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Performance assessment of gridded climate datasets for precipitation and temperature monitoring in a Mediterranean inland region

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Abstract

Accurate and spatially consistent climate information is essential for environmental monitoring, climate change assessment, and resource management in Mediterranean inland regions characterised by complex orography and ground-based observational networks with low spatial density. This study assesses the suitability of three widely used gridded climate datasets—CHIRPS, ERA5-Land and TerraClimate—for climate monitoring purposes in the Alto Bradano area (southern Italy) over the period 2005–2024, using observations from four meteorological stations as reference. The evaluation focuses on annual and seasonal cumulative precipitation, as well as maximum and minimum air temperatures, combining error-based metrics, efficiency indicators, and trend analysis based on the Mann–Kendall test and Sen's slope estimator.

The results highlight substantial dataset-dependent differences, particularly for precipitation. CHIRPS shows the best overall performance in reproducing observed precipitation variability and identifies a statistically significant decline in annual precipitation across most of the study area, supporting its suitability for long-term pluviometric monitoring. ERA5-Land captures temporal variability but exhibits weak and non-significant precipitation trends, while TerraClimate shows systematic underestimation and limited robustness in trend detection. In contrast, temperature trends are more consistent across datasets. Both ERA5-Land and TerraClimate reveal a strong and spatially coherent warming of maximum temperature, while minimum temperature displays widespread nocturnal warming, more robust in ERA5-Land. Overall, the findings emphasise the importance of dataset-specific validation and support the targeted use of gridded climate products for environmental monitoring and climate impact assessments in Mediterranean inland regions.

1. Introduction

Air temperature and precipitation are fundamental components of the climate system, regulating a wide range of physical, biological, and socio-economic processes. Air temperature, in particular, represents a key climatic variable influencing ecosystem primary productivity and numerous biological processes, from enzymatic activity and biogeochemical cycles to species distribution and population dynamics, with important implications for agriculture, forestry, and energy demand (Huang et al., 2019; Still et al., 2019; Almeida & Coelho, 2023). Precipitation constitutes the primary forcing of the hydrological cycle, controlling water resource availability and influencing the occurrence of extreme events, with direct consequences for hydro-meteorological risk, land management, and environmental sustainability (Sun et al., 2022; Shazil et al., 2025). In the context of climate change, the accurate characterisation of both variables—considering mean conditions as well as variability and trends—has become central to operational climate monitoring and to environmental and hydrological modelling applications (Lavers et al., 2022; Yan et al., 2024).

In situ observations from automatic and conventional meteorological stations remain the primary source of information for climate analysis and are widely used as forcing inputs in hydrological models and for

the validation of climate datasets and projections (Andrade et al., 2014; Lima et al., 2023). However, the quality, continuity, and representativeness of observed time series are strongly dependent on network density and are often affected by non-climatic factors such as sensor accuracy, maintenance practices, station relocation, instrumental changes, and sampling frequency. These issues may introduce gaps and inhomogeneities in the data, making quality control and homogenisation procedures necessary (Gubler et al., 2017; Almeida & Coelho, 2023). Such limitations are particularly evident in hilly and mountainous areas, where complex orography enhances spatial variability and complicates the management and long-term stability of monitoring networks (Beniston et al., 1997; Rolland, 2003; Bonshoms Martí et al., 2022).

To overcome these limitations, the use of gridded climate datasets derived from interpolation techniques, satellite observations, and numerical modelling—especially atmospheric reanalyses—has increased substantially in recent decades. Reanalysis products combine numerical weather prediction models with data assimilation systems that integrate historical observations, providing spatially and temporally continuous multivariate climate fields (Parker, 2016). Within the Copernicus Climate Change Service, the ERA5 reanalysis has become one of the most widely used datasets for climate monitoring due to its global coverage, temporal consistency, and availability of uncertainty estimates (Hersbach et al., 2020; Lavers et al., 2022). Nevertheless, the relatively coarse spatial resolution of reanalyses and the uneven distribution of observations may limit their ability to accurately reproduce local-scale processes and extremes, highlighting the need for targeted performance assessments across different climatic and orographic contexts (Lavers et al., 2022; Yan et al., 2024).

To improve the representation of land surface processes, the ERA5-Land dataset was developed by forcing a land surface model with ERA5 atmospheric fields, providing climate variables at higher spatial resolution (approximately 9 km; 0.1°) (Muñoz-Sabater et al., 2021). Several studies report satisfactory performance of ERA5 and ERA5-Land for air temperature estimation, particularly for mean conditions, although non-negligible biases have been documented in specific regions, including the Mediterranean basin, and at finer temporal scales (McNicholl et al., 2021; Velikou et al., 2022). While ERA5-Land generally improves temperature estimates compared with ERA5, strong elevation gradients and complex terrain can still lead to local inaccuracies, with better performance typically observed in lowland areas than in mountainous regions (Araújo et al., 2022; Li et al., 2022; Zhao & He, 2022). The evaluation of precipitation remains particularly challenging, as systematic biases in gridded products may propagate into hydrological simulations and impact assessments (Sun et al., 2022; Lavers et al., 2022).

Alongside reanalysis products, hybrid gridded climate datasets are widely used for environmental monitoring and climate impact studies. TerraClimate provides monthly climate and water balance variables at approximately 4 km spatial resolution over long historical periods, making it suitable for climate and hydrological analyses at regional to global scales (Abatzoglou et al., 2018). However, as a global product, its performance may vary locally, requiring site-specific evaluation, particularly in regions with sparse observational coverage (Filgueiras et al., 2022). For precipitation, the CHIRPS dataset integrates satellite-based infrared observations with rain gauge data, offering high-resolution (0.05°)

precipitation estimates from 1981 onwards and supporting applications such as drought monitoring through standardised indices (Funk et al., 2015; Wu et al., 2019). Despite these advantages, numerous studies demonstrate that the performance of both reanalysis- and satellite-based products is strongly influenced by topography and local climatic conditions, making validation against ground-based observations essential, especially in Mediterranean regions characterised by complex orography (Yan et al., 2024; Shazil et al., 2025).

Within southern Europe, inland Mediterranean regions exhibit pronounced seasonal and interannual climate variability, strong orographic control, and increasing exposure to droughts and intense precipitation events. These characteristics make the assessment of the reliability of gridded climate datasets particularly relevant for environmental monitoring and resource management. In Italy, these challenges are especially evident in the Apennine and southern regions, where morphological complexity is coupled with a progressive reduction in meteorological observation networks, limiting the availability of long and homogeneous climate records.

In this context, the Basilicata region in southern Italy represents a relevant case study for the evaluation of gridded climate products, as it combines marked orographic and microclimatic heterogeneity with increasingly sparse observational coverage. Within the region, the Alto Bradano area, located in north-eastern Basilicata, is a predominantly hilly and mountainous territory characterised by hot, dry summers and cold, wet winters, with precipitation mainly concentrated in autumn and winter. The progressive reduction of the local meteorological network—currently limited to four operational stations managed by the Civil Protection Department and the Lucanian Agency for Development and Innovation in Agriculture (ALSIA)—poses clear constraints on climate monitoring and trend analysis at the local scale.

Against this background, the present study aims to evaluate the suitability of CHIRPS, ERA5-Land and TerraClimate, for climate monitoring purposes in the Alto Bradano area through comparison with available ground-based observations. Specifically, the objectives are to: (i) quantify discrepancies between gridded and observed data for precipitation and air temperature; (ii) assess the temporal and seasonal consistency of the datasets; and (iii) identify the most suitable products for representing local climatic conditions in an inland Mediterranean region that is particularly sensitive to precipitation variability and drought.

2. Materials and Methods

2.1 Study area and climate datasets

The study area, known as Alto Bradano, is located in the north-eastern part of the Basilicata region, in southern Italy (Fig. 1). Geographically, it extends between 15° and 16° E longitude and 40° and 41° N latitude, encompassing the municipalities of Acerenza, Banzi, Forenza, Genzano di Lucania, Oppido Lucano, Palazzo San Gervasio, San Chirico Nuovo, and Tolve. The area covers approximately 756 km², with elevations ranging from 200 to 800 m a.s.l., and is characterised by a complex orography, marked by

pronounced elevation gradients, heterogeneous terrain morphology and alternating hilly and mountainous sectors over short spatial distances. This topographic complexity strongly influences local climatic conditions and enhances the spatial variability of precipitation and air temperature across the basin (Fig. 2).

The climate of the area is typically Mediterranean, with hot, dry summers and cold, wet winters. Precipitation is mainly concentrated between October and March, while summers are generally dry, often leading to soil moisture deficits that negatively affect agricultural productivity.

From a socio-economic perspective, the Alto Bradano area is predominantly agricultural, with extensive cereal cultivation (mainly durum wheat), interspersed with olive groves and pastureland. These agro-ecosystems are highly dependent on local climatic conditions, particularly rainfall distribution and temperature fluctuations, which directly influence crop growth, water demand, and soil moisture dynamics.

Despite its agricultural relevance, the local meteorological observation network has been progressively reduced over recent decades. At present, only four operational meteorological stations provide continuous climatic observations within the study area. These stations are managed by the Civil Protection Department of Basilicata and the Lucanian Agency for Development and Innovation in Agriculture (ALSIA) and represent the main source of ground-based climatic information available for the basin (Table 1). The available observations cover a reference period from 2005 to 2024. Although the stations record air temperature and precipitation at daily resolution, their limited spatial coverage, combined with occasional data gaps, constrains the ability to fully capture the spatial variability of climatic conditions across the basin, particularly in relation to the complex orographic setting.

To overcome these limitations, this study integrates ground-based measurements with three global gridded climate datasets widely used in regional-scale analyses. ERA5-Land (Muñoz-Sabater et al., 2021) provides hourly reanalysis data of land surface variables at 0.1° (~ 9 km) spatial resolution, offering high temporal consistency; daily mean maximum and minimum air temperatures and daily cumulative precipitation were derived from these data. TerraClimate (Abatzoglou et al., 2018) delivers monthly climate and water balance variables at approximately 4 km spatial resolution by integrating climatological normals, reanalysis fields, and satellite information; this dataset provides maximum and minimum air temperatures and cumulative precipitation aggregated at monthly scale. CHIRPS (Funk et al., 2015) supplies quasi-global daily cumulative precipitation data at 0.05° (~ 5 km) spatial resolution, derived from the integration of infrared satellite imagery and ground-based observations, but does not include temperature variables.

These datasets were selected for their complementary characteristics: ERA5-Land provides high temporal resolution and physically consistent fields; TerraClimate offers long-term climatological information suitable for trend analysis; and CHIRPS ensures a detailed spatial representation of precipitation, particularly valuable in regions with limited station density and complex terrain. All gridded datasets were accessed via Google Earth Engine (GEE) and extracted for the same period as the ground-

based observations (2005–2024), enabling a comprehensive validation of air temperature (maximum and minimum) and precipitation patterns in the Alto Bradano area.

