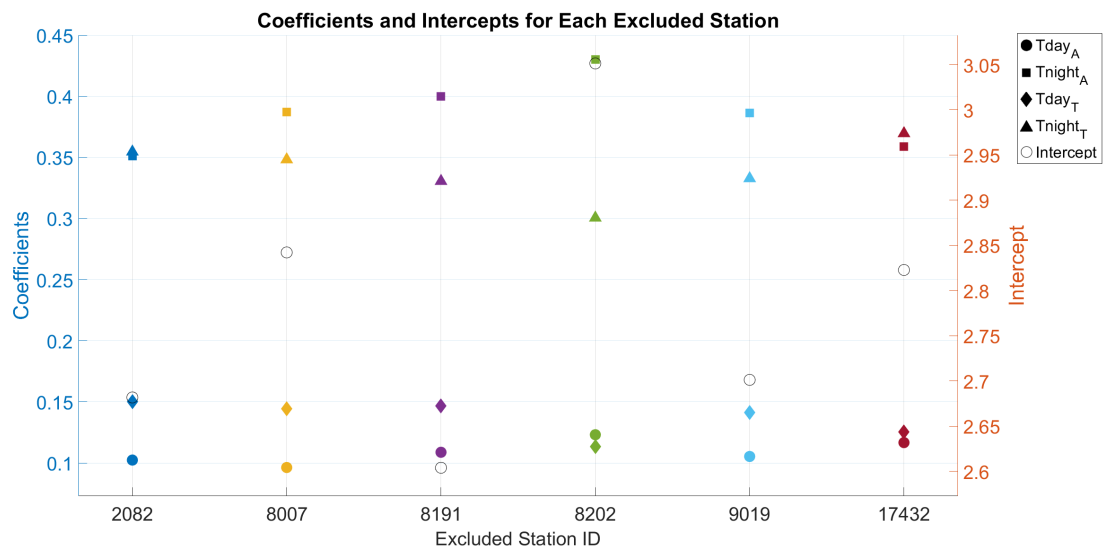


Figure 29. Regression coefficients and intercept obtained from each LOOCV iteration. The **x-axis** represents the ID of the excluded station; the **left y-axis** shows the coefficients of the four predictors (Tday_A, Tnight_A, Tday_T, Tnight_T), while the **right y-axis** shows the intercept of each regression model (black circles).

The variability of the regression coefficients across the LOOCV iterations provides insight into the influence of each monitoring station on model calibration. Large variations would indicate that the excluded station has a substantial impact on the estimated regression parameters, whereas limited variations suggest that the model is robust and that no single station dominates the calibration.

As shown in Figure 29, both the regression coefficients and the intercept remain relatively stable regardless of the excluded station. No systematic changes in the parameter values are observed, indicating that the relationship between MODIS LST and ARPA air temperature is consistent across the study area.

Spatially varying calibration approaches, such as geographically weighted regression or station-specific models, may be advantageous when a sufficiently dense monitoring network is available to reliably estimate local regression parameters. In the present study, calibration was based on six reliable ARPA monitoring stations distributed over a relatively small study area (approximately 30×40 km). Furthermore, the LOOCV results showed only limited variability in the estimated regression coefficients among stations, suggesting that the relationship between MODIS LST and near-surface air temperature is reasonably homogeneous across the study area. Therefore, a single multiple linear regression model was considered sufficient to provide a robust and representative description of this relationship.

5.8. TASK 7.2.1 – Linear regression applied to MODIS LST data at ARPA stations

The LOOCV results presented in Task 7.1 demonstrated that the regression coefficients remained stable across the different calibration iterations and that model performance was consistently high. These findings support the use of a single regression model for the whole Oltrepò Pavese study area. Accordingly, the final regression model was calibrated using all six reliable monitoring stations (ID 2082, 8007, 8191, 8202, 9019, and 17432). Station 8002 was excluded because it only contains observations for part of 2018, providing insufficient temporal coverage for reliable calibration. This task implements the calibration of MODIS Land Surface Temperature (LST) against ARPA ground-based air temperature (T_{air}). The complete implementation is reported in Script 10.

The workflow is structured as follows:

1. **LINEAR_REGRESSION** – Loads the MODIS-ARPA dataset and creates a robust linear regression model, *mdl_6_MS*, after excluding station 8002.
2. **MODIS_DERIVED_8dAvg_LR** – Applies the trained model *mdl_6_MS* to MODIS LST observations to estimate air temperature (T_{air}) for all available observations.
3. **PLOT_TempARPA_TempMODIS_derived_AVG_8_LR** – Compares 8-day mean MODIS-derived temperatures with ARPA ground measurements, calculating differences and performance metrics (mean, RMSE) for each station.

The regression model was calibrated using the robust regression option available in MATLAB (`fitlm` with `RobustOpts = 'on'`). Unlike ordinary least squares, which assigns equal weight to all observations, robust regression iteratively reduces the influence of observations with large residuals by assigning them lower weights during model fitting. This approach limits the impact of potential outliers arising from measurement errors, residual cloud contamination, or local discrepancies between satellite-derived land surface temperature and ground-based air temperature, resulting in regression coefficients that are less sensitive to anomalous observations.

Script 10. MATLAB function for calibrating the final robust linear regression model using MODIS LST and ARPA 8-day mean air temperature.

```
function LINEAR_REGRESSION()  
  
load('Dati_meteo_MODIS_ARPA.mat');  
  
Remove station 8002 (has little data)  
L=whole_modis_arp.ID== "8002";  
whole_modis_arp(L, :) = [];  
a=whole_modis_arp(:,[5:8,13]);  
b= "Tmedia_ARPA";  
mdl = fitlm(a,b, 'RobustOpts', 'on')  
filename = 'mdl_6_MS.mat';  
save(filename, 'mdl');  
end
```

The formula for the linear regression model is given in Equation (8).

$$\hat{T}_{air} = 2.8012 + 0.10734 \cdot T_{dA} + 0.38378 \cdot T_{nA} + 0.13649 \cdot T_{dT} + 0.34268 \cdot T_{nT} \quad (8)$$

Where T_{dA} and T_{nA} are the MODIS daytime and nighttime LST from AQUA, and T_{dT} and T_{nT} are the corresponding TERRA observations.

The estimated regression coefficients, together with their standard errors and p-values, are reported in Table 9. All predictors are statistically significant ($p < 0.05$), confirming that each MODIS LST variable contributed significantly to the estimation of air temperature.

Table 9. Regression coefficients, standard errors, and p-values of the linear regression model.

Predictor	Coefficient	Standard Error	p-value
Intercept	2.8012	0.093071	8.4551e-153
T_{dA}	0.10734	0.014972	1.2384e-12
T_{nA}	0.38378	0.02416	3.1105e-52
T_{dT}	0.13649	0.016843	1.1818e-15
T_{nT}	0.34268	0.025829	7.3954e-38

The model achieves a Root Mean Square Error (RMSE) of 1.09 °C and an R^2 of 0.981, indicating excellent predictive performance. The regression coefficients show that nighttime temperatures (T_{nA} and T_{nT}) contribute more strongly than daytime temperatures. This may be explained by the fact that, in the absence of solar heating, nocturnal conditions reduce the influence of surface heterogeneity and radiative forcing, resulting in a closer coupling between land surface and near-surface air temperatures [45].

The calibrated regression model was then applied to the complete MODIS dataset to estimate the corresponding 8-day mean air temperature. The implementation of this prediction step is reported in Script 11.

Script 11. MATLAB function for estimating 8-day mean air temperature from MODIS LST.

```
function MODIS_DERIVED_8dAvg_LR()
```

```
load('Dati_meteo_MODIS_ARPA.mat');  
load('mdl_6_MS.mat');
```

```
a=whole_modis_arpa(:,[5:8]);  
mdl_6_MS=mdl  
bpred=predict(mdl_6_MS,a);  
T_MODIS_pred=whole_modis_arpa;  
T_MODIS_pred.T_MODIS_pred_LR= bpred;  
save('MODIS_pred.mat', 'T_MODIS_pred');
```

Scatter plot: predicted vs measured

```
Y = whole_modis_arpa(:, 13);  
figure;  
scatter(bpred,Y,'b','filled');  
hold on;  
  
lm = fitlm(bpred, Y);  
x_fit = linspace(min(bpred), max(bpred), 150);  
y_fit = lm.Coefficients.Estimate(2) * x_fit + lm.Coefficients.Estimate(1);  
plot(x_fit, y_fit, '-r', 'LineWidth', 5);
```

Calculating R² and RMSE considering the 6 monitoring stations

```
R2 = lm.Rsquared.Ordinary;  
RMSE = sqrt(nanmean((Y - bpred).^2));  
str = sprintf('R^2 = %.3f\nRMSE = %.2f °C', R2, RMSE);  
text(min(x_fit)+1, max(y_fit)-1, str, 'FontSize', 24, 'FontWeight', ...  
'bold', 'BackgroundColor', 'w');  
set(gca, 'FontSize', 18);  
xlabel('MODIS-derived Tair (°C)', 'FontSize', 24, 'FontWeight', 'bold');  
ylabel('Measured ARPA Temperature (°C)', 'FontSize', 24, 'FontWeight', 'bold');  
title('Calibration of MODIS LST against ARPA Air Temperature (8-day mean)', ...  
'FontSize', 30, 'FontWeight', 'bold');  
  
grid on;  
ylim([min(Y) - 2, max(Y) + 2]);  
  
legend({'Data', 'Regression Line'}, 'Location', 'best', 'FontSize', 24);  
hold off;  
end
```

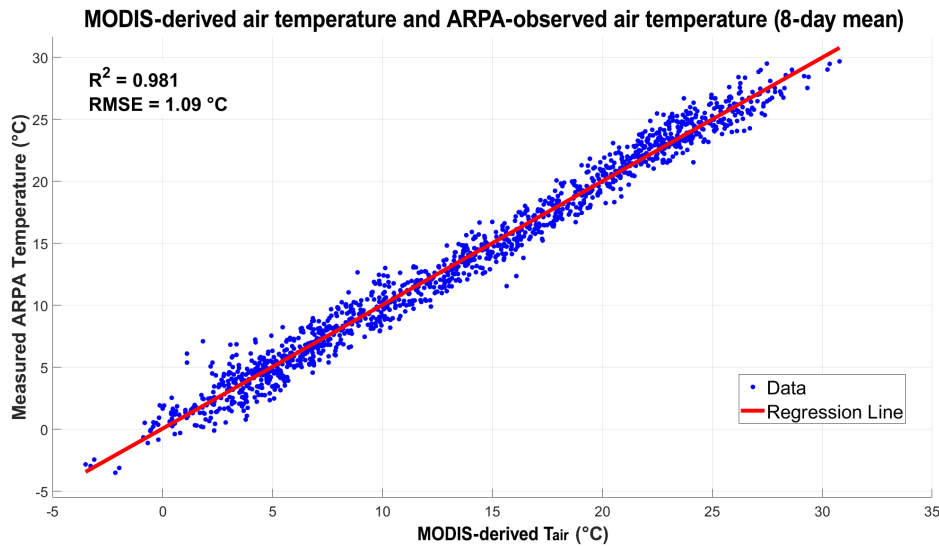


Figure 30. Calibration of MODIS LST against ARPA air temperature measurements (8-day mean) using the 6-station robust linear-regression model.

The scatter plot (Figure 30) compares measured ARPA T_{air} (y-axis) with MODIS-derived T_{air} (x-axis). The red line represents the regression fit, while blue dots indicate individual observations. The model shows excellent agreement with observations, achieving $R^2 = 0.981$ and $RMSE = 1.09\text{ }^{\circ}\text{C}$, confirming a strong linear relationship and high predictive accuracy.

To evaluate the temporal performance of the global regression model at each monitoring station, the MODIS-derived and ARPA 8-day mean air temperature time series were compared. The complete procedure is reported in Script 12.

Script 12. MATLAB function for comparing MODIS-derived and ARPA 8-day mean air temperature time series at each monitoring station.

```
function PLOT_TempARPA_TempMODIS_derived_AVG_8_LR()

load('MODIS_pred.mat');

Color Map
colorIDs = [2082, 8002, 8007, 8191, 8202, 9019, 17432];
colorValues = [0 0.4470 0.7410;
    0.8500 0.3250 0.0980;
    0.9290 0.6940 0.1250;
    0.4940 0.1840 0.5560;
    0.4660 0.6740 0.1880;
    0.3010 0.7450 0.9330;
    0.6350 0.0780 0.1840];
Colors = containers.Map(colorIDs, num2cell(colorValues, 2));
```

Monitoring stations

```
ID_MonitoringStations=[2082 8002 8007 8191 8202 9019 17432]';
Location={'Varzi Nivione';'Varzi via Mazzini';'Fortunago';'Voghera via Cambiaso';'Santa Margherita di Staffora Casanova';'Canevino'; 'Broni'};
Quotaslm=[500 485 501 95 575 455 77]';
DATI_MS_ARPA= table(ID_MonitoringStations,Location,Quotaslm);
```

Calculate the difference column (Estimated - True)

```
T_MODIS_pred.delta_LR=T_MODIS_pred.T_MODIS_pred_LR-T_MODIS_pred.Tmedia_ARPA;
ID=unique(T_MODIS_pred.ID);
Plot single figure
for i=1:length(ID)
    curID=ID(i);
    L=T_MODIS_pred.ID==[curID];
    curID=char(curID);
    T_MODIS_curID=T_MODIS_pred(L,:);
    A=str2double(curID);
    CurColor = Colors(A);
    location = DATI_MS_ARPA.Location{i};
    quota = num2str(DATI_MS_ARPA.Quotaslm(i));
    Calculation of mean deviations and RMSE
    m=nanmean(T_MODIS_curID.delta_LR);
    s=1.4826*mad(T_MODIS_curID.delta_LR,1);
    RMSE=sqrt(m^2+s^2);
    B=table(m,s,RMSE);
    figure
    plotID(T_MODIS_curID,CurColor,curID,location,quota,B)
end
end
```

```
function plotID(T_MODIS_curID, CurColor,curID,location,quota,B)
set(gca, 'FontSize', 18);
yyaxis left
ax = gca;
ax.YColor = CurColor;
plot(T_MODIS_curID.data_modis,T_MODIS_curID.Tmedia_ARPA,'-','LineWidth',2, 'DisplayName', ['Tair ARPA ID ',char(T_MODIS_curID{1,1})], 'Color', CurColor)
hold on
plot(T_MODIS_curID.data_modis,T_MODIS_curID.T_MODIS_pred_LR,'--','LineWidth',1.5, 'DisplayName', 'Tavg from MODIS - LR', 'Color', CurColor)
hold on
ylim([-5 35]);
title({'Comparison between ARPA temperature and MODIS derived 8-day mean (Linear Regression)', ['ID ' curID ' - ' location ' - height a.s.l. ' quota ' m ']} , 'Fontsize', 24);
```

```

xlabel('Date', 'FontSize', 19, 'FontWeight', 'bold');
ylabel('Temperature [°C]', 'FontSize', 19, 'FontWeight', 'bold');

yyaxis right
ax = gca;
ax.YColor = [0.47,0.47,0.47];
plot(T_MODIS_curID.data_modis,T_MODIS_curID.delta_LR, '-',
'LineWidth', 1,'DisplayName', 'Δ T', 'Color', [0.47,0.47,0.47])
ylim([-10 5]);
ylabel('Δ T [°C]', 'FontSize', 19, 'FontWeight', 'bold');
grid on
lgd=legend('Location', 'best', 'FontSize', 16);
lgd.Title.String = 'Legend';
str = sprintf('Mean (m): %.2f\nRMSE: %.2f', B.m, B.RMSE);
dim = [0.15 0.6 0.3 0.1];
annotation('textbox', dim, 'String', str, 'FitBoxToText', 'on',
'BackgroundColor', 'white', 'FontSize', 16);
yline(0)
end

```

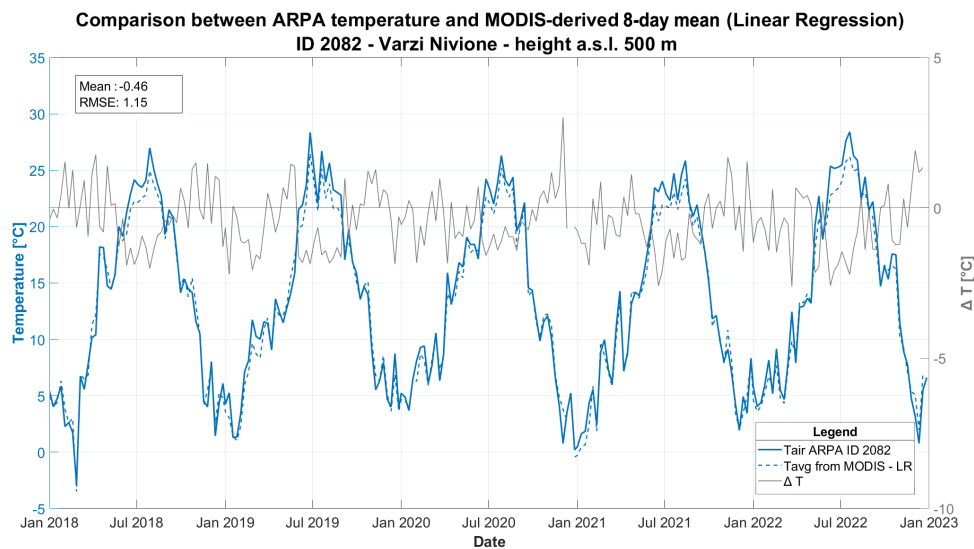


Figure 31. Comparison between ARPA 8-day mean air temperature (solid line) measured at monitoring station ID 2082 (Varzi Nivione, 500 m a.s.l.) and the MODIS-derived air temperature estimated via linear regression (dashed line). The temperature difference (ΔT , grey line) between the two datasets is shown on the secondary y-axis. The mean bias (-0.46 °C) and root mean square error ($\text{RMSE} = 1.15$ °C) are reported in the inset.

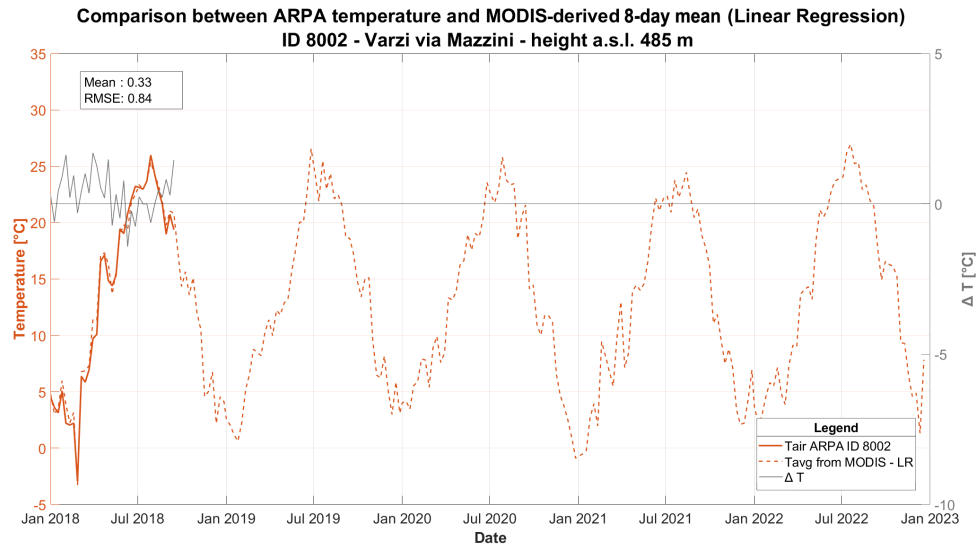


Figure 32. Comparison between ARPA 8-day mean air temperature (solid line) measured at monitoring station ID 8002 (Varzi via Mazzini, 485 m a.s.l.) and the MODIS-derived air temperature estimated via linear regression (dashed line). The temperature difference (ΔT , grey line) between the two datasets is shown on the secondary y-axis. The mean bias (0.33 °C) and root mean square error (RMSE = 0.84 °C) are reported in the inset. Data are less reliable due to the limited availability of ARPA observations at this site.

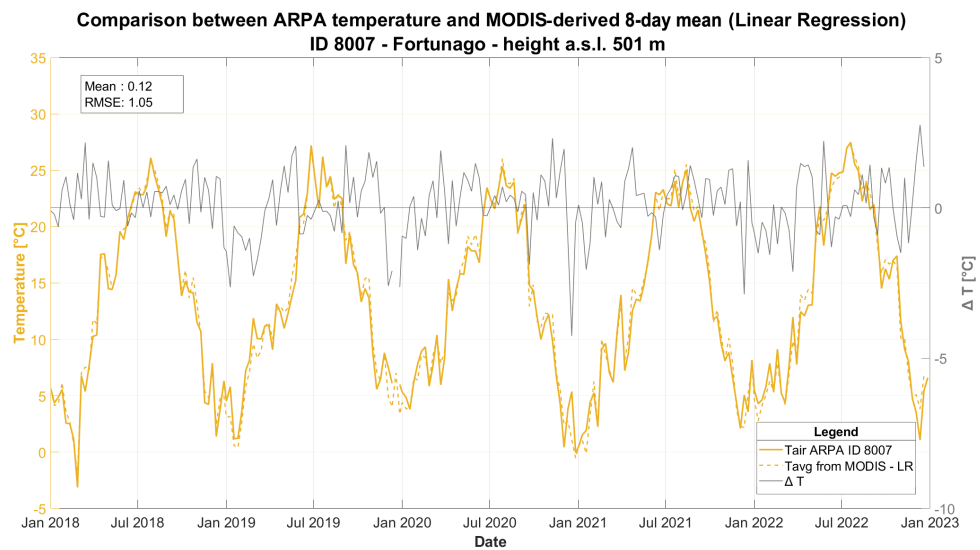


Figure 33. Comparison between ARPA 8-day mean air temperature (solid line) measured at monitoring station ID 8007 (Fortunago, 501 m a.s.l.) and MODIS-derived air temperature estimated via linear regression (dashed line). The temperature difference (ΔT , grey line) between the two datasets is shown on the secondary y-axis. The mean bias (0.12 °C) and root mean square error (RMSE = 1.05 °C) are reported in the inset.

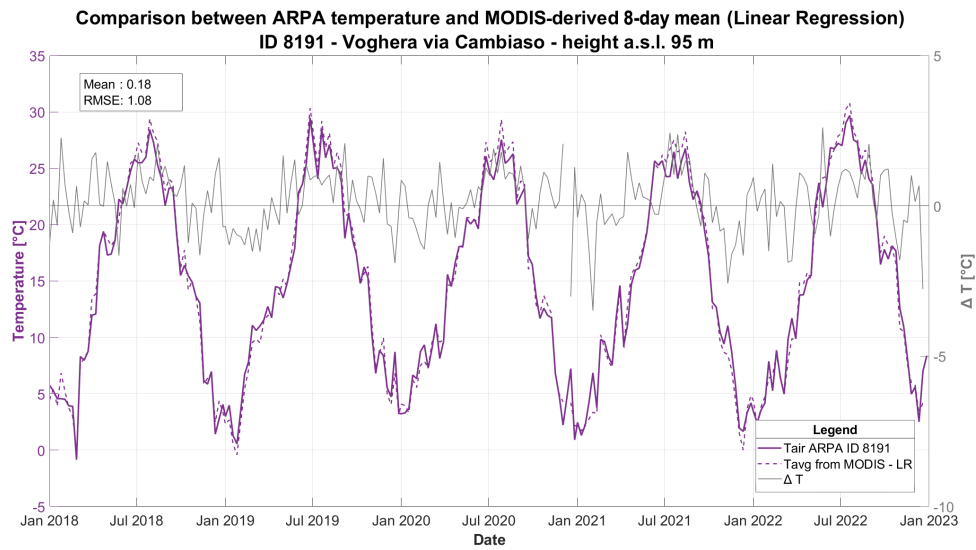


Figure 34. Comparison between ARPA 8-day mean air temperature (solid line) measured at monitoring station ID 8191 (Voghera via Cambiaso, 95 m a.s.l.) and MODIS-derived air temperature estimated via linear regression (dashed line). The temperature difference (ΔT , grey line) between the two datasets is shown on the secondary y-axis. The mean bias (0.18 °C) and root mean square error (RMSE = 1.08 °C) are reported in the inset.

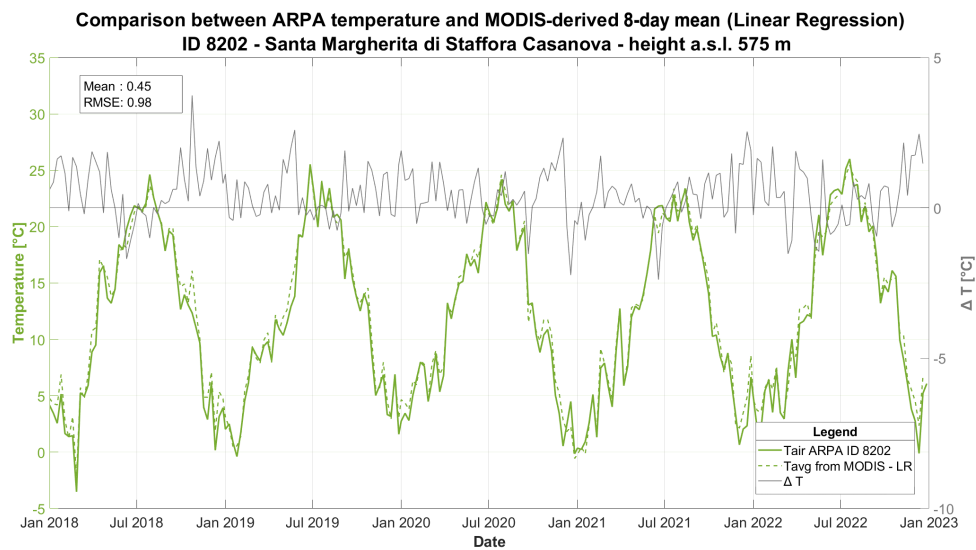


Figure 35. Comparison between ARPA 8-day mean air temperature (solid line) measured at monitoring station ID 8202 (Santa Margherita di Staffora Casanova, 575 m a.s.l.) and MODIS-derived air temperature estimated via linear regression (dashed line). The temperature difference (ΔT , grey line) between the two datasets is shown on the secondary y-axis. The mean bias (0.45 °C) and root mean square error (RMSE = 0.98 °C) are reported in the inset.

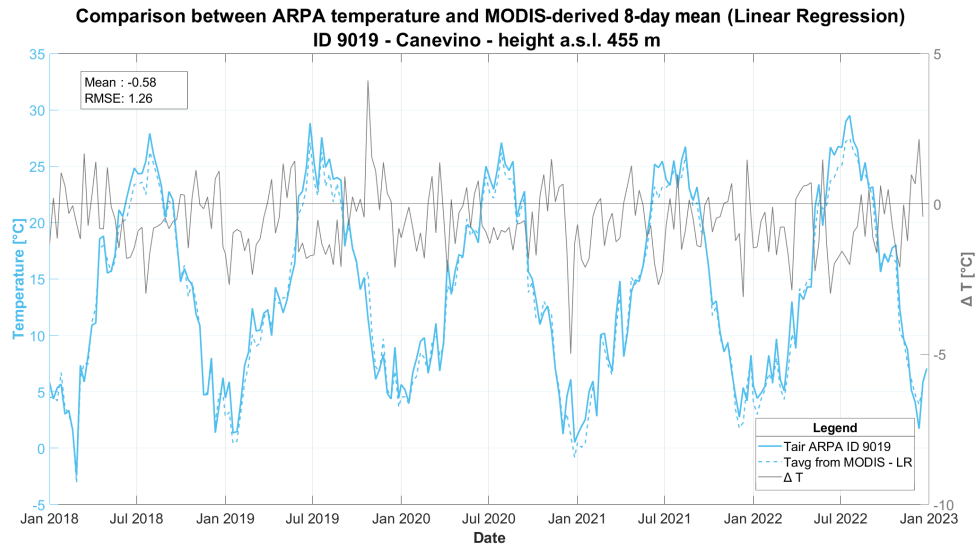


Figure 36. Comparison between ARPA 8-day mean air temperature (solid line) measured at monitoring station ID 9019 (Canevino, 455 m a.s.l.) and MODIS-derived air temperature estimated via linear regression (dashed line). The temperature difference (ΔT , grey line) between the two datasets is shown on the secondary y-axis. The mean bias ($-0.58\text{ }^{\circ}\text{C}$) and root mean square error ($\text{RMSE} = 1.26\text{ }^{\circ}\text{C}$) are reported in the inset.

