Spatiotemporal Modelling of Ground-Level Air Temperature in an agricultural context: Rigorous Evaluation of LST Modis and Landsat-8 Imagery Data

Marica Teresa Rocca [1]*, Andrea Bergamaschi [2], Christian Massimiliano Baldin [1], Fabio Dell’Acqua [2], Vittorio Marco Casella [1]

[1] Dept. of Civil Engineering and Architecture, University of Pavia, Pavia, Italy - (maricateresa.rocca, christianmassimiliano.baldin, vittorio.casella)@unipv.it
[2] Dept. of Industrial and Information Engineering, University of Pavia, Pavia, Italy - andrea.bergamaschi02@universitadipavia.it, fabio.dellacqua@unipv.it

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Abstract

Ground-level air temperature (T_{air}) is an essential variable for climate monitoring, agricultural management, and hazard prevention. Conventional ground-based measurements often fail to capture the fine-scale spatial variability, especially in regions with complex terrain. Land Surface Temperature (LST) remote sensing offers a complementary solution, providing spatially continuous and temporally frequent observations. This study evaluates the potential of MODIS and Landsat-8 LST products to estimate T_{air} in a heterogeneous agricultural landscape. We developed spatiotemporal regression models linking satellite-derived LST to ground observations from meteorological stations over the five years 2018–2022. MODIS data provided high temporal coverage through 8-day composites, while Landsat-8 offered higher spatial resolution LST via the Statistical Mono-Window algorithm. The models were validated using Leave-One-Out Cross-Validation, achieving high predictive accuracy for MODIS-based T_{air} estimation ($R^2 = 0.981$, RMSE = 1.1 °C), whereas Landsat-8 captured finer spatial variability ($R^2 = 0.859$, RMSE = 3.4 °C). Our results demonstrate that integrating multi-resolution LST products enables accurate, dense mapping of T_{air}, supporting operational forecasting for precision agriculture. The study also discusses limitations related to land-cover heterogeneity, temporal representativeness, and potential extensions using spatial correlation methods or radar-derived crop-structure information.

1. Introduction

Ground-level air temperature (T_{air}) is a key environmental variable that influences climate monitoring, agricultural management, and hazard prevention. Accurate spatial representation of air temperature is necessary for operational forecasting systems supporting precision agriculture, especially in regions with complex orography and heterogeneous land cover.
Air temperature measurements are typically collected through meteorological monitoring networks managed by public environmental agencies. While these networks provide reliable data, their limited spatial coverage often fails to capture fine-scale spatial thermal variability, particularly in heterogeneous or complex terrain. As a result, air temperature fields derived solely from ground-based observations may inadequately represent local conditions.
Remote sensing offers a complementary approach by providing spatially continuous and temporally frequent observations through Land Surface Temperature (LST) products.
Sensors such as MODIS and Landsat-8 OLI/TIRS enable consistent monitoring of surface thermal patterns at different spatial and temporal resolutions. Although LST and T_{air} are physically distinct variables, since LST is influenced by solar radiation, surface emissivity, moisture conditions, and land cover, numerous studies have demonstrated strong empirical relationships between satellite-derived LST and near-surface air temperature (Cristóbal et al., 2008; Benali et al., 2012; Rocca et al., 2024).
Previous research has shown that MODIS LST products are well-suited to capturing temporal dynamics due to their frequent revisit time, whereas Landsat-8 provides greater spatial detail, which is critical for resolving local-scale temperature variability. However, a systematic evaluation of the relative and combined performance of these sensors for air temperature estimation in complex agricultural environments has not been carried out yet, to the best of the authors’ knowledge.
The present study addresses this gap by evaluating LST-based air temperature modelling using MODIS and Landsat-8 observations integrated with ground-based meteorological data in an agricultural setting, i.e., a wine-producing area in Northern Italy (Bergamaschi et al., 2025; Dell’Acqua et al., 2025).