Table 1
Geographical characteristics and descriptive statistics of the meteorological stations operating in the Alto Bradano area during the period 2005–2024

	Acerenza	**Genzano di Lucania**	**Oppido Lucano**	**Palazzo S. Gervasio**
Latitude (N)	40°48'30.6"	40°47'39.6"	40° 45' 50"	40° 56' 5"
Longitude (E)	15°59'02.3"	16°05'30.9"	15° 59' 8"	15° 58' 19"
Altitude (m a.s.l)	368	315	761	471
Daily precipitation series	9132	9036	7348	7351
Daily maximum temperature series	9216	9098	7284	7351
Daily minimum temperature series	9216	9098	7284	7351
Mean daily precipitation	1.82	1.30	1.87	1.78
Mean daily maximum temperature	20.60	21.58	17.35	20.72
Mean daily minimum temperature	8.55	9.81	10.25	11.21
Daily precipitation standard deviation	5.84	4.29	5.31	5.17
Daily temperature standard maximum deviation	9.31	9.06	8.49	8.99
Daily temperature standard minimum deviation	6.44	6.54	6.68	6.64

2.2 Data validation methods

2.2.1 Statistical indicators

Annual and seasonal cumulative precipitation, as well as annual and seasonal maximum and minimum air temperatures, both observed and estimated from gridded climate datasets, were analysed at the meteorological stations using a *pixel-to-point* approach (Shazil et al., 2025). For each station, the values of the grid cells intersecting the station location were extracted according to the spatial resolution of each dataset.

The accuracy of the gridded estimates was assessed by comparing them with ground-based observations using a set of statistical indicators commonly applied in climate data validation studies.

The following metrics were computed:

- Mean Error (ME), which quantifies the average difference between observed and estimated values:

$$ME = \frac{1}{n} \sum_{i=1}^{n} (S_i - G_i)$$

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where S_i denotes the observed value at the station, G_i the value estimated by the gridded dataset, n the total number of paired observations, and i the individual observation index. Negative ME values indicate underestimation, whereas positive values indicate overestimation. The ideal value of ME is 0.

- Bias, which measures the systematic tendency of the dataset to overestimate or underestimate the observations:

$$Bias = \frac{\sum S_i}{\sum G_i} - 1$$

2

Values close to zero and with low magnitude indicate high accuracy.

- Mean Absolute Error (MAE), which represents the average magnitude of the errors regardless of their sign:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |S_i - G_i|$$

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- Root Mean Square Error (RMSE), which provides an overall measure of error, giving greater weight to larger deviations:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - G_i)^2}$$

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Both MAE and RMSE range from 0 to +∞, with lower values indicating better model performance.

- Pearson's correlation coefficient (R), which measures the strength of the linear relationship between observed and estimated values:

$$R = \frac{\sum \left(S_i - \overline{S}\right)\left(G_i - \overline{G}\right)}{\sqrt{\sum \left(S_i - \overline{S}\right)^2 \sum \left(G_i - \overline{G}\right)^2}}$$

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where $\overline{S}$ and $\overline{G}$ are the mean observed and estimated values, respectively. This coefficient ranges from − 1 to + 1, where values close to + 1 indicate a strong positive correlation, values near − 1 indicate a strong negative correlation, and values close to 0 indicate a weak or no correlation.

- Nash–Sutcliffe Efficiency coefficient (NSE_c), which evaluates the predictive skill of the gridded estimates relative to the mean of the observations:

$$NSE_c = 1 - \frac{\sum_{i=1}^{n}(S_i - G_i)^2}{\sum_{i=1}^{n}\left(S_i - \overline{G}\right)^2}$$

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Values approaching 1 indicate excellent agreement with observations, whereas negative values reflect poor model performance.

Overall, the combined use of error-based (ME, MAE, RMSE, Bias) and correlation-based (R, NSE_c) metrics allows a robust assessment of the ability of the gridded climate datasets to reproduce the annual and seasonal variability of precipitation and air temperature (maximum and minimum) in the study area.

2.2.2 Sen's slope and Mann–Kendall test

To analyse the temporal trends in annual and seasonal cumulative precipitation and in annual and seasonal maximum and minimum air temperatures, estimated from gridded climate datasets, the Sen's slope method was applied over the study period (Sen, 1968). Sen's slope is a non-parametric method widely used in climate and hydrological studies to quantify monotonic trends in time-series data, as it is robust to outliers, insensitive to missing values, and does not require any assumption regarding data distribution.

The magnitude of the trend is estimated as the median of all possible pairwise slopes computed from the time series, according to the following formulation:

$$slope = median\left(\frac{G_k - G_j}{k - j}\right), \qquad \forall\, k > j$$

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where G_q and G_p represent the gridded values of precipitation or air temperature at times *k* and *j*, respectively, with $1 \le j < k \le m$, and *m* denoting the total number of years in the analysed period. A positive slope indicates an increasing trend in the climatic variable, whereas a negative slope denotes a decreasing trend.

The statistical significance of the trends identified by Sen's slope was subsequently assessed using the Mann–Kendall (MK) test, a non-parametric and distribution-free approach commonly employed for detecting monotonic trends in climatological and hydrological time series (Kendall, 1975; Mann, 1945). The MK test evaluates the null hypothesis that the data are randomly distributed over time (i.e. no significant trend) against the alternative hypothesis of a statistically significant increasing or decreasing trend.

The Mann–Kendall test is particularly suitable for precipitation and temperature analyses because it is not affected by non-normal data distributions and is relatively insensitive to extreme values. Statistical significance was evaluated at the 95% confidence level; trends were considered significant when the associated *p-value* was lower than 0.05 ($p < 0.05$), indicating rejection of the null hypothesis and the presence of a significant monotonic trend.

3. Results and discussion

3.1 Statistical evaluation of annual climatic variables

The performance of the gridded climate datasets in estimating annual cumulative precipitation and annual maximum and minimum air temperatures was evaluated through comparison with ground-based observations using the error-based and model efficiency indicators described in the previous section. This integrated analysis assesses both the magnitude and direction of deviations from observed values and the ability of the datasets to reproduce interannual variability across the study area. Overall, the results reveal substantial differences among datasets and marked spatial variability, reflecting the strong influence of local conditions and orography.

For annual cumulative precipitation, the Mean Error (ME) shows contrasting behaviour among datasets. CHIRPS exhibits values close to zero at Acerenza and Oppido Lucano, while overestimating precipitation at Genzano di Lucania and underestimating it at Palazzo S. Gervasio (Fig. 3). ERA5-Land clearly overestimates precipitation at Genzano di Lucania, with smaller deviations elsewhere. TerraClimate systematically underestimates precipitation at all stations except Genzano di Lucania, with the largest negative deviations at Oppido Lucano and Palazzo S. Gervasio. These patterns are confirmed by the Bias metric, indicating a general underestimation of annual totals. Absolute error indicators (MAE and RMSE) show the highest errors for ERA5-Land at Genzano di Lucania, while CHIRPS and TerraClimate display intermediate performance; in all cases, RMSE exceeds MAE, indicating occasional large errors. Pearson's correlation coefficient (R) indicates variable skill in reproducing interannual variability, with ERA5-Land generally showing the highest correlations, CHIRPS moderate values, and TerraClimate lower

and sometimes near-zero values. Consistently, the Nash–Sutcliffe Efficiency coefficient (NSEc) highlights good performance for ERA5-Land and CHIRPS at some stations, while negative values—particularly at Genzano di Lucania—suggest limited representativeness without bias correction.

For annual maximum air temperature, both ERA5-Land and TerraClimate show good agreement with observations, despite systematic and spatially variable biases (Fig. 4). ERA5-Land tends to underestimate temperatures at Acerenza and Genzano di Lucania and overestimate them at Oppido Lucano and Palazzo S. Gervasio, whereas TerraClimate underestimates at lower-elevation stations and overestimates at Oppido Lucano, with near-zero deviations at Palazzo S. Gervasio. These patterns likely reflect elevation and local topographic effects (Almeida & Coelho, 2023; Araújo et al., 2022). Temperature errors (MAE and RMSE) are substantially lower than for precipitation, indicating better overall performance. Pearson's R values are consistently high (> 0.8 for ERA5-Land) and NSEc values are positive and often close to unity, confirming strong predictive skill.

A similar behaviour is observed for annual minimum air temperature (Fig. 5). ERA5-Land shows small deviations, with slight underestimation at Oppido Lucano and Palazzo S. Gervasio, while TerraClimate tends to overestimate minimum temperatures at Acerenza and Genzano di Lucania. Error magnitudes remain low and comparable to those for maximum temperature. High correlation coefficients (generally > 0.8) and positive NSEc values at most stations further confirm the strong ability of both datasets—particularly ERA5-Land—to reproduce interannual variability in minimum temperatures.

3.2 Statistical evaluation of seasonal climatic variables

The seasonal analysis of cumulative precipitation highlights marked differences among datasets and a strong dependence on season and station, confirming the annual-scale patterns and revealing additional issues related to the intra-annual rainfall distribution (Table 2).

In spring, CHIRPS shows satisfactory performance at Acerenza and Oppido Lucano, with moderate biases and positive NSEc values, while a pronounced overestimation is observed at Genzano di Lucania (Bias = 0.24) associated with a negative NSEc value. ERA5-Land exhibits a systematic spring overestimation, particularly at Genzano di Lucania (ME = 86.91 mm; NSEc = − 2.92), but performs well at Oppido Lucano and Palazzo S. Gervasio, where correlation coefficients are high and NSEc exceeds 0.75. TerraClimate shows widespread underestimation at nearly all stations, with high absolute errors and low or near-zero NSEc values, indicating limited reliability.

In summer, all datasets show reduced biases and errors. CHIRPS and ERA5-Land display comparable performance, with low biases, small MAE and RMSE values, and positive NSEc values at most stations. TerraClimate exhibits systematic underestimation across nearly all stations, as indicated by negative NSEc values.

In autumn, the strongest limitations emerge. CHIRPS and ERA5-Land strongly overestimate precipitation at Genzano di Lucania (Bias > 0.35), with markedly negative NSEc values, while maintaining good

performance at Oppido Lucano and Palazzo S. Gervasio. TerraClimate performs poorest, with high errors, weak correlations, and negative NSEc values at most stations.

In winter, ERA5-Land and CHIRPS reproduce seasonal variability well at Oppido Lucano and Palazzo S. Gervasio ($R > 0.85$; $NSEc > 0.70$), but both overestimate precipitation at Genzano di Lucania, where NSEc remains strongly negative. TerraClimate shows heterogeneous behaviour, with good performance at Oppido Lucano and Palazzo S. Gervasio, underestimation at Acerenza, and poor reliability at Genzano di Lucania.