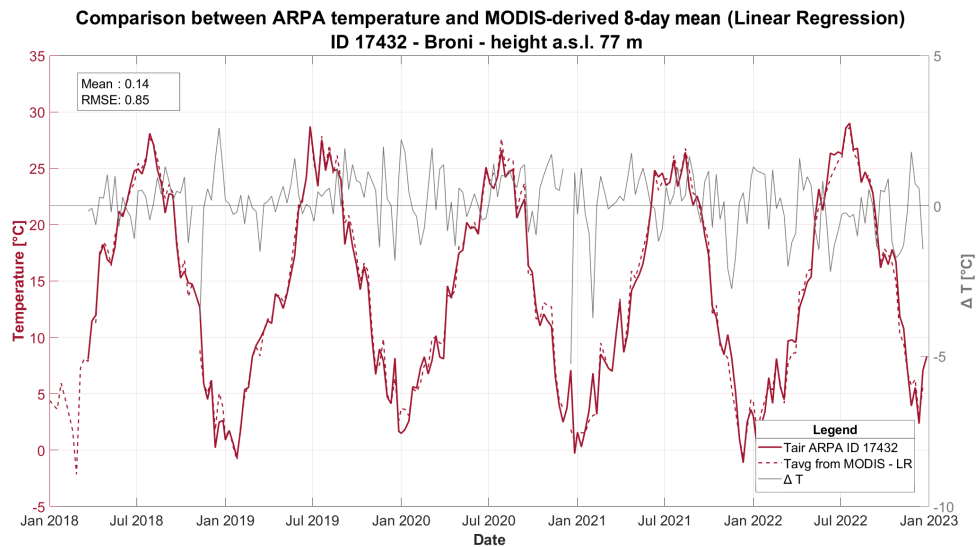


Figure 37. Comparison between ARPA 8-day mean air temperature (solid line) measured at monitoring station ID 17432 (Broni, 77 m a.s.l.) and MODIS-derived air temperature estimated via linear regression (dashed line). The temperature difference (ΔT , grey line) between the two datasets is shown on the secondary y-axis. The mean bias ($0.14\text{ }^{\circ}\text{C}$) and root mean square error ($\text{RMSE} = 0.85\text{ }^{\circ}\text{C}$) are reported in the inset.

Across all monitoring stations, the MODIS-derived air temperature estimates obtained through linear regression show good agreement with the ARPA 8-day mean air temperature observations. The relatively small biases, ranging from $-0.58\text{ }^{\circ}\text{C}$ to $+0.45\text{ }^{\circ}\text{C}$, indicate that the model does not exhibit a pronounced tendency to systematically overestimate or underestimate air temperature. Similarly, the RMSE values remain close to $1\text{ }^{\circ}\text{C}$ at all stations, confirming that the regression successfully reproduces the temporal evolution of air temperature.

Inspection of the time series (Figures 31–37) shows that the temperature differences (ΔT) fluctuate around zero over the five-year period, indicating that the regression model maintains comparable accuracy in both warm and cold seasons.

Some differences are instead associated with site characteristics. The lowland stations, particularly Broni (ID 17432, 77 m a.s.l.), show the best agreement (bias = $0.14\text{ }^{\circ}\text{C}$; RMSE = $0.85\text{ }^{\circ}\text{C}$), whereas the hilly sites (Varzi Nivione, Fortunago, Santa Margherita di Staffora and Canevino) generally exhibit slightly larger RMSE values, reaching $1.26\text{ }^{\circ}\text{C}$ at Canevino. This behaviour is likely related to the greater spatial heterogeneity of topography, land cover, and local microclimatic conditions in the hilly sector, which are only partially represented by the 1-km MODIS pixels and by the global regression model.

Overall, no long-term drift or systematic deterioration of model performance is evident during the 2018–2022 period. The temporal consistency of the residuals, together with the low bias and RMSE values, confirms that the calibrated regression provides stable estimates of 8-day mean air temperature across the different environmental features of the Oltrepò Pavese.

Figure 38 summarises the seasonal distribution of the residuals ($\Delta T = \text{MODIS-derived } T_{\text{air}} - \text{ARPA } T_{\text{air}}$). The median error remains close to $0\text{ }^{\circ}\text{C}$ in all seasons, indicating the absence of a systematic seasonal bias. The interquartile range is similar throughout the year, suggesting that model accuracy is relatively stable across seasons. Winter exhibits a larger number of negative outliers, whereas autumn shows a few positive outliers. These isolated cases likely reflect specific meteorological conditions, such as temperature inversions, snow cover or temporary decoupling between land surface and near-surface air temperature, rather than a systematic seasonal limitation of the regression model.

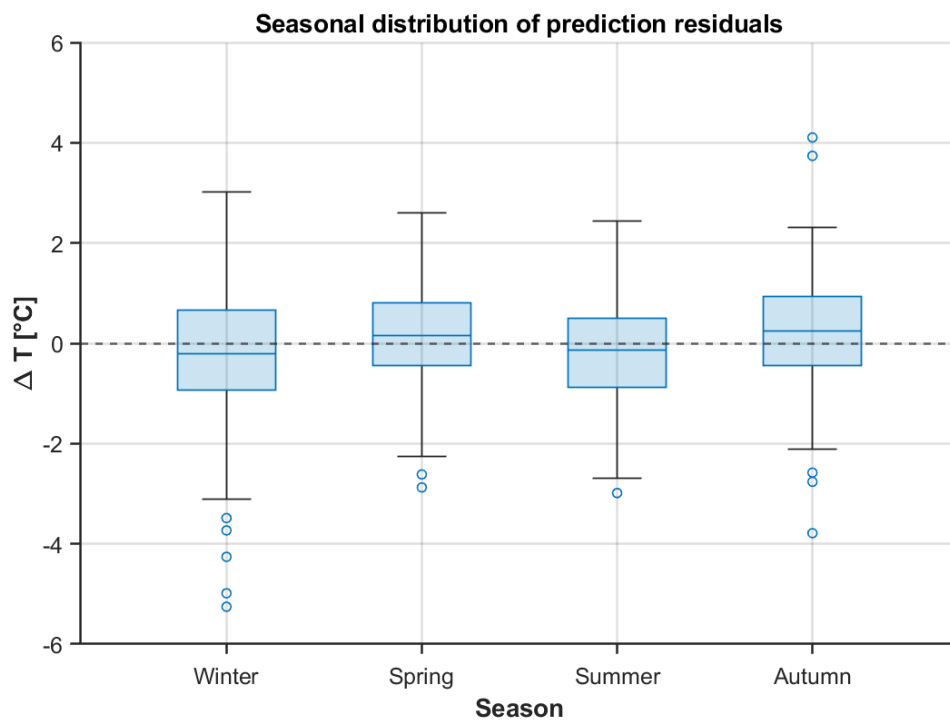


Figure 38. Seasonal distribution of residuals ($\Delta T = \text{MODIS-derived } T_{\text{air}} - \text{ARPA } T_{\text{air}}$) grouped by meteorological season. The boxplots indicate no evident seasonal bias, while a limited number of outliers occur mainly during winter and autumn.

5.9. TASK 7.2.2 – Station-by-station analysis

While the LOOCV analysis (Task 7.1) demonstrated that a global regression model can be successfully transferred across the monitoring network, it does not quantify the potential benefit of local calibration. Therefore, a station-by-station analysis was performed by calibrating an independent regression model for each monitoring station.

The objective of this analysis is to investigate the local relationship between MODIS LST and air temperature at each monitoring station and compare it with the global regression model presented in Task 7.2.1. This comparison enables evaluation of whether the additional complexity of station-specific calibration is justified or whether a single model is sufficient for the study area. Residuals are also analysed separately for each monitoring station to identify possible site-specific effects that may be masked in the global calibration. Starting from the complete MODIS-ARPA dataset, a separate linear regression model was calibrated for each monitoring station using only observations collected at that site. The complete workflow is reported in Script 13.

Script 13. MATLAB function for station-specific calibration of MODIS LST against ARPA 8-day mean air temperature using linear regression.

```
function LINEAR_REGRESSION_SINGLE_MS()

load('Dati_meteo_MODIS_ARPA.mat');



---


Excluded monitoring station due to the limited availability of data
L=whole_modis_arpa.ID=="8002";
whole_modis_arpa(L, :) = [];



---


Color Map
colorIDs = [2082, 8002, 8007, 8191, 8202, 9019, 17432];
colorValues = [0 0.4470 0.7410;
               0.8500 0.3250 0.0980;
               0.9290 0.6940 0.1250;
               0.4940 0.1840 0.5560;
               0.4660 0.6740 0.1880;
               0.3010 0.7450 0.9330;
               0.6350 0.0780 0.1840];
Colors = containers.Map(colorIDs, num2cell(colorValues, 2));



---


ID_MonitoringStations=[2082 8007 8191 8202 9019 17432]';
Location={'Varzi Nivione'; 'Fortunago'; 'Voghera via Cambiaso'; 'Santa
Margherita di Staffora Casanova'; 'Canevino'; 'Broni'};
Quotaslm=[500 501 95 575 455 77]';
DATI_MS_ARPA= table(ID_MonitoringStations,Location,Quotaslm);
results = table('Size',[0, 6], 'VariableTypes',{'double', 'cell', ...
'double','double','double','cell'},'VariableNames',{'StationID', ...
'Coefficients','RMSE','R2','PValue','PredictorNames'});
```

Loop over each station

```
for i = 1:length(ID_MonitoringStations)
    station_id = ID_MonitoringStations(i);
    model_data=whole_modis_arpa(whole_modis_arpa.ID==categorical ...
        (station_id), :);
    Independent variables (predictors) and dependent variable (Tair)
    X = model_data(:,[5:8,13]);
    Y = "Tmedia_ARPA";
    mdl = fitlm(X,Y,'RobustOpts','on');
    Predict temperatures
    a = model_data(:,[5:8]);
    Y_estimated = predict(mdl, a);
    station_table=table(model_data.data_modis,model_data.Tmedia_ARPA, ...
        Y_estimated,'VariableNames',{'date','ARPA_Temperature', ...
        'MODIS_Estimated'});
    Save the table in the structure
    station_results.(sprintf('Station_%d_Tmodis_pred',station_id)) = ...
        station_table;
    coefficients = mdl.Coefficients.Estimate';
    rmse = mdl.RMSE;
    r2 = mdl.Rsquared.Ordinary;
    p_values = mdl.Coefficients.pValue';
    predictor_names = mdl.CoefficientNames;
    results=[results;{station_id, coefficients, rmse, r2, p_values, ...
        predictor_names}];
end
disp(results);
```

Compute column of differences (Testimated - Treal)

```
station_fields = fieldnames(station_results);
for i = 1:length(station_fields)
    station_name = station_fields{i};
    T_MODIS_pred = station_results.(station_name);
    T_MODIS_pred.delta_T = T_MODIS_pred.MODIS_Estimated - ...
        T_MODIS_pred.ARPA_Temperature;
    station_results.(station_name) = T_MODIS_pred;
end
```

Plot single figure

```
for i=1:length(station_fields)
    station_name = station_fields{i};
    T_MODIS_curID = station_results.(station_name);
    m=nanmean(T_MODIS_curID.delta_T);
    s=1.4826*mad(T_MODIS_curID.delta_T,1);
```

```

    RMSE=sqrt(m^2+s^2);
    B=table(m,s,RMSE);
    location = DATI_MS_ARPA.Location{i};
    quota = num2str(DATI_MS_ARPA.Quotaslm(i));
    curID=ID_MonitoringStations(i);
    CurColor = Colors(curID);
    figure
    plotID(T_MODIS_curID, CurColor, curID, location, quota, B)
end
end

```

```

function plotID(T_MODIS_curID, CurColor, curID, location, quota, B)
set(gca, 'FontSize', 18);
yyaxis left
ax = gca;
ax.YColor = CurColor;
plot(T_MODIS_curID.date, T_MODIS_curID.ARPA_Temperature, '-',
'LineWidth', 2, 'DisplayName', ['Tair ARPA ID', num2str(curID)], 'Color', CurColor)
hold on
plot(T_MODIS_curID.date, T_MODIS_curID.MODIS_Estimated, '--',
'LineWidth', 1.5, 'DisplayName', 'Tavg from MODIS', 'Color', CurColor)
hold on
ylim([-5 35]);
title(['Comparison between ARPA temperature and MODIS derived 8 days
average (Linear Regression) - Single MS', ['ID ' num2str(curID) ' - '
location ' - height a.s.l. ' quota ' m ']], 'FontSize', 24);
xlabel('Date', 'FontSize', 19, 'FontWeight', 'bold');
ylabel('Temperature [°C]', 'FontSize', 19, 'FontWeight', 'bold');
yyaxis right
ax = gca;
ax.YColor = [0.47, 0.47, 0.47];
plot(T_MODIS_curID.date, T_MODIS_curID.delta_T, '-', 'LineWidth', 1,
'DisplayName', 'ΔT', 'Color', [0.47, 0.47, 0.47])
ylim([-10 5]);
ylabel('ΔT [°C]', 'FontSize', 19, 'FontWeight', 'bold');
grid on
lgd=legend('Location', 'best', 'FontSize', 16);
lgd.Title.String = 'Legend';
str = sprintf('Mean (m): %.2f\nRMSE: %.2f', B.m, B.RMSE);
dim = [0.15 0.6 0.3 0.1];
annotation('textbox', dim, 'String', str, 'FitBoxToText', 'on', ...
'BackgroundColor', 'white');
yline(0)
end

```

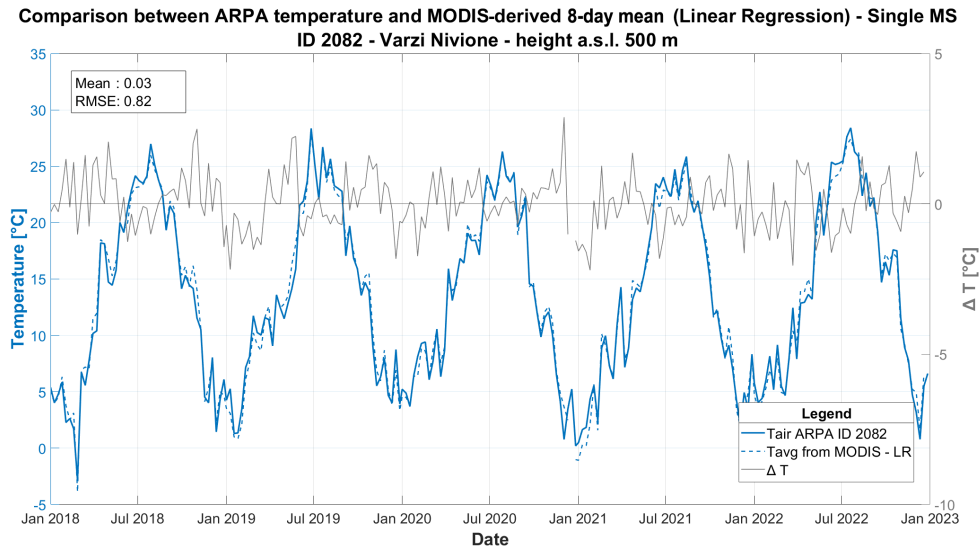



Figure 39. Comparison between ARPA 8-day mean air temperature (solid line) at monitoring station ID 2082 (Varzi Nivione, 500 m a.s.l.) and MODIS-derived air temperature estimates obtained using a station-specific linear regression model.

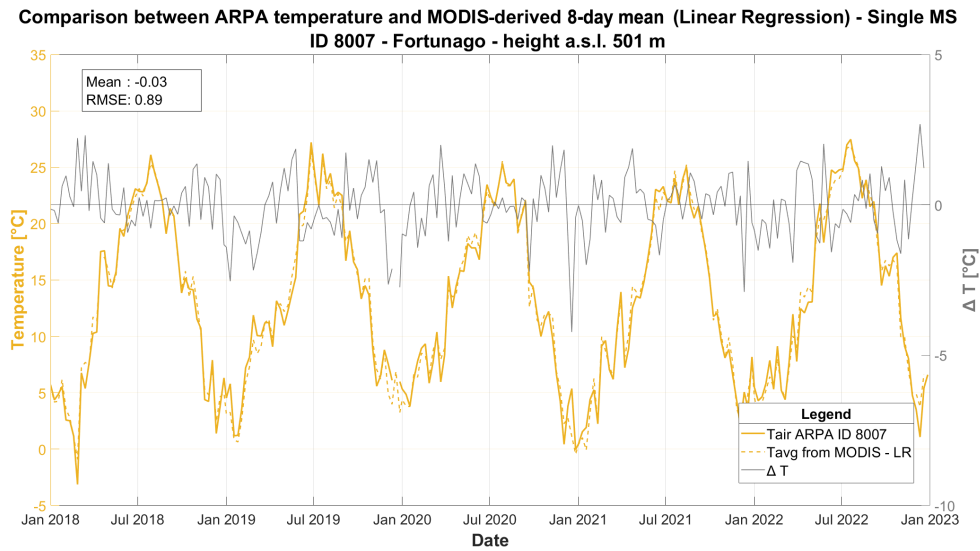


Figure 40. Comparison between ARPA 8-day mean air temperature (solid line) at monitoring station ID 8007 (Fortunago, 501 m a.s.l.) and MODIS-derived air temperature estimates obtained using a station-specific linear regression model.

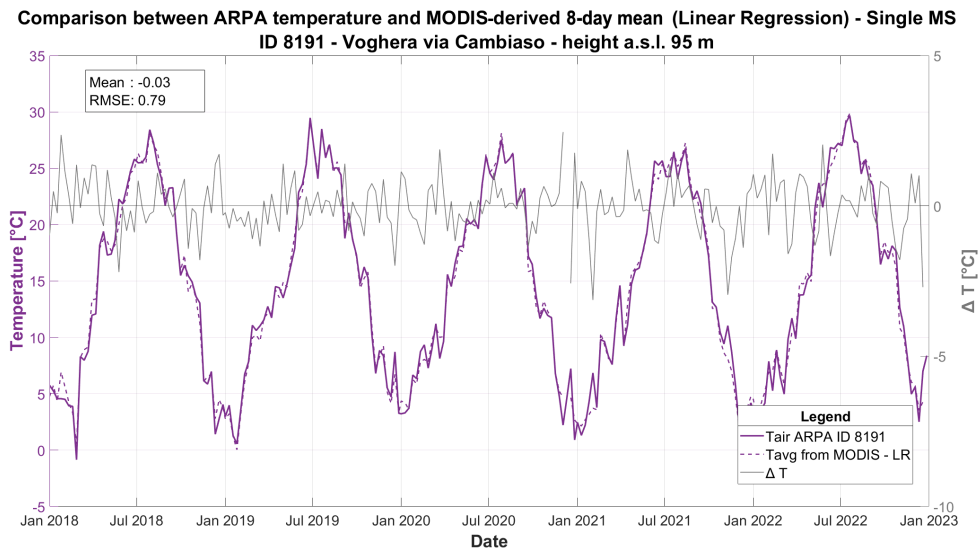


Figure 41. Comparison between ARPA 8-day mean air temperature (solid line) at monitoring station ID 8191 (Voghera via Cambiaso, 95 m a.s.l.) and MODIS-derived air temperature estimates obtained using a station-specific linear regression model.

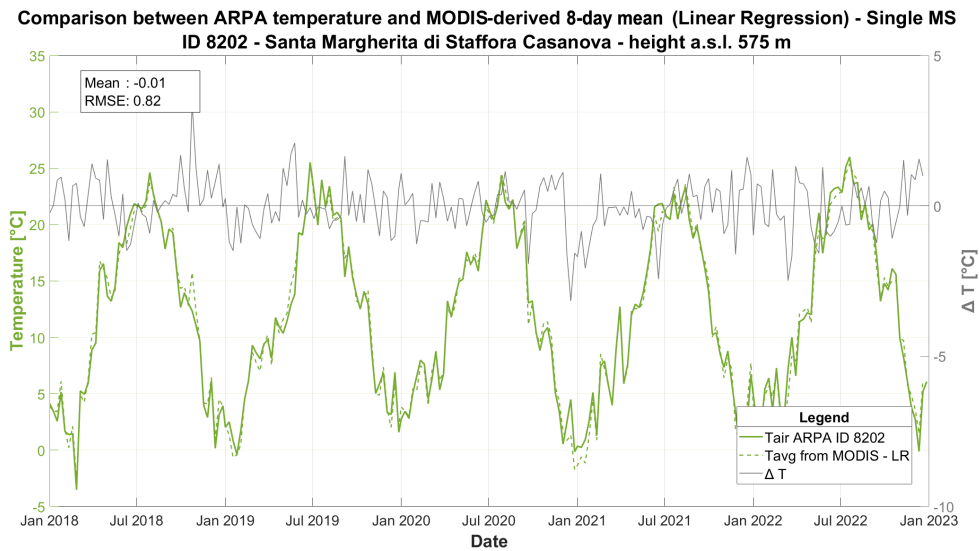


Figure 42. Comparison between ARPA 8-day mean air temperature (solid line) at monitoring station ID 8202 (Santa Margherita di Staffora Casanova, 575 m a.s.l.) and MODIS-derived air temperature estimates obtained using a station-specific linear regression model.

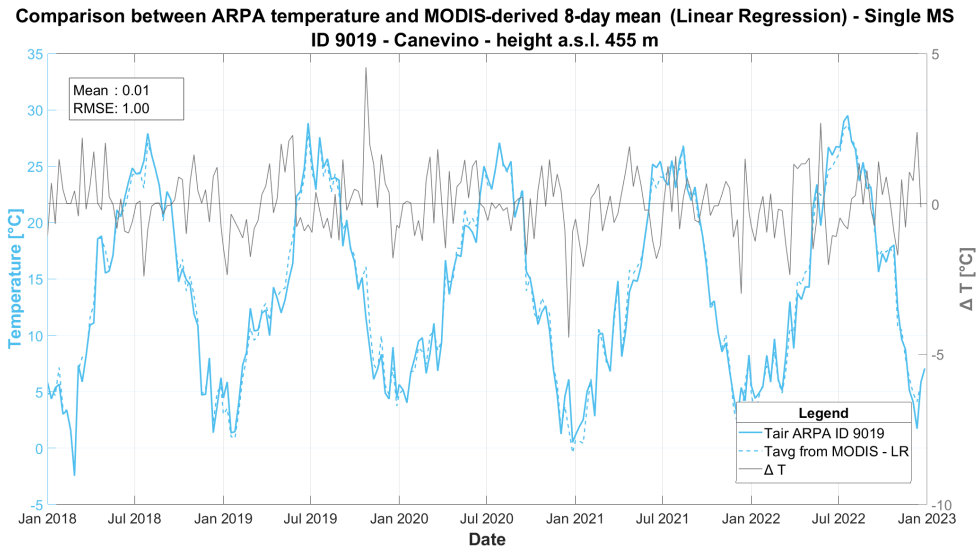


Figure 43. Comparison between ARPA 8-day mean air temperature (solid line) at monitoring station ID 9019 (Canevino, 455 m a.s.l.) and MODIS-derived air temperature estimates obtained using a station-specific linear regression model.

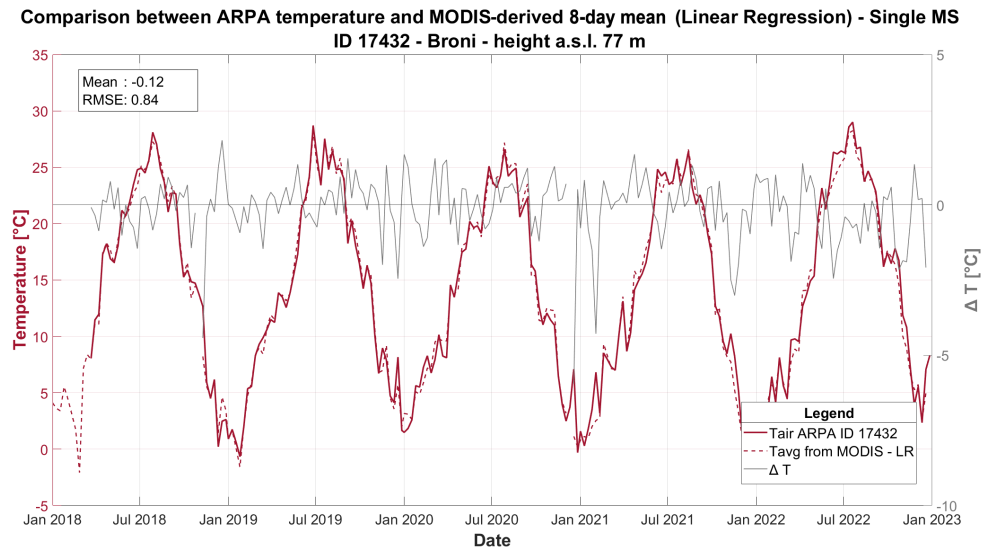


Figure 44. Comparison between ARPA 8-day mean air temperature (solid line) at monitoring station ID 17432 (Broni, 77 m a.s.l.) and MODIS-derived air temperature estimates obtained using a station-specific linear regression model.

The station-specific time series presented in Figures 39–44 show that the local regression models reproduce the temporal evolution of air temperature with slightly smaller residuals than the global model. To quantify these differences, the performance of the two regression approaches is compared in Table 10.

Table 10. Comparison between station-specific regression models and the global regression model fitted to the complete ARPA dataset.

Sensor ID	RMSE Station-specific [°C]	RMSE global model [°C]	Bias Station-specific [°C]	Bias global model [°C]
Varzi Nivione (ID 2082)	0.82	1.15	0.03	−0.46
Fortunago (ID 8007)	0.89	1.05	−0.03	0.12
Voghera (ID 8191)	0.79	1.08	−0.03	0.18
Santa Margherita (ID 8202)	0.82	0.98	−0.01	0.45
Canevino (ID 9019)	1.00	1.26	0.01	−0.58
Broni (ID 17432)	0.84	0.85	−0.12	0.14

The lower RMSE obtained by the station-specific models does not contradict the stability of the global model. Each local model is calibrated and evaluated using observations from the same site and can therefore adapt to local characteristics, resulting in a lower fitting error. Conversely, the global model was assessed through LOOCV analysis (Task 7.1) and maintained stable coefficients and predictive errors at independent stations. The global model was therefore retained for spatial mapping because it provides the most robust and transferable solution, whereas the station-specific models were used diagnostically to quantify possible local improvements.

Further analyses, including monthly regressions, elevation as an additional predictor, and non-linear regression models implemented with the MATLAB *Regression Learner App*, did not provide improvements sufficient to justify the increased model complexity. Therefore, the robust linear regression calibrated over the five-year period using the six reliable monitoring stations was retained for all subsequent analyses.

5.10. TASK 8 – MODIS-derived Tair

After defining the chosen linear regression model, MODIS-derived air temperature (Tair) rasters were generated. Script 14 loads the pre-processed MODIS dataset together with the calibrated regression model and applies it to predict the 8-day Tair values for each pixel over the five-year study period. The estimated temperatures are stored in a georeferenced structure consistent with the original MODIS data and exported as GeoTIFF files for spatial analysis. Figure 45 illustrates this process for the 8-day period from 20 to 27 July 2022.