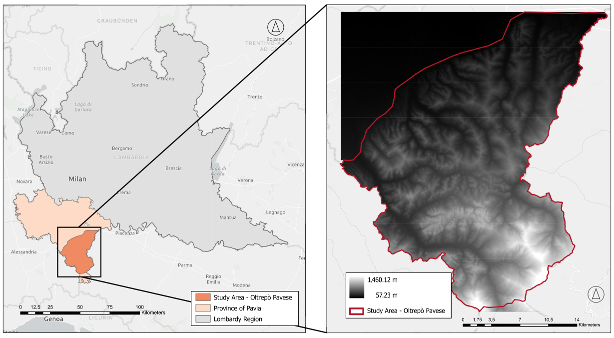
The specific objectives are:

- To assess the spatial and temporal coherence between satellite-derived and ground-based temperatures.
- To develop a spatiotemporal regression model linking LST to T_{air}.
- To compare the predictive performance of MODIS (high temporal resolution) and Landsat-8 (high spatial resolution).

2. Study Area and Data

2.1 Study Area

The study was conducted in the Oltrepò Pavese region, in the southern part of the Province of Pavia (Lombardy, Northern Italy), bordering Piedmont and Emilia-Romagna (Figure 1a). The area covers approximately 100,000 hectares and is characterized by pronounced topographic variability and heterogeneous land cover.
Elevation within the study area ranges from about 57 m to 1,460 m above sea level (Figure 1b). This broad elevation range contributes to substantial spatial variability in near-surface air temperature and surface thermal properties, making the region particularly suitable for evaluating satellite-based temperature modelling approaches (Dell’Acqua et al., 2025).



(a) (b)

Figure 1. Location of the Study Area in the province of Pavia and the Lombardy Region (**a**), with a focus on the Digital Terrain Model (DTM) to highlight altitude variations across the Oltrepò Pavese (**b**).

2.2 Satellite Data

2.2.1 MODIS LST Data is a product of the MODerate Resolution Imaging Spectroradiometer (MODIS) sensor, onboard NASA's Terra and Aqua satellites. The MODIS sensor acquires data in 36 spectral bands, including those that measure Earth's surface temperature (NASA, 2024).

Specifically, MODIS LST data are derived using the MODIS Generalized Split-Window LST Algorithm. This method utilizes surface emissivities and brightness temperatures from bands 31 (10.780–11.280 µm) and 32 (11.770-12.270 µm) to retrieve accurate temperatures of the Earth's surface.

In this study, the Terra MODIS LST (MOD11A2) and Aqua MODIS LST (MYD11A2) Collection 6.1 products were used. These datasets provide 8-day composite Land Surface Temperature and Emissivity values at a spatial resolution of 1 km. Each pixel value represents the average of all valid daily MOD11A1 and MYD11A1 LST observations acquired during the corresponding 8-day period (Wan et al., 2024).

Although MODIS offers daily LST products, these often contain a high proportion of missing data due to cloud cover. Therefore, the 8-day composite products were selected to ensure greater spatial completeness and temporal stability.

2.2.2 LandSat-8 is part of a series of satellites launched by NASA starting in 1972. Landsat observatories have provided measurements of Earth's surface with continuous, near-global coverage, ranging from multispectral data acquisition to thermal infrared observations. Specifically, Landsat-8 is equipped with the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). OLI operates across nine shortwave spectral bands (visible, NIR, SWIR) at 30m spatial resolution, supplemented by a 15 m panchromatic band. TIRS collects data in two thermal bands with a 100 m resolution. Both instruments cover a 185 km swath.

Unlike MODIS, Landsat-8 does not provide a standard LST-ready-to-use product. To get around this limitation, Land Surface Temperature was derived using a Google Earth Engine (GEE) implementation of the Statistical Mono-Window (SMW) algorithm (Ermida et al., 2020).

The SMW approach estimates LST by exploiting an empirical relationship between the Top-Of-Atmosphere (TOA) brightness temperature derived from the TIRS thermal band B10, the surface emissivity, and the surface temperature. Emissivity values are calculated from the Normalized Difference Vegetation Index (NDVI), computed from the OLI sensor's red and near-infrared (NIR) bands. The model parameters are determined from a linear regression analysis of different atmospheric column water vapor classes.

The resulting LST maps have a spatial resolution of 30m and represent instantaneous surface temperature conditions at the satellite overpass time. Landsat-8 has a nominal revisit time of 16 days, which is reduced to approximately 7–9 days in the study area due to overlapping satellite swaths.

2.3 Ground-Based Observations

Ground-based air temperature observations were obtained from the meteorological monitoring network managed by ARPA Lombardy. This network consists of fixed stations measuring several climatic variables, including near-surface air temperature. Stations located within or near the study area were selected (Figure 2).

