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Comparing the use of ERA5 reanalysis dataset and ground-based agrometeorological data under different climates and topography in Italy

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A R T I C L E I N F O

Keywords:
Weather ground-based observation
Reanalysis dataset
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A B S T R A C T

Study region: The study region is represented by seven irrigation districts distributed under different climate and topography conditions in Italy.

Study focus: This study explores the reliability and consistency of the global ERA5 single levels and ERA5-Land reanalysis datasets in predicting the main agrometeorological estimates commonly used for crop water requirements calculation. In particular, the reanalysis data was compared, variable-by-variable (*e.g.*, solar radiation, R_s; air temperature, T_{air}; relative humidity, RH; wind speed, u_{10}; reference evapotranspiration, ET_0), with *in situ* agrometeorological observations obtained from 66 automatic weather stations (2008–2020). In addition, the presence of a climate-dependency on their accuracy was assessed at the different irrigation districts.

New hydrological insights for the region: A general good agreement was obtained between observed and reanalysis agrometeorological variables at both daily and seasonal scales. The best performance was obtained for T_{air}, followed by RH, R_s, and u_{10} for both reanalysis datasets, especially under temperate climate conditions. These performances were translated into slightly higher accuracy of ET_0 estimates by ERA5-Land product, confirming the potential of using reanalysis datasets as an alternative data source for retrieving the ET_0 and overcoming the unavailability of observed agrometeorological data.

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1. Introduction

The quantitative estimation of the evapotranspiration (ET) fluxes exchanged within the soil-plant-atmosphere *continuum* is a precondition for rational irrigation scheduling, crop yield forecasting, and hydrological modelling applications (Hupet and Vanclooster, 2001). Nowadays, the crop reference ET (ET_0) formulation, proposed by Penman-Monteith (P-M) and popularized by the FAO-56 paper as a reference methodology for calculating crop water requirements (Allen et al., 1998), is still largely used for practical purposes (Pereira et al., 2015). The use of the P-M approach calls for the necessity of having a reliable and complete set of site-specific agrometeorological data. In fact, the P-M approach calculates the ET_0 for a standard surface, requiring a complete set of ground-based agrometeorological data, such as the air temperature (T_{air}), the wind speed (u_2), the solar radiation (R_s), and the relative humidity (RH), to parameterize the surface and aerodynamic resistances. Commonly, agrometeorological variables are measured by automatic weather stations. Their data integrity is ensured by proper data quality assessment and control procedures (De Pauw et al., 2000). However, ground-based observations could be affected by several errors, mainly due to the sensor properties, such as their accuracy, settings, instrument drift or temporal data sampling frequency (Beven, 1979; Hupet and Vanclooster, 2001; Meyer et al., 1989). Other shortcomings are related to the agrometeorological time-series consistency. The time series can suffer from substantial time gaps (Capra et al., 2013) and often protocols for correcting and/or estimating poor quality or missing data need to be applied (see, *e.g.*, Pereira et al., 2015). Moreover, the agrometeorological data representativeness of well-watered conditions needs to be checked before implementing them in the ET_0 approach (Pereira et al., 2015). Despite the utmost importance of observed agrometeorological data for agriculture purposes, the agrometeorological networks are often sparse over the territory, especially in arid zones (De Pauw et al., 2000). Sometimes, data access is another critical point for end-users because data is managed and distributed by different regional services at the National level (Pelosi et al., 2021). To compensate for the lack of spatial and temporal distributed information, other weather data sources have steadily developed, such as the use of interpolation methods from gauge-based observations, the adoption of satellite-based datasets, or the creation of gridded datasets obtained by adjusting the spatial interpolation estimates with satellite observations (Pelosi et al., 2020). Moreover, during the last century, great advances have been reached in agrometeorological data forecasting using global and regional numerical weather prediction (NWP) models. Several studies have already exploited their potential for supporting sustainable irrigation management (*e.g.* Negm et al., 2017; Chirico et al., 2018; Longo- Minnolo et al., 2020; Medina et al., 2018; Pelosi et al., 2016; Vanella et al., 2020). As an example, Vanella et al. (2020) showed that the use of forecast agrometeorological estimates provided by the Consortium for Small-scale Modelling (COSMO, http://www.cosmo-model.org) opens promising perspectives for assessing the ET_0 in different agriculture contexts, particularly under conditions of water scarcity, instead than using past agrometeorological data. Besides the NWP models, the use of atmospheric reanalysis is another alternative weather data source. Atmospheric reanalysis has generated increasing interest in the recent decade, due to its ability to provide complete and consistent time-series of multiple meteorological parameters at a global scale by covering several decades (Tarek et al., 2020). From a theoretical point of view, the reanalysis process is a retrospective analysis of past historical data. This process makes use of the ever-increasing computational resources, recent versions of NWP models and assimilation schemes. In general, the reanalysis approaches assimilate a wide array of atmospheric and ocean measured and remotely sensed information within a dynamical–physical coupled numerical model (Poli et al., 2016). One of the recognized advantages of using reanalysis approaches is that their outputs are not directly dependent on the density of ground-based observational networks. Thus they have the potential to provide variables in areas with little and/or no surface coverage (Tarek et al., 2020). Moreover, Pelosi et al. (2020) reported that reanalysis data can represent an efficient data source for planning and design studies applied to irrigation water management.