Script 14. MATLAB function for generating 8-day MODIS-derived air temperature (Tair) raster maps.

```
function struct_MODIS_Tair_estimated()

load('whole_modis_fill.mat');
load('mdl_6_MS.mat');
dir_Tair_estimate='MODIS_5anni_estimatedTair';

predicted_y = zeros(size(modis.day_aqua));
Loop for applying the regression to each pixel and date
for day = 1:230
    for row = 1:38
        for col = 1:48
            T_Day_A = modis.day_aqua(row, col, day);
            T_Night_A = modis.night_aqua(row, col, day);
            T_Day_T = modis.day_terra(row, col, day);
            T_Night_T = modis.night_terra(row, col, day);
            X = [T_Day_A, T_Night_A, T_Day_T, T_Night_T];
            predicted_y(row, col, day) = predict mdl, X;
        end
    end
end
Add 'predicted' field to the original struct
MODIS_Tair_estimated.date = modis.date;
MODIS_Tair_estimated.georef = modis.georef;
MODIS_Tair_estimated.estimated_Tair = predicted_y;
cur_file_name=(string(MODIS_Tair_estimated(1).date));
cur_file_name='../'+dir_Tair_estimate+"\ "+cur_file_name+"_EstimatedTair";
for i=1:length(cur_file_name)
    cur_file_name1=cur_file_name(i);
    cur_image=MODIS_Tair_estimated.estimated_Tair(:,:,i);
    cur_georef=MODIS_Tair_estimated.georef;
    geotiffwrite(cur_file_name1,cur_image,cur_georef)
end
save('MODIS_Tair_estimated.mat', 'MODIS_Tair_estimated');
end
```

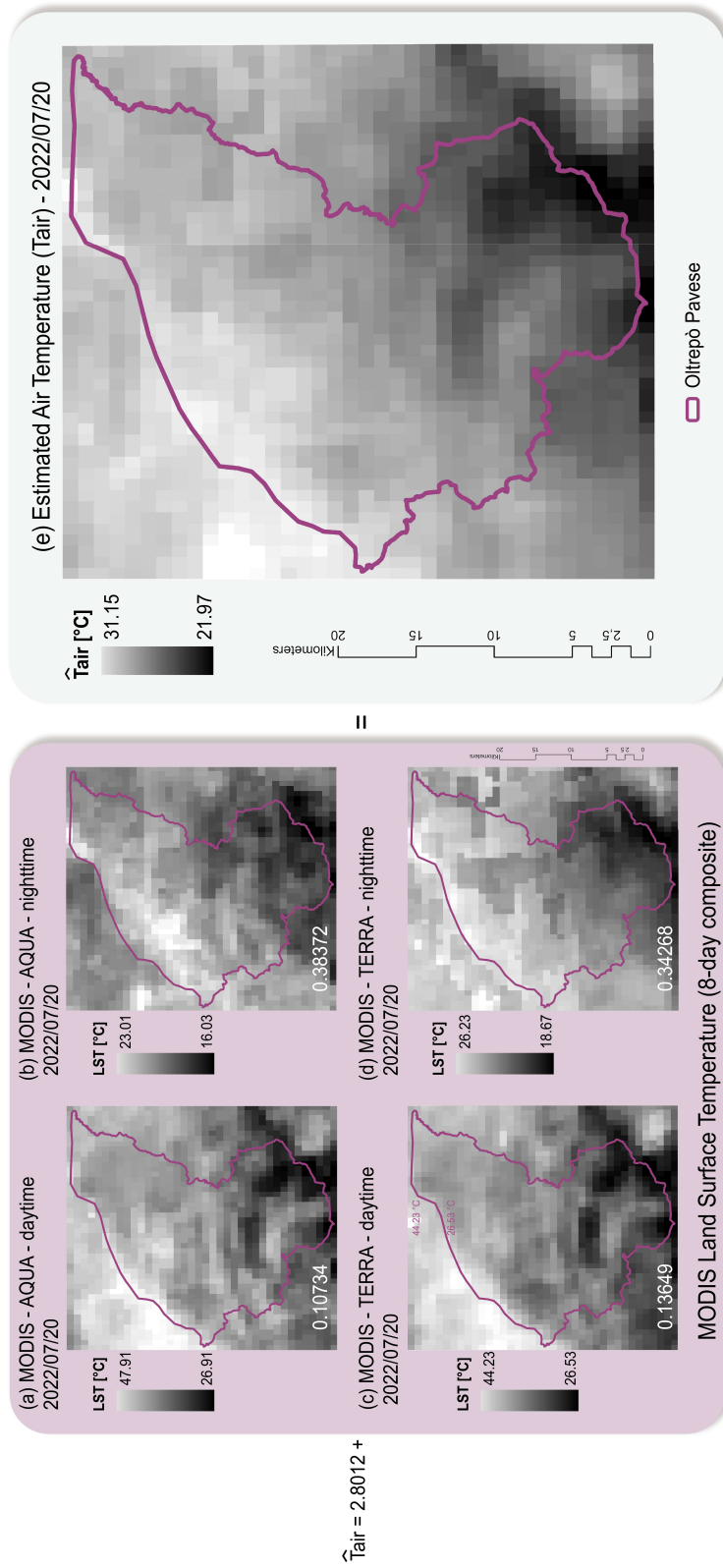


Figure 45. Raster images covering the 8-day period from 20/07/2022 to 27/07/2022. Air temperature ($\hat{T}_{air}$) was estimated by combining the four MODIS LST predictors: (a) AQUA daytime, (b) AQUA nighttime, (c) TERRA daytime and (d) TERRA nighttime, using their respective regression coefficients and the model intercept. The resulting raster is displayed on the right (e).

5.11. Winkler Index determination

In this study, the Winkler Index (WI) was first calculated from daily air temperature observations collected at the ARPA monitoring stations, which were considered the reference value. The reference WI was then compared with WI estimates derived from MODIS-based air temperature and from ARPA datasets aggregated to coarser temporal resolutions. This comparison was designed to distinguish the uncertainty introduced by temporal aggregation from that associated with the MODIS-derived air temperature estimates.

5.11.1. Winkler Index from ARPA

The reference Winkler Index (WI) was evaluated using daily in situ temperature measurements recorded at the ARPA monitoring stations during 2018–2022. The procedure imports daily mean temperature records from each monitoring station and calculates the WI according to the standard growing season (1 April–31 October). Missing records were handled conservatively: if gaps occurred in the daily series for a given station and year, the WI value was set to NaN.

The temporal evolution of WI across stations and years is shown in Figure 46, providing a comparative view of climatic variability in the study area. This daily ARPA-derived WI represents the reference against which all subsequent WI estimation methods are evaluated. The complete implementation of the WI calculation is reported in Script 15.

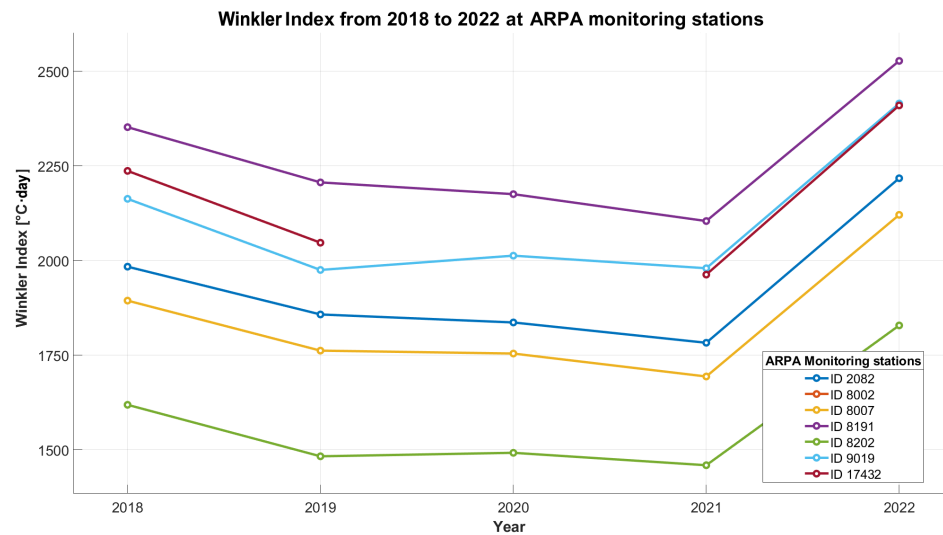


Figure 46. Temporal evolution of the Winkler Index (WI) for the selected monitoring stations over 2018–2022, used as the reference value.

Script 15. MATLAB function for computing the annual Winkler Index from daily ARPA air temperature data and plotting its temporal evolution for each monitoring station.

```
function WI_ARPA()
```

```
dir_arpa= "dati_arpa_5anni";
dir_save= "codici_matlab_VM";
wholepath_stazioni= "..\"+dir_arpa+"*DailyMean*.mat";
meteoFileNames={dir(wholepath_stazioni).name}';
anno=[2018:2022];
```

Winkler Index calculated using daily ARPA data

```
WI_ARPA_Table = table('Size', [0, 3], 'VariableTypes', {'double', ...
'double', 'double'}, 'VariableNames', {'ID', 'Year', 'WI_vero'});
for i=1:numel(meteoFileNames)
    file_dati_giornalieri=".." + dir_arpa + "\" + string(meteoFileNames(i));
    load(file_dati_giornalieri);
    for j=1:length(anno)
        curyear=anno(j);
        dati=cur_TT2;
        L= year(dati.DataOra)=curyear;
        WI_array=winkler1(dati,curyear);
        newRow = {dati.IdSensore(1,1), curyear, WI_array(1,2)};
        WI_ARPA_Table = [WI_ARPA_Table; newRow];
    end
end
L=WI_ARPA_Table{:, :}=0;
WI_ARPA_Table{:, :}(L) = NaN;
WI_ARPA_Table = sortrows(WI_ARPA_Table, 'ID');
plotta(WI_ARPA_Table,dati);
filename = 'WI_ARPA_veri.mat';
filename=".." + dir_save + "\" + filename;
save(filename, 'WI_ARPA_Table');
end
```

```
function wi=winkler1(dati,curyear)
anno=curyear;
m=size(anno,1);
wi=zeros(m,2);
for i=1:m
    wi(i,1)=anno(i);
    data1=datetime(anno(i),4,1);
    data2=datetime(anno(i),10,31);
```

```

    trange=timerange(data1,data2+days(1));
    expected_dates = (data1:data2)';
    actual_dates = dati.DataOra(trange);
    if isequal(expected_dates, actual_dates)
        A=dati.Tmedia_interp(trange)-10;
        B=A;
        B(A ≤ 0) = 0;
        wi(i,2)=sum(B);
    else
        wi(i,2) = NaN;
    end
end
end

```

```

function plotta(WI_ARPA_Table,dati)
figure;
hold on;
set(gca, 'FontSize', 18);
uniqueIDs=unique(WI_ARPA_Table.ID);
for i = 1:length(uniqueIDs)
    idx = WI_ARPA_Table.ID == uniqueIDs(i);
    currentData = WI_ARPA_Table(idx, :);
    plot(currentData.Year,currentData.WI_vero,'-','LineWidth',3, ...
        'DisplayName', ['ID',num2str(currentData{1,1})], 'Marker','o', ...
        'MarkerFaceColor','auto','MarkerSize',7);
end
hold off;

xlabel('Years','FontSize', 19,'FontWeight','bold');
ylabel('Winkler Index [°C·day]','FontSize', 19, 'FontWeight', 'bold');
title('Winkler Index from 2018 to 2022 for ARPA Monitoring stations',
'FontSize',24);

lgd=legend('Location','best','FontSize',16);
lgd.Title.String = 'ARPA Monitoring stations';

grid on;
ax = gca;
ax.XTick = currentData.Year;
ax.YTick = 0:250:3000;
axis padded
end

```

5.11.2. Winkler Index estimation at monitoring stations

The daily ARPA-based WI presented in Section 5.11.1 was used as the reference value throughout this analysis. The subsequent comparisons were designed to distinguish the effect of temporal aggregation from that of the MODIS-derived air temperature estimates on WI computation. To this end, three approaches were evaluated:

1. The reference WI calculated from daily ARPA observations.
2. The WI calculated from ARPA temperatures aggregated to 8-day means and then expanded to daily values by repetition.
3. The WI calculated from MODIS-derived 8-day air temperatures using the same expansion procedure.

The second approach serves as an intermediate control, allowing the effect of the 8-day temporal resolution to be isolated from the uncertainty introduced by the satellite-derived temperature estimates.

Because MODIS provides air temperature estimates every 8 days, each value was assigned to the corresponding eight consecutive days to reconstruct a daily series suitable for WI calculation. The same procedure was applied to the aggregated ARPA temperatures, ensuring that both datasets had an identical temporal support. An excerpt of the resulting daily time series obtained after the expansion procedure is reported in Table 11.

Table 11. Excerpt of 8-day mean ARPA and MODIS-derived air temperatures expanded by repetition into daily series.

Date	ID	ARPA T _{air} [°C]	MODIS-derived T _{air} [°C]	Daily ARPA [°C]	Daily MODIS [°C]
2018/01/01	2082	5.3995	5.0050	5.3995	5.0050
2018/01/02	2082	-	-	5.3995	5.0050
2018/01/03	2082	-	-	5.3995	5.0050
2018/01/04	2082	-	-	5.3995	5.0050
2018/01/05	2082	-	-	5.3995	5.0050
2018/01/06	2082	-	-	5.3995	5.0050
2018/01/07	2082	-	-	5.3995	5.0050
2018/01/08	2082	-	-	5.3995	5.0050
2018/01/09	2082	4.0234	3.9880	4.0234	3.9880
2018/01/10	2082	-	-	4.0234	3.9880
2018/01/11	2082	-	-	4.0234	3.9880
...	...	...	...	...	...

The complete implementation for generating the daily temperature series and calculating the Winkler Index from MODIS-derived air temperature is provided in Script 16.

Script 16. MATLAB function for reconstructing daily air temperature series from 8-day MODIS-derived estimates and calculating the corresponding annual Winkler Index at the monitoring stations.

```
function WI_MODIS()

load('MODIS_pred.mat');

T=removevars(T_MODIS_pred,['fi','la','temp_day_modis_A', ...
    'temp_night_modis_A', 'temp_day_modis_T', 'temp_night_modis_T', ...
    'time_day_A', 'time_night_A', 'time_day_T', 'time_night_T']);
T.ID=double(string(T.ID));
cur_TT1 = table2timetable(T, 'RowTimes', 'data_modis');
[G,Y] = findgroups(cur_TT1.data_modis.Year);
[H, ID_groups] = findgroups(cur_TT1.ID);

for x=1:size(ID_groups, 1)
    cur_TT2=cur_TT1(cur_TT1.ID==ID_groups(x),:);
    DTTDaily = retime(cur_TT2, 'daily');
    for j=1:height(cur_TT2)-1
        weekIndices=(DTTDaily.data_modis ≥ cur_TT2.data_modis(j)) & ...
            (DTTDaily.data_modis < cur_TT2.data_modis(j + 1));
        DTTDaily.ID(weekIndices) = cur_TT2.ID(j);
        DTTDaily.T_MODIS_pred_LR(weekIndices)=cur_TT2.T_MODIS_pred_LR(j);
        DTTDaily.Tmedia_ARPA(weekIndices) = cur_TT2.Tmedia_ARPA(j);
    end
    if x==1
        DailyTT=DTTDaily;
    else
        DailyTT=[DailyTT;DTTDaily];
    end
end

filename = 'dailyTT_MODIS.mat';
save(filename, 'DailyTT');

Calculate WI using MODIS-derived data
dati=DailyTT;
uniqueIDs=unique(DailyTT.ID);
uniqueYears=unique(year(DailyTT.data_modis));
WI_MODIS_Table=table('Size',[0,3],'VariableTypes',{'double','double', ...
    'double'}, 'VariableNames', {'ID', 'Year', 'WI'});
for i=1:length(uniqueIDs)
    for j=1:length(uniqueYears)
        curyear=uniqueYears(j);
        L=dati.ID==uniqueIDs(i) & year(dati.data_modis)==curyear;
```

```

        curdati=dati(L, :);
        WI_array=winkler1(curdati,curyear);
        newRow = {curdati.ID(1), curyear, WI_array(1,2)};
        WI_MODIS_Table = [WI_MODIS_Table; newRow];
    end
end

L=WI_MODIS_Table{:,}=0;
WI_MODIS_Table{:,}(L)=NaN;
filename = 'WI_MODIS_pred.mat';
save(filename, 'WI_MODIS_Table');
disp (WI_MODIS_Table);
end

```

```

function wi=winkler1(dati,curyear)
anno=curyear;
m=size(anno,1);
wi=zeros(m,2);

for i=1:m
    wi(i,1)=anno(i);
    data1=datetime(anno(i),4,1);
    data2=datetime(anno(i),10,31);
    trange=timerange(data1, data2+days(1));
    expected_dates = (data1:data2)';
    actual_dates = dati.data_modis(trange);
    if isequal(expected_dates, actual_dates)
        A=dati.T_MODIS_pred_LR(trange)-10;
        B=A;
        B(A ≤ 0) = 0;
        wi(i,2)=sum(B);
    else
        wi(i,2) = NaN;
    end
end
end

```

The data are presented in Figure 47, which displays a comparative plot of ARPA-derived and MODIS-derived WI.

WI Comparison

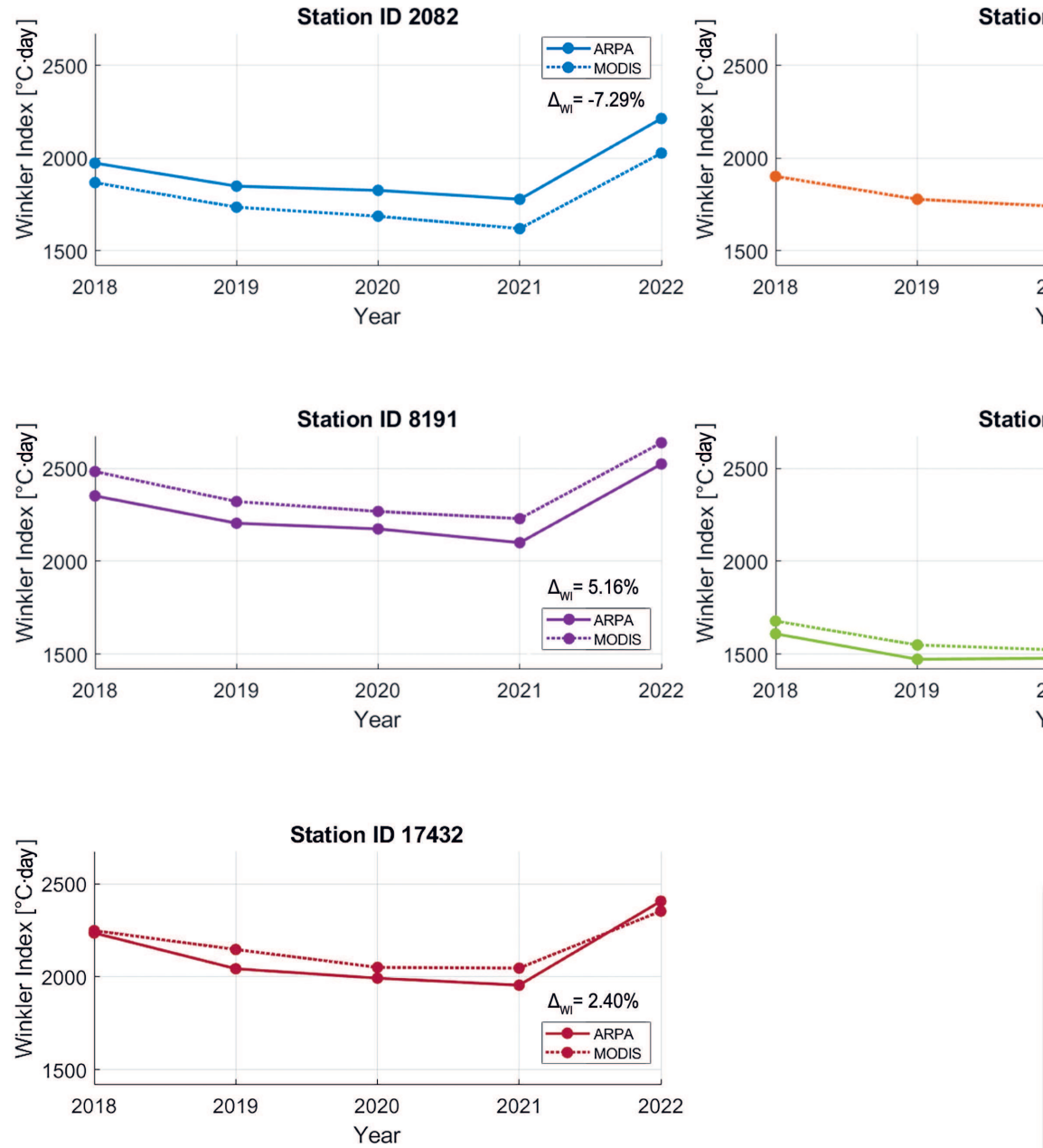
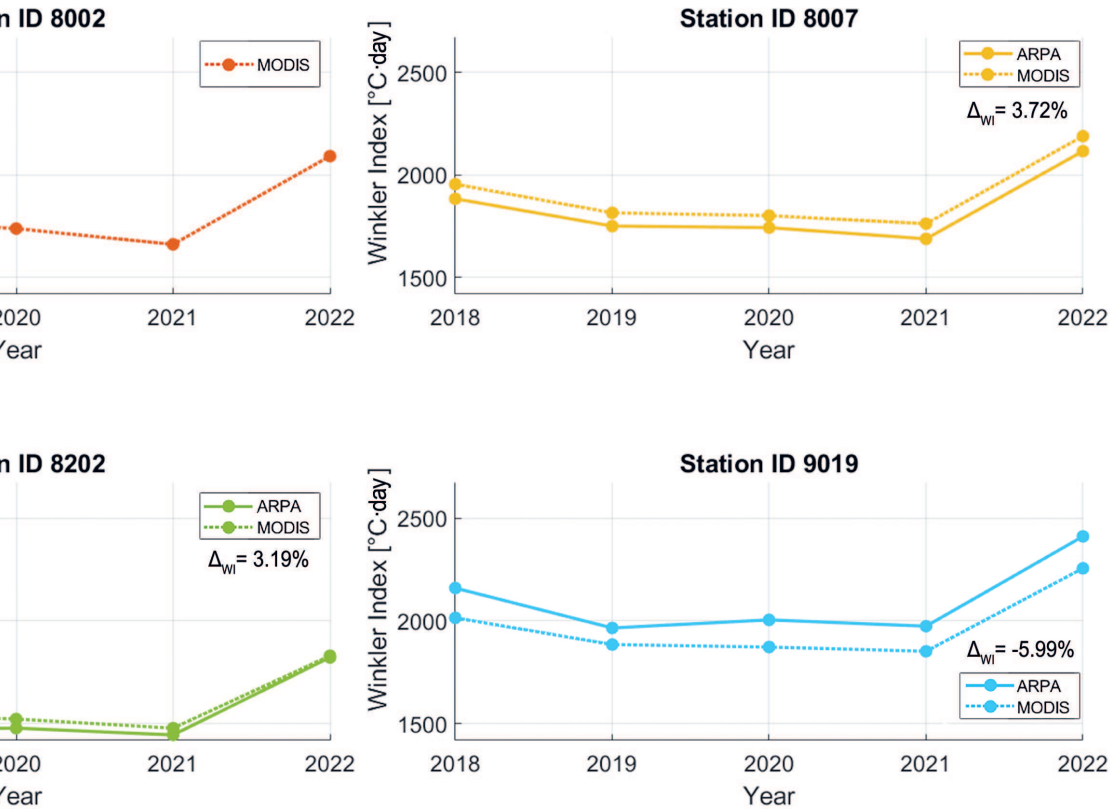


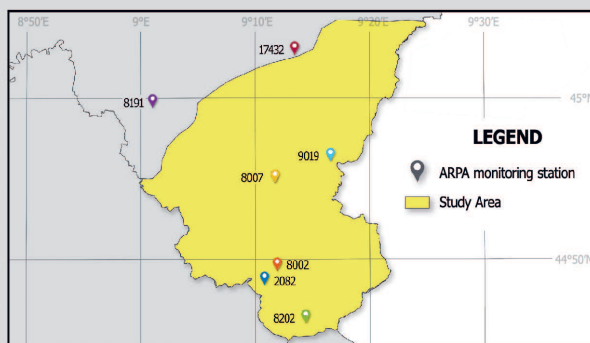
Figure 47. Temporal evolution of the Winkler Index (WI) – comparison between WI ARPA

Comparison: ARPA vs MODIS



$$\Delta_{WI} (\%) = \frac{WI_{MODIS} - WI_{ARPA}}{WI_{ARPA}} \times 100$$

Sensor ID	Location	Elevation (a.s.l. m)
2082	Varzi Nivione	500
8002	Varzi Via Mazzini	485
8007	Fortunago	501
8191	Voghera	95
8202	Santa Margherita	575
9019	Canevino	455
17432	Broni	77



and WI MODIS-derived (8-day mean) at the monitoring stations locations over 2018–2022.

Table 14 summarises the WI values obtained with the different calculation approaches. The daily ARPA-based WI is used as the reference, while the remaining methods quantify the effects of temporal aggregation and of the MODIS-derived air temperature estimates.



Figure 48. Schematic representation of the three interpolation methods tested for temperature data.

The procedures involve different interpolation and temporal aggregation models, which are schematically illustrated in Figure 48.

- **Method A:** the 8-day mean temperatures for both ARPA and MODIS-derived datasets were assigned to the beginning of the 8-day period and then repeated for 8 consecutive days (Figure 48.a).
- **Method B and C:** starting from the same 8-day mean temperatures, each mean value was positioned at the midpoint of the corresponding 8-day period, and then interpolated using either Linear Interpolation (LI) (Figure 48.b) or Nearest Neighbour (NN) (Figure 48.c).

An excerpt of the resulting daily temperature series is reported in Table 12.

In addition to the 8-day aggregation, the Winkler Index was also computed using monthly mean air temperatures from both ARPA and MODIS datasets. Monthly Winkler Index contributions were approximated as the positive difference between the monthly mean air temperature and the 10 °C base temperature, multiplied by 30 days, as shown in Table 13.

Table 12. Excerpt of daily temperature series obtained from 8-day ARPA and MODIS means interpolated using Linear Interpolation (LI) – Method B and Nearest Neighbour (NN) – Method C.

Date	ID	ARPA T _{air} [°C]	MODIS-derived T _{air} [°C]	ARPA LI [°C]	MODIS LI [°C]	ARPA NN [°C]	MODIS NN [°C]
2018/01/01	2082	-	-	5.9155	5.3864	5.3995	5.0050
2018/01/02	2082	-	-	5.7435	5.2593	5.3995	5.0050
2018/01/03	2082	-	-	5.5715	5.1322	5.3995	5.0050
2018/01/04	2082	5.3995	5.0050	5.3995	5.0050	5.3995	5.0050
2018/01/05	2082	-	-	5.2275	4.8779	5.3995	5.0050
2018/01/06	2082	-	-	5.0555	4.7508	5.3995	5.0050
2018/01/07	2082	-	-	4.8835	4.6236	5.3995	5.0050
2018/01/08	2082	-	-	4.7115	4.4965	4.0234	3.9880
2018/01/09	2082	-	-	4.5395	4.3694	4.0234	3.9880
2018/01/10	2082	-	-	4.3674	4.2422	4.0234	3.9880
2018/01/11	2082	-	-	4.1954	4.1151	4.0234	3.9880
2018/01/12	2082	4.0234	3.9880	4.0234	3.9880	4.0234	3.9880
2018/01/13	2082	-	-	4.1176	4.0439	4.0234	3.9880
2018/01/14	2082	-	-	4.2117	4.0999	4.0234	3.9880
2018/01/15	2082	-	-	4.3058	4.1559	4.0234	3.9880
2018/01/16	2082	-	-	4.3999	4.2118	4.7764	4.4357
...	...	...	...	...	...	...	...

Table 13. Excerpt of monthly mean air temperature from ARPA and MODIS data used to evaluate WI. $\Delta T = \text{MODIS-derived} - \text{ARPA}$

Date	ID	ARPA 30-day mean T [°C]	MODIS-derived 30- day mean T [°C]	ΔT [°C]
2018 Jan	2082	5.02	4.94	-0.08
2018 Feb	2082	0.95	1.48	0.53
2018 Mar	2082	7.56	7.86	0.30
2018 Apr	2082	11.68	11.77	0.08
2018 May	2082	16.24	16.33	0.09
2018 Jun	2082	21.86	20.49	-1.37
2018 Jul	2082	24.58	23.12	-1.45
2018 Aug	2082	22.75	21.86	-0.89
2018 Sep	2082	18.55	18.38	-0.17
2018 Oct	2082	10.99	11.19	0.21
2018 Nov	2082	7.66	8.29	0.63
2018 Dec	2082	4.98	5.02	0.04
...	...	...	...	...