ARPA stations measure air temperature at an hourly temporal resolution, providing highly accurate point-based observations of T_{air}. However, the network's spatial density is relatively low, with approximately one station per 100 km² across Lombardy and about one station per 92 km² within the study area. Such sparse spatial coverage is known to introduce uncertainty when interpolating temperature fields, particularly in regions characterized by complex topography and heterogeneous surface conditions (Díaz et al., 2010; Morales-Salinas et al., 2023).

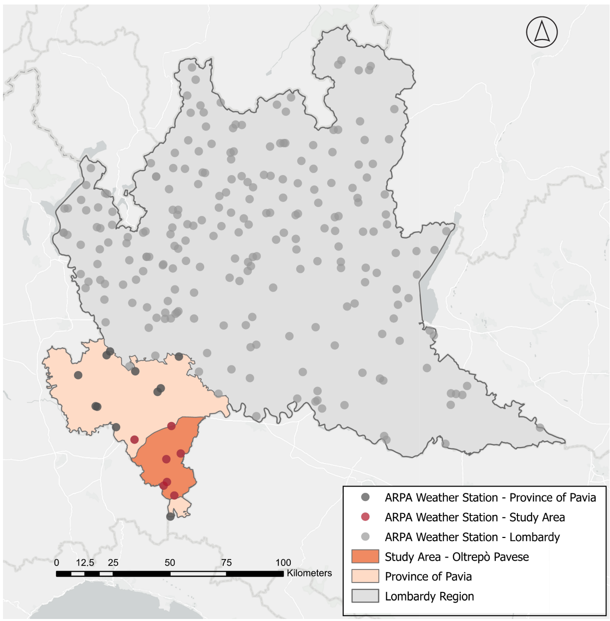


Figure 2. ARPA Weather Stations distribution in the Lombardy Region.

Table 1 summarizes the dataset used in the study, including spatial and temporal resolution.

Dataset	Variable	Spatial resolution	Temporal resolution
MODIS Terra (MOD11A2)	LST (day/night)	1 km	8-day composite
MODIS Aqua (MYD11A2)	LST (day/night)	1 km	8-day composite
Landsat-8 OLI/TIRS	LST	30 m	7-9 days (instantaneous)
Monitoring stations	T_{air}	point-based	hourly

Table 1. Dataset summary

3. Methodology

Near-surface air temperature (T_{air}) was estimated using regression models in which satellite-derived Land Surface Temperature (LST) is the primary explanatory variable. The methodological workflow consists of three main steps:

- satellite data pre-processing and harmonization,
- integration with ground-based observations,
- statistical modelling.

MODIS provides temporally composited LST observations at moderate spatial resolution, whereas Landsat-8 supplies instantaneous LST measurements at higher spatial resolution. The combination of these datasets enables the investigation of both temporal and spatial details in air temperature estimation.

3.1 Data pre-processing and harmonization

All satellite datasets were pre-processed to ensure spatial, temporal, and radiometric consistency before modelling. MODIS LST products were provided at 1 km spatial resolution as 8-day composites, while Landsat-8 LST products were derived at 30m spatial resolution. All raster datasets were reprojected to a common geographic coordinate system (WGS84, EPSG:4326). Cloud-contaminated pixels were identified and filtered out using the quality assessment bands (QA) provided with each dataset, retaining only clear-air observations with reliable LST retrieval. LST values were converted from Kelvin to Celsius and scaled according to product specifications. To enable point-based sampling and multisensor integration, MODIS LST data were resampled to 30m resolution using bilinear interpolation. This resampling was performed solely to ensure spatial consistency during data extraction and does not enhance the intrinsic spatial information content of the MODIS data. Landsat-8 LST products, already available at 30m resolution, did not require spatial resampling.
Temporal harmonization involved aligning satellite acquisition dates with hourly ground-based air temperature measurements. MODIS 8-day composites were associated with the corresponding 8-day mean T_{air} values, while Landsat-8 acquisitions were matched to the same-hour ground observations (Figure 3).