Currently, several modelling centres provide reanalysis products at variable spatial and temporal scales (Lindsay et al., 2014; Chaudhuri et al., 2013). As an example, the European Centre for Medium-Range Weather Forecasts (ECMWF) periodically applies its forecast models and data assimilation systems to reanalyse archived observations for generating global data sets describing the recent history of the atmosphere, land surface, and oceans. The latest released ECMWF reanalysis products are ERA5 single levels (ERA5) and ERA5 Land (ERA5-L), which are being produced within the Copernicus Climate Change Service and freely distributed since 2019. The first dataset, ERA5, covers the entire globe from 1979 at a spatial resolution of about 30 km (depending on latitude). The second dataset, ERA5-L, has been produced by replaying the land component of the ERA5 climate reanalysis, with a horizontal spatial resolution of 9 km. Specifically, ERA5-L uses air temperature (T_{air}), air humidity and air pressure, in a process of atmospheric forcing, as input to control the simulated land fields. These atmospheric variables are corrected to account for the altitude difference between the grid of the forcing and the higher resolution grid of ERA5-L (Muñoz-Sabater, 2019). A comprehensive review of the state-of-the-art associated with the use of ERA5-L for land and environmental applications is presented by Muñoz-Sabater et al. (2021). They demonstrated the added value of ERA5-L reanalysis products, in comparison to ERA-Interim and ERA5, for estimating a wide range of *in situ* observations, even if they have not evaluated the performance of the reanalysis products in predicting ET fluxes.

The specific objective of this study was to explore the effectiveness of using the most advanced global ECMWF reanalysis data (ERA5 single levels and ERA5-L) as a potential data source for predicting the main agrometeorological variables and estimating the ET_0 in different climate contexts within the Italian territory, at daily and seasonal scales. In addition, visual Geographic Information System (GIS) based user-friendly tools have been developed in this study for guiding the users in the reanalyses data pre-processing steps.

2. Materials and methods

The methodological approach proposed in this study was carried out in the framework of the research project *INtegrated Computer modeling and monitoring for Irrigation Planning in Italy* (INCIPIT). The general aim of the INCIPIT project is to identify a shared set of modelling tools and monitoring techniques for the assessment of irrigation water uses in seven irrigation districts distributed over the

Italian territory. In this context, time series of daily values of the agrometeorological variables registered in 66 weather stations, referred to as the INCIPIT irrigation districts (Table 1 and Fig. 1), were collected. The use of the new generation ECMWF reanalysis datasets was then evaluated in comparison to the retrieved ground-based agrometeorological data for the ET_0 estimation.

2.1. *Ground-based agrometeorological variables at the study sites*

The observed agrometeorological data was acquired on a daily scale from 66 weather stations located in six different Italian administrative regions (Campania, Emilia-Romagna, Lombardy, Apulia, Sardinia, and Sicily), within the reference period 2008–2020 (from January 1st 2008 to December 31st 2020). Due to the trans-regional component of this study, the observed agrometeorological data were provided from multiple ground-based sources managed by different Regional meteorological agencies located in each of the irrigation districts of interest (Fig. 1 and Table 1).

The set of agrometeorological variables under investigation was composed of solar radiation (R_s, W m^{-2}), maximum and minimum T_{air} measured at 2 m (°C), maximum and minimum relative humidity (RH, %), wind speed measured at 2 m (u_2, m s^{-1}) and 10 m (u_{10}, m s^{-1}), respectively, and ET_0 estimates calculated with the P-M approach (mm d^{-1}).

The selection of the weather stations was based on a twofold criterion. Firstly, they were identified by setting a maximum distance (50 km) between the centroid of each of the 7 irrigation districts under study (whose coordinates are reported in Table 1) and the candidate weather stations. Secondly, the selection was refined based on the temporal consistency (*i.e.* continuous time series) and completeness (*i.e.* the complete set of data) of the available agrometeorological series. Under these criteria, more than 50 million records were acquired from 66 weather stations, covering a great range of climatic conditions, mainly in terms of the different irrigation district geographic locations (*i.e.*, northern, central and insular Italy) and elevation features (Table 1). Note that the available dataset for Sardinia sites was only composed of the ET_0 estimates.