Table 14. Comparison of ARPA-derived and MODIS-derived Winkler Index

Winkler Index [°C·day]					
Year	Station ID	ARPA daily reference	ARPA – 8-day Method A	MODIS – 8-day Method A	ARPA – 8-day Method B – LI
2018	2082	1983.85	1973.64	1868.27	1972.18
2019	2082	1857.68	1849.05	1735.56	1839.11
2020	2082	1836.55	1826.40	1686.98	1822.42
2021	2082	1782.89	1778.16	1619.79	1764.94
2022	2082	2217.35	2214.23	2027.35	2205.72
2018	8002	NaN	NaN	1902.03	NaN
2019	8002	NaN	NaN	1778.40	NaN
2020	8002	NaN	NaN	1738.68	NaN
2021	8002	NaN	NaN	1661.64	NaN
2022	8002	NaN	NaN	2092.08	NaN
2018	8007	1894.21	1884.50	1955.14	1882.90
2019	8007	1762.11	1750.79	1815.51	1741.06
2020	8007	1754.46	1743.35	1801.80	1739.68
2021	8007	1693.84	1688.96	1762.39	1675.93
2022	8007	2120.68	2116.90	2189.59	2108.72
2018	8191	2352.29	2351.54	2482.38	2351.00
2019	8191	2206.38	2204.45	2321.16	2199.33
2020	8191	2175.35	2173.73	2267.93	2173.25
2021	8191	2104.34	2100.79	2228.90	2092.93
2022	8191	2527.23	2522.92	2637.26	2520.14
2018	8202	1619.08	1610.55	1678.45	1608.37
2019	8202	1483.11	1464.81	1549.53	1457.26
2020	8202	1492.35	1474.97	1522.76	1466.70
2021	8202	1459.54	1444.58	1478.47	1430.76
2022	8202	1828.72	1823.88	1830.43	1815.73
2018	9019	2162.97	2158.26	2014.84	2156.47
2019	9019	1975.21	1965.63	1884.79	1961.69
2020	9019	2012.91	2004.95	1872.77	2004.38
2021	9019	1979.70	1974.14	1852.19	1963.91
2022	9019	2414.69	2410.72	2255.69	2404.12
2018	17432	2236.77	2209.16	2248.38	2209.07
2019	17432	2047.16	2044.41	2146.78	2040.14
2020	17432	NaN	1993.56	2050.62	1988.78
2021	17432	1962.87	1956.13	2046.57	1948.24
2022	17432	2409.63	2407.54	2352.97	2403.30

values [°C-day] obtained using the different temporal reconstruction methods.

Winkler Index [°C-day]				
MODIS – 8-day Method B – LI	ARPA – 8-day Method C – NN	MODIS – 8-day Method C – NN	ARPA – 30-day	MODIS – 30-days
1866.77	1975.01	1870.02	1699.33	1594.26
1724.94	1847.64	1733.66	1605.28	1504.80
1683.87	1828.50	1689.22	1649.94	1521.25
1607.87	1773.88	1616.47	1589.57	1442.94
2019.09	2215.73	2027.65	1930.09	1750.64
1899.46	NaN	1902.61	NaN	1625.20
1772.97	NaN	1777.03	NaN	1554.06
1735.37	NaN	1740.42	NaN	1566.41
1648.35	NaN	1658.65	NaN	1489.74
2084.20	NaN	2092.08	NaN	1811.32
1953.51	1885.75	1956.52	1615.21	1673.00
1810.33	1749.55	1813.98	1517.40	1576.65
1799.53	1745.56	1804.06	1573.85	1629.03
1753.71	1685.02	1759.11	1513.34	1564.28
2180.55	2118.50	2189.69	1852.70	1902.74
2480.70	2353.20	2482.39	2043.53	2157.40
2316.97	2202.00	2320.47	1901.24	2015.17
2268.32	2175.69	2270.81	1975.70	2070.11
2218.71	2096.18	2224.72	1852.52	1962.62
2632.45	2525.54	2638.07	2215.24	2322.43
1676.04	1611.61	1680.11	1361.06	1419.28
1539.62	1464.81	1548.94	1281.31	1351.87
1517.42	1475.85	1524.52	1304.86	1363.15
1464.41	1441.86	1475.57	1319.13	1333.62
1823.25	1823.88	1831.03	1595.92	1576.07
2014.02	2159.26	2016.67	1868.26	1732.16
1879.74	1963.38	1882.83	1698.68	1627.09
1870.58	2007.57	1875.14	1821.85	1696.30
1842.05	1969.31	1848.50	1746.57	1637.13
2247.95	2413.06	2255.93	2110.05	1964.71
2245.95	2212.42	2251.71	1912.84	1950.05
2142.62	2043.03	2146.09	1768.74	1860.93
2050.10	1995.00	2053.44	1803.43	1866.00
2036.02	1953.00	2043.12	1749.13	1809.66
2345.47	2409.41	2353.25	2107.07	2055.91

As reported in Table 14, the WI values derived from the *ARPA daily reference* and *ARPA – 8-day (Method A)* approaches should, in theory, yield identical results. In practice, however, minor discrepancies arise due to differences in data-aggregation methods. When the index is computed using the 8-day mean, all temperature values – even those below 10 °C – are included in the mean and then multiplied by 8. Conversely, the daily summation approach excludes temperatures below 10 °C from the accumulation. These methodological distinctions account for the small numerical differences observed between the ARPA-based interpolation methods. The resulting average deviation of approximately 10 °C·day is considered negligible.

When comparing MODIS-derived WI values against those from ARPA, differences of about 100 °C·day were observed. Such discrepancies are still regarded as acceptable for applications in viticultural zoning and climate classification. To better explain those differences, the root-mean-square deviation Δ_i was calculated for each dataset combination using the following equations:

METHOD A	$\Delta_1 = \sqrt{\frac{\sum_i^{29} (ARPA_{8di} - ARPA_{daily_i})^2}{29}} = 9.71$	[°C·day] (9)
METHOD B	$\Delta_2 = \sqrt{\frac{\sum_i^{29} (MODIS_{8di} - ARPA_{daily_i})^2}{29}} = \mathbf{104.83}$	[°C·day] (10)
METHOD B	$\Delta_3 = \sqrt{\frac{\sum_i^{29} (ARPA_{8d-LI_i} - ARPA_{daily_i})^2}{29}} = 15.31$	[°C·day] (11)
METHOD B	$\Delta_4 = \sqrt{\frac{\sum_i^{29} (MODIS_{8d-LI_i} - ARPA_{daily_i})^2}{29}} = \mathbf{105.90}$	[°C·day] (12)
METHOD C	$\Delta_5 = \sqrt{\frac{\sum_i^{29} (ARPA_{8d-NN_i} - ARPA_{daily_i})^2}{29}} = 9.84$	[°C·day] (13)
METHOD C	$\Delta_6 = \sqrt{\frac{\sum_i^{29} (MODIS_{8d-NN_i} - ARPA_{daily_i})^2}{29}} = \mathbf{104.71}$	[°C·day] (14)

Based on the results obtained from Equations¹ (10), (12), and (14), the three temporal reconstruction methods produced very similar root-mean-square deviations for the MODIS-derived WI values.

Therefore, for the final analyses and subsequent mapping of the Winkler Index (WI), the simplest approach (*Method A*) was adopted. This method directly uses the available MODIS-derived raster dataset by repeating each *layer* over its corresponding 8-day interval.

¹ Where $n=29$ is the number of valid station–year pairs.

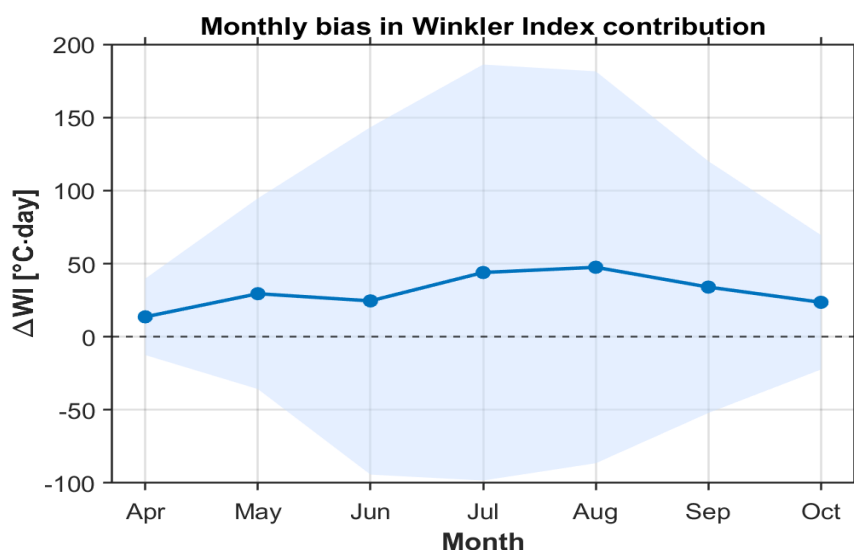


Figure 49. Monthly mean bias ($\Delta WI = WI_{MODIS} - WI_{ARPA}$) in the contribution to the Winkler Index (April–October). The line shows the average monthly difference across all monitoring stations and years (2018–2022), while the shaded area represents ± 1 standard deviation.

Here, MODIS-derived WI refers to the index calculated from air-temperature estimates obtained after calibration of MODIS LST against ARPA observations. Figure 49 shows that the mean monthly bias is generally positive throughout the growing season, indicating that MODIS-derived temperatures tend to overestimate the monthly contribution to the Winkler Index. The largest mean differences occur during July and August, whereas smaller differences are observed during April and October. The shaded area represents one standard deviation around the monthly mean and reflects the variability observed across all monitoring stations and study years (2018–2022). Its greater width during the summer months indicates that, although the mean monthly bias represents only a small fraction of the cumulative seasonal Winkler Index, the magnitude of the differences varies considerably among monitoring stations and study years.

This seasonal pattern is consistent with the definition of the Winkler Index. During the summer months, daily air temperatures remain well above the 10 °C threshold, so nearly every day contributes to heat accumulation. Consequently, even small differences between measured and estimated air temperatures accumulate over several weeks, producing the largest monthly deviations in WI. Conversely, at the beginning and the end of the growing season, temperatures are closer to the threshold and heat accumulation is lower, resulting in smaller monthly differences.

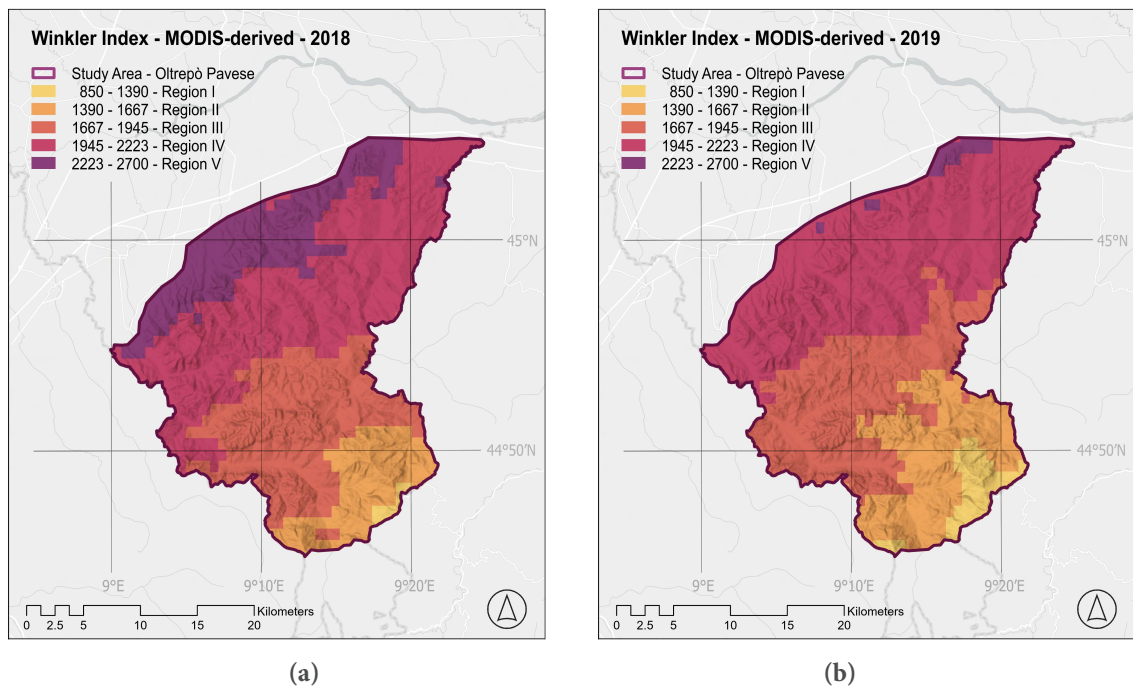
From a viticultural perspective, the largest deviations therefore occur during the period of maximum heat accumulation, when thermal conditions play an important role in grapevine development. Nevertheless, the observed differences remain relatively limited compared with the cumulative seasonal Winkler Index, suggesting that the MODIS-derived air temperature estimates preserve the overall climatic classification. A more detailed assessment of the potential implications of these differences for grapevine phenology and other viticultural processes would require dedicated agronomic analyses.

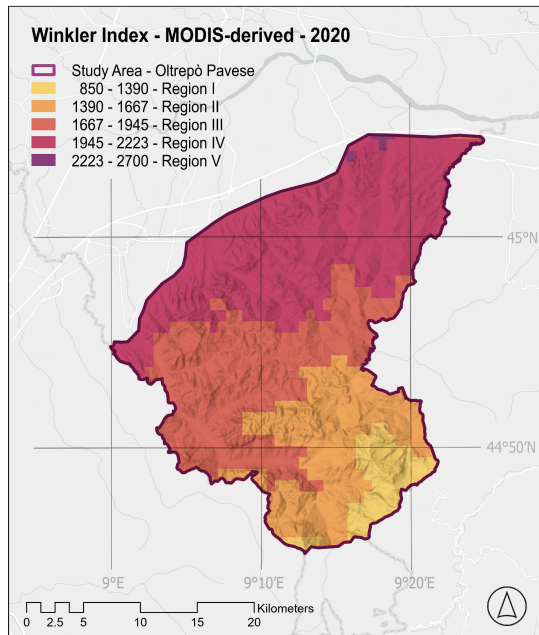
5.11.3. Winkler Index mapping from MODIS data

Script 17 was developed to compute the Winkler Index (WI) from the MODIS-derived air temperature dataset. As MODIS provides 8-day composite temperature products, these data were expanded to daily temperature rasters by repeating each value over eight consecutive days. This temporal transformation was necessary to adapt the MODIS dataset to the daily framework required for WI computation.

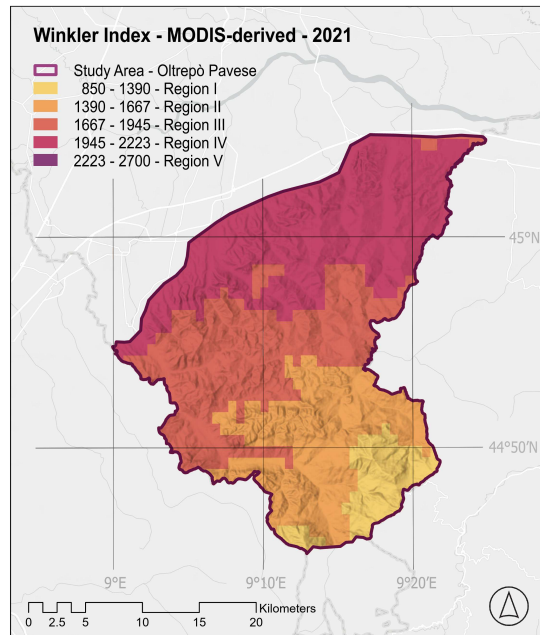
Once daily temperature rasters were generated, the Winkler Index was calculated for each year. The WI represents the cumulative sum of the positive differences between daily mean air temperature and the 10 °C base temperature during the standard growing season (1 April–31 October). Only temperatures above this threshold contribute to the index, following the classical definition by Winkler and Amerine [47]. The procedure was applied year by year (2018–2022), producing spatially continuous maps of the WI. Each annual raster represents the accumulated growing degree-days estimated from MODIS data across the study area and was saved as a GeoTIFF file.

The annual maps show a persistent spatial thermal gradient together with marked interannual variability. The years 2020 and 2021 were relatively cooler, whereas 2022 showed the largest expansion of Winkler Regions IV and V. From a viticultural perspective, warmer years may accelerate *Pinot Noir* phenology and ripening, potentially increasing sugar accumulation and reducing acidity, whereas cooler years may favour slower ripening and acidity preservation, particularly at higher elevations.

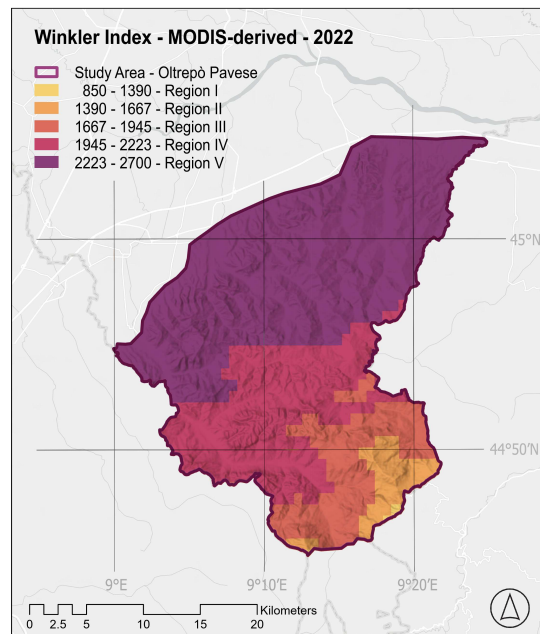




(c)



(d)



(e)

Figure 50. Spatial distribution of the MODIS-derived Winkler Index [$^{\circ}\text{C}\cdot\text{day}$] for the Oltrepò Pavese area over 2018–2022. Panels (a–e) illustrate the interannual variability of the index.

Script 17. MATLAB function for calculating pixel-wise Winkler Index maps from MODIS-derived air temperature and exporting the results as GeoTIFF files.

```
function WI_Raster_MODIS()

load ('MODIS_Tair_estimated.mat');

years = unique(year(MODIS_Tair_estimated.date));
for i = 1:length(years)
    day_counter = 1;
    daily_rasters = struct();
    year_idx = year(MODIS_Tair_estimated.date) == years(i);
    yearly_Tair = MODIS_Tair_estimated.estimated_Tair(:,:,year_idx);
    yearly_dates = MODIS_Tair_estimated.date(year_idx);

    Loop through each time step and repeat the raster for 8 days
    for j = 1:length(yearly_dates)
        current_date = yearly_dates(j);
        current_raster = yearly_Tair(:,:,j);
        Year=year(current_date);
        data=datetime(Year,12,26);

        if current_date ≤ data
            for k = 1:8
                daily_rasters(day_counter).date = current_date+days(k - 1);
                daily_rasters(day_counter).Tair = current_raster;
                daily_rasters(day_counter).georef= MODIS_Tair_estimated.georef;
                day_counter = day_counter + 1;
            end
        else
            break;
        end
    end

    Calculate WI
    WI_estimated=winkler1(daily_rasters);

    Save the .tif map containing the WI_modis estimated
    georef = MODIS_Tair_estimated(1).georef;
    output_filename = ['WI_estimated_', num2str(Year), '.tif'];
    geotiffwrite(output_filename, WI_estimated, georef);
end
end
```

```
function wi=winkler1(Daily_Struct)
m=length(Daily_Struct);
n=size(Daily_Struct(1).Tair);
wi=zeros(n);
Year = year(Daily_Struct(1).date);
start_date = datetime(Year,4,1);
end_date   = datetime(Year,10,31);
for i = 1:m
    current_date = Daily_Struct(i).date;
    current_Tair = Daily_Struct(i).Tair;
    if current_date ≥ start_date && current_date ≤ end_date
        T_diff = current_Tair - 10;
        T_diff(T_diff < 0) = 0;
        wi = wi + T_diff;
    end
end
end
```

5.12. COPERNICUS data

Since Copernicus ERA5-Land provides air temperature data at 2 m above the ground, no regression or empirical correction was required before calculating the Winkler Index. Daily mean temperatures were directly used for WI computation, following the same methodological framework previously applied to the MODIS-derived dataset.

First, the daily 2 m air temperature fields were extracted and spatially interpolated at the locations of the selected ARPA monitoring stations. The resulting WI values were then compared with those calculated from the daily ARPA observations (Figure 51), providing an independent assessment of the Copernicus dataset.

The annual spatial distribution of the Copernicus-derived Winkler Index is presented in Figure 52. The maps reproduce the main climatic gradients across the Oltrepò Pavese, although they appear spatially smoother than the MODIS-derived maps because of the coarser spatial resolution (about 9 km).

To complement the qualitative comparison between the MODIS-derived (Figure 50) and Copernicus (Figure 52) maps, the spatial extent of each Winkler Region was quantified by calculating the percentage of the study area assigned to each climatic class over the five-year study period. The average distributions are reported in Table 15.

Table 15. Average percentage of the study area assigned to each Winkler Region by the Copernicus ERA5-Land and MODIS-derived datasets during 2018–2022.

Winkler Region	Copernicus [%]	MODIS-derived [%]	MODIS – Copernicus [%]
I	3.8	4.0	0.2
II	38.7	15.6	–23.1
III	33.4	26.0	–7.4
IV	19.2	39.2	20.0
V	5.0	15.2	10.2
Too hot	0.0	0.0	0.0

The quantitative comparison confirms that the two datasets reproduce similar large-scale climatic patterns but differ in the spatial distribution of the Winkler Regions. In particular, the MODIS-derived maps consistently assign a larger proportion of the study area to the warmer Regions IV and V, whereas Copernicus ERA5-Land classifies a greater extent within the intermediate Regions II and III. These differences become particularly evident during warm years, such as 2022, when MODIS identifies a substantially larger area classified as Region V.

The observed differences are consistent with the previous validation against the ARPA monitoring stations. As shown in Section 5.11.2 and Figure 47, the MODIS-derived differences ranged from -7.29% to $+5.16\%$, whereas the Copernicus-derived WI shows larger deviations (from -21.75% to -8.11%). The improved agreement achieved by the MODIS-derived product can be attributed to the calibration of the satellite-derived air temperature using local ARPA observations, combined with its finer spatial resolution (1 km), which enables a better representation of local thermal variability. Conversely, the coarser 9 km resolution of the Copernicus ERA5-Land dataset produces smoother temperature fields, reducing the spatial extent of the warmer Winkler Regions.

WI Comparison:

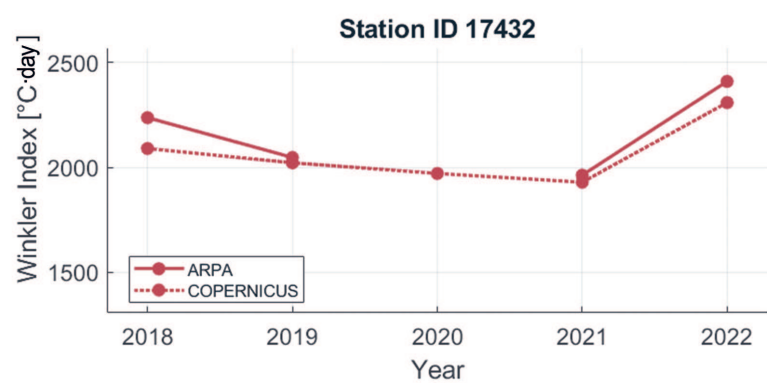
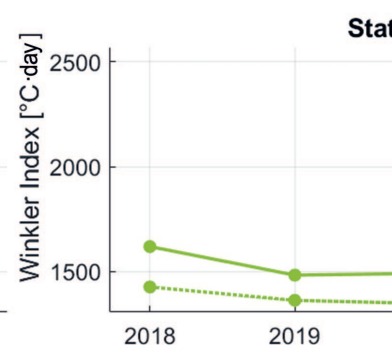
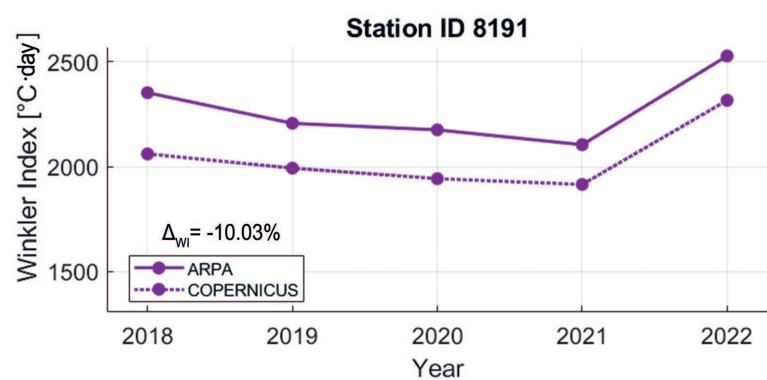
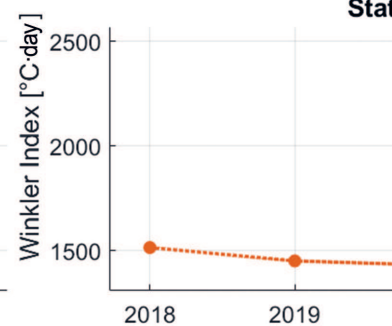
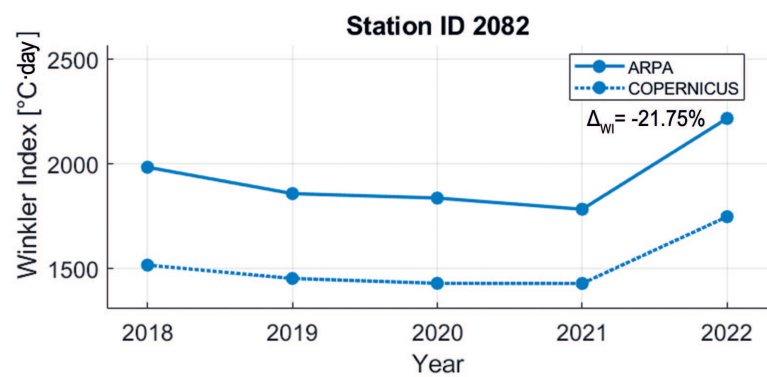
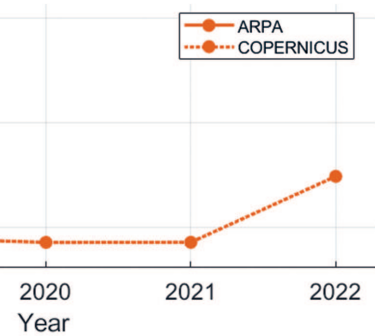


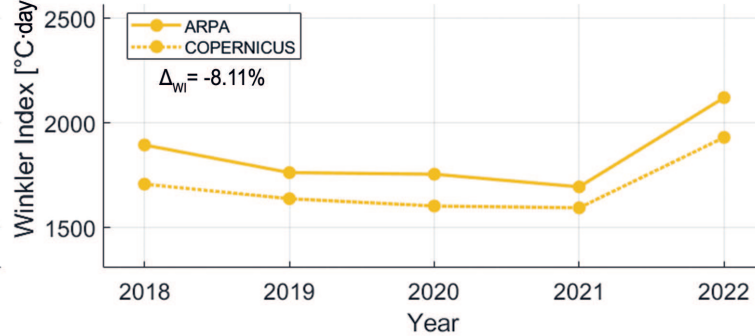
Figure 51. Temporal evolution of the Winkler Index (WI) – comparison between WI ARPA

ARPA vs COPERNICUS

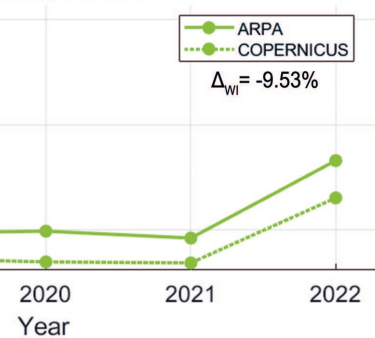
Station ID 8002



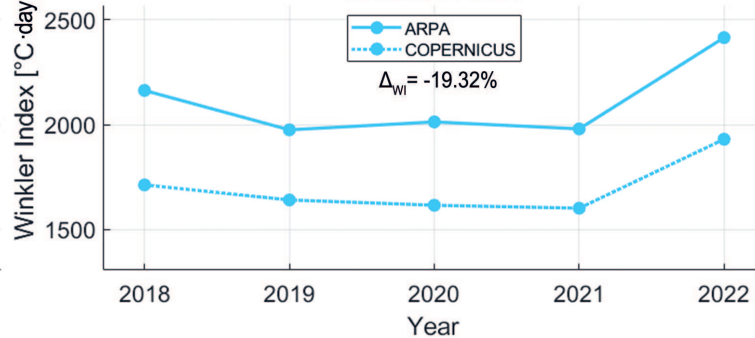
Station ID 8007



Station ID 8202

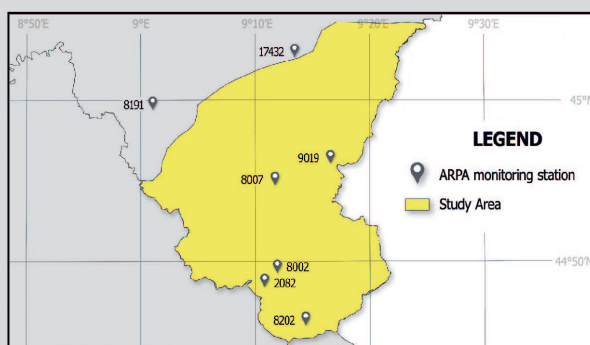


Station ID 9019



$$\Delta_{WI} (\%) = \frac{WI_{COPERNICUS} - WI_{ARPA}}{WI_{ARPA}} \times 100$$

Sensor ID	Location	Elevation (a.s.l. m)
2082	Varzi Nivione	500
8002	Varzi Via Mazzini	485
8007	Fortunago	501
8191	Voghera	95
8202	Santa Margherita	575
9019	Canevino	455
17432	Broni	77



and COPERNICUS-derived WI (daily) at the monitoring stations locations over 2018–2022.