The seasonal analysis of maximum air temperature indicates high performance for both datasets, with limited errors and strong temporal coherence across stations (Table 3). In spring, ERA5-Land slightly underestimates maximum temperature at Acerenza and Genzano di Lucania (ME between − 1.00 and − 1.63) and overestimates at Oppido Lucano (ME = 2.13), while TerraClimate shows similar behaviour. MAE and RMSE values are generally below 2, with high correlation ($R \approx 0.80–0.90$) and NSEc values ≥ 0.97. In summer, errors increase, particularly for TerraClimate at Acerenza and Genzano di Lucania (ME down to − 3.19), while ERA5-Land maintains MAE below 2.7. At Oppido Lucano, both datasets show slight overestimation with very high R (≥ 0.94) and NSEc (> 0.94). Palazzo S. Gervasio exhibits the best performance.

In autumn, performance remains high overall, but both datasets overestimate at Oppido Lucano (ME = 3.09 for ERA5-Land; 1.98 for TerraClimate), with increased RMSE and reduced NSEc (0.51 and 0.62, respectively). In winter, both datasets slightly underestimate maximum temperature at Acerenza and Genzano di Lucania ($MAE < 1.50$), while overestimating at Oppido Lucano, more markedly for ERA5-Land. At Palazzo S. Gervasio, model performance is excellent ($MAE < 0.50$; $R \approx 0.98$; $NSEc \approx 1$), particularly for ERA5-Land.

Minimum air temperature shows greater seasonal and spatial variability (Table 4). In spring, ERA5-Land shows near-zero ME at Acerenza and Genzano di Lucania, with underestimation at Oppido Lucano and Palazzo S. Gervasio ($ME \approx − 1.32/−1.43$), while TerraClimate strongly overestimates at Acerenza and Genzano di Lucania ($ME > 1.80$) with negative NSEc values. Better TerraClimate performance is observed at Oppido Lucano and Palazzo S. Gervasio. In summer, ERA5-Land slightly overestimates at Acerenza and underestimates at Oppido Lucano and Palazzo S. Gervasio, with negative NSEc values at the latter stations. TerraClimate continues to overestimate at Acerenza and Genzano di Lucania but performs well at Oppido Lucano and Palazzo S. Gervasio. In autumn, ERA5-Land shows limited biases at Genzano di Lucania but underestimates at Oppido Lucano and Palazzo S. Gervasio, where NSEc becomes negative. TerraClimate maintains overestimation at Acerenza and Genzano di Lucania, with negative NSEc values, but shows improved performance at Oppido Lucano and Palazzo S. Gervasio. In winter, ERA5-Land systematically underestimates minimum temperature at all stations (ME down to − 1.88), with reduced R and NSEc values close to zero or negative. TerraClimate overestimates at Acerenza and Genzano di Lucania, underestimates at Palazzo S. Gervasio, and shows generally low NSEc values, except at Oppido Lucano.

Overall, CHIRPS emerges as the most reliable dataset for precipitation, offering the best compromise between limited biases, moderate errors, and the ability to reproduce interannual and seasonal variability, despite localised limitations at Genzano di Lucania. ERA5-Land captures temporal variability well but tends to overestimate precipitation, limiting its direct use without bias correction, while TerraClimate shows systematic underestimation.

For air temperature, ERA5-Land provides the most reliable results for both maximum and minimum temperatures, with limited biases, low errors, and consistently high R and NSEc values. TerraClimate performs well for maximum temperature but shows clear limitations for minimum temperature, particularly at lower elevations and in winter.

Table 2
Error and performance indicators of seasonal cumulative precipitation for CHIRPS, ERA5-Land, and TerraClimate, evaluated against observations at four gauged stations

		ME	Bias	MAE	RMSE	R	NSEc
Spring							
CHIRPS	Acerenza	-13.46	-0.07	66.86	81.41	0.45	0.19
	Genzano di Lucania	30.24	0.24	47.40	58.43	0.35	-0.34
	Oppido Lucano	-19.84	-0.11	37.12	53.39	0.74	0.59
	Palazzo S. Gervasio	-39.58	-0.21	47.97	58.16	0.65	0.31
ERA5-Land	Acerenza	37.49	0.21	54.64	61.90	0.85	0.53
	Genzano di Lucania	86.91	0.68	86.91	99.93	0.65	-2.92
	Oppido Lucano	22.21	0.12	33.12	39.08	0.89	0.78
	Palazzo S. Gervasio	9.04	0.05	20.29	28.67	0.88	0.83
TerraClimate	Acerenza	-30.64	-0.17	58.56	75.90	0.65	0.29
	Genzano di Lucania	20.14	0.16	50.28	56.68	0.41	-0.26
	Oppido Lucano	-44.47	-0.24	45.61	59.98	0.85	0.48
	Palazzo S. Gervasio	-52.29	-0.28	52.41	67.70	0.67	0.06
Summer							
CHIRPS	Acerenza	-5.39	-0.05	34.52	43.22	0.65	0.41
	Genzano di Lucania	9.26	0.10	38.79	43.41	0.56	0.27
	Oppido Lucano	-22.77	-0.19	41.58	57.13	0.69	0.31
	Palazzo S. Gervasio	-11.21	-0.10	21.59	30.90	0.72	0.45
ERA5-Land	Acerenza	-5.88	-0.06	37.20	46.01	0.61	0.33
	Genzano di Lucania	11.13	0.12	32.75	39.86	0.69	0.39
	Oppido Lucano	-22.56	-0.18	37.69	52.67	0.72	0.41
	Palazzo S. Gervasio	-20.21	-0.19	29.69	36.96	0.70	0.21
TerraClimate	Acerenza	-26.12	-0.25	47.94	59.61	0.33	-0.13
	Genzano di Lucania	-8.11	-0.09	37.67	45.17	0.49	0.21
	Oppido Lucano	-42.00	-0.34	54.52	76.57	0.36	-0.25
	Palazzo S. Gervasio	-35.90	-0.33	42.32	51.29	0.48	-0.52

		ME	Bias	MAE	RMSE	R	NSEc
Autumn							
CHIRPS	Acerenza	-5.72	-0.03	56.32	66.26	0.34	0.01
	Genzano di Lucania	54.47	0.38	64.14	87.40	0.00	-1.51
	Oppido Lucano	-8.93	-0.04	39.96	45.69	0.62	0.35
	Palazzo S. Gervasio	9.79	0.06	48.46	57.02	0.55	0.26
ERA5-Land	Acerenza	-1.74	-0.01	35.04	43.44	0.76	0.58
	Genzano di Lucania	50.41	0.35	57.00	78.60	0.39	-1.03
	Oppido Lucano	-4.40	-0.02	28.09	34.31	0.82	0.63
	Palazzo S. Gervasio	16.18	0.09	28.97	37.73	0.86	0.67
TerraClimate	Acerenza	-7.26	-0.04	56.14	70.89	0.39	-0.13
	Genzano di Lucania	49.47	0.34	78.59	94.80	0.04	-1.95
	Oppido Lucano	-21.07	-0.10	48.97	63.80	0.44	-0.27
	Palazzo S. Gervasio	-4.90	-0.03	46.62	61.77	0.49	0.13
Winter							
CHIRPS	Acerenza	9.52	0.06	42.16	57.74	0.44	-0.02
	Genzano di Lucania	73.31	0.67	73.31	85.87	0.56	-2.40
	Oppido Lucano	11.95	0.07	31.58	38.58	0.87	0.76
	Palazzo S. Gervasio	-15.72	-0.09	28.18	34.32	0.89	0.78
ERA5-Land	Acerenza	24.56	0.14	43.55	58.77	0.64	-0.05
	Genzano di Lucania	78.74	0.72	78.74	95.00	0.60	-3.16
	Oppido Lucano	19.49	0.12	38.56	43.53	0.83	0.70
	Palazzo S. Gervasio	-0.06	0.00	19.43	24.34	0.92	0.89
TerraClimate	Acerenza	-12.75	-0.07	46.75	56.82	0.50	0.01
	Genzano di Lucania	42.31	0.39	47.65	70.31	0.37	-1.29
	Oppido Lucano	-10.86	-0.07	26.96	38.32	0.86	0.76
	Palazzo S. Gervasio	-36.55	-0.22	36.57	45.52	0.92	0.61

Table 3
Error and performance indicators of seasonal maximum air temperature for ERA5-Land and TerraClimate, evaluated against observations at four gauged stations

Spring							
		ME	Bias	MAE	RMSE	R	NSEc
ERA5-Land	Acerenza	-1.63	-0.09	1.63	1.77	0.81	0.98
	Genzano di Lucania	-1.00	-0.05	1.07	1.12	0.79	0.99
	Oppido Lucano	2.13	0.15	2.13	2.22	0.87	0.90
	Palazzo S. Gervasio	-0.94	-0.05	0.94	1.03	0.92	0.99
TerraClimate	Acerenza	-1.65	-0.09	1.66	1.81	0.79	0.98
	Genzano di Lucania	-1.86	-0.10	1.86	1.93	0.69	0.97
	Oppido Lucano	1.04	0.07	1.04	1.16	0.83	0.97
	Palazzo S. Gervasio	-1.57	-0.09	1.57	1.68	0.85	0.97
Summer							
ERA5-Land	Acerenza	-2.61	-0.08	2.61	2.74	0.89	0.97
	Genzano di Lucania	-1.57	-0.05	1.73	1.79	0.79	0.99
	Oppido Lucano	2.35	0.09	2.35	2.38	0.96	0.94
	Palazzo S. Gervasio	-1.11	-0.04	1.11	1.21	0.95	0.99
TerraClimate	Acerenza	-3.19	-0.10	3.19	3.32	0.95	0.96
	Genzano di Lucania	-3.14	-0.10	3.14	3.26	0.69	0.95
	Oppido Lucano	0.78	0.03	0.81	0.98	0.94	0.99
	Palazzo S. Gervasio	-2.34	-0.07	2.34	2.41	0.97	0.96
Autumn							
ERA5-Land	Acerenza	-1.32	-0.06	1.32	1.41	0.96	0.99
	Genzano di Lucania	-0.80	-0.04	0.85	0.93	0.94	0.99
	Oppido Lucano	3.09	0.18	3.09	4.84	0.95	0.51
	Palazzo S. Gervasio	-0.66	-0.03	0.71	0.80	0.95	0.99
TerraClimate	Acerenza	-1.42	-0.07	1.42	1.60	0.92	0.98
	Genzano di Lucania	-1.36	-0.06	1.36	1.54	0.87	0.98
	Oppido Lucano	1.98	0.12	2.00	4.26	0.90	0.62