3.2 Gap Reconstruction and spatiotemporal interpolation

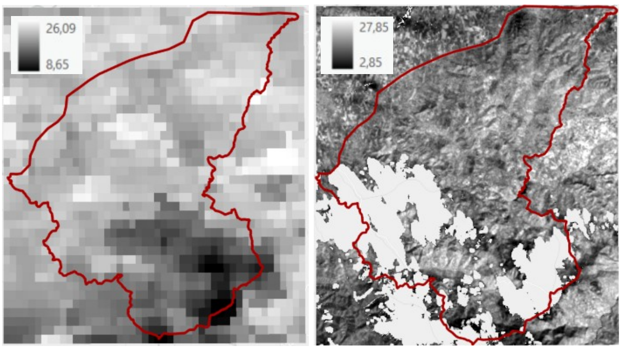
Due to cloud cover and sensor acquisition gaps, missing LST observations were present in both the MODIS and Landsat-8 datasets. To reduce data discontinuities and enable consistent regression modelling, a spatiotemporal interpolation procedure was applied where appropriate.
For MODIS LST, the interpolation exploited neighboring valid observations within defined spatial and temporal windows, assuming continuity in temperature patterns. This procedure proved effective at filling most cloud-related gaps, leaving only a small number of isolated pixels with missing values after processing.
In contrast, Landsat-8 provides instantaneous, high-resolution observations with a longer revisit time, resulting in larger spatial gaps and reduced suitability for interpolation. When extended gaps were present - due to persistent cloud cover or a lack of acquisitions - no extrapolation was performed. Pixels with insufficient surrounding data were intentionally left as missing (NaN) to avoid introducing artificial or physically unrealistic temperature values.
Overall, interpolation was applied only when sufficient spatial and temporal support was available; otherwise, missing data were preserved. This conservative strategy ensured that the resulting LST datasets remained physically consistent and that regression modelling relied exclusively on reliable observations. Subsequently, LST values from both sensors were sampled at the locations of ground-based meteorological stations to construct the regression datasets, ensuring that only valid and consistent observations were used for T_{air} estimation.

3.3 MODIS-Based Regression Modelling

Each MODIS acquisition consists of four LST variables: daytime and nighttime observations from both Terra and Aqua platforms. These variables were stacked into a multiband composite dataset, and LST values were sampled at the locations of ARPA meteorological stations to build the regression input dataset. Ground-level air temperature (T_{air}), expressed as an 8-day mean, was used as the dependent variable. A multivariate linear regression model was used to describe the relationship between satellite-derived LST variables and observed T_{air}. This modelling approach was selected for its interpretability, robustness, and suitability for operational applications. Model performance was assessed by comparing observed and estimated air temperatures.
A Leave-One-Out Cross-Validation (LOOCV) scheme was employed to evaluate model robustness given the limited number of available ground stations. The Root Mean Squared Error (RMSE) and the coefficient of determination (R^2) were computed to quantify model performance.

3.4 Landsat-8 LST Retrieval

Unlike MODIS products, Landsat-8 Collection 2 does not provide a directly available LST product. Therefore, LST was retrieved using a Google Earth Engine implementation of the Statistical Mono-Window (SMW) algorithm (Ermida et al., 2020). The SMW approach estimates LST through a linear empirical relationship between top-of-atmosphere (ToA) brightness temperature derived from a single thermal infrared (TIR) band and surface emissivity. Emissivity was estimated using vegetation indices computed from red and near-infrared (NIR) bands. At the same time, atmospheric effects were accounted for through regression coefficients parameterized by Total Column Water Vapor (TCWV) classes. The resulting Landsat-8 LST products were cloud-masked and processed using the same workflow applied to MODIS data, including gap reconstruction and sampling at meteorological station locations. Regression modelling followed the same linear framework used for the MODIS-based analysis.



(a) (b)

Figure 3. (**a**) MODIS data: raster with 1 km^2 tiles depicting the average LST, captured by the Aqua satellite from 30th March 2018 to 7th April 2018. (**b**) Landsat-8: raster with 30m^2 tiles depicting the temperature on 2nd April 2018.

3.5 Multisensor Integration Strategy

To leverage the complementary strengths of MODIS and Landsat-8, a multisensor regression framework was explored. MODIS provides high temporal resolution and stable composite-based LST estimates, while Landsat-8 offers high spatial resolution and can capture fine-scale thermal variability.
In the multisensor model, Landsat-8 LST was integrated with MODIS daytime and nighttime observations from both Terra and Aqua platforms to mitigate the limitations of each sensor when used independently. Although exploratory, this approach establishes a foundation for multisensor air temperature mapping in heterogeneous environments and supports future developments, including the incorporation of land-cover-specific parameters and spatial correlation modelling techniques.