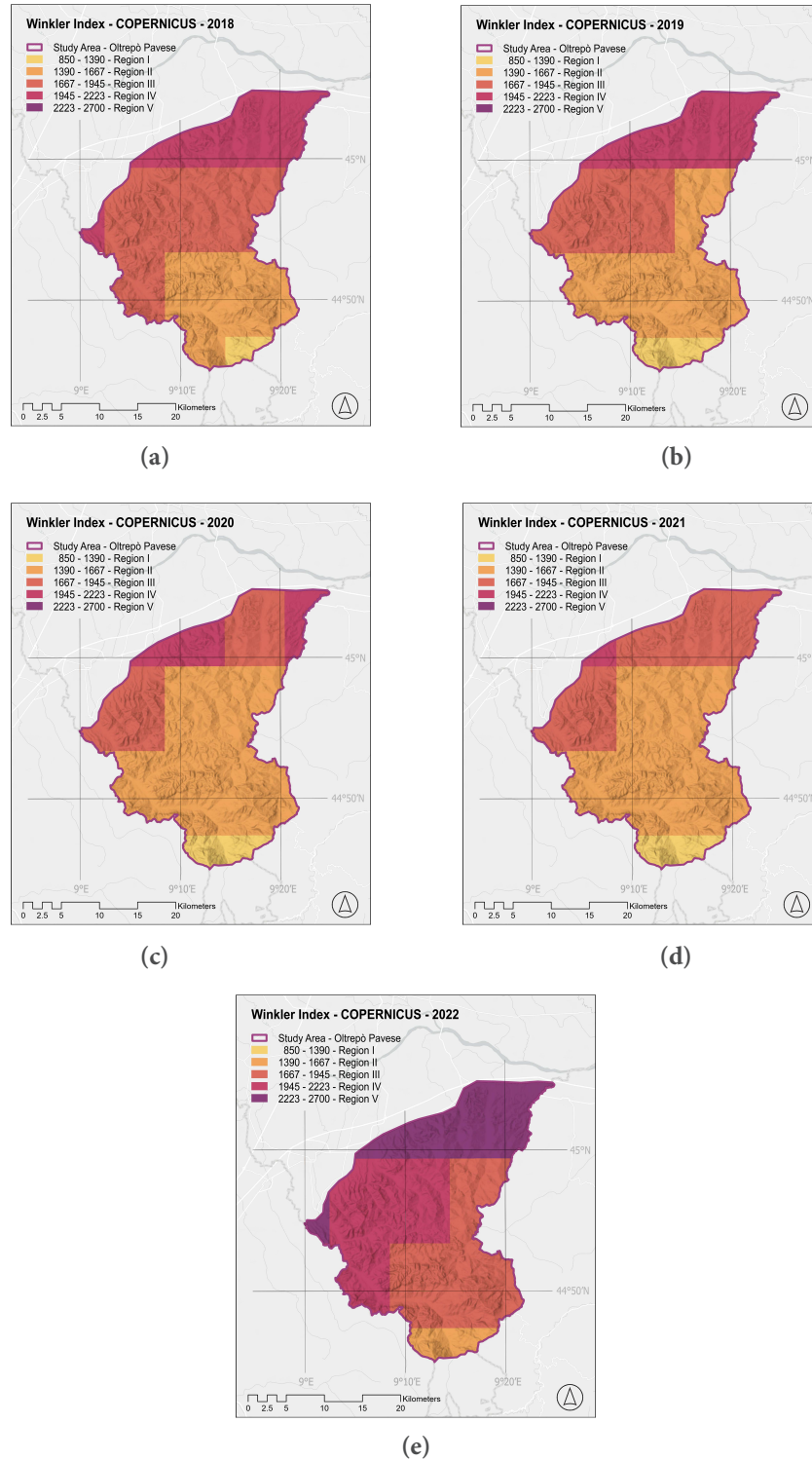


Figure 52. Spatial distribution of the Copernicus ERA5-Land Winkler Index over the Oltrepò Pavese during 2018–2022. Panels (a–e) illustrate the interannual variability of the index.

6. TDO validation

An independent set of air-temperature observations was provided by *Terre D'Oltrepò* (TDO), which owns meteorological stations in several vineyards across the study area. Unlike the ARPA measurements used to calibrate the MODIS-based regression model, the TDO observations were not included in model development. They therefore provide an external dataset for assessing the transferability of the calibration to independent vineyard locations. Figure 53 shows the spatial distribution of the TDO stations and vineyards together with the ARPA monitoring network.

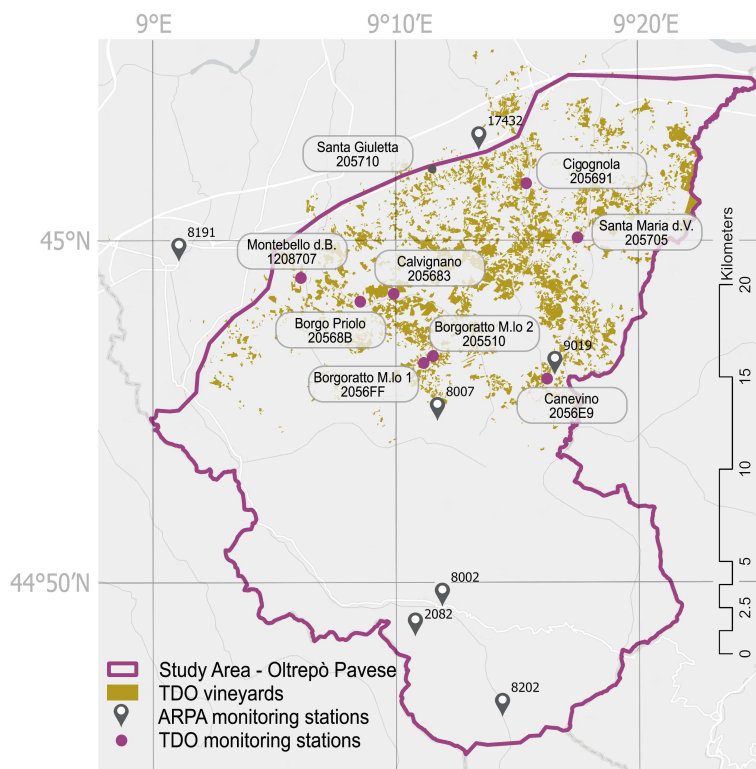


Figure 53. Study area showing the vineyards of *Terre D'Oltrepò* and ARPA and TDO monitoring stations.

As an initial assessment, MODIS-derived air temperatures were compared with observations from the TDO station at Canevino (ID 2056E9). Measurements from the nearby ARPA Canevino station (ID 9019), located approximately 500 m from the TDO station, were also included as an additional ground-based reference. Script 18 processes the air-temperature observations recorded at the TDO Canevino station and compares them with ARPA observations and MODIS-derived estimates. The TDO records were imported from an Excel file, converted into a timetable, and aggregated into 8-day means to match MODIS temporal resolution. MODIS-derived temperatures were extracted at the TDO station coordinates, while ARPA observations were aggregated over the same temporal windows.

Residuals were calculated and evaluated using the mean bias, standard deviation, median bias, median absolute deviation (MAD), and a robust estimate of dispersion.

Script 18. MATLAB function for validating MODIS-derived air temperature against observations from the Canevino TDO weather station. The script extracts MODIS and ARPA temperatures, aggregates TDO data into 8-day means, and computes temperature differences together with descriptive statistics.

```
function TDO_SingleStation()

load('MODIS_Tair_estimated.mat');
MODIS_dates= MODIS_Tair_estimated.date(:);
dir_arpa= "dati_arpa_5anni";
load("..\" + dir_arpa + "\\DailyMean_ARPA_9019.mat");
dir_TDO= 'TDO_WS';
data_file=fullfile("..",dir_TDO,"2056E9_station_data_Canevino.xlsx");
T = readtable(data_file);



---


Data preparation
T.Data_Ora = datetime(T.Data_Ora,'InputFormat','yyyy-MM-dd HH:mm:ss');
x = T.Xcoord(1);
y = T.Ycoord(1);
utmCRS = projcrs(32632);
[lat, lon] = projinv(utmCRS, x, y);
[row, col] = geographicToIntrinsic(MODIS_Tair_estimated.georef,lat,lon);
TT=table2timetable(T(:,{'Data_Ora','Tavg'}),'RowTimes','Data_Ora');
TT_8d=timetable(MODIS_dates,Nan(numel(MODIS_dates),1),'VariableNames',...
{'Tavg_8d'});

for i = 1:numel(MODIS_dates)
    mask=TT.Data_Ora ≥ MODIS_dates(i) & TT.Data_Ora ≤ MODIS_dates(i)+days(7);
    TT_8d.Tavg_8d(i) = mean(TT.Tavg(mask), 'omitnan');
end

modis_temp = Nan(size(MODIS_dates));
arpa_temp = Nan(size(MODIS_dates));



---


Extraction of MODIS and ARPA temperatures
for i = 1:numel(MODIS_dates)
    raster = MODIS_Tair_estimated.estimated_Tair(:,:,i);
    modis_temp(i) = interp2(raster, col, row, 'linear', Nan);
    mask=cur_TT2.DataOra ≥ MODIS_dates(i) & cur_TT2.DataOra ≤ MODIS_dates(i)...
+ days(7);
    arpa_temp(i) = mean(cur_TT2.Tmedia(mask), 'omitnan');
end
```


Results

```
results=table(TT_8d.MODIS_dates,TT_8d.Tavg_8d,arpa_temp,modis_temp, ...  
'VariableNames', {'Date','t_TDO','t_arpa9019','t_modis'});  
results.delta_modis = results.t_TDO - results.t_modis;  
results.delta_arpa = results.t_TDO - results.t_arpa9019;
```

Statistics

```
ii = isoutlier(results.delta_modis);  
num_outliers = sum(ii);  
  
media_delta = mean(results.delta_modis(~ii),'omitnan');  
std_delta = std(results.delta_modis(~ii),'omitnan');  
mediana_delta = median(results.delta_modis,'omitnan');  
mad_delta = mad(results.delta_modis,1);  
sigma = 1.4826 * mad_delta  
end
```

The comparison among 8-day mean TDO Canevino measurements, ARPA 9019 data, and MODIS-derived air temperatures shows a high level of agreement. After removing outliers, the mean difference between TDO and MODIS temperatures is 0.85 °C, with a standard deviation of 0.91 °C. The median residual is 0.90 °C, and the median absolute deviation (MAD) is 0.65 °C, resulting in a robust estimate of dispersion of approximately 0.97 °C.

When compared with ARPA 9019 measurements, the mean difference between TDO and ARPA temperatures is -0.60 °C, with a standard deviation of 0.44 °C. The median difference (-0.52 °C) and the robust dispersion estimate ($\sigma \approx 0.51$ °C) indicate low variability.

Because the TDO observations were not used to calibrate the regression model, this analysis constitutes an independent external validation rather than an additional calibration step.

6.1. Validation of MODIS-derived temperatures at TDO stations

Following the preliminary comparison at Canevino, the independent validation was extended to all available *Terre D'Oltrepò* (TDO) meteorological stations within the study area. TDO temperature records were aggregated into 8-day means corresponding to the MODIS compositing periods. For each date, the MODIS-derived air-temperature raster was sampled at the locations of each TDO station. Only intervals containing valid values in both datasets were retained. Residuals were defined as the difference between MODIS-derived and TDO-observed air temperature. Positive residuals therefore indicate overestimation by the MODIS-based model, whereas negative residuals indicate underestimation.

Across the nine TDO stations, RMSE values ranged from 1.02 to 1.75 °C, correlation coefficients were close to 0.99, and residual standard deviations ranged from 0.98 to 1.37 °C (see Table 16). The high correlations indicate that the MODIS-derived estimates reproduced the temporal variability of the TDO observations. However, the non-zero mean residuals recorded at some stations reveal small site-dependent biases.

Figure 54 presents the station-specific residual distributions. Most distributions are centred close to zero, although shifts are visible at some locations. Overall, the independent TDO comparison shows that the global model maintains relatively low prediction errors at vineyard locations that were not used during calibration.

Table 16. External validation of MODIS-derived air temperature against TDO station observations aggregated into 8-day means. Residuals are calculated as MODIS-derived minus TDO-observed temperature.

TDO Station	Station ID	Valid pairs	Mean residual [°C]	Residual Std [°C]	RMSE [°C]	Correlation coefficient
Montebello d.B.	1208707	164	0.33	1.29	1.33	0.988
Borgoratto M.lo 2	205510	151	0.49	1.29	1.38	0.989
Calvignano	205683	216	0.94	1.21	1.52	0.992
Borgo Priolo	2056B	219	1.20	1.26	1.75	0.991
Cigognola	205691	219	0.41	1.05	1.12	0.992
Canevino	2056E9	219	−0.82	1.00	1.29	0.992
Borgoratto M.lo	2056FF	219	−0.29	0.98	1.02	0.993
Santa Maria d.V.	205705	215	0.09	1.37	1.37	0.993
Santa Giuletta	205710	180	0.30	1.26	1.29	0.990

Histograms of Residuals (MODIS – TDO) for Each Station

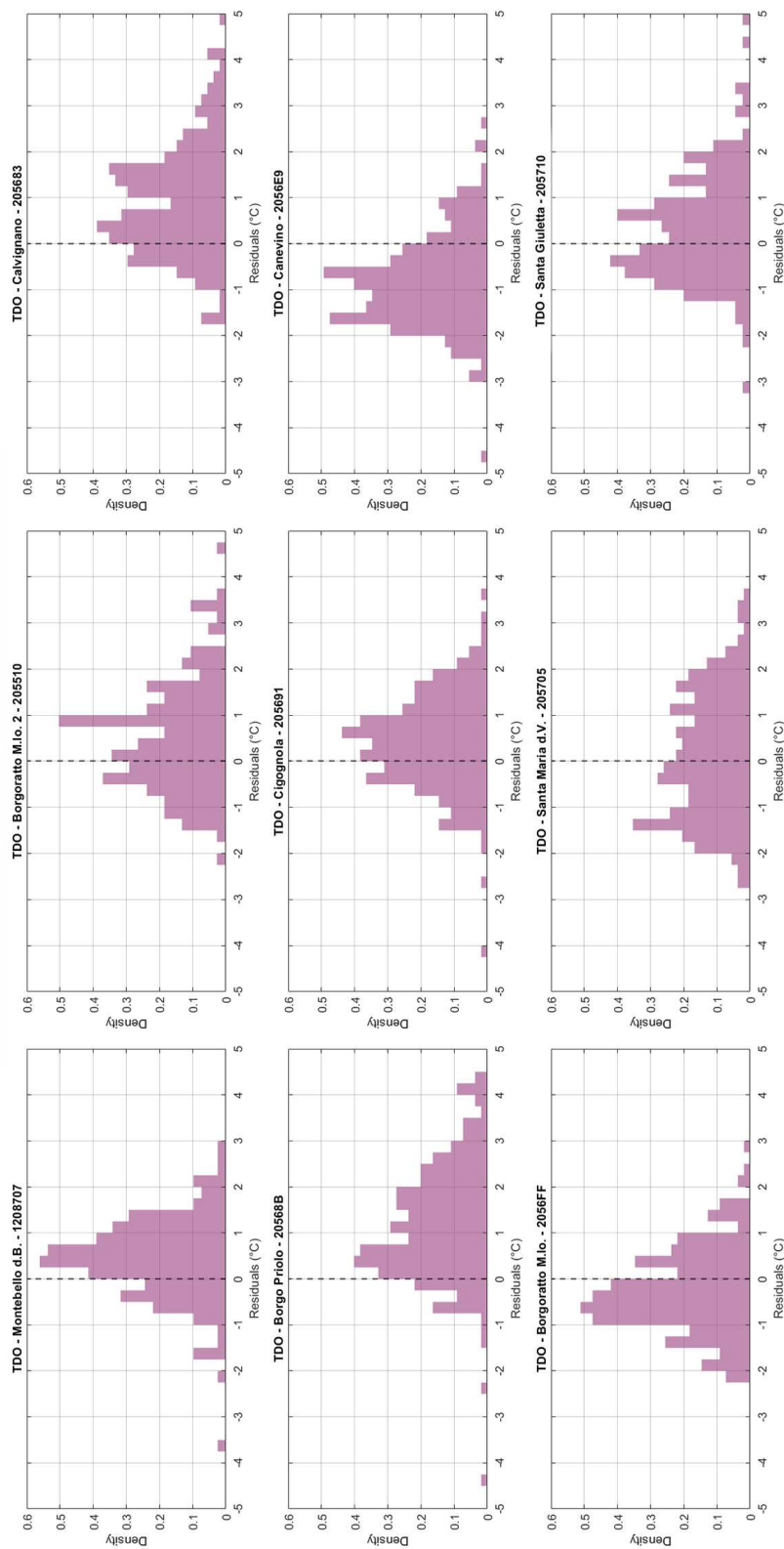


Figure 54. Histograms of residuals between MODIS-derived air temperatures and TDO measurements. Residuals are defined as MODIS-derived minus TDO temperature; positive values indicate MODIS overestimation and negative values indicate underestimation.

7. Suitability Maps

The assessment of land suitability for viticulture requires the interaction of numerous variables, including climatic, pedological, and topographic factors which collectively determine the viticultural potential of a territory [48]. Suitability maps are an important decision-support tool for identifying areas where conditions allow the optimal growth of a specific grape variety. Their accuracy depends on both the quality of the spatial dataset and the methodological framework used to integrate heterogeneous criteria [10]. The environmental parameters affecting vine development – temperature, soil properties, solar radiation, rainfall, slope, and aspect – do not contribute equally. For this reason, Multi-Criteria Decision Analysis (MCDA) is widely used to combine and weight factors according to their agronomic relevance. In viticulture, MCDA approaches implemented in Geographic Information Systems (GIS) are particularly effective, as they allow pixel-level analysis over complex landscapes [49]. Among the various MCDA techniques, the Weighted Overlay method implemented in the *Suitability Modeler* of ArcGIS Pro was adopted in this study. This approach represents an operational application of the Weighted Sum Model (WSM) and is commonly used in GIS-based analyses due to its conceptual simplicity.

For each pixel of the study area, the final suitability score is computed as the weighted sum of all contributing factors, as expressed in Equation (15):

$$Suitability = \sum_{j=1}^n w_j \cdot a_{ij} \quad (15)$$

Where:

- w_j = weight of criterion j
- a_{ij} = adequacy value of the pixel i respect to criterion j

The Weighted Sum Model assumes additive and partially compensatory relationships among the criteria. Favourable conditions were assigned high suitability scores, whereas unfavourable conditions received low or zero scores. The weights therefore express the relative importance of the criteria. Partial compensation among factors was accepted because no single continuous environmental variable was considered sufficient to determine suitability independently. However, compensation was prevented for non-convertible land-cover classes through exclusion constraints.

The main challenge of Weighted Overlay (WO) approaches is defining appropriate weights, which can significantly influence the results and introduce subjective bias if not properly justified. To overcome this limitation, the present study adopts the Analytic Hierarchy Process (AHP), one of the most widely used methods in land suitability assessments. It uses pairwise comparisons to determine the relative importance of each criterion [50].

More recently, Fuzzy Logic has increasingly been applied to land-suitability analysis to represent gradual transitions, uncertainty, and nonlinear interactions among environmental criteria [51–53].

7.1. Selection of Criteria for Pinot Noir Suitability

Pinot Noir is one of the most environmentally sensitive grape varieties, requiring well-balanced climatic conditions, moderate vigour, and specific soil characteristics. Based on viticultural literature and regional expert knowledge, the suitability analysis in this study includes four main groups of criteria: topographic, climatic, pedological, and land-use factors, summarised in Table 17 and described in the following sections [54].

All criteria were resampled to a common 10 m grid to enable raster integration. This common cell size should be interpreted as the computational resolution of the final model rather than as the intrinsic spatial resolution of every input dataset, because some climatic and pedological layers originate from coarser sources.

This study builds upon previous work in the field (notably by Professor Attilio Scienza [13]), offering a more in-depth and spatially precise analysis.

Table 17. Overview of the datasets and criteria used to build the layers for the *Pinot Noir* suitability analysis.

Category	Criteria	Importance for <i>Pinot Noir</i>	Data Source
Topography	Elevation	Temperature, phenology, frost	Geoportale Lombardia (5 m DTM)
	Slope	Drainage, mechanisation, erosion	
	Aspect	Exposure and microclimate	
Climate	Winkler Index (temperature)	Heat availability	ARPA, MODIS-derived T_{air}
	PAR	Photosynthesis and berry development	Derived from ArcGIS solar radiation
	Total rainfall	Water availability, disease pressure, dilution	NASA IMERG
Pedology	Soil type	Rooting zone, vigour, nutrient, water storage	Geoportale Lombardia (pedological map)
	Soil depth		
	pH		
Land Use	LULC	Exclusion of non-agricultural areas	ESRI land-use map

7.1.1. Topographic Criteria

Topographic attributes influence microclimate, soil moisture, erosion dynamics, and solar radiation. In this study, the following parameters were considered:

- **Elevation** – 5 m Digital Terrain Model (DTM);
- **Slope** and **Aspect** derived from the DTM.

Moderate slopes favour water drainage and improve air circulation, while south-facing exposures often receive more radiation, enhancing grape ripening and phenological development.

Aspect is a circular variable because 0° and 360° represent the same north-facing direction. For the MCDA analysis, the continuous aspect raster was reclassified into directional classes, grouping equivalent orientations at the beginning and end of the angular scale. For example, north-facing slopes included directions close to both 0° and 360° . In the Fuzzy Model, the membership functions were defined to preserve the same circular continuity.

Digital Terrain Model (DTM) – Lombardy Region (5 m)

The Lombardy Regional DTM [5] is a digital elevation model with $5\text{ m} \times 5\text{ m}$ spatial resolution distributed as a GRID raster and made available as open data through the Lombardy Geoportal (WMS service).

From this dataset, slope [%] and aspect rasters were generated using dedicated ArcGIS analysis tools (Figure 55).

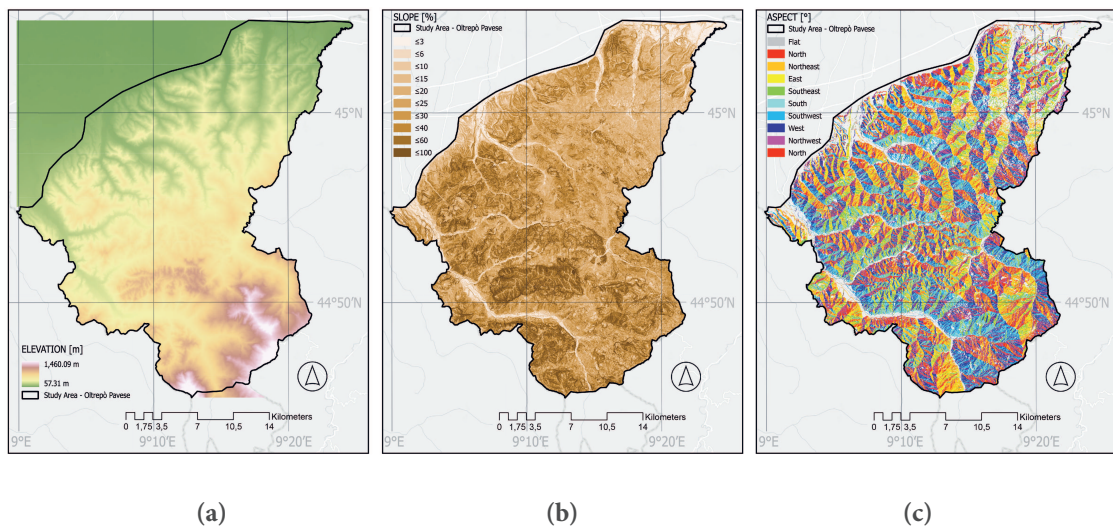


Figure 55. Topographic layers derived from the 5 m Digital Terrain Model (DTM) of the Lombardy Region. (a) Elevation [m]; (b) Slope [%]; (c) Aspect [degrees, 0° and 360° = North].

7.1.2. Climatic criteria

For the suitability assessment, the climatic variables illustrated in Figure 56 were selected.

- **Temperature**, expressed through the Winkler Index [$^{\circ}\text{C}\cdot\text{day}$];
- **Photosynthetically Active Radiation (PAR)** [$\text{MJ m}^{-2} \text{ year}^{-1}$];
- **Total rainfall** [mm] during the vegetative period (April–October).

Pinot Noir thrives in relatively cool conditions, with optimal average temperatures typically ranging between 15–22 $^{\circ}\text{C}$ [30].

Excessive heat or radiation can result in unbalanced ripening, while insufficient heat limits physiological activity and delays maturation.

Rainfall also plays a critical role: while lower precipitation levels can be compensated for with adequate irrigation, excessive rainfall – particularly during the summer and pre-harvest period – increases disease pressure and may negatively affect berry quality, requiring careful vineyard management.

Winkler Index (WI)

The Winkler Index, a bioclimatic indicator widely used in viticulture, was previously computed following the procedure described in Chapter 5, as the primary focus of this thesis. It quantifies heat accumulation during the growing season (April–October) and provides a temperature-based assessment of regional suitability for grape growing.

For this analysis, the Winkler Index was averaged over 2018–2022.

Photosynthetically Active Radiation (PAR)

Photosynthetically Active Radiation was derived from annual solar radiation, averaged over the five-year period 2018–2022, estimated using the *Raster Solar Radiation* tool in ArcGIS Pro from the 5 m DTM. PAR represents the fraction of incoming solar energy in the 400–700 nm wavelength range available for photosynthesis [55]. It was calculated as 46% of the total solar radiation [56] and converted to $\text{MJ m}^{-2} \text{ year}^{-1}$ according to Equation (16).

$$PAR_i = SR_{i,kWh} \cdot 3.6 \cdot 0.46 \quad (16)$$

Where:

- PAR_i = Photosynthetically Active Radiation for pixel i [$\text{MJ m}^{-2} \text{ year}^{-1}$]
- $SR_{i,kWh}$ = annual solar radiation for pixel i [$\text{kWh m}^{-2} \text{ year}^{-1}$]
- 3.6 = conversion factor from kWh to MJ
- 0.46 = fraction of solar radiation that is photosynthetically active

The threshold values used to define suitability classes for solar radiation were derived from the manual by Professor Attilio Scienza [13] and from the specifications of the *Disciplinare Di Produzione Dei Vini A Denominazione Di Origine Controllata “Pinot Nero Dell’oltrepò Pavese”* [54].

Rainfall

Annual precipitation is a key factor influencing vine growth, with optimal values for *Pinot Noir* typically ranging between 350 and 700 mm during the growing season (April–October) [57]. Both the amount and timing of rainfall are critical: winter and early-season precipitation support vine development, whereas excessive precipitation during summer and early autumn can damage berries and affect wine quality. In this study, monthly precipitation data were obtained from the NASA IMERG dataset [58] at 0.1° spatial resolution (about 9 km) and aggregated to compute the average total rainfall during the April–October period over 2018–2022.