Spring							
	Palazzo S. Gervasio	-1.23	-0.06	1.27	1.42	0.90	0.98
Winter							
ERA5-Land	Acerenza	-1.35	-0.12	1.48	2.60	0.67	0.92
	Genzano di Lucania	-1.26	-0.10	1.28	2.40	0.68	0.93
	Oppido Lucano	1.64	0.20	1.64	1.71	0.98	0.85
	Palazzo S. Gervasio	-0.47	-0.04	0.49	0.57	0.98	0.99
TerraClimate	Acerenza	-1.09	-0.10	1.27	2.54	0.69	0.93
	Genzano di Lucania	-1.38	-0.11	1.40	2.52	0.68	0.93
	Oppido Lucano	0.91	0.11	0.91	1.06	0.98	0.96
	Palazzo S. Gervasio	-1.28	-0.12	1.28	1.41	0.98	0.96

Table 4
Error and performance indicators of seasonal minimum air temperature for ERA5-Land and TerraClimate, evaluated against observations at four gauged stations

		ME	Bias	MAE	RMSE	R	NSEc
Spring							
ERA5-Land	Acerenza	0.02	0.00	0.44	0.60	0.65	0.38
	Genzano di Lucania	-0.08	-0.01	0.38	0.45	0.79	0.59
	Oppido Lucano	-1.32	-0.17	1.32	1.37	0.92	0.49
	Palazzo S. Gervasio	-1.43	-0.17	1.43	1.50	0.86	0.47
TerraClimate	Acerenza	2.50	0.38	2.50	2.57	0.70	-10.23
	Genzano di Lucania	1.88	0.26	1.88	1.93	0.80	-6.50
	Oppido Lucano	0.35	0.05	0.45	0.50	0.86	0.93
	Palazzo S. Gervasio	0.05	0.01	0.34	0.43	0.78	0.96
Summer							
ERA5-Land	Acerenza	0.57	0.04	0.59	0.69	0.91	0.35
	Genzano di Lucania	-0.02	0.00	0.31	0.39	0.91	0.78
	Oppido Lucano	-1.20	-0.07	1.20	1.26	0.93	-0.45
	Palazzo S. Gervasio	-1.50	-0.08	1.50	1.53	0.95	-1.38
TerraClimate	Acerenza	2.80	0.17	2.80	2.82	0.91	-9.90
	Genzano di Lucania	1.61	0.09	1.61	1.65	0.90	-2.80
	Oppido Lucano	0.42	0.02	0.56	0.67	0.87	0.59
	Palazzo S. Gervasio	-0.35	-0.02	0.43	0.60	0.88	0.64
Autumn							
ERA5-Land	Acerenza	0.56	0.06	0.60	0.64	0.95	0.50
	Genzano di Lucania	-0.01	0.00	0.29	0.35	0.94	0.84
	Oppido Lucano	-0.53	-0.05	1.44	2.32	0.88	0.28
	Palazzo S. Gervasio	-1.18	-0.10	1.18	1.24	0.93	-0.87
TerraClimate	Acerenza	2.75	0.28	2.75	2.79	0.85	-8.49
	Genzano di Lucania	1.96	0.18	1.96	1.98	0.94	-4.39
	Oppido Lucano	1.04	0.10	1.12	2.66	0.86	0.05

		ME	Bias	MAE	RMSE	R	NSEc
	Palazzo S. Gervasio	0.16	0.01	0.38	0.47	0.88	0.73
Winter							
ERA5-Land	Acerenza	-0.92	-0.39	1.03	1.93	0.56	0.12
	Genzano di Lucania	-1.39	-0.41	1.39	2.24	0.52	-0.17
	Oppido Lucano	-1.58	-0.51	1.58	1.71	0.90	0.15
	Palazzo S. Gervasio	-1.88	-0.46	1.88	2.24	0.73	-0.40
TerraClimate	Acerenza	1.82	0.78	2.32	2.47	0.59	-0.44
	Genzano di Lucania	1.26	0.38	1.90	2.13	0.56	-0.06
	Oppido Lucano	0.50	0.16	0.61	0.77	0.89	0.69
	Palazzo S. Gervasio	-0.61	-0.15	0.66	1.33	0.73	0.51

3.3 Climate trend analysis

The analysis of climate trends over the period 2005–2024 was conducted using a consistent methodological framework based on the combined application of the non-parametric Mann–Kendall test and Sen's slope estimator. This approach enables a joint assessment of the statistical significance, direction, and magnitude of long-term changes in cumulative precipitation and maximum and minimum air temperatures, as estimated from the gridded datasets analysed in this study (Wu et al., 2019; Shazil et al., 2025). By jointly interpreting these complementary indicators, it is possible to distinguish between robust climatic signals and weak or non-significant variations, and to identify structural differences among datasets related to their underlying data sources, spatial resolution, and modelling assumptions Lavers et al., 2022; Yan et al., 2024). The trend analysis is interpreted in close connection with the results of the annual and seasonal performance evaluation, providing an integrated assessment of the suitability of each dataset for climate change analysis in a Mediterranean inland area characterised by complex orography and limited observational coverage.

3.3.1 Trend analysis of annual and seasonal cumulative precipitation using Sen's slope and the Mann–Kendall test

The Mann–Kendall maps show that CHIRPS identifies a predominantly negative and statistically significant trend over most of the study area, with approximately 71% of the surface affected by a significant decrease in annual precipitation, while the remaining area exhibits a non-significant decrease (Fig. 6a). This pattern is consistent with ground-based observations and indicates a good capability of CHIRPS to capture a progressive reduction in annual precipitation, a feature commonly reported for Mediterranean inland regions (Wu et al., 2019; Lavers et al., 2022; Shazil et al., 2025). The associated Sen's slope values predominantly range between − 8 and − 4 mm yr^{-1}, with more intense decreases

(down to < − 12 mm yr^{-1}) in the southern sector of the basin, indicating a decrease that is both spatially widespread and climatically relevant (Fig. 6b).

In contrast, ERA5-Land exhibits a markedly different behaviour. The Mann–Kendall test indicates a clear prevalence of positive but non-significant trends, affecting approximately 89% of the study area, while the remaining portion (≈ 11%) is characterised by a non-significant decrease (Fig. 6c). No statistically significant trends, either positive or negative, are detected. Consistently, Sen's slope shows predominantly positive values of moderate magnitude, with large portions of the area characterised by slopes exceeding 2 mm yr^{-1}, and locally higher values, particularly in the central and southern sectors of the basin (Fig. 6d). This configuration suggests a weak tendency towards increasing annual precipitation, which is not supported by statistical significance and therefore represents a signal of limited climatic robustness. This behaviour is likely related to the model-based nature of ERA5-Land and its tendency to smooth interannual variability (Yan et al., 2024; Shazil et al., 2025; Sun et al., 2022).

TerraClimate displays a spatially uniform pattern of decreasing precipitation, although without statistical significance. The Mann–Kendall maps indicate that 100% of the study area is characterised by a non-significant negative trend, with no areas showing statistically significant increases or decreases (Fig. 6e). Sen's slope is consistently negative across the entire area, with values predominantly between − 8 and − 4 mm yr^{-1} (Fig. 6f). Despite the non-negligible magnitude of these slopes, the lack of statistical significance suggests that the signal identified by TerraClimate is weak and not climatically robust, in agreement with the systematic underestimation of precipitation and the limited ability of the dataset to reproduce interannual variability highlighted by the performance analysis.

Overall, the annual precipitation trend analysis confirms CHIRPS as the most reliable dataset for long-term pluviometric assessments in the Alto Bradano area, as it consistently reproduces both the sign and the magnitude of the observed trend. ERA5-Land captures the direction of change but tends to smooth its intensity and significance, while TerraClimate appears less suitable for precipitation trend analysis due to weak and poorly robust signals.

The seasonal analysis of precipitation trends, based on the mean Sen's slope values and the associated p-values, highlights a generally weak and statistically non-significant behaviour across all datasets and seasons, indicating the absence of robust seasonal precipitation trends over the study period (Table 5).

In spring, CHIRPS and ERA5-Land exhibit slightly positive mean Sen's slope values (0.6 and 1.0 mm yr^{-1}, respectively), suggesting a weak tendency towards increasing precipitation. However, the high p-values ($p = 0.93$ for CHIRPS and $p = 0.72$ for ERA5-Land) indicate that these trends are not statistically significant. By contrast, TerraClimate shows a negative mean slope (− 1.4 mm yr^{-1}), pointing to a weak decrease in spring precipitation, although this signal is also not significant ($p = 0.55$).

During summer, all datasets indicate positive mean Sen's slope values, ranging from 1.0 mm yr^{-1} (TerraClimate) to 2.2 mm yr^{-1} (ERA5-Land), suggesting a tendency towards increased summer precipitation. Nevertheless, the associated p-values (0.23–0.71) remain well above the significance

threshold, confirming that these trends lack statistical robustness. ERA5-Land shows the largest magnitude, but without sufficient statistical support.

In autumn, the estimated trends are again weak and positive for all datasets, with mean Sen's slope values of 1.6 mm yr^{-1} for CHIRPS, 1.2 mm yr^{-1} for ERA5-Land, and 0.3 mm yr^{-1} for TerraClimate. The very high p-values ($p \geq 0.54$) indicate a high level of uncertainty, suggesting that no meaningful trend in autumn precipitation can be inferred from the analysed period.

In winter, CHIRPS shows a slight negative mean slope (− 0.5 mm yr^{-1}), while ERA5-Land and TerraClimate indicate a more pronounced decrease (− 4.8 and − 3.7 mm yr^{-1}, respectively). Despite the larger magnitudes, particularly for ERA5-Land and TerraClimate, the associated p-values ($p = 0.21$ and $p = 0.09$) remain above the conventional significance threshold, indicating that these decreasing winter trends are suggestive but not statistically significant.

Overall, the seasonal analysis confirms that no statistically significant precipitation trends are detected for any season across the three datasets. The observed seasonal variations in Sen's slope magnitude highlight dataset-dependent differences in the direction and intensity of potential changes, but the consistently high p-values suggest that these signals should be interpreted with caution and cannot be considered robust evidence of seasonal precipitation change over the study period.