In particular, under the improved Köppen-Geiger classification, recently provided at 1-km resolution by Beck et al. (2018), a number of 7 weather stations located in Apulia are characterized by arid, steppe, cold climate (BSk); 24 sites, placed in Campania, Sicily (Eastern and Western part) and Sardinia, are featured by dry and hot-summer temperate climate (Csa); and 32 sites, located in Emilia-Romagna and Lombardy, are referred to no dry season, hot summer temperate climate conditions (Cfa).

The quality of the ground-based data was checked according to the procedure proposed in Allen (1996). Daily ground-based data was aggregated in 4 periods for seasonality analyses on the astronomical basis, as follows: winter (1st January–19th March and 21st-31st December), spring (20th March–20th June), summer (21st June– 22nd September), and autumn (23rd September–20th December).

Table 1
Denominations and locations of the investigated irrigation districts, climate characterization and number of referred weather stations, including the name of the regional meteorological agencies.

Italian Region		Irrigation districts	Latitude (°)	Longitude (°)	Average altitude (± standard error) (m, a.s.l.)	Climate condition	Number of weather station	Regional meteorological agencies
Lombardy		n. 4 districts – Adda river basin	45.37	9.54	150.0 ± 28.5	Temperate, no dry season, hot summer (Cfa)	21	Arpa Lombardia (https://www.arpalombardia.it/)
Emilia-Romagna		n. 7 districts – Consorzio di Bonifica Renana	44.52	11.24	274.2 ± 113.9		14	Arpae Emilia-Romagna (https://simc.arpae.it/dext3r/)
Campania		Consorzio di Bonifica del Bacino Inferiore del Volturno	41.20	14.15	64.5 ± 26.8	Temperate, dry and hot summer (Csa)	6	Protezione Civile Campania
Sicily	Western	n. 1 district “1 A” – Consorzio di Bonifica Sicilia Occidentale	37.78	12.95	247.0 ± 94.3		5	Servizio Informativo Agrometeorologico Siciliano (www.sias.regione.sicilia.it)
	Eastern	n. 1district “Quota 102.50” – Consorzio di Bonifica Sicilia Orientale	37.39	14.74	435.3 ± 135.2		7	
Sardinia		n. 2 districts “Cedrino” and “Posada” - Consorzio di Bonifica della Sardegna Centrale	40.39	15.48	553.9 ± 139.6		6	Sardegna Arpa (http://www.sar.sardegna.it/)
Apulia		n. 1 district 10 -Consorzio di Bonifica della Capitanata	41.3	15.75	120.0 ± 37.5	Arid, steppe, cold (BSk)	7	Consorzio di Bonifica della Capitanata