4. Results

4.1 MODIS-Based Air Temperature Estimation

The multivariate regression model based on MODIS LST data demonstrated strong predictive capability for estimating ground-level air temperature. The final model integrates daytime and nighttime LST observations from both Aqua and Terra satellites and is expressed as:

$$\hat{T}_{air} = 2.8012 + 0.10734 \cdot T_{dA} + 0.38372 \cdot T_{nA} + 0.13649 \cdot T_{dT} + 0.34268 \cdot T_{nT} \quad (1)$$

where T_{dA}= Aqua daytime temperature LST
T_{nA}= Aqua nighttime temperature LST
T_{dT} = Terra daytime temperature LST
T_{nT} = Terra nighttime temperature LST

With a Root Mean Squared Error (RMSE) of 1.11 °C, an R-squared of 0.981, and a p-value of 0, the model has an overall excellent fit. Spatially, the MODIS-based model produces smooth and temporally stable air temperature fields.
Figure 5 illustrates an example of a grayscale map of estimated air temperature derived from combining the four MODIS LST inputs for the 8-day period from 30th March–07th April 2018, highlighting coherent thermal patterns consistent with the regional topography and land use.

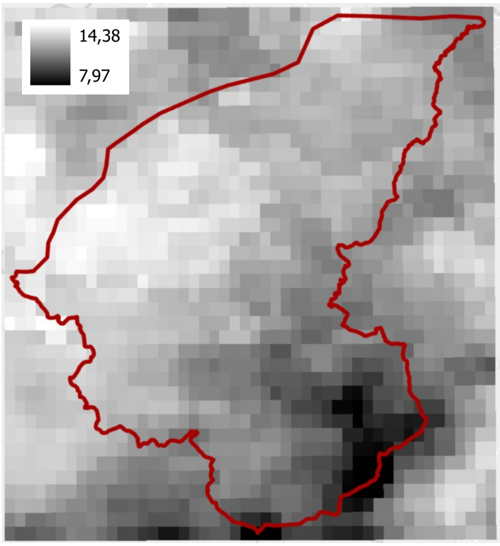


Figure 5. MODIS-estimated T_{air} (8-day average) from 30th March 2018 to 7th April 2018. Brighter shades of gray mean higher temperatures, in accordance with the palette on top left.

4.2 Landsat-Based Air Temperature Estimation

The same regression modelling framework was applied to Landsat-8-derived LST to assess the potential of high-spatial-resolution data for estimating air temperature. Landsat-8 provides instantaneous LST measurements at 30m resolution, enabling the detection of fine-scale thermal variability associated with land cover and topographic features.
The linear regression has a Root Mean Squared Error of 3.44 °C and an R^2 of 0.859, indicating lower predictive accuracy than the MODIS-based model. This reduced performance can be attributed primarily to the limited temporal representativeness of Landsat-8 acquisitions, which capture instantaneous surface conditions rather than temporally averaged thermal states.
Landsat-8-derived air temperature maps show detailed spatial variation, especially in heterogeneous agricultural regions. This highlights the sensor's ability to detect localized temperature gradients that coarser datasets cannot resolve.

4.3 MODIS vs Landsat: temporal representativeness

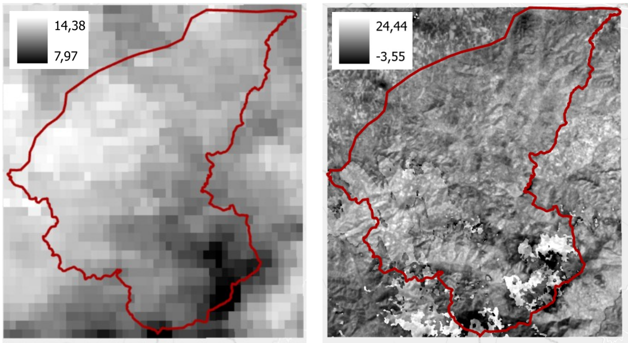
The contrasting performance of MODIS and Landsat-8 highlights a fundamental trade-off between temporal and spatial resolution. MODIS 8-day composite LST products reduce short-term variability and noise, resulting in more stable regression relationships with daily mean air temperature. In contrast, Landsat-8 observations are instantaneous and more sensitive to transient atmospheric and surface conditions, which affect their direct correspondence with daily mean T_{air}.
As a result, MODIS-based models outperform Landsat-only approaches in overall predictive accuracy, while Landsat-8 provides valuable spatial detail that complements MODIS's temporal robustness. These characteristics motivate the exploration of multisensor integration strategies.