Table 5
Seasonal mean Sen's slope values (mm yr^{-1}) and associated p-values derived from the Mann–Kendall test for cumulative precipitation over the period 2005–2024, based on CHIRPS, ERA5-Land, and TerraClimate datasets

	CHIRPS		**ERA5-LAND**		**TERRACLIMATE**	
	Sen's slope mean value (mm/yr)	***p***	**Sen's slope mean value (mm/yr)**	***p***	**Sen's slope mean value (mm/yr)**	***p***
Spring	0.6	0.93	1.0	0.72	-1.4	0.55
Summer	1.2	0.71	2.2	0.23	1.0	0.46
Autumn	1.6	0.70	1.2	0.54	0.3	0.90
Winter	-0.5	0.71	-4.8	0.21	-3.7	0.09

3.3.2 Trend analysis of annual and seasonal maximum and minimum air temperature using Sen's slope and the Mann–Kendall test

Both ERA5-Land and TerraClimate show a strong, spatially coherent, and statistically significant warming signal for annual maximum temperature across the entire study area. For ERA5-Land, the Mann–Kendall test indicates a significant positive trend over 100% of the territory, pointing to a robust and generalised increase in maximum temperatures (Fig. 7a). Sen's slope confirms this signal, with uniformly positive values predominantly ranging between 0.065 and 0.095°C yr^{-1}, and locally higher values, especially in the northern and central sectors of the basin (Fig. 7b).

TerraClimate exhibits a similar pattern in terms of trend direction and significance, with a statistically significant increase across the whole area and no evidence of null or negative trends (Fig. 7c). However, the estimated slopes are generally lower than those of ERA5-Land, with values predominantly between 0.050 and 0.080°C yr^{-1}, indicating a widespread but slightly less intense warming (Fig. 7d).

Overall, maximum temperature trends are characterised by greater consistency and robustness than precipitation trends, with both datasets capturing a clear warming signal. Nevertheless, ERA5-Land tends to estimate slightly higher warming rates than TerraClimate, suggesting a greater sensitivity in representing the intensification of daytime temperatures.

The analysis of annual minimum air temperature reveals a generalised nocturnal warming across the study area. Since minimum air temperature is typically reached during nighttime or early morning hours, statistically significant positive trends in Tmin can be interpreted as evidence of nocturnal warming. For ERA5-Land, the Mann–Kendall test indicates a significant positive trend over 100% of the study area (Fig. 8a), highlighting a spatially coherent and statistically robust signal. Sen's slope further supports this interpretation, showing uniformly positive values, generally ranging between 0.050 and 0.080°C yr^{-1}, with locally higher rates in the southern and western sectors of the basin (Fig. 8b), indicating a climatically relevant and spatially widespread nocturnal warming. TerraClimate shows a broadly consistent pattern in terms of trend direction, but with a more limited extent of statistically significant areas (Fig. 8c). While positive trends dominate, a smaller proportion of grid cells exhibits significant increases compared with ERA5-Land (about 65%). Sen's slope remains uniformly positive, with values predominantly between 0.035 and 0.050°C yr^{-1}, and locally lower values approaching 0.0035°C yr^{-1}, indicating a generalised but less intense warming (Fig. 8d).

In summary, minimum temperature trends confirm the presence of widespread nocturnal warming in the study area, while also highlighting a greater sensitivity to the choice of dataset than observed for maximum temperature. ERA5-Land provides a stronger and statistically more robust signal, whereas TerraClimate yields a more moderate increase that is often not statistically significant, consistent with its greater tendency to smooth temporal variability (Filgueiras et al., 2022; Shazil et al., 2025).

The seasonal analysis of maximum and minimum air temperature trends, based on the mean Sen's slope values and the associated p-values, reveals a clear seasonal dependence of the warming signal, with statistically significant increases concentrated mainly in summer and autumn, while weaker and non-significant trends characterise spring and, in part, winter (Table 6). In spring, both ERA5-Land and TerraClimate show slightly negative mean Sen's slope values (− 0.017 and − 0.004°C yr^{-1}, respectively), indicating a weak tendency towards decreasing maximum temperatures. However, the high p-values ($p = 0.67$ for ERA5-Land and $p = 0.87$ for TerraClimate) indicate that these trends are not statistically significant, suggesting the absence of a robust spring signal. During summer, a positive warming trend emerges for both datasets. ERA5-Land shows a mean Sen's slope of 0.069°C yr^{-1}, although this increase is not statistically significant ($p = 0.23$), whereas TerraClimate exhibits a stronger and statistically significant increase (0.096°C yr^{-1}; $p = 0.01$). This indicates a more pronounced and robust summer

warming signal in TerraClimate. In autumn, both datasets consistently indicate a strong and statistically significant increase in maximum temperature, with mean Sen's slope values of 0.145°C yr^{-1} for ERA5-Land and 0.085°C yr^{-1} for TerraClimate ($p = 0.01$ for both). Autumn therefore represents the season with the strongest and most robust warming signal for maximum temperature. In winter, ERA5-Land and TerraClimate also show positive and statistically significant trends, with mean Sen's slope values of 0.117°C yr^{-1} ($p = 0.02$) and 0.098°C yr^{-1} ($p = 0.03$), respectively, indicating a consistent warming of winter daytime temperatures.

For minimum temperature, spring is characterised by weak negative trends for both datasets (– 0.013°C yr^{-1} for ERA5-Land and – 0.054°C yr^{-1} for TerraClimate), but with non-significant p-values ($p = 0.62$ and $p = 0.16$, respectively), suggesting no robust trend. In summer, both ERA5-Land and TerraClimate show strong and statistically significant increases in minimum temperature, with identical p-values ($p = 0.01$) and mean Sen's slope values of 0.096°C yr^{-1} and 0.084°C yr^{-1}, respectively. This indicates a pronounced and coherent nocturnal warming during the summer season.

In autumn, the warming signal for minimum temperature remains strong and statistically significant for both datasets, with mean Sen's slope values of 0.125°C yr^{-1} for ERA5-Land ($p = 0.01$) and 0.066°C yr^{-1} for TerraClimate ($p < 0.01$), confirming autumn as a key season for nocturnal warming. In winter, ERA5-Land indicates a positive but non-significant trend (0.061°C yr^{-1}; $p = 0.19$), while TerraClimate shows an even weaker and non-significant increase (0.039°C yr^{-1}; $p = 0.33$), suggesting greater uncertainty in winter minimum temperature trends.

Overall, the seasonal analysis highlights that summer and autumn represent the seasons with the most robust and statistically significant warming signals for both maximum and minimum temperatures. ERA5-Land generally estimates higher warming rates for maximum temperature, particularly in autumn and winter, while TerraClimate shows a slightly stronger signal in summer. For minimum temperature, both datasets consistently capture a pronounced nocturnal warming in summer and autumn, whereas trends in spring and winter remain weak and statistically non-significant.

Table 6
Seasonal mean Sen's slope values (mm yr^{-1}) and associated p-values derived from the Mann–Kendall test for maximum and minimum temperature over the period 2005–2024, based on ERA5-Land and TerraClimate datasets

	MAXIMUM TEMPERATURE				MINIMUM TEMPERATURE			
	ERA5-LAND		TERRACLIMATE		ERA5-LAND		TERRACLIMATE	
	Mean Sen's slope (mm/yr)	*p*	Mean Sen's slope (mm/yr)	*p*	Mean Sen's slope (mm/yr)	*p*	Mean Sen's slope (mm/yr)	*p*
Spring	-0.017	0.67	-0.004	0.87	-0.013	0.62	-0.054	0.16
Summer	0.069	0.23	0.096	0.01	0.096	0.01	0.084	0.01
Autumn	0.145	0.01	0.085	0.01	0.125	0.01	0.066	0.00
Winter	0.117	0.02	0.098	0.03	0.061	0.19	0.039	0.33

Conclusions

This study presents an integrated assessment of the performance and long-term climatic trends of the gridded datasets CHIRPS, ERA5-Land, and TerraClimate in the Alto Bradano area, an inland Mediterranean region characterised by complex orography and limited observational coverage. Through comparison with ground-based observations and the application of the Mann–Kendall test and Sen's slope estimator for the period 2005–2024, the analysis distinguishes robust climatic signals from dataset-dependent uncertainties, providing guidance for the use of gridded products in data-scarce environments (Wu et al., 2019; Lavers et al., 2022; Yan et al., 2024).

Precipitation emerges as the most critical variable, with marked differences among datasets. CHIRPS shows the highest reliability, accurately reproducing observed interannual and seasonal variability and identifying a statistically significant decline in annual precipitation over much of the study area, consistent with ground observations and known Mediterranean drying trends (Wu et al., 2019; Lavers et al., 2022). ERA5-Land captures temporal variability but tends to overestimate precipitation and smooth trend magnitude and significance, limiting its direct applicability without bias correction. TerraClimate systematically underestimates precipitation and exhibits weak, non-robust trend signals, reducing its suitability for local-scale precipitation analysis.

Air temperature displays more consistent behaviour across datasets. Both ERA5-Land and TerraClimate reveal a clear and spatially coherent warming in annual maximum temperature, statistically significant across the study area. Minimum temperature trends indicate widespread nocturnal warming, more pronounced and statistically robust in ERA5-Land, while TerraClimate generally produces smoother and less significant signals.

Seasonal analyses indicate that the strongest and most significant warming occurs in summer and autumn for both maximum and minimum temperatures, whereas seasonal precipitation trends remain weak and statistically non-significant. This suggests that recent climate change in the Alto Bradano area is primarily expressed through rising air temperatures rather than systematic shifts in seasonal precipitation.

Overall, the results underline the importance of local-scale validation of gridded climate datasets prior to their application in environmental monitoring and impact studies, particularly in regions with complex terrain and limited observational network coverage (Yan et al., 2024; Shazil et al., 2025). For the Alto Bradano area, CHIRPS is the most suitable dataset for precipitation monitoring, while ERA5-Land provides the most reliable representation of air temperature. TerraClimate remains useful for large-scale assessments but shows clear limitations at the local scale, particularly for precipitation. These findings support informed dataset selection for water resource management, agriculture, climate risk assessment, and environmental monitoring in Mediterranean inland regions.

Declarations

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Author contributions Conceptualisation: [Domenica Mirauda]; Methodology: [Domenica Mirauda] and [Francesca Rinaldi]; Dataset processing and management: [Francesca Rinaldi]; Validation of data processing and results: [Domenica Mirauda]; Writing—original draft preparation: [Francesca Rinaldi]; Writing—review and editing: [Domenica Mirauda].

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Data availability The datasets used in this study were accessed and processed via the Google Earth Engine (GEE) platform. The CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) dataset is provided by the Climate Hazards Center at the University of California, Santa Barbara (https://chc.ucsb.edu/data/chirps). The ERA5-Land precipitation and temperature data are provided by the Copernicus Climate Change Service (C3S) through the Climate Data Store (https://cds.climate.copernicus.eu/). The TerraClimate precipitation and temperature datasets are provided by the Climatology Lab at the University of California, Merced (https://www.climatologylab.org/terraclimate.html). All data are openly available through their respective providers and the GEE data catalogue.