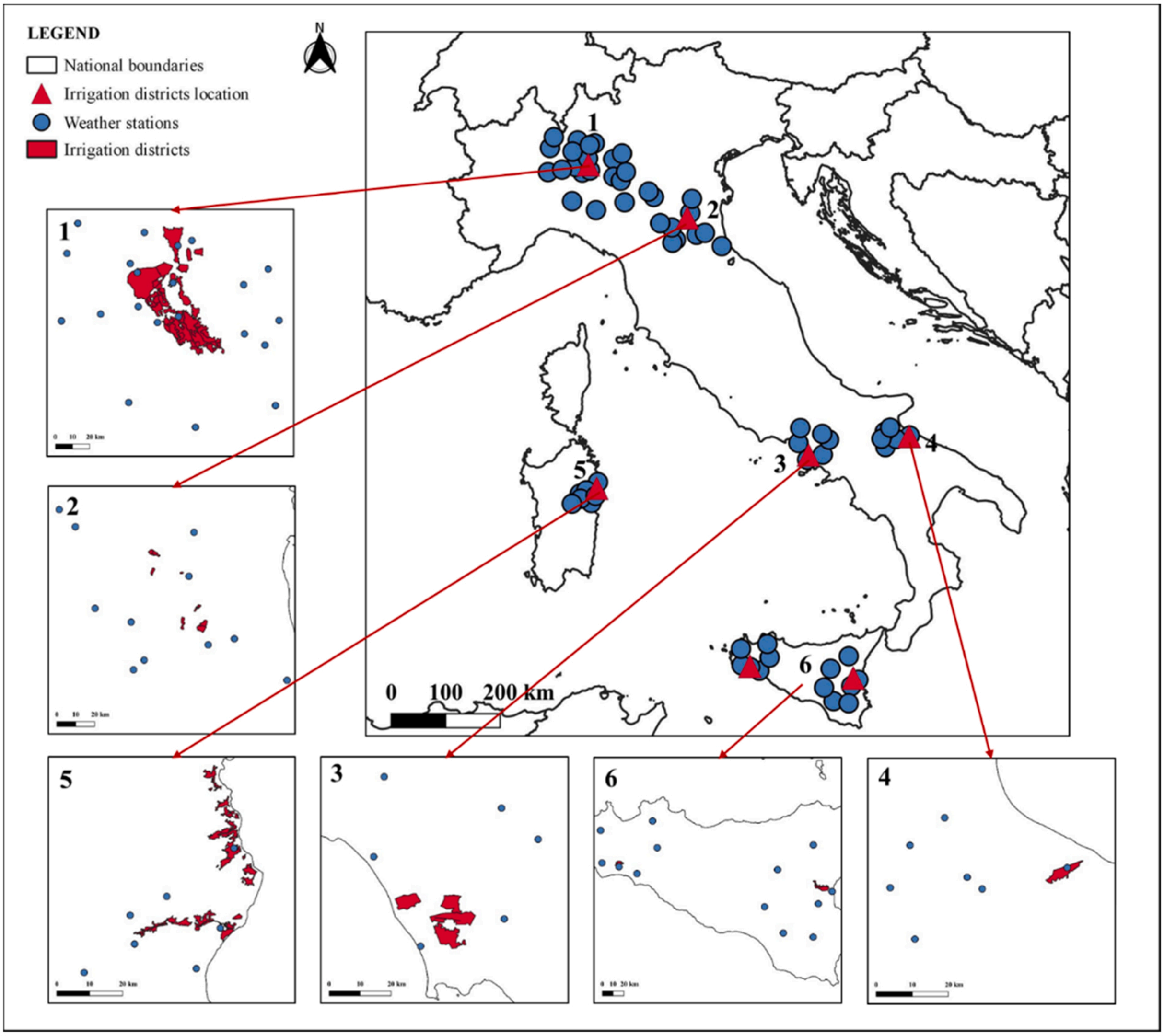

Fig. 1. Location of the weather stations selected over the investigated irrigation districts within the Italian peninsula: (1) Lombardy; (2) Emilia-Romagna; (3) Campania; (4) Apulia; (5) Sardinia; and (6) Sicily (Eastern and Western sides).

2.2. Reanalysis datasets description

The technical characteristics of the used reanalysis datasets (ERA5 single levels and ERA5-L) and the related data-processing steps are described in Sections 2.2.1 and 2.2.2, respectively.

2.3. Reanalysis data collection and characteristics

In this study, the most advanced global reanalysis data produced in Europe by ECMWF has been used: ERA5 single levels (Hersbach

Table 2
Main technical details of the reanalysis datasets used in this study.

Reanalysis dataset characteristics	ERA5	ERA5-L
Data type	Gridded	
Projection	Regular latitude-longitude grid	
Horizontal coverage	Global	
Horizontal resolution (atmosphere)	0.25° x 0.25°	0.1° x 0.1°
Temporal coverage	1979 to present	1950 to present
Temporal resolution	Hourly	

et al., 2020) and ERA5-L (Muñoz-Sabater, 2019). The main technical details of these reanalysis datasets are reported in Table 2.

The ERA5 dataset is the 5th generation of ECMWF global reanalysis succeeding ERA-Interim and covering the entire globe from 1979, at a spatial resolution of about 30 km. The ERA5-L dataset is generated for the entire globe with a native horizontal resolution of about 9 km (released on a regular 0.1∘ x 0.1∘ grid) by replaying the land component of ERA5 climate reanalysis, from 1981 to 2–3 months before the present. Specifically, the atmospheric forcing in ERA5-L is provided by land fields of ERA5 atmospheric variables. In ERA5, T_{air}, air humidity and air pressure are corrected to account for the elevation difference between the grid of the forcing and the higher-resolution grid of ERA5-L, according to the so-called lapse rate correction (Muñoz-Sabater, 2019). Although ERA5-L runs at the enhanced spatial resolution, there is a limit that data are not provided for numerical grid points falling on the sea surface or in the proximity of the coastline (Pelosi et al., 2020).