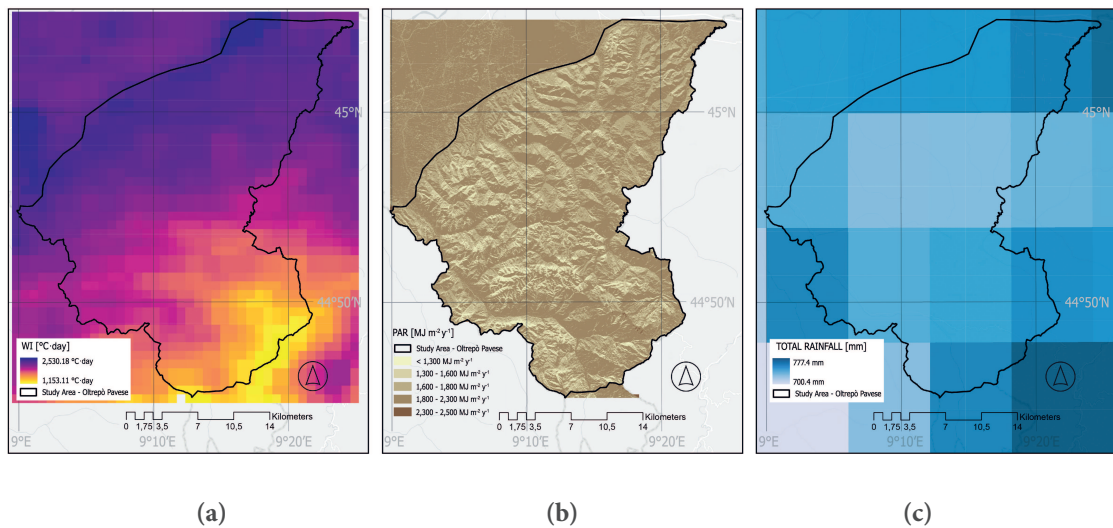


Figure 56. Climatic layers of the study area: (a) Winkler Index [°C-day]; (b) Photosynthetically Active Radiation (PAR) [$\text{MJ m}^{-2} \text{y}^{-1}$], derived from solar radiation; (c) Total growing-season rainfall (April–October) [mm].

7.1.3. Pedological Criteria

Soil characteristics play a fundamental role in determining vine vigour, water availability, and nutrient uptake. The considered pedological dataset included the following parameters:

- Soil type;
- Soil depth;
- Soil pH.

The analysis is based on the Lombardy regional pedological map at a 1:250,000 scale, which provides the spatial distribution of soils and associated properties such as depth and pH [59] (Figure 57).

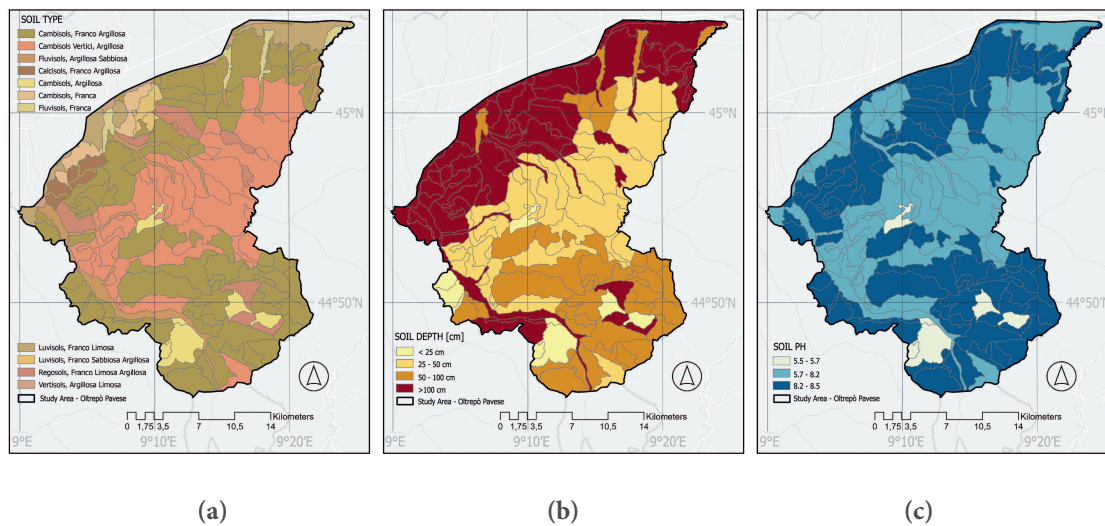


Figure 57. Pedological layers of the study area, derived from the Lombardy Region Geoportal: (a) Soil type; (b) Soil depth [cm]; (c) Soil pH.

7.1.4. Land Use/Land Cover (LULC)

The Land Use/Land Cover (LULC) dataset was obtained from the ESRI Sentinel-2 Land Cover Explorer, which provides annual global LULC maps at 10 m spatial resolution [60]. The product is generated by ESRI in collaboration with Impact Observatory using a deep learning-based classification model. The dataset includes nine LULC classes – water, trees, flooded vegetation, crops, built area, bare ground, snow/ice, clouds, rangeland – and provides global coverage for the period 2017–2024.

Land Use/Land Cover was not interpreted as an intrinsic measure of the biophysical suitability of *Pinot Noir*. Instead, it was used primarily as a feasibility and exclusion criterion. Built-up areas, water bodies, and other non-convertible surfaces were classified as unsuitable or excluded from the analysis, whereas potentially convertible agricultural and semi-natural areas were retained. LULC therefore acted mainly as a spatial constraint rather than as a continuous environmental driver of grapevine suitability.

For the present analysis, the 2024 LULC raster – the most recent version available – was downloaded from the ArcGIS Living Atlas and clipped to the study area, see Figure 58.

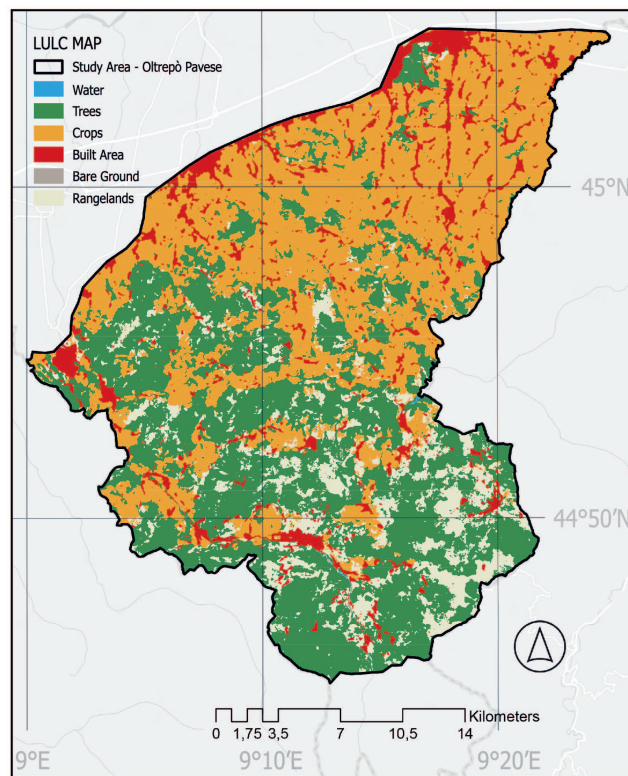


Figure 58. LULC map of the study area for 2024 provided by the ESRI ArcGIS Living Atlas.

7.2. Suitability Criteria

Suitability analysis for vineyard assessment is essential to define the full potential of land resources for sustainable viticultural production. It reflects the interaction between grapevine requirements and the physical and environmental characteristics of a region, providing a quantitative measure of how well local conditions meet crop needs [53]. A widely adopted reference framework for land evaluation is provided by the Food and Agriculture Organisation of the United Nations (FAO), which defines a structured system for categorising land suitability for specific uses [52]. According to the FAO (1976), land is classified based on its capacity to support a given use. At the highest level of generalisation, the land suitability order distinguishes between *suitable* (S) and *not suitable* (N) land. Within the suitable order, three classes are typically identified: *highly suitable* (S1), *moderately suitable* (S2), and *marginally suitable* (S3). Although additional subclasses may be specified in some applications, this study focuses exclusively on these four categories.

In both scientific literature and applied spatial analysis, two main approaches are commonly used to generate suitability maps. These methods differ in how they handle spatial criteria, constraints, and expert knowledge.

The first approach relies on Multi-Criteria Decision Analysis (MCDA) using a weighted overlay technique. In this framework, each variable is reclassified on a common suitability scale, and weights are assigned to reflect the relative importance of each criterion for vineyard development. The weighted layers are then aggregated into a single suitability surface. This approach is highly transparent and reproducible, since both the classification thresholds and the weighting schemes are explicitly defined.

The second approach is based on Fuzzy Logic, which is particularly effective in handling uncertainty and gradual transitions in environmental variables. By integrating expert knowledge from thematic literature, a set of rules can be defined to represent the relationships among key site-selection criteria. These relationships are expressed through membership functions, allowing for continuous suitability values rather than rigid threshold-based classifications [51].

7.3. Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) [61, 62] is essential in MCDA for assigning weights to the criteria. Weight values were obtained by calculating the principal eigenvector of the square reciprocal matrix of pairwise comparisons, and then normalising its components so that their sum equals 1 [63]. The pairwise comparison matrix was constructed based on winemakers' practical knowledge and expert opinions on the selected criteria.

The results obtained are summarised in Figure 59.

After deriving the most suitable set of weights, the degree of consistency was verified using the Consistency Ratio (CR), computed according to Equation (17).

$$CR = \frac{\lambda_{max} - n}{(n - 1) \cdot RI} \quad (17)$$

Where:

- CR = Consistency Ratio
- λ_{max} = Maximum eigenvalue
- n = Number of evaluation parameters
- RI = Random consistency Index (provided by the author [62])

A standard cutoff value of $CR = 0.1$ is commonly adopted in the literature to evaluate the acceptability of the pairwise comparisons in AHP applications [50]. When $CR \leq 0.1$, the matrix is considered to have an acceptable internal consistency, and the derived weights can be used.

In this study, the calculated Consistency Ratio was 2.56%, well below the 10% threshold. Therefore, since the pairwise comparison matrix is consistent, the obtained weights are considered reliable.

Although AHP improves transparency and consistency, the resulting weights remain dependent on expert judgement and should not be interpreted as uniquely optimal.

Comparison Matrix

Criteria	Elevation	Slope	Aspect	WI	PAR	pH	Soil Depth	Soil Type	Rainfall	Land Use
Elevation	1.00	0.25	0.50	0.33	0.50	4.00	2.00	2.00	0.50	5.00
Slope	4.00	1.00	2.00	2.00	2.00	7.00	4.00	4.00	3.00	8.00
Aspect	2.00	0.50	1.00	0.50	1.00	6.00	2.00	2.00	1.00	6.00
WI	3.00	0.50	2.00	1.00	1.00	7.00	3.00	3.00	2.00	7.00
PAR	2.00	0.50	1.00	1.00	1.00	6.00	2.00	2.00	1.00	6.00
pH	0.25	0.14	0.17	0.14	0.17	1.00	0.20	0.33	0.50	1.00
Soil Depth	0.50	0.25	0.50	0.33	0.50	5.00	1.00	1.00	0.50	3.00
Soil Type	0.50	0.25	0.50	0.33	0.50	3.00	1.00	1.00	0.50	3.00
Rainfall	2.00	0.33	1.00	0.50	1.00	2.00	2.00	2.00	1.00	5.00
Land Use	0.20	0.13	0.17	0.14	0.17	1.00	0.33	0.33	0.20	1.00
Total	15.45	3.85	8.83	6.29	7.83	42.00	17.53	17.67	10.20	45.00

Numeric Value	Definition (a_i, a_j)
1	a_i, a_j are equally important
3	a_i is moderately more important than a_j
5	a_i is strongly more important than a_j
7	a_i is evidently more important than a_j
9	a_i is extremely more important than a_j
2-4-6-8	intermediate judgments
Reciprocal	If a_i element has one of the above numbers compared to element a_j , then a_j has the opposite value when compared to a_i .

Normalised Matrix

Criteria	Elevation	Slope	Aspect	WI	PAR	pH	Soil Depth	Soil Type	Rainfall	Land Use	Sum	Priority	Eigen Value
Elevation	0.06	0.06	0.06	0.05	0.06	0.10	0.11	0.11	0.05	0.11	0.79	0.08	1.214
Slope	0.26	0.26	0.23	0.32	0.26	0.17	0.23	0.23	0.29	0.18	2.41	0.24	0.929
Aspect	0.13	0.13	0.11	0.08	0.13	0.14	0.11	0.11	0.10	0.13	1.18	0.12	1.043
WI	0.19	0.13	0.23	0.16	0.13	0.17	0.17	0.17	0.20	0.16	1.70	0.17	1.066
PAR	0.13	0.13	0.11	0.16	0.13	0.14	0.11	0.11	0.10	0.13	1.26	0.13	0.988
pH	0.02	0.04	0.02	0.02	0.02	0.02	0.01	0.02	0.05	0.02	0.24	0.02	1.014
Soil Depth	0.03	0.06	0.06	0.05	0.06	0.12	0.06	0.06	0.05	0.07	0.62	0.06	1.086
Soil type	0.03	0.06	0.06	0.05	0.06	0.07	0.06	0.06	0.05	0.07	0.57	0.06	1.010
Rainfall	0.13	0.09	0.11	0.08	0.13	0.05	0.11	0.11	0.10	0.11	1.02	0.10	1.041
Land Use	0.01	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.21	0.02	0.953
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	10.00	1.00	10.343

$\lambda_{\max}$

CI	3.81%	Consistency Index	
RI	1.49	Random Consistency Index	
CR	2.56%	Consistency Ratio	

n	3	4	5	6	7	8	9	10
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

if $CR \leq 10\%$ the matrix is consistent
if $CR > 10\%$ the matrix is inconsistent

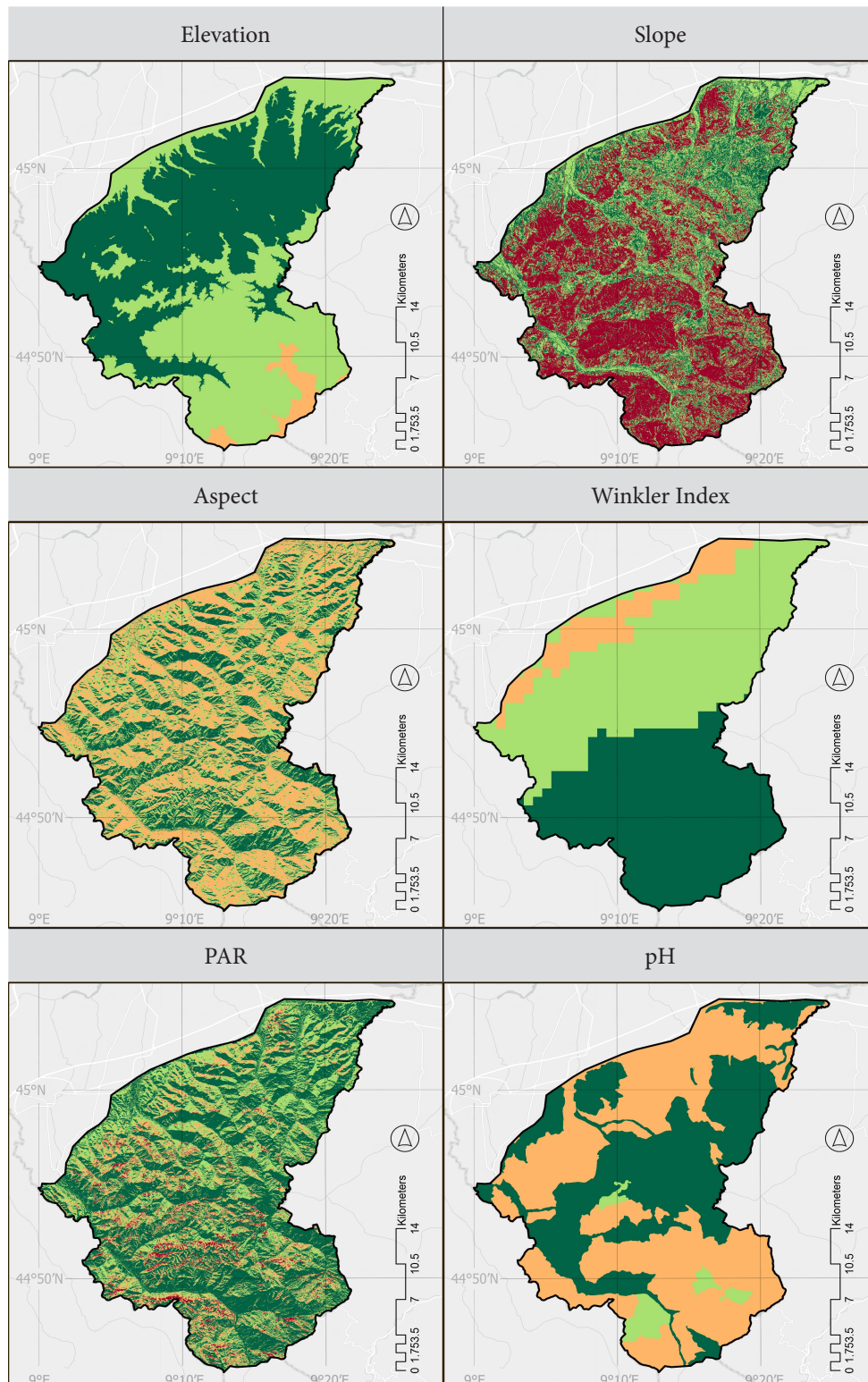
Figure 59. Analytic Hierarchy Process (AHP) implementation for criteria weighting. The figure shows: (top) the pairwise comparison matrix; (bottom) the normalised matrix, and the calculation of Consistency Ratio (CR). The resulting CR value (2.56%) indicates acceptable consistency in the pairwise comparisons ($CR < 10\%$) and supports the use of the derived weights.

7.4. ArcGIS Pro Suitability Modeler – MCDA

All the raster datasets were resampled to match the cell size and spatial alignment of the ESRI LULC layer, using a target resolution of 10 m, considered appropriate for maintaining spatial detail and computational efficiency. Specifically, the DTM raster and its derived layers (slope and aspect) were resampled. The Winkler Index, Photosynthetically Active Radiation, and rainfall rasters were first computed as five-year averages and subsequently resampled.

From the pedological vector dataset (*Carta Pedologica 250k shapefile*), Soil Type information was extracted using a composite field derived from the WRB taxonomic group associated with the Soil Typological Unit (UTS), combined with the *TXT_1M* attribute, which represents the soil texture class averaged over the first meter of soil. These attributes were then converted to raster format. The same rasterisation procedure was applied to Soil pH (*PH_1M* field) and effective Soil Depth (*PROF_UTIL* field, expressed in centimetres).

After generating all input variables, the *Suitability Modeler* in ArcGIS Pro was employed to integrate the co-registered raster layers and assign suitability ranks and weights to each variable. Each criterion was reclassified into four ordinal suitability classes (*0 = not suitable, 1 = marginally suitable, 2 = moderately suitable, and 3 = highly suitable*) and assigned a relative weight according to its importance for *Pinot Noir* cultivation. Figure 60 and Table 18 summarise the ten input layers, their corresponding weights, suitability rankings, and classification criteria.



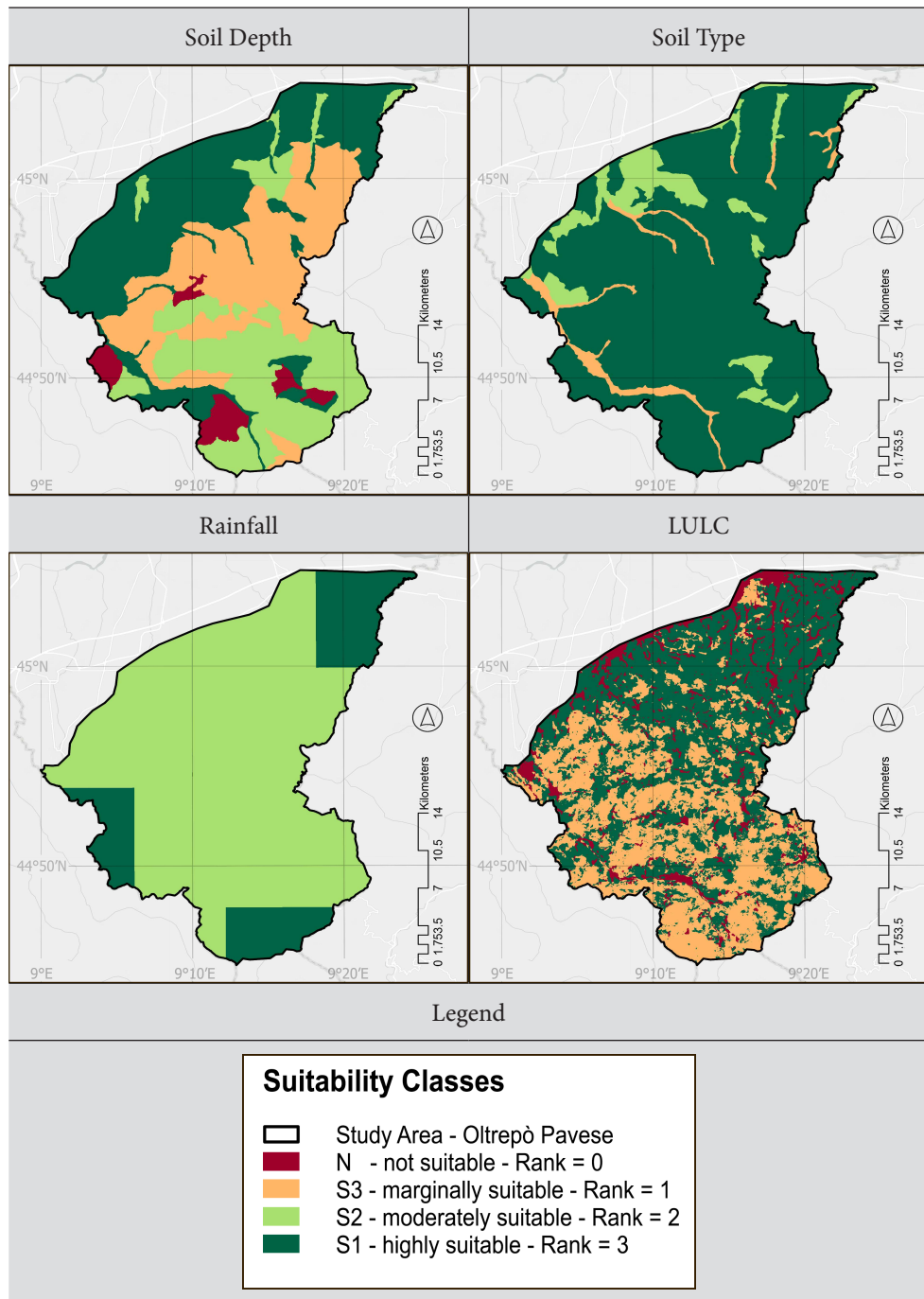


Figure 60. Environmental criteria classified into the suitability scale used in the MCDA model.

Table 18. Classification ranges, suitability ranks (0 = *not suitable*, 1 = *marginally suitable*, 2 = *moderately suitable*, and 3 = *highly suitable*), and weights assigned to each criterion for *Pinot Noir* suitability analysis.

Criteria	Class	Rank	Weight [%]
Elevation	≤150 m	2	8
	150–450 m	3	
	450–1,000 m	2	
	>1,000 m	1	
Slope	0–5 %	2	24
	5–15 %	3	
	15–25 %	2	
	>25 %	0	
Aspect	North North–East North–West	1	12
	East West	2	
	South South–East South–West	3	
Winkler Index	0–850 °C·day	0	17
	850–1,370 °C·day	3	
	1,370–1,650 °C·day	3	
	1,650–1,930 °C·day	3	
	1,930–2,200 °C·day	2	
	2,200–2,700 °C·day	1	
Soil Type	CALCISOLS Franco Argillosa	3	6
	CAMBISOLS Argillosa	3	
	CAMBISOLS Franca	2	
	CAMBISOLS Franco Argillosa	3	
	CAMBISOLS Vertici Argillosa	3	
	FLUVISOLS Argillosa Sabbiosa	1	
	FLUVISOLS Franca	2	
	LUVISOLS Franco Limosa	3	
	LUVISOLS Franco Sabbiosa Argillosa	2	
	REGOSOLS Franco Limosa Argillosa	2	
	VERTISOLS Argillosa Limosa	2	

Criteria	Class	Rank	Weight [%]
Soil pH	<5.5	0	2
	5.5–5.7	2	
	5.7–8.2	3	
	>8.2	1	
Soil Depth	<25 cm	0	6
	25–50 cm	1	
	50–100 cm	2	
	>100 cm	3	
Total Rainfall (Apr–Oct)	<250 mm	0	10
	250–450 mm	1	
	450–750 mm	2	
	750–800 mm	3	
	800–900 mm	2	
	900–1,250 mm	1	
	>1,250 mm	0	
PAR	<1,300 MJ m ⁻² y ⁻¹	0	13
	1,300–1,600 MJ m ⁻² y ⁻¹	1	
	1,600–1,800 MJ m ⁻² y ⁻¹	2	
	1,800–2,300 MJ m ⁻² y ⁻¹	3	
	2,300–2,500 MJ m ⁻² y ⁻¹	2	
	2,500–2,700 MJ m ⁻² y ⁻¹	1	
	>2,700 MJ m ⁻² y ⁻¹	0	
LULC	Crops	3	2
	Rangelands		
	Flooded Vegetation	2	
	Bare Ground		
	Trees	1	
	Water		
	Built Area	0	
	Snow/Ice		
	Clouds		

Using the weights defined in §7.3, the ArcGIS Pro *Suitability Modeler* was used to generate the final suitability surface, which was subsequently classified into the four previously defined suitability classes. Land Use/Land Cover was incorporated into the analysis as both a criterion and a constraint: LULC classes compatible with viticulture were included as a weighted criterion, while water bodies and built areas were masked and assigned a suitability value of zero (N). The resulting map is shown in Figure 61.

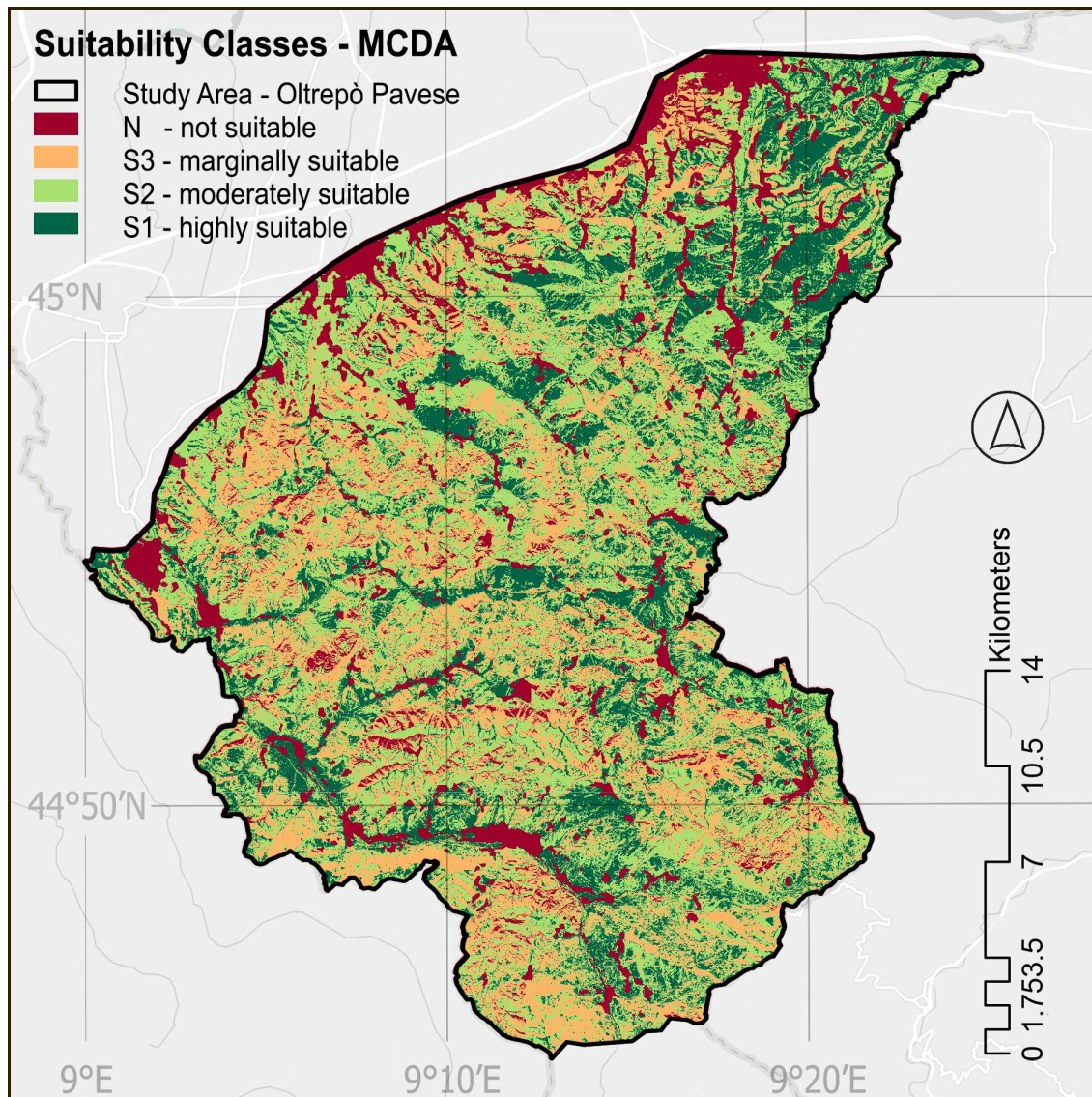


Figure 61. Suitability Map of the Oltrepò Pavese – ArcGIS Pro Suitability Modeler (MCDA).