All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

Competing interests The authors declare no competing interests.

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Figures

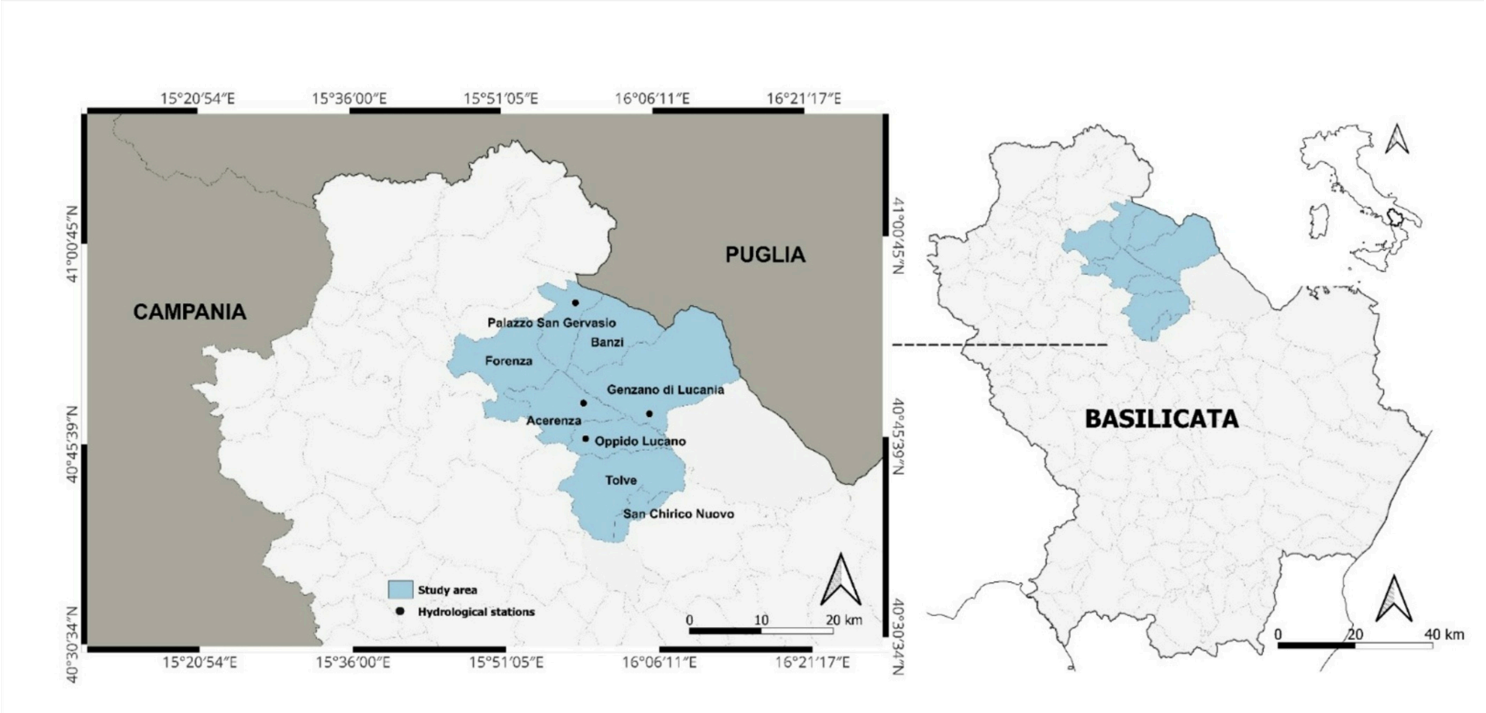


Figure 1

Study area with gauged stations

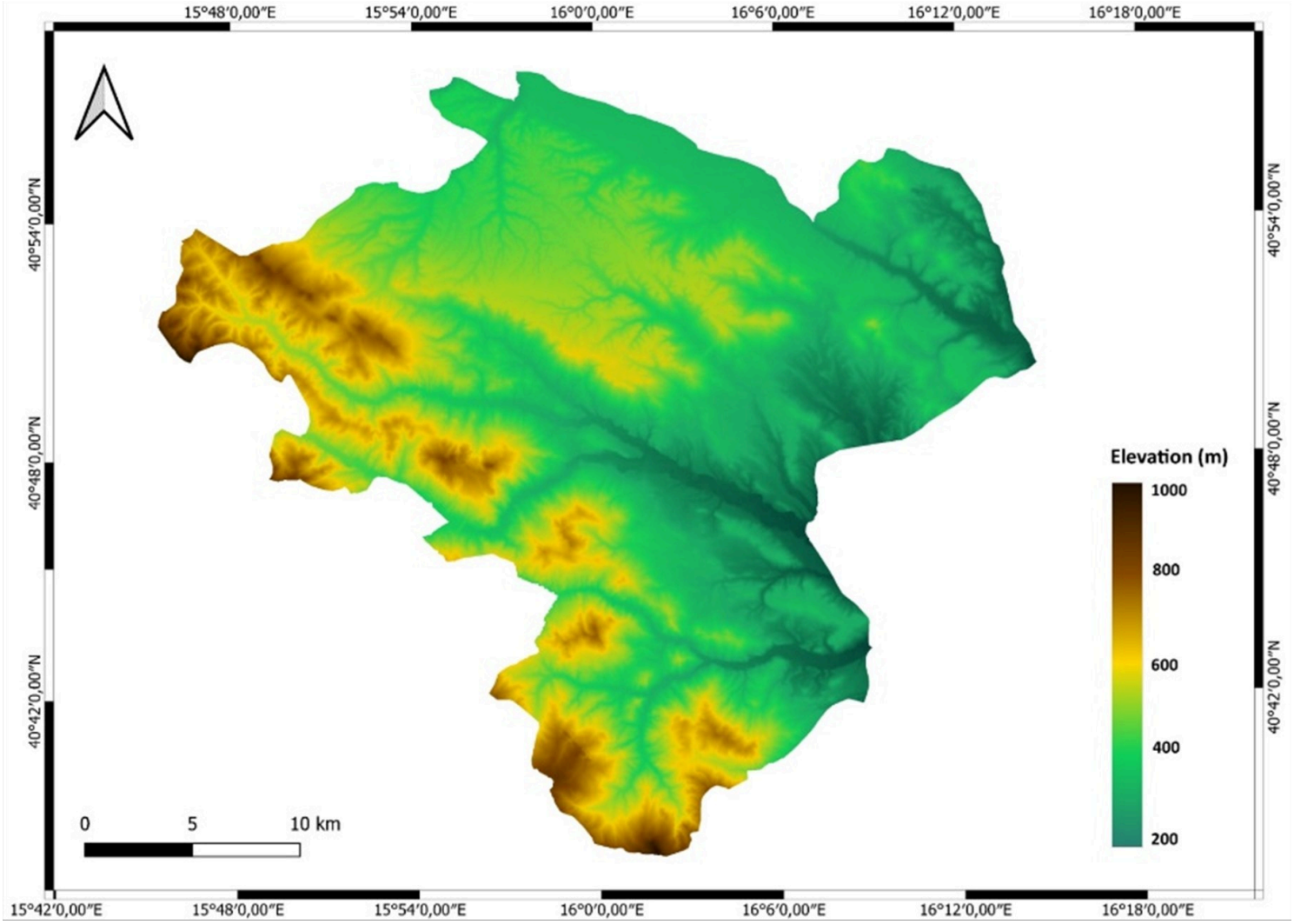


Figure 2

Digital Elevation Model (DEM) of the Alto Bradano area

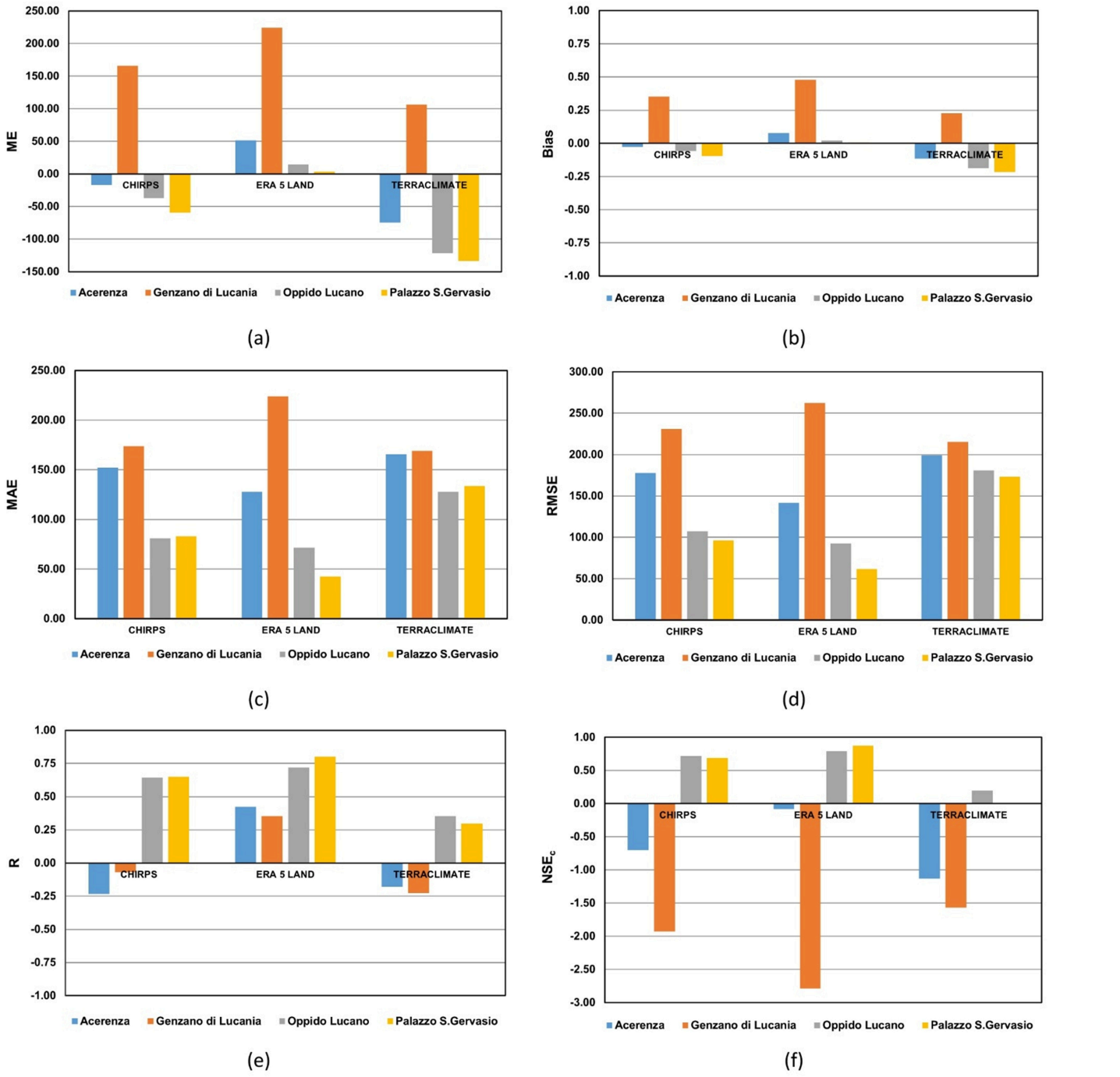


Figure 3

Error and performance indicators of annual cumulative precipitation for CHIRPS, ERA5-Land, and TerraClimate, evaluated against observations at four gauged stations: a) ME; b) Bias; c) MAE; d) RMSE; e)R ; f) NSEc