4.4 Comparison of MODIS and Landsat-8-derived air temperature

Figure 6 presents the estimated air temperature fields obtained from MODIS and Landsat-8 data. The MODIS-derived map (Figure 6) shows a relatively uniform spatial distribution, with temperatures ranging from 7.97 to 14.38 °C. This more even pattern results from the 8-day composite employed in the MODIS LST products, which reduces short-term fluctuations and local temperature extremes.
In contrast, the Landsat-8-derived map (Figure 6) exhibits both positive and negative local extremes, with values ranging from -3.55 to 24.44 °C. Negative anomalies are likely due to residual cloud or cloud-shadow contamination, which can lead to artificially low land-surface temperature estimates despite cloud-masking procedures.
Conversely, high temperature peaks may be explained with two factors, partly involved also in negative peaks:

- the instantaneous nature of Landsat acquisitions, as opposed to MODIS time averages;
- fine spatial variability of emissivity, which cannot be estimated accurately everywhere;
- the strong influence of surface properties (e.g., bare soil or urban materials), which can reach significantly higher temperatures than the near-surface air.

These discrepancies highlight a key limitation of using high-resolution LST as a proxy for T_{air}.



(a) (b)

Figure 6. Spatial distribution of near-surface air temperature (T_{air}) estimated from (**a**) MODIS LST (30th March – 7th April 2018) and (**b**) Landsat-8 LST acquisition (2nd April 2018).

4.5 Multisensor Air Temperature estimation

A preliminary multisensor regression model was explored by integrating Landsat-8 LST with MODIS daytime and nighttime observations from both Terra and Aqua platforms. The objective of this exploratory analysis was to assess whether combining high-spatial-resolution and temporally aggregated thermal information could improve air temperature estimation.
Although the multisensor model yielded intermediate performance metrics ($R^2 = 0.921$; RMSE = 2.56 °C), it did not outperform the MODIS-only approach and therefore does not represent a definitive improvement in air temperature estimation. This result highlights a conceptual limitation of directly merging instantaneous and temporally averaged thermal observations within a single regression framework.

From an application-oriented perspective, multisensor integration is likely more meaningful when applied to cumulative agroclimatic indicators, such as Growing Degree Days (GDD), rather than to instantaneous or short-term air temperature estimates. GDD inherently integrates thermal conditions over time and is less sensitive to temporal mismatches between sensors. Consequently, a more robust assessment of multisensor approaches will be pursued in future work by deriving GDD from both satellite-based temperature estimates and comparing them with station-based GDD computed from ARPA meteorological observations.

5. Discussion

The results highlight the complementary roles of MODIS and Landsat-8 in estimating near-surface air temperature from satellite-derived LST. MODIS-based models achieve higher predictive accuracy by exploiting temporally aggregated LST composites that reduce short-term variability and more closely approximate 8-day mean air temperature. The inclusion of both daytime and nighttime observations from the Terra and Aqua platforms further improves model robustness by capturing different components of the surface–atmosphere thermal regime.

By contrast, Landsat-8 provides instantaneous LST observations at a much finer spatial resolution. This enables the detection of small-scale thermal variability driven by land cover and topography but also increases sensitivity to transient surface and atmospheric conditions, thereby limiting its direct correspondence with mean air temperature. Consequently, the pronounced spatial variability observed in Landsat-based temperature maps should not be interpreted solely as due to higher spatial discriminability, but rather as a direct response to surface thermal conditions. Because the modelling framework is driven by surface temperature, the estimated air temperature fields tend to inherit the spatial discontinuities and noise characteristic of high-resolution LST data.

These results confirm the inherent trade-off between temporal representativeness and spatial detail when using satellite-derived LST for air temperature modelling. While MODIS provides temporally stable and spatially coherent temperature fields suitable for regional-scale analyses, Landsat-8 enhances spatial detail for applications requiring fine-scale information, such as vineyard management in heterogeneous terrains.