The ERA5 and ERA5-L reanalysis datasets were freely downloaded from the Climate Change Service Copernicus platform (https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset) through the Climate Data Store web interface v.1.0 in Network common data form (NetCDF) format for the entire Italian domain (1221.79 ×916.46 km), as for the ground-based observations, within the reference period 2008–2020. The hourly agrometeorological variables of interest were: the T_{air} ('2m_temperature', t2m, °C) and the dew point temperatures (T_{dew}, named as '2m_dewpoint_temperature d2m, m s^{-1}'); the R_s ('surface_solar_radiation_downwards', ssrd, J m^{-2}) and; the vertical and horizontal component of the wind speed ('10m_u_component_of_wind', U10, m s^{-1}, and '10m_v_component_of_wind', V10, m s^{-1}).

2.3.1. Data pre-processing steps

Both hourly ERA5 single levels and ERA5-L data were aggregated at a daily time step to be compared variable-by-variable with the ground-based observations.

The daily minimum and maximum T_{air} and T_{dew} values were obtained from the hourly data. The daily T_{air} comparisons were carried out considering the average of the daily maximum (T_{max}) and minimum temperatures (T_{min}). The daily R_s values were aggregated on 24 h basis. The daily RH was calculated as the ratio between the actual (e_a) and the saturation (e_o(T)) vapour pressure using the average T_{air} and T_{dew} derived on 24 h basis as inputs, according to the formula proposed in Allen et al. (1998):

$$RH = 100 \bullet \frac{e_a}{e_o(T)} \tag{1}$$

$$e_a = e^o(T_{dew}) = 0.6108 \bullet exp \left(\frac{17.27 \quad T_{dew}}{T_{dew} + \quad 237.3}\right) \tag{2}$$

$$e_o(T) = 0.6108 \bullet exp \left(\frac{17.27 \quad T_{air}}{T_{air} + \quad 237.3}\right) \tag{3}$$

The daily wind speed at 10 m (u_{10}, m s^{-1}) was calculated using the horizontal and vertical components (V10 and U10) retrieved by ERA5 and ERA5-L datasets, as reported in Allen et al. (1998). Note that the wind speed comparison between the ground-based and reanalysis observations was performed on the u_{10} basis. The wind speed at 2 m (u_2) was rescaled, from the logarithmic wind profile, for being used as input in the ET_0 calculation using the P-M approach (see Section 2.3).

The above-mentioned reanalysis datasets data pre-processing steps were performed using five *ad hoc* GIS-based toolboxes developed in ArcPy (ESRI©) (see "Supplementary materials" section). The reanalysis post-processed data were extracted from the overall domain at the weather stations' location variable-by-variable (Fig. 1). Finally, as for the daily ground-based data, the reanalysis data were aggregated in four periods for seasonality analyses using the same time step as used for the ground-based data.

2.4. Calculating daily ET_0 estimates

Although ERA5 single levels and ERA5-L provide potential evapotranspiration data (ET_p), this variable is conceptually different from ET_0 estimates as defined in the FAO-56 paper (Allen et al., 1998). In particular, ET_p is computed in ERA5 based on surface energy balance calculations with the vegetation parameters set to "crops/mixed farming" and assuming "no stress from soil moisture" (Hersbach et al., 2018), whereas, ET_p in ERA5-L is computed as open water evaporation assuming that the atmosphere is not affected by the artificial surface condition (Muñoz 2019). Thus, in this study daily ET_0 estimates were obtained by implementing the reanalysis of agrometeorological data through the Penman-Monteith (PM) method (Penman, 1956; Monteith, 1965), as follows:

$$ET_0 = \frac{0.408 \quad \Delta \bullet (R_n - G) \quad + \quad \gamma \quad \bullet \quad \frac{C_n}{T+273} \bullet u_2 \bullet \quad (e_s - e_a)}{\Delta \quad + \quad \gamma \bullet (1 + C_d u_2)} \tag{4}$$

where, R_n is the net radiation at the grass surface and G is the soil heat flux density (in MJ m^{-2} d^{-1} for a 24-h daily time step); C_n and C_d are constants, equal to 900 and 0.34, respectively, which vary according to the time step, the reference crop type and daytime/nighttime ratio; T is the mean daily T_{air} (°C); γ is the slope of the saturation vapour pressure curve at T_{air} (kPa °C^{-1}); γ is the psychrometric constant (kPa °C^{-1}); e_s is the saturation vapour pressure at T_{air} (kPa); e_a is the average daily actual vapour pressure (kPa); and u_2 is the average daily wind speed at 2 m height (m s^{-1}).

Note that the daily ET_0 ground-based estimates (mm d^{-1}) were provided at all site locations by the Regional meteorological agencies (Table 1), except for Campania and Emilia-Romagna regions for which daily ET_0 values were estimated by Eq. 4 using the

Table 3
Daily and seasonal performance obtained by comparing the predicted agrometeorological estimates from the ERA5 