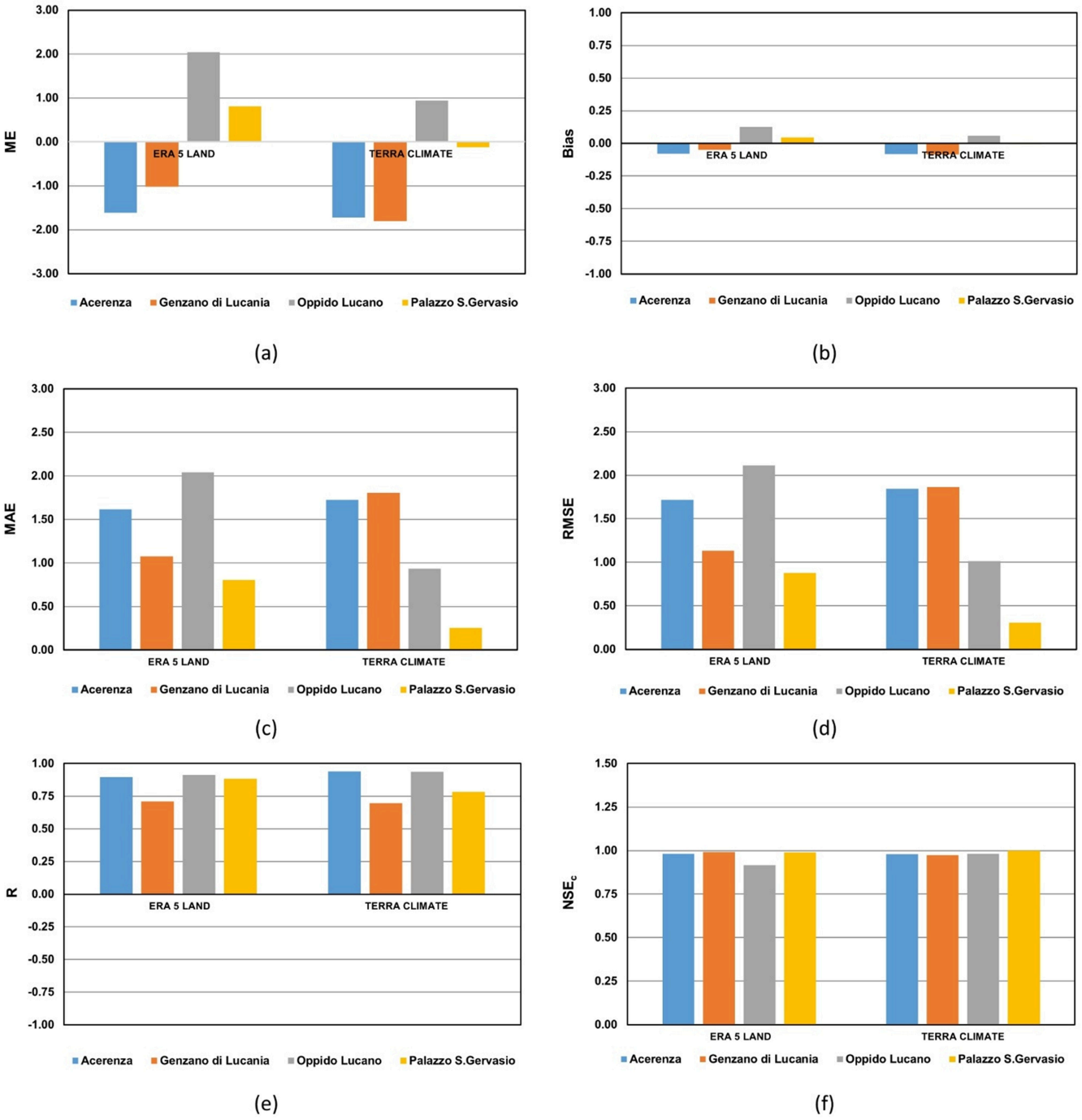


Figure 4

Error and performance indicators of annual maximum temperature for ERA5-Land and TerraClimate, evaluated against observations at four gauged stations: a) ME; b) Bias; c) MAE; d) RMSE; e)R ; f) NSEc

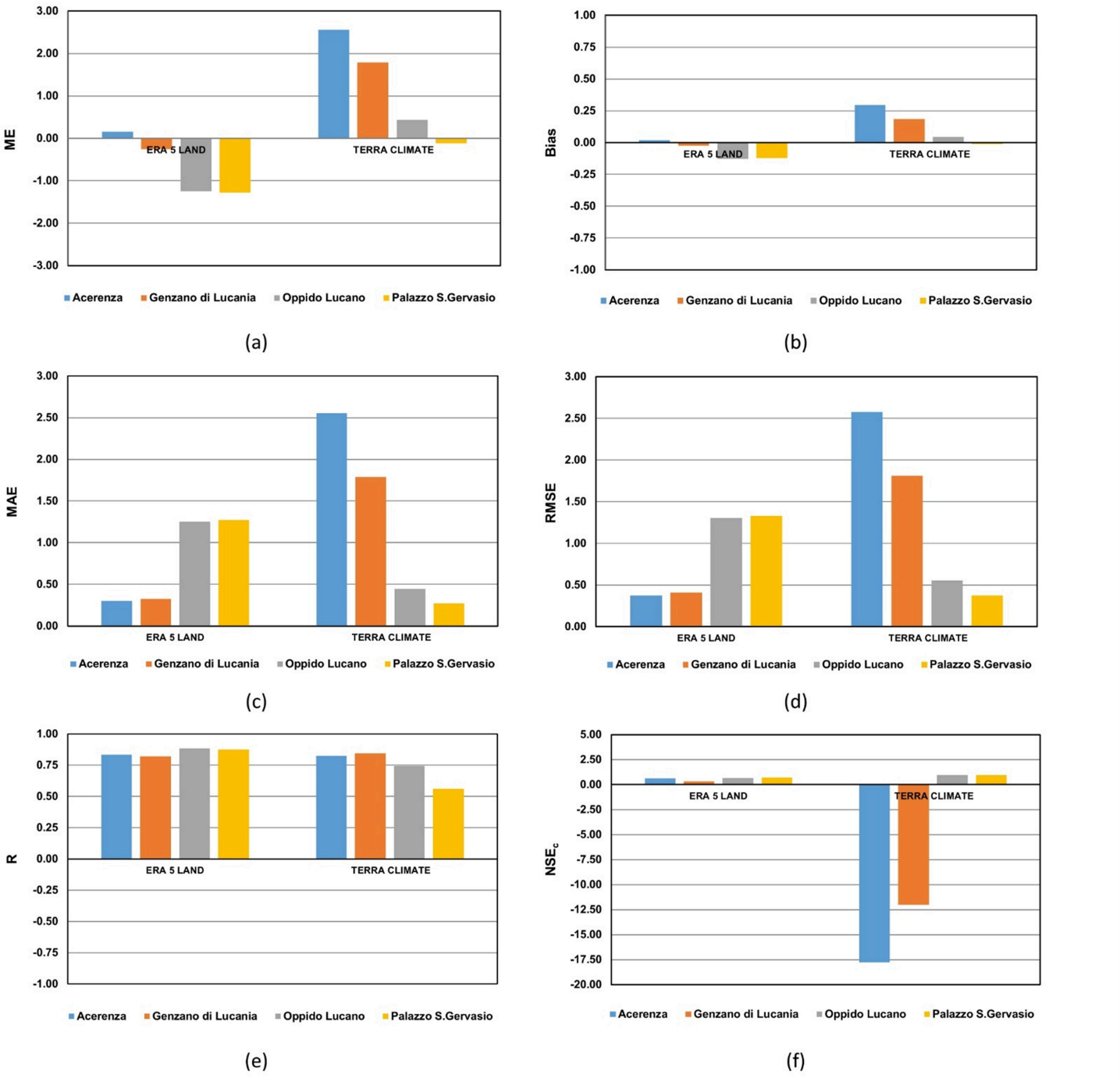


Figure 5

Error and performance indicators of annual minimum temperature for ERA5-Land and TerraClimate, evaluated against observations at four gauged stations: a) ME; b) Bias; c) MAE; d) RMSE; e)R ; f) NSEc