7.5. Fuzzy Logic-based Suitability Model

Fuzzy Logic has increasingly been applied to land suitability analysis and viticultural zoning because it can represent gradual transitions and uncertainty in complex environmental systems [51–53]. In this study, a Fuzzy Logic-based approach was implemented to assess land suitability for *Pinot Noir* cultivation across the study area.

7.5.1. Fuzzy Inference System design

The Fuzzy Inference System (FIS) was developed using the MATLAB *Fuzzy Logic Modeler App*, which enables graphical definition of input variables, membership functions, and inference rules. Each environmental criterion was represented as an input variable, and its influence on vineyard suitability was described through fuzzy membership functions corresponding to different suitability levels: *not suitable*, *marginally suitable*, *moderately suitable*, and *highly suitable*. Thresholds and membership ranges were defined based on viticultural expertise and values reported in the scientific literature for *Pinot Noir*. The output variable represents overall land suitability and is expressed as a continuous index normalised to the range 0–1.

The FIS architecture (Figure 62) was implemented using a Type-1 Mamdani inference system, widely adopted in land suitability and agricultural modelling. Once defined and calibrated, the Fuzzy Model was exported as a .fis file to enable its application to spatial datasets through automated MATLAB scripts.

Creating the fuzzy inference system required an iterative calibration process. Input variables and their associated membership functions were progressively refined to accurately capture the relative influence of environmental factors on *Pinot Noir* suitability. Similarly, the output variable was adjusted to ensure a realistic representation of the suitability classes. The vineyard dataset was not used to optimise membership-function parameters or inference rules. The calibration was based on the literature and viticultural expertise, while the observed vineyard distribution was considered only during the subsequent spatial consistency assessment.

This iterative approach ensured that the FIS was mathematically consistent and agronomically meaningful. The resulting Fuzzy Model represents the cumulative outcome of this calibration process and provides the basis for the suitability analysis presented in this study.

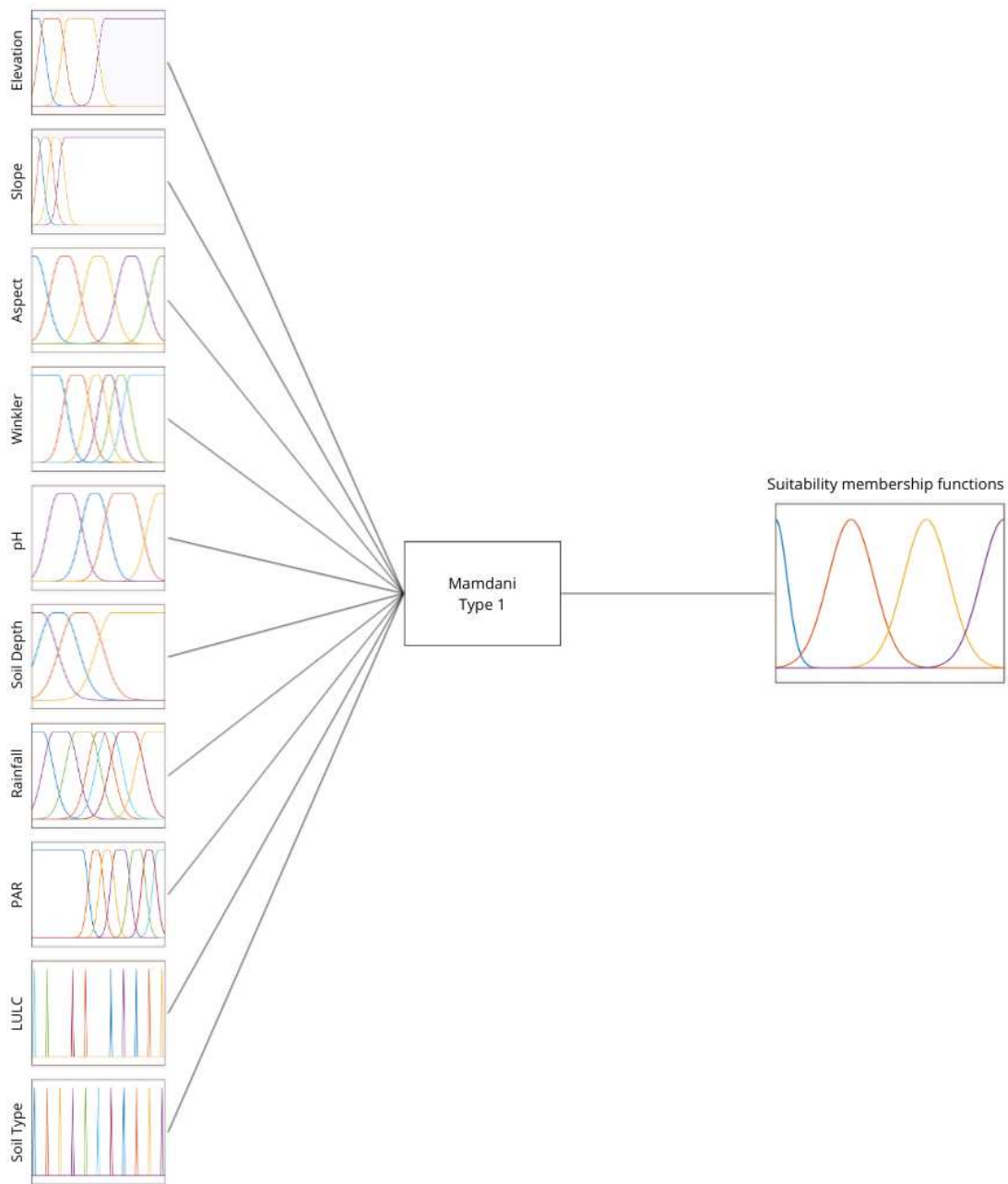


Figure 62. Architecture of the Fuzzy Inference System, including input variables and output suitability membership functions. The output is expressed as a continuous suitability score ranging from 0 to 1.

7.5.2. Spatial implementation in MATLAB

To apply the Fuzzy Inference System at the pixel level, the `.fis` file generated with the *Fuzzy Logic Modeler App* was integrated into a MATLAB-based processing workflow, as reported in Script 19.

Before inference, all raster inputs were aligned to a common spatial extent, coordinate reference system, and 10 m computational grid. Pixels containing missing values were masked. The FIS was then evaluated pixel by pixel, producing a continuous suitability index ranging from 0 to 1, which was subsequently reclassified into the four suitability classes.

In addition to combining the environmental criteria, the workflow explicitly accounted for conditions incompatible with vineyard establishment through veto rules. Whereas most variables contributed gradually to the final suitability score, selected Land Use/Land Cover classes were treated as hard constraints to prevent unrealistic vineyard allocation. In particular, pixels corresponding to water bodies and built-up areas were identified through their respective fuzzy membership functions. When the associated membership value met or exceeded a predefined threshold, the final suitability score was set to zero.

After the veto rules were applied, all suitability values were constrained to the interval [0, 1] and reassembled into a raster preserving the original spatial reference. The resulting GeoTIFF, shown in Figure 63, represents the final Fuzzy Logic-based suitability map for *Pinot Noir* cultivation.

Script 19. MATLAB script for pixel-based implementation of the fuzzy inference system. The script loads the environmental raster layers, evaluates the fuzzy suitability for each valid pixel, applies veto rules to unsuitable land-use classes, and exports the final suitability map as a GeoTIFF.

Load the Fuzzy Inference System

```
fis = readfis('2025_12_29_suitability_new.fis');
```

Load the raster datasets

```
rasPath = fullfile('RASTER DATA');  
[ELEV, R] = readgeoraster(fullfile(rasPath, 'DTM_ELEVATION.tif'));  
[SLOPE, ~] = readgeoraster(fullfile(rasPath, 'DTM_SLOPE.tif'));  
[ASPECT, ~] = readgeoraster(fullfile(rasPath, 'DTM_ASPECT.tif'));  
[WINKLER, ~] = readgeoraster(fullfile(rasPath, 'WINKLER5Y.tif'));  
[SOILPH, ~] = readgeoraster(fullfile(rasPath, 'SOIL_PH.tif'));  
[SOILDEPTH, ~] = readgeoraster(fullfile(rasPath, 'SOIL_DEPTH.tif'));  
[RAIN, ~] = readgeoraster(fullfile(rasPath, 'RAINFALL_APROCT.tif'));  
[PAR, ~] = readgeoraster(fullfile(rasPath, 'PAR_new.tif'));  
[LULC, ~] = readgeoraster(fullfile(rasPath, 'LULC_ESRI.tif'));  
[SOILTYPE, ~] = readgeoraster(fullfile(rasPath, 'SOIL_TYPE.tif'));  
targetSize = [3683 3279];
```

Convert to double

```
ELEV = double(ELEV);  
SLOPE = double(SLOPE);  
ASPECT = double(ASPECT);
```

```

WINKLER = double(WINKLER);
SOILPH = double(SOILPH);
SOILDEPTH = double(SOILDEPTH(1:targetSize(1),1:targetSize(2)));
RAIN = double(RAIN(1:targetSize(1),1:targetSize(2)));
PAR = double(PAR(1:targetSize(1),1:targetSize(2)));
LULC = double(LULC);
SOILTYPE = double(SOILTYPE);

Manage and mask NoData
ASPECT(ASPECT < 0 | ASPECT > 360) = NaN;
SLOPE(SLOPE ≥ 3.30e+38) = NaN;
PAR(PAR == 0) = NaN;
RAIN(RAIN == 0) = NaN;
SOILDEPTH(SOILDEPTH ≥ 255) = NaN;
SOILPH(SOILPH ≤ -1.70e+308) = NaN;
SOILTYPE(SOILTYPE == 15) = NaN;
mask = ~isnan(ELEV) & ~isnan(SLOPE) & ~isnan(ASPECT) & ...
        ~isnan(WINKLER) & ~isnan(SOILPH) & ~isnan(SOILDEPTH) & ...
        ~isnan(RAIN) & ~isnan(PAR) & ~isnan(LULC) & ~isnan(SOILTYPE);

Input FIS
inputs=[ELEV(mask),SLOPE(mask),ASPECT(mask),WINKLER(mask), ...
        SOILPH(mask), SOILDEPTH(mask), RAIN(mask), PAR(mask), LULC(mask), ...
        SOILTYPE(mask)];
S_fis = evalfis(fis, inputs);

Raster constraints
vetoThreshold = 0.6;
veto = false(size(inputs,1),1);

LULC: water OR built area
mf_water = fis.Inputs(9).MembershipFunctions(6);
mf_built = fis.Inputs(9).MembershipFunctions(1);
mu_lulc_water = evalmf(mf_water, inputs(:,9));
mu_lulc_built = evalmf(mf_built, inputs(:,9));
veto(max(mu_lulc_water, mu_lulc_built) ≥ vetoThreshold) = true;

Final aggregation
S_fis(veto) = 0;
S_fis = min(max(S_fis,0),1);

Output raster
suitability = nan(size(ELEV));
suitability(mask) = S_fis;
epsgCode = 32632;
geotiffwrite('suitability_fuzzy_final_suit_20251229_newrules.tif',
suitability, R, 'CoordRefSysCode', epsgCode);

```

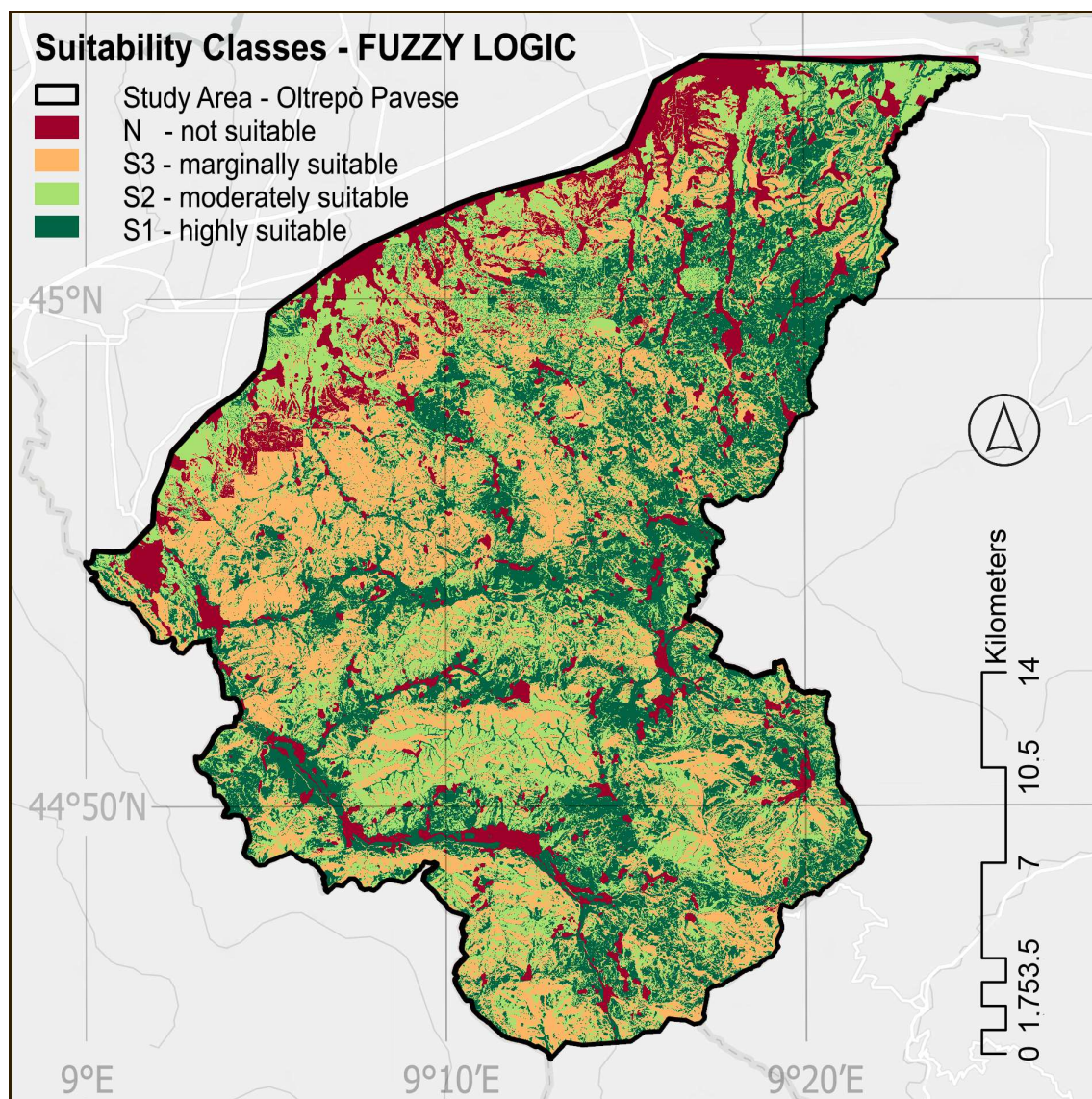



Figure 63. Fuzzy Logic-based suitability map for *Pinot Noir* cultivation in the Oltrepò Pavese.

7.6. Comparison MCDA VS Fuzzy Logic results

To assess the consistency and complementarity of the two modelling approaches adopted in this study, a systematic comparison was performed between the suitability map derived from GIS-based Multi-Criteria Decision Analysis (MCDA) and the map obtained through Fuzzy Logic modelling (Figure 64). Although both methods are based on the same environmental criteria, they differ conceptually: MCDA applies crisp thresholds and weighted linear aggregation, whereas Fuzzy Logic allows for gradual transitions and nonlinear interactions between variables.

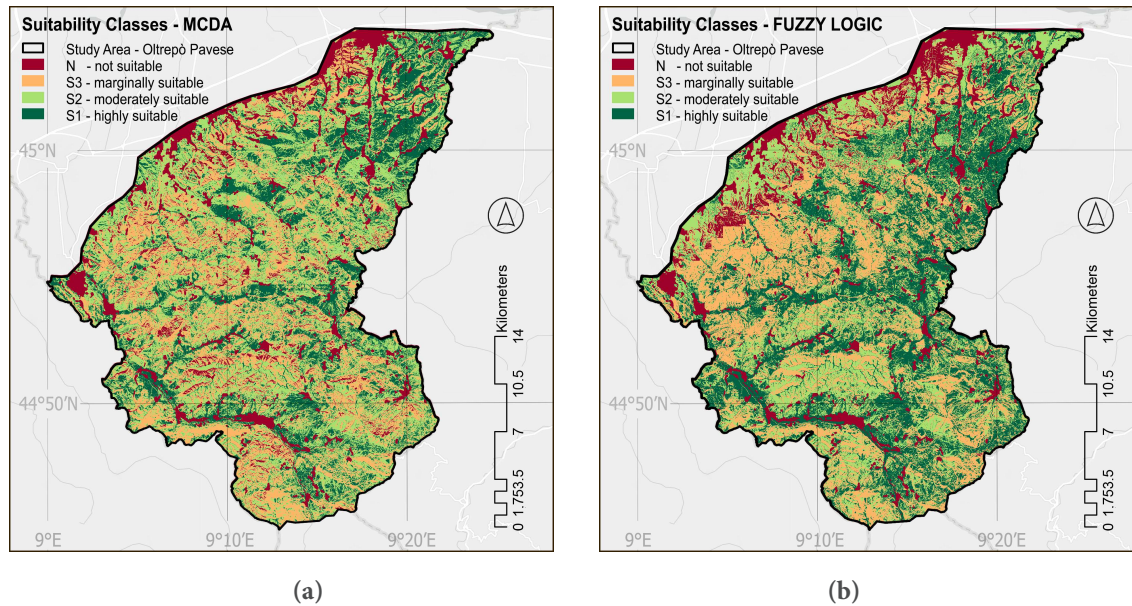


Figure 64. Visual comparison between land suitability maps obtained using (a) MCDA and (b) Fuzzy Logic approaches.

The comparison was designed to evaluate (i) the spatial agreement between the two results, (ii) the magnitude and spatial distribution of the discrepancies, and (iii) the implications of these differences for vineyard suitability assessment and land-use planning.

As shown in Table 19, both approaches assign a very similar proportion of the study area to the *not suitable* class. The main differences concern the higher suitability classes: the MCDA approach allocates a larger proportion of the study area to the *moderately suitable* (S2) class, whereas the Fuzzy Logic model assigns a larger proportion to the *highly suitable* (S1) class. This quantitative comparison confirms that the two approaches produce broadly comparable suitability patterns, while reflecting differences between the crisp weighted aggregation and the gradual membership-based inference framework.

Table 19. Percentage of the study area assigned to each suitability class by the MCDA and Fuzzy Logic approaches.

Suitability class	MCDA (%)	Fuzzy Logic (%)
0 - not suitable	53.32	52.73
1 - marginally suitable	13.57	14.08
2 - moderately suitable	20.87	15.71
3 - highly suitable	12.24	17.47

7.6.1. Raster difference analysis

A raster difference map was generated by subtracting the MCDA-based suitability classes from the Fuzzy Logic-based classes on a cell-by-cell basis. Prior to comparison, both suitability maps were reclassified into the same four suitability classes (*not suitable*, *marginally suitable*, *moderately suitable*, and *highly suitable*), ensuring consistency in spatial resolution, spatial extent, and classification scheme.

The resulting difference map (Figure 65) shows that most pixels have difference values of -1 , 0 , or $+1$. A difference value of zero indicates agreement in the assigned suitability class between the two approaches, while ± 1 reflects minor discrepancies limited to adjacent suitability classes. Larger differences appear spatially limited and do not show an evident systematic pattern in the mapped results.

The frequency distribution of class differences (Figure 66) confirms that absolute differences of two or more classes ($|\Delta| \geq 2$) are negligible. Pixels characterised by ± 1 differences are mainly located along suitability boundaries, where the environmental conditions are close to threshold values. This behaviour reflects the Fuzzy Logic approach's ability to smooth abrupt transitions and better represent gradual environmental gradients. Consequently, these differences should be interpreted as complementary rather than modelling errors.

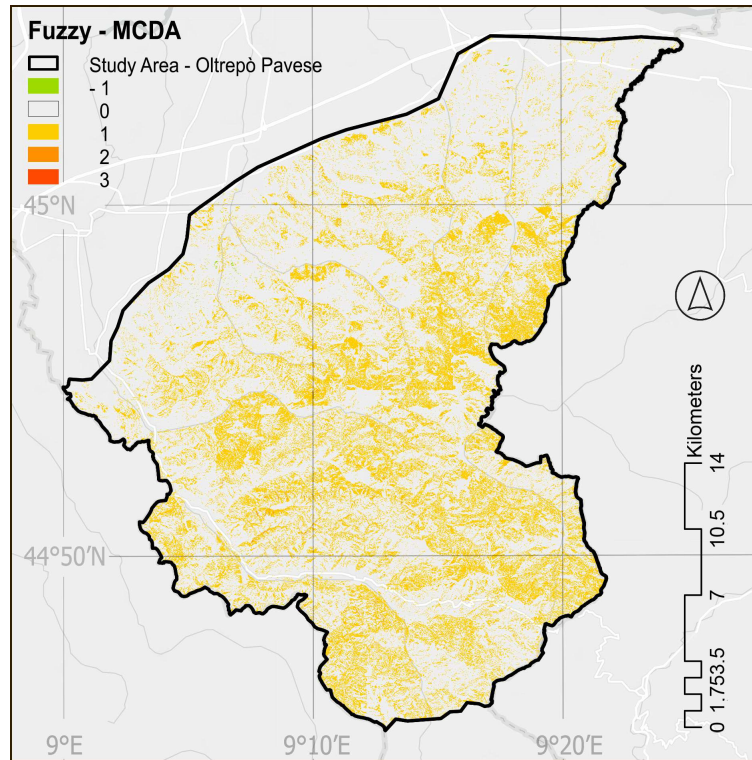


Figure 65. Pixel-by-pixel difference map between Fuzzy Logic-based and MCDA-based suitability classifications, calculated as Fuzzy minus MCDA. Positive values indicate higher suitability assigned by the Fuzzy Model, whereas negative values indicate higher suitability assigned by MCDA.

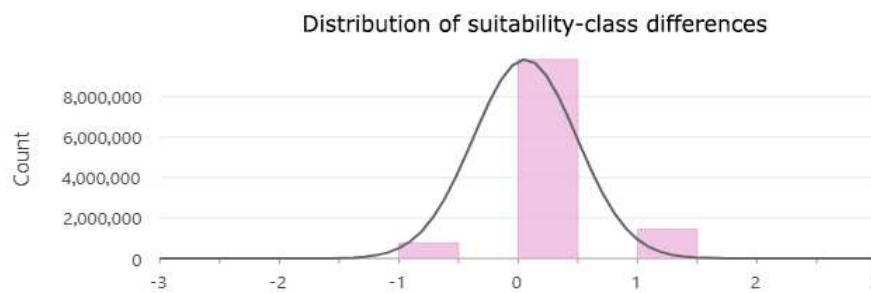


Figure 66. Frequency distribution of the pixel-by-pixel differences between Fuzzy Logic-based and MCDA-based suitability classes, calculated as Fuzzy minus MCDA.

7.6.2. Agreement matrix and quantitative evaluation

Quantitative agreement between the two suitability classifications was evaluated using a contingency table derived from the *Combine* tool in ArcGIS. This tool generates a raster and an associated attribute table reporting the frequency of all class-to-class combinations between the two input maps. For the four suitability classes considered in this study, 16 possible combinations were obtained, as shown in Figure 67.

These combinations were subsequently organised into an agreement matrix (Table 20), with rows representing MCDA suitability classes and columns representing Fuzzy Logic classes. The diagonal elements of the matrix correspond to pixels assigned to the same suitability class by both approaches, indicating agreement, whereas the off-diagonal elements indicate class disagreement. The result shows that agreement is stronger for extreme classes (*not suitable* and *highly suitable*), while intermediate classes exhibit greater overlap, reflecting gradual transitions in environmental suitability.

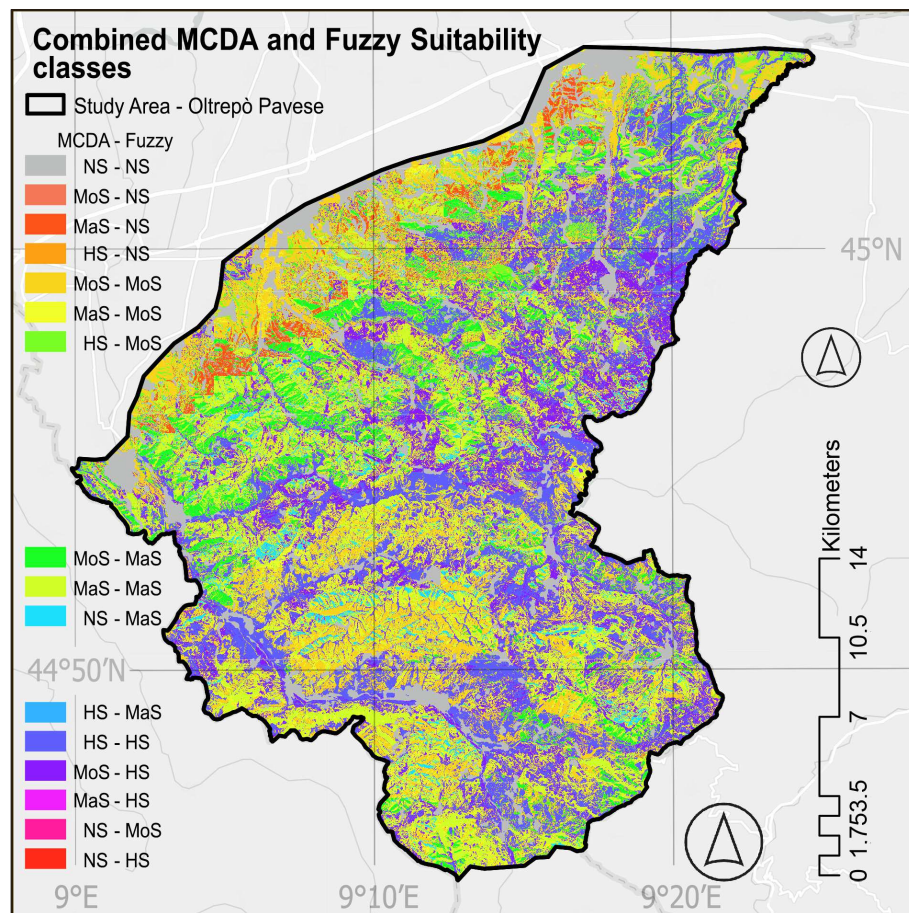


Figure 67. Cross-classification map of the MCDA and Fuzzy Logic suitability outputs.

Table 20. Agreement matrix MCDA- vs. Fuzzy-based suitability classifications (pixel count).

Fuzzy MCDA	0	1	2	3
0	6,253,790	175,733	9,638	27
1	108,887	1,134,571	382,501	12,796
2	4,273	390,249	1,243,201	882,508
3	595	182	262,681	1,214,925

The overall agreement was calculated as the proportion of pixels assigned to the same suitability class by both models, as expressed in Equation (18).

$$Agreement = \frac{\sum_{i=1}^l n_{ii}}{N} = 0.815 \quad (18)$$

Where:

- n_{ii} = diagonal elements of the agreement matrix
- l = number of suitability classes
- N = total number of pixels

An overall agreement of 0.815 indicates that over 81% of the study area is assigned to the same suitability class by both models.

Furthermore, Cohen's Kappa coefficient (k) was computed with Equation (19) to evaluate the agreement beyond that expected by chance.

$$k = \frac{P_o - P_e}{1 - P_e} = 0.714 \quad (19)$$

Where:

- P_o = observed agreement (overall agreement)
- P_e = expected agreement by chance, computed as Equation (20)

$$P_e = \sum_{i=1}^l \left(\frac{n_{i+}}{N} \cdot \frac{n_{+i}}{N} \right) = 0.354 \quad (20)$$

Where:

- n_{i+} = total number of pixels assigned to the class i by the MCDA model (sum of rows)
- n_{+i} = total number of pixels assigned to the class i by the Fuzzy Logic model (sum of columns)

The resulting Kappa coefficient ($k = 0.714$) indicates substantial agreement between the two classification frameworks.