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The multisensor regression framework explored in this study should therefore be regarded as an exploratory step rather than a definitive improvement over MODIS-only modelling. While integrating Landsat-8 and MODIS LST improves spatial detail relative to Landsat-only estimates, it does not surpass the accuracy of temporally aggregated MODIS-based air temperature models. From an agroclimatic perspective, multisensor integration is likely more meaningful when applied to cumulative indicators that integrate temperature over time, such as Growing Degree Days (GDD), rather than to instantaneous or short-term air temperature estimates. This aspect represents a key direction for future research.

5.1 Model generalizability

The modelling framework was evaluated over a multi-year period, encompassing different seasons and a wide range of temperature conditions. The strong performance of the MODIS-based model suggests that the relationship between temporally aggregated LST and daily mean air temperature remains stable across seasonal cycles within the agricultural context of the study area.
However, generalizability beyond the study region should be considered with caution. The Oltrepò Pavese area is characterized by complex topography and predominantly agricultural land cover, which strongly influence surface–atmosphere energy exchanges. In regions with contrasting climatic regimes, urbanized surfaces, or more heterogeneous land-cover compositions, the LST–T_{air} relationship and the corresponding regression coefficients may differ. Nevertheless, the proposed methodological framework is transferable and can be recalibrated using local ground-based observations to support broader applications.

5.2 Landcover effects

The relationship between land surface temperature and air temperature varies with land cover, vegetation density, and surface moisture conditions. In this study, land cover effects were not explicitly parameterized in the regression models, primarily due to the relatively homogeneous agricultural character of the study area and the limited number of meteorological stations available for stratified modelling.

Future research could extend the proposed approach by incorporating land-cover-dependent regression schemes, vegetation indices, or ancillary variables, such as NDVI, to better account for surface heterogeneity and further improve air temperature estimates, particularly in precision agriculture applications.

5.3 Spatial correlation and kriging

In the present context, the limited number of meteorological stations constrained the applicability of purely geostatistical models. The adopted methodology therefore prioritized spatial completeness and reduced dependence on ground-based networks, which is essential for operational and large-area applications.
Despite the fine spatial detail provided by Landsat-8 and multisensor integration, the resulting air temperature maps may exhibit local peaks and spatial noise that do not fully reflect the smoother behavior of atmospheric temperature fields. This effect arises from using land surface temperature as the primary predictor, which captures surface heterogeneity (e.g., variations in emissivity and heat capacity) rather than the inherently more continuous distribution of near-surface air temperature.
To mitigate these effects, regression-kriging approaches could be applied by spatially interpolating the residuals of the LST–T_{air} regression model according to the observed autocorrelation structure. This would allow the generation of more physically plausible air temperature fields while preserving the fine-scale information provided by high-resolution satellite sensors. As a simpler alternative, local spatial averaging or neighborhood-based smoothing could be employed to attenuate extreme discontinuities and reduce spatial noise. Future work will investigate and compare these strategies, particularly in heterogeneous and orographically complex landscapes.

6. Conclusions

This study investigated the use of satellite-derived Land Surface Temperature (LST) to estimate ground-level air temperature in a heterogeneous agricultural landscape. By integrating MODIS and Landsat-8 observations with ground-based meteorological data, a spatiotemporal regression framework was developed and evaluated over five years.

The results demonstrate that MODIS LST composites, combining daytime and nighttime observations from the Terra and Aqua platforms, provide highly accurate air temperature estimates due to their strong temporal representativeness. Landsat-8-derived LST, while less accurate for direct air temperature estimation due to its instantaneous nature, captures fine-scale spatial variability, essential for local agricultural applications. The exploratory multisensor integration approach effectively exploits both the potential and the limitations of directly combining multi-resolution LST products for air temperature modelling. While spatial detail is enhanced relative to Landsat-only estimates, temporal aggregation remains the dominant factor controlling model accuracy. Consequently, future work will focus on applying satellite-based temperature estimates to cumulative agroclimatic indicators, such as Growing Degree Days, and validating them against station-derived metrics.

The proposed framework offers a practical and transferable solution for generating spatially continuous air temperature maps in regions where ground observations are sparse or unevenly distributed.
While the current implementation does not explicitly account for land-cover variability or spatial autocorrelation, these aspects are promising directions for future research. In particular, integrating land-cover-dependent modelling strategies, vegetation indices, and geostatistical approaches may further enhance the accuracy and applicability of satellite-based air temperature estimates for precision agriculture and climate impact studies.

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