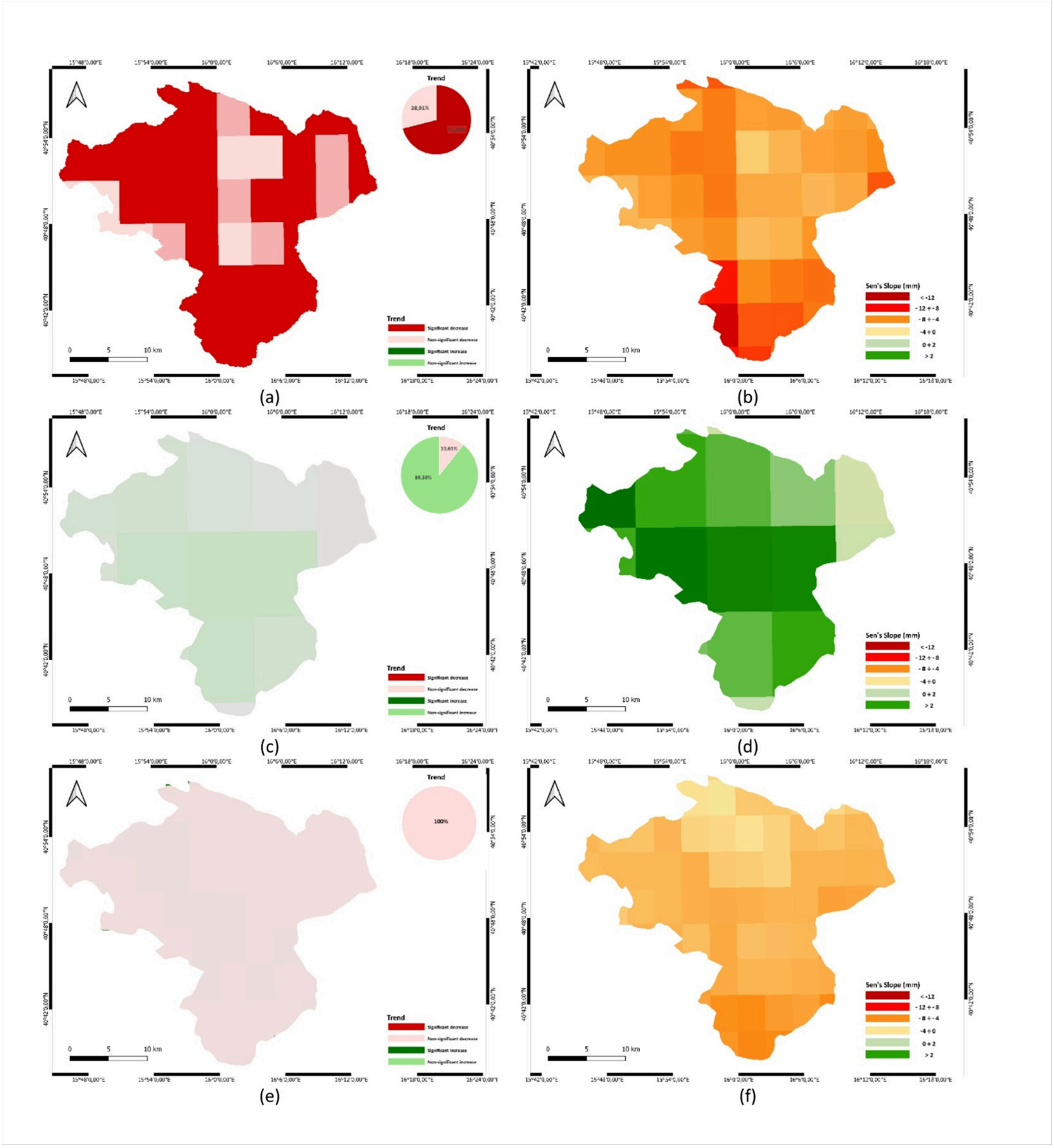


Figure 6

Spatial distribution of annual cumulative precipitation trends over the period 2005–2024 derived from the CHIRPS, ERA5-Land, and TerraClimate datasets. Panels (a), (c) and (e) show the results of the Mann–Kendall test, while panels (b), (d), and (f) display the corresponding Sen's slope values (mm yr^{-1})

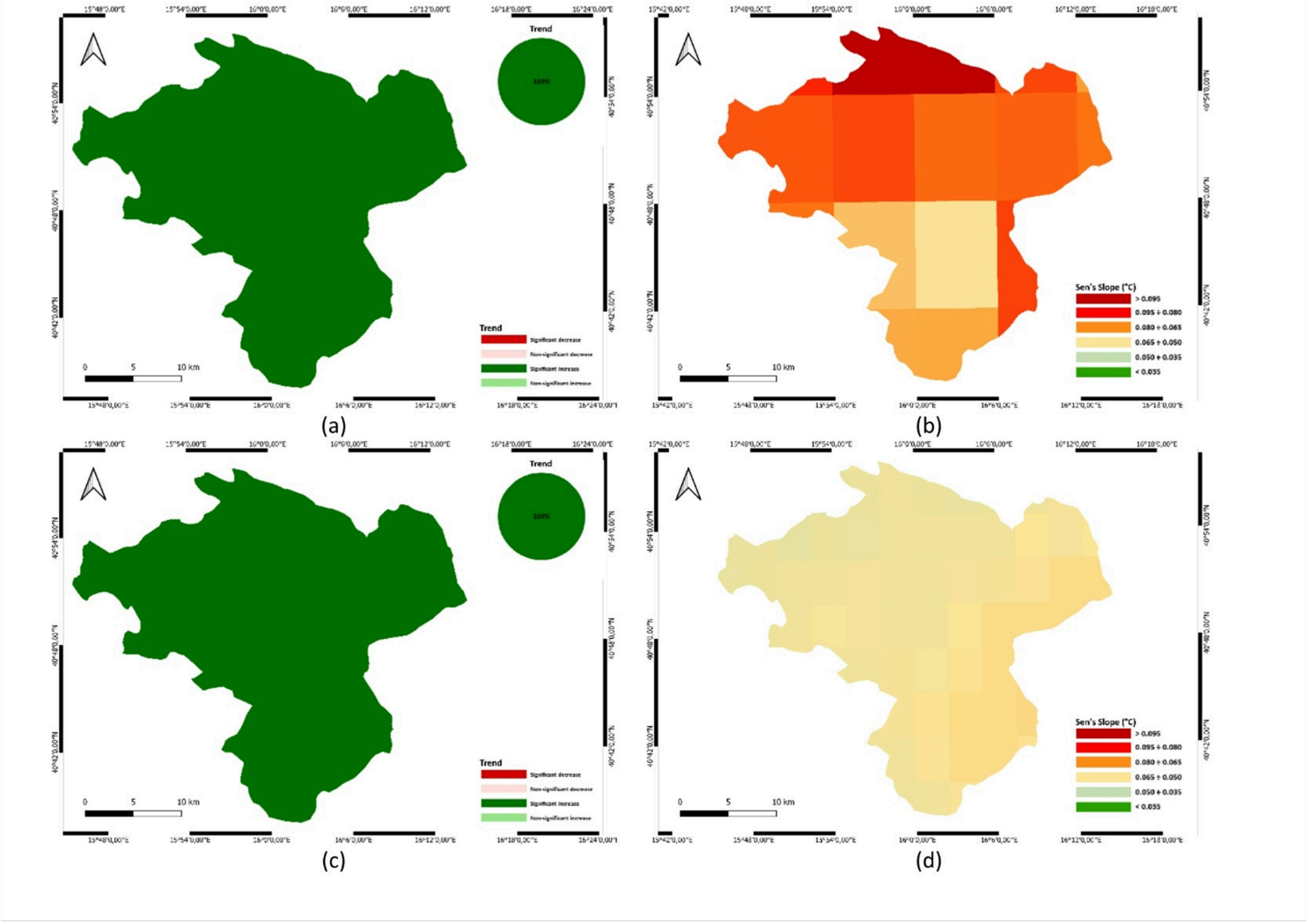


Figure 7

Spatial patterns of trends in annual maximum air temperature over the period 2005–2024 derived from ERA5-Land and TerraClimate. Panels (a) and (c) show the results of the Mann–Kendall test, while panels (b) and (d) display the corresponding Sen's slope values (°C yr^{-1})

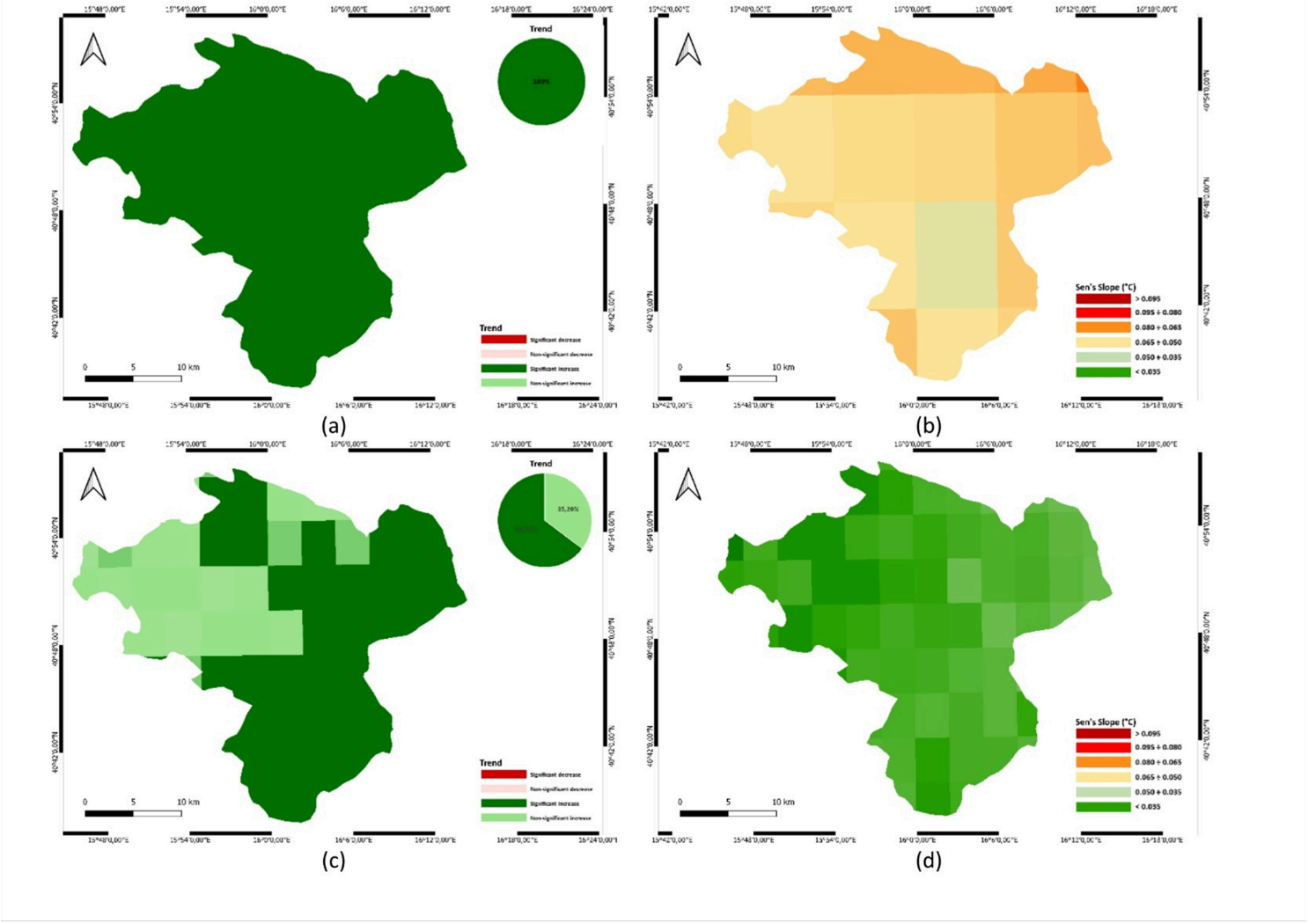


Figure 8

Spatial patterns of trends in annual minimum air temperature over the period 2005–2024 derived from ERA5-Land and TerraClimate. Panels (a) and (c) show the results of the Mann–Kendall test, while panels (b) and (d) display the corresponding Sen's slope values (°C yr⁻¹)