7.6.3. Implications for viticultural planning

Quantitative agreement analysis is consistent with the raster difference map (Figure 68), which shows that most discrepancies are limited to adjacent suitability classes. These differences should therefore be interpreted as complementary rather than contradictory. Areas classified as highly suitable by both models can be regarded as priority zones for vineyard-planning assessments, while minor disagreements indicate transitional suitability where site-specific field surveys and agronomic evaluation are advisable.

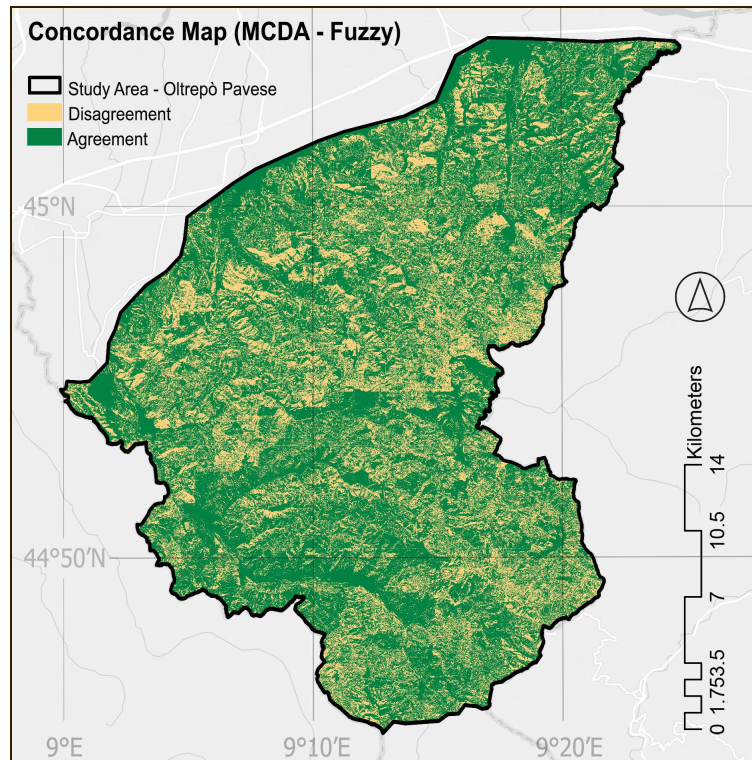


Figure 68. Spatial distribution of agreement and disagreement between the MCDA and Fuzzy Logic suitability classifications.

Class-specific agreement was calculated row-wise as the proportion of pixels assigned to each MCDA class that were assigned to the same class by the Fuzzy Model. The highest agreement rates were observed for the not suitable class (97.1%) and the highly suitable class (82.2%), indicating stable identification of extreme conditions. Lower concordance for intermediate classes reflects the inherent uncertainty associated with transitional environmental conditions and methodological differences between crisp and fuzzy classification frameworks. In these cases, small variations in criterion weighting (MCDA) or membership function calibration (Fuzzy Logic) can lead to different class assignments. Overall, the Fuzzy Logic model produces suitability patterns largely consistent with those derived from MCDA, while offering greater flexibility in representing gradual environmental gradients. This characteristic suggests that the fuzzy approach may be particularly useful for assessing viticultural suitability in heterogeneous landscapes and supports its integration with traditional GIS-based decision-making frameworks.

7.7. Validation of Suitability Maps

The suitability maps derived from the MCDA and Fuzzy Logic approaches were assessed using the vineyard parcel data provided by *Terre D'Oltrepò* Winery. This validation should be interpreted as a spatial consistency assessment rather than as direct verification of agronomic performance, because the available vineyard dataset does not include yield, grape quality, economic performance, or long-term vine-health indicators. The dataset consists of a shapefile containing attribute information for each vineyard parcel. The data refer to 2009, and no more recent information was available. Potential land-use changes between 2009 and the period represented by the environmental layers may therefore introduce temporal inconsistency into the validation. A critical issue with the original dataset (*ParticelleVitate_2009.shp*) was the presence of numerous duplicate polygons, associated with different establishment years and varieties, which made direct use of the shapefile within a GIS environment problematic.

To address this matter, a MATLAB procedure was used to remove overlapping polygons. When multiple records referred to the same parcel (OBJECTID), priority was given to the most recent planting year. Furthermore, *Pinot Noir* was maintained as the dominant attribute wherever the variety was present in the parcel history and was prioritised over other varieties when multiple cultivars were recorded simultaneously. The process produced a new shapefile (*ParticelleVitate_2009_Harmonized.shp*) used as reference dataset for the validation analyses.

The assessment framework was organised into three steps:

1. General assessment, considering all vineyard parcels within the study area, independently of grape variety, to evaluate which ones may potentially be best suited for growing *Pinot Noir*;
2. Varietal validation, focusing exclusively on parcels where *Pinot Noir* is present;
3. Expert-based validation, comparing the suitability results of the study with the territorial zoning proposed by Scienza et al. (2008) [13], which identifies six Territorial Units (UT) in the northern Oltrepò Pavese.

7.7.1. General vineyard distribution

For the first validation, all vineyards within the study area were considered. Zonal statistics were computed in ArcGIS Pro to extract, for each parcel, the majority suitability class from the MCDA- and Fuzzy-based maps. Two complementary indicators were used for validation: the number of vineyard parcels assigned to each suitability class and the total vineyard area associated with each class. Parcel counts describe the distribution of individual vineyard units, whereas area-based statistics account for differences in parcel size. The results in Table 21 show that the majority of the parcels fall within the moderately and highly suitable classes for both approaches.

Approximately 69% of vineyards are classified as moderately or highly suitable by the MCDA model, while the Fuzzy Logic approach assigns about 63% of vineyards to the same suitability range. Only a limited proportion, between 12% and 16%, is located in areas classified as not suitable.

Table 21. Frequency table for MCDA and Fuzzy approaches (total vineyard parcels).

Suitability Class	Count MCDA	% MCDA	Count Fuzzy	% Fuzzy
0 – Not Suitable	6,646	11.92%	8,783	15.76%
1 – Marginally Suitable	10,811	19.40%	12,007	21.54%
2 – Moderately Suitable	23,228	41.67%	17,686	31.73%
3 – Highly Suitable	15,052	27.01%	17,261	30.97%
Total	55,737	100.00%	55,737	100.00%

The outcome confirms the overall spatial coherence between the suitability models and the observed vineyard distribution. While both approaches identify a predominance of moderate-to-high suitability classes, the MCDA model tends to concentrate vineyard parcels within the moderately suitable class. In contrast, Fuzzy Logic produces a more balanced distribution between the two classes, suggesting a greater ability to represent gradual environmental transitions.

To complement the parcel-based frequency analysis, the spatial extent of the vineyards assigned to each suitability class was also quantified by calculating the total vineyard area (Table 22).

Table 22. Distribution of the total vineyard area among suitability classes derived from the MCDA and Fuzzy Logic approaches.

Suitability Class	MCDA [km ²]	% MCDA	Fuzzy [km ²]	% Fuzzy
0 – Not Suitable	10.44	11.68%	14.29	15.99%
1 – Marginally Suitable	17.91	20.04%	19.26	21.55%
2 – Moderately Suitable	36.55	40.89%	28.31	31.67%
3 – Highly Suitable	24.49	27.39%	27.53	30.80%
Total	89.39	100.00%	89.39	100.00%

The area-based results confirm the general trend observed in the parcel-count analysis: most of the vineyard area is located within the moderately and highly suitable classes in both models. When vineyard area rather than parcel count is considered, 68% of the vineyard area falls within the moderately or highly suitable classes in the MCDA model, compared with 62% in the Fuzzy Model.

After evaluating the distribution of vineyards in terms of both parcel counts and vineyard area, the agreement between the two models was assessed at parcel level using an agreement matrix (Table 23). About 63% of vineyard parcels are classified into the same suitability class by both models, totalling 35,188 parcels.

Table 23. Agreement matrix MCDA- vs. Fuzzy-based suitability classifications (total vineyard parcels).

MCDA \ Fuzzy	0 – NS	1 – MaS	2 – MoS	3 – HS	Total MCDA
0 – NS	5,954	574	88	30	6,646
1 – MaS	2,652	7,148	947	64	10,811
2 – MoS	134	4,167	11,923	7,004	23,228
3 – HS	43	118	4,728	10,163	15,052
Total Fuzzy	8,783	12,007	17,686	17,261	55,737

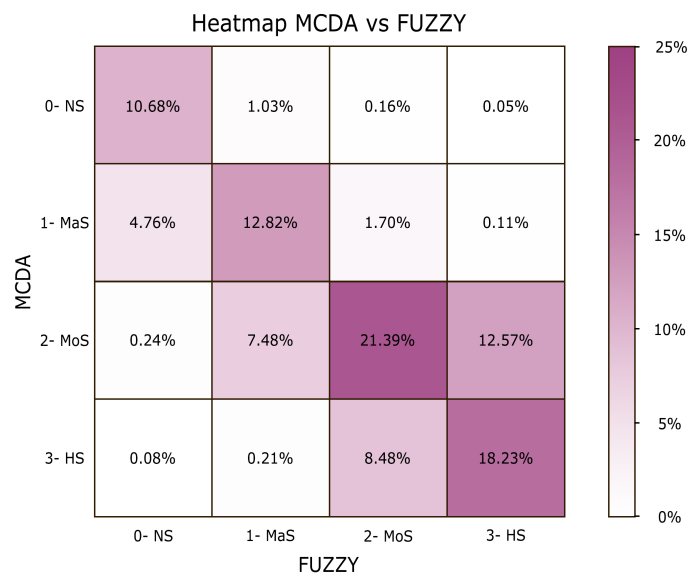


Figure 69. Heatmap of the agreement matrix – total vineyard parcels.

The 4×4 heatmap in Figure 69 highlights that the highest frequencies are concentrated along the main diagonal, indicating a strong agreement between the two classifications. Most discrepancies occur between adjacent suitability classes, whereas extreme mismatches are negligible, supporting the overall consistency of the two suitability classifications and their complementary use in viticultural zoning analyses.

7.7.2. Pinot Noir vineyards

For the varietal validation, parcels associated with *Pinot Noir* were selected, and the same analyses were performed using the MCDA and Fuzzy Logic suitability classes.

Table 24. Frequency table for MCDA and Fuzzy approaches (*Pinot Noir* vineyard parcels).

Suitability Class	Count MCDA	% MCDA	Count Fuzzy	% Fuzzy
0 – Not Suitable	1,085	11.60%	1,411	15.08%
1 – Marginally Suitable	1,682	17.98%	1,769	18.91%
2 – Moderately Suitable	4,070	43.51%	3,132	33.48%
3 – Highly Suitable	2,517	26.91%	3,042	32.52%
Total	9,354	100.00%	9,354	100.00%

The results in Table 24 show that approximately 70% of *Pinot Noir* vineyards are classified as moderately or highly suitable by the MCDA approach, while the Fuzzy Logic method yields approximately 66%. A limited fraction of parcels (around 12–15%) falls within the not suitable class.

Table 25. Distribution of the total *Pinot Noir* vineyard area among suitability classes derived from the MCDA and Fuzzy Logic approaches.

Suitability Class	MCDA [km ²]	% MCDA	Fuzzy [km ²]	% Fuzzy
0 – Not Suitable	2.28	11.69%	3.05	15.62%
1 – Marginally Suitable	3.40	17.37%	3.49	17.86%
2 – Moderately Suitable	8.15	41.70%	6.80	34.77%
3 – Highly Suitable	5.72	29.24%	6.21	31.75%
Total	19.55	100.00%	19.55	100.00%

The area-based results in Table 25 show that most of the *Pinot Noir* vineyard area falls within the moderately or highly suitable classes under both models: about 71% for MCDA and 67% for Fuzzy Logic. However, MCDA concentrates a larger proportion in the moderately suitable class (41.70%), whereas the Fuzzy Model provides a more balanced distribution between the moderately suitable (34.77%) and highly suitable (31.75%) classes. The Fuzzy Model also assigns a slightly larger share to the highly suitable class than MCDA (29.24%).

After evaluating *Pinot Noir* vineyard distribution in terms of both parcel counts and area, agreement between the two suitability models was assessed at the parcel level using the heatmap shown in Figure 70.

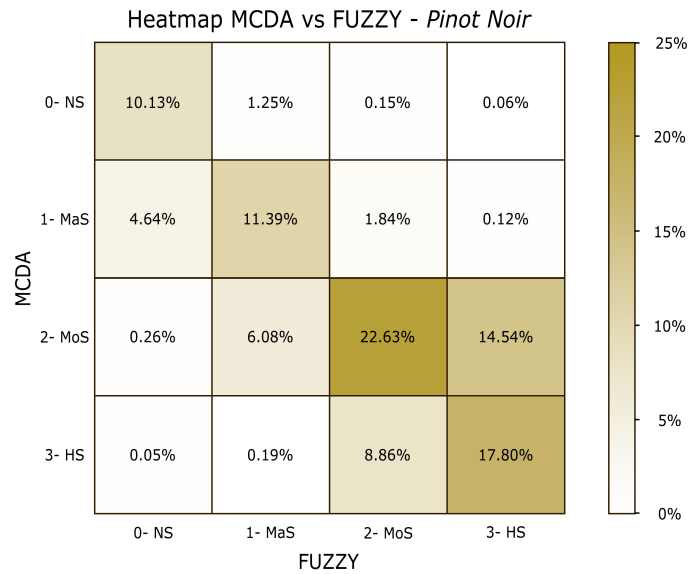


Figure 70. Heatmap of the percentage of *Pinot Noir* vineyard parcels classified using MCDA and Fuzzy Logic methods. Percentages are calculated relative to the total set of 9,354 parcels.

Overall, both the MCDA and Fuzzy Logic approaches indicate that most *Pinot Noir* vineyard parcels fall within the moderately or highly suitable classes. The parcel-level agreement matrix shows that 5,795 of the 9,354 parcels were assigned to the same class by both models, corresponding to an overall agreement of 61.95%. Most disagreements occurred between adjacent suitability classes, whereas differences of two or more classes involved less than 1% of the parcels.

Nevertheless, the presence of *Pinot Noir* within a parcel does not necessarily imply optimal environmental performance, because planting decisions may also reflect historical, economic, regulatory, and management factors not represented by the models. Consequently, parcels located in areas classified as marginally suitable or unsuitable should not automatically be interpreted as evidence of model error. Although yield and grape-quality data were unavailable, the spatial correspondence between the modelled suitability patterns and the observed distribution of *Pinot Noir* vineyards, together with the agreement between the two classifications, provides indirect support for the consistency of the proposed methodology at the varietal scale.

7.7.3. Comparison with Prof. Scienza’s territorial zoning

The territorial zoning proposed by Prof. Scienza provides an independent qualitative reference for interpreting the distribution of *Pinot Noir* vineyards in the *Oltrepò Pavese DOCG* [13]. The zoning identifies six Territorial Units (UT) characterised by different viticultural and oenological vocations, including sparkling-wine production, red vinification, mixed vocation, and generic base-wine production (Table 26 and Figure 71). Since this zoning describes production vocation, whereas the models developed in this study estimate environmental suitability for *Pinot Noir*, the comparison should be regarded as contextual and qualitative rather than as a direct validation of the suitability classifications.

Table 26. Summary of the viticultural vocation of the six Territorial Units.

UT	<i>Pinot Noir</i> Viticultural Vocation
1	<i>Pinot Noir</i> – Sparkling wine
2	<i>Pinot Noir</i> – Mixed vocation (sparkling and red)
3	Generic base wine production
4	<i>Pinot Noir</i> – Red wine
5	<i>Pinot Noir</i> – Sparkling wine
6	<i>Pinot Noir</i> – Red wine

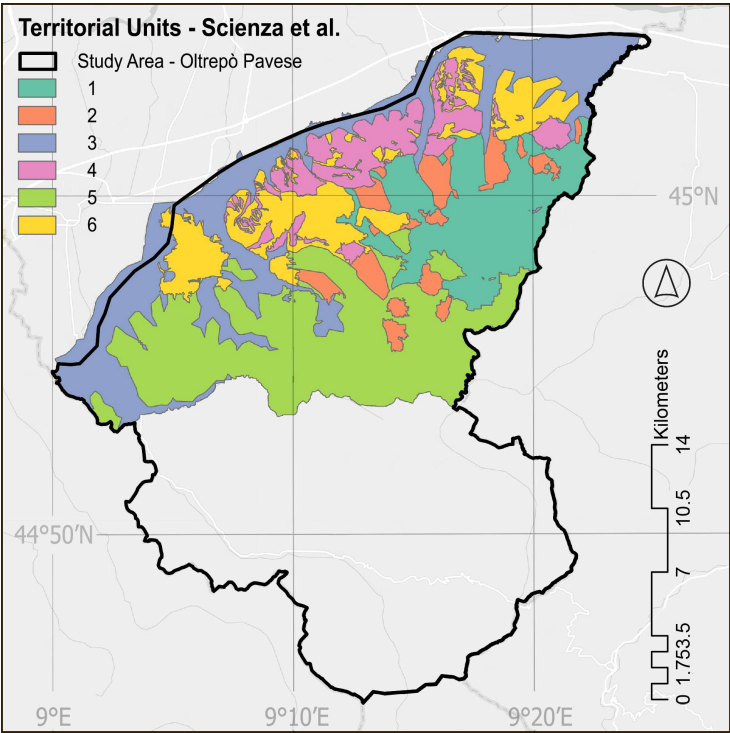


Figure 71. Territorial Units of the *Oltrepò Pavese DOCG*.

Using a *Spatial Join* in ArcGIS Pro, each *Pinot Noir* vineyard parcel was assigned to the Territorial Unit containing its centroid (see Table 27). Of the 9,354 parcels, 9,333 were assigned to one of the six Territorial Units, whereas 21 parcels, corresponding to approximately 0.22% of the dataset, fell outside the mapped zoning coverage. The distribution of MCDA and Fuzzy Logic suitability classes were subsequently analysed within each UT using the same subset of 9,333 parcels.

Table 27. Distribution of *Pinot Noir* vineyards among the six Territorial Units.

UT	Number of <i>Pinot Noir</i> vineyards
Outside mapped UTs	21
1	2,901
2	854
3	1,390
4	1,278
5	1,406
6	1,504
Total	9,354

The first comparison is based on the number of vineyard parcels classified into each suitability class by the MCDA and Fuzzy Logic models (Table 28).

Table 28. Frequency table (a) MCDA – UT and (b) Fuzzy – UT (*Pinot Noir* parcels count).

UT MCDA	1	2	3	4	5	6
0 – NS	380	107	175	130	152	140
1 – MaS	599	128	232	236	225	256
2 – MoS	1,325	377	563	532	624	635
3 – HS	597	242	420	380	405	473

UT FUZZY	1	2	3	4	5	6
0 – NS	472	122	236	172	207	197
1 – MaS	623	171	235	232	250	254
2 – MoS	831	267	531	472	488	535
3 – HS	975	294	388	402	461	518

The parcel-count analysis shows that, in every Territorial Unit, more than 60% of the vineyard parcels associated with *Pinot Noir* were classified as moderately or highly suitable by both modelling approaches. Under MCDA, the moderately suitable class contained the largest number of parcels in all six UTs. Under Fuzzy Logic, the highly suitable class was the most frequent in UT1 and UT2, whereas the moderately suitable class remained the most frequent in UT3–UT6.

Thus, vineyard parcels in the sparkling-wine-oriented UT1 and UT5, the mixed-vocation UT2, the red-wine-oriented UT4 and UT6, and the generic base-wine UT3 were generally concentrated in the two higher suitability classes, indicating that existing *Pinot Noir* vineyards tend to occupy environmentally favourable parcels throughout the different Territorial Units.

Since vineyard parcels differ considerably in size, parcel counts alone do not fully represent the spatial distribution of *Pinot Noir* cultivation. An additional analysis was therefore performed using the total area of the vineyard parcels assigned to each suitability class within each UT. The resulting percentage distributions for the MCDA and fuzzy logic models are reported in Table 29.

Table 29. Distribution (%) of *Pinot Noir* vineyard area (a) MCDA – UT and (b) Fuzzy – UT. Percentages are calculated relative to the total vineyard-parcel area within each UT.

UT MCDA	1	2	3	4	5	6
0 – NS	12.44%	9.14%	9.92%	14.6%	11.87%	11.16%
1 – MaS	20.88%	13.16%	15.33%	14.91%	15.80%	18.49%
2 – MoS	45.60%	40.89%	36.36%	39.78%	43.91%	40.02%
3 – HS	21.08%	36.81%	38.40%	30.71%	28.42%	30.33%

UT FUZZY	1	2	3	4	5	6
0 – NS	15.90%	11.94%	14.99%	16.20%	17.80%	15.91%
1 – MaS	22.37%	18.35%	15.05%	15.54%	15.49%	16.28%
2 – MoS	30.34%	32.13%	39.06%	38.10%	33.66%	37.78%
3 – HS	31.39%	37.58%	30.90%	30.16%	33.05%	30.03%

The area-based analysis confirms the general trend observed in the parcel-count analysis. In every UT, most of the vineyard-parcel area was classified as moderately or highly suitable by both models. The combined proportion of the moderately and highly suitable classes ranged from 66.68% to 77.70% under MCDA and from 61.73% to 69.96% under Fuzzy Logic.

Nevertheless, the two approaches differed in the allocation of vineyard area among the individual suitability classes. MCDA assigned a greater proportion of area to the moderately suitable class in four of the six UTs. Conversely, the Fuzzy Logic model assigned a larger proportion to the highly

suitable class in UT1, UT2, and UT5, with the most pronounced differences occurring in UT1 and UT5. In UT1, for example, the highly suitable share increased from 21.08% under MCDA to 31.39% under Fuzzy Logic, whereas the moderately suitable share decreased from 45.60% to 30.34%.

UT4 showed the most similar area distribution between the two approaches and remained dominated by the moderately suitable class under both models. UT6 was also predominantly classified as moderately suitable, although the Fuzzy Logic model assigned a somewhat larger proportion to the not suitable class. In UT3, the Fuzzy Logic model assigned less area to the highly suitable class than MCDA—30.90% compared with 38.40%—and more area to the not suitable class—14.99% compared with 9.92%.

The predominance of moderately and highly suitable vineyard areas across all six UTs provides qualitative evidence of consistency between the modelled environmental suitability patterns and the existing distribution of *Pinot Noir* vineyards. This correspondence is noteworthy because the models were developed independently of the expert-based zoning and rely exclusively on quantitative environmental variables. However, the comparison should not be interpreted as a direct validation of the specific sparkling-wine or red-wine vocation attributed to each Territorial Unit, since the suitability models do not represent vinification objectives or wine-production styles.

Partial differences between the model outputs and the territorial zoning proposed by Scienza et al. [13] may arise from their different conceptual foundations. The present models rely on climatic, topographic, pedological, and land-use variables, whereas the expert-based zoning also incorporates viticultural, oenological, historical, and management considerations. Local discrepancies may additionally reflect historical planting decisions, site-specific vineyard management, and technological adaptations that allow *Pinot Noir* to be cultivated under less favourable environmental conditions.

Overall, the combined parcel-count and area-based assessments support the internal spatial consistency of the proposed suitability framework. The correspondence observed across the general vineyard distribution, the varietal-specific analysis, and the qualitative comparison with the expert-based territorial zoning indicates that both MCDA and Fuzzy Logic can provide useful information for viticultural suitability assessment in complex wine-growing regions. Nevertheless, the absence of independent yield and grape-quality observations means that these results should be interpreted as evidence of spatial consistency rather than as direct agronomic validation.

8. Conclusions

This thesis aimed to identify environmentally suitable areas for *Pinot Noir* cultivation in the Oltrepò Pavese through a spatial modelling framework based on climatic, topographic, pedological, and land-use data. The study responds to the growing need for transparent, reproducible, and data-driven decision-support tools for vineyard planning, particularly for climate-sensitive cultivars under changing climatic conditions.

A major challenge addressed in this research was the limited availability of spatially continuous air-temperature data. ARPA monitoring stations provide accurate, high-temporal-resolution observations, but their point-based nature limits their direct use in continuous spatial analyses. To address this limitation, TERRA and AQUA MODIS Land Surface Temperature data were calibrated against ARPA air-temperature observations. The resulting regression model enabled the generation of spatially continuous 8-day mean air-temperature rasters across the study area. Its predictive performance was assessed through LOOCV and independently evaluated using observations from the Terre D'Oltrepò monitoring network.

The MODIS-derived air-temperature dataset was subsequently used to calculate and map the Winkler Index, a widely adopted indicator of growing-season heat accumulation. The analysis highlighted both stable spatial gradients associated with topography and marked interannual variability over the 2018–2022 period. Seasonal error analysis showed that most of the cumulative difference between ARPA and MODIS-derived Winkler Index values developed during the warmest months, particularly July and August. However, the resulting differences were generally limited relative to the total seasonal heat accumulation and did not substantially alter the climatic classification at most monitoring locations.

The thermal layer was integrated with elevation, slope, aspect, solar radiation, rainfall, soil characteristics, and Land Use/Land Cover data to generate *Pinot Noir* suitability maps. Two complementary approaches were compared: a GIS-based Multi-Criteria Decision Analysis and a Fuzzy Logic model implemented in MATLAB. MCDA produced a discrete weighted classification, whereas the Fuzzy Logic Model represented gradual transitions and nonlinear combinations among environmental conditions.

The two suitability outputs showed substantial spatial agreement. A total of 81.53% of the study-area pixels were assigned to the same suitability class by both models, with a Cohen's Kappa coefficient of 0.714. The remaining differences were mainly concentrated between adjacent classes and reflected the different aggregation principles of the two approaches rather than major spatial contradictions.

The suitability maps were subsequently assessed at the vineyard-parcel level. Across all vineyard parcels classified by both models, the moderately and highly suitable classes accounted for 68.68% of parcels under MCDA and 62.70% under Fuzzy Logic. When parcel area was considered, the corresponding proportions were 68.29% and 62.47%, respectively. The varietal-scale analysis produced comparable results for the 9,354 vineyard parcels associated with *Pinot Noir*. The moderately and highly suitable classes accounted for 70.42% of these parcels under MCDA and

66.00% under Fuzzy Logic. In area terms, the corresponding proportions were 70.94% and 66.52%. The two models assigned the same suitability class to 5,795 parcels, corresponding to an overall agreement of 61.95%.

The comparison with the expert-based territorial zoning proposed by Scienza et al. [13] provided an additional qualitative assessment of the modelled spatial patterns. Of the 9,354 parcels associated with *Pinot Noir*, 9,333 were located within the six mapped Territorial Units and were included in the zoning comparison. In every UT, most of the vineyard-parcel area was classified as moderately or highly suitable by both models. The combined proportion of these two classes ranged from 66.68% to 77.70% under MCDA and from 61.73% to 69.96% under Fuzzy Logic.

This correspondence provides qualitative support for the spatial consistency of the suitability framework. However, the territorial zoning describes viticultural and oenological vocation, including suitability for sparkling-wine production, red vinification, and generic base-wine production, whereas the models developed in this thesis estimate environmental suitability for *Pinot Noir* without distinguishing among production objectives. The comparison should therefore be regarded as contextual evidence rather than as a direct validation of the specific vocation assigned to each Territorial Unit.

Overall, the results demonstrate that open geospatial data, satellite observations, ground-based meteorological measurements, and bioclimatic indicators can be integrated to produce operationally useful suitability maps for viticultural planning. The maps are intended to support preliminary site assessment and territorial planning rather than replace field surveys, agronomic evaluation, or local expertise.

The proposed framework is transferable in structure to other wine-growing regions and grape varieties. However, such applications would require local adaptation of suitability thresholds, AHP weights, fuzzy membership functions, inference rules, and validation datasets to reflect the environmental requirements of the target cultivar and the characteristics of the new study area.

Several opportunities for future development remain. The 10 m output grid represents the computational resolution of the suitability model rather than the intrinsic resolution of all input datasets, some of which originate from coarser climatic and pedological sources. The integration of additional satellite datasets with complementary spatial and temporal characteristics, such as Landsat and Sentinel-3, could improve air-temperature modelling. Expanding the study area would increase the number and environmental diversity of monitoring stations, while extending the temporal series would support more robust analyses of interannual variability and long-term climate trends. Finally, yield, grape-composition, wine-quality, phenological, and management data would enable direct agronomic validation and the development of models linking environmental suitability with production performance.

The raster-based structure of the methodology also allows updated climatic datasets and future climate projections to be incorporated without changing the overall analytical framework. This capability could support periodic updating of suitability maps and the assessment of potential shifts in *Pinot Noir* suitability under alternative climate scenarios. The thesis therefore provides a reproducible and adaptable framework for spatially explicit, climate-responsive viticultural planning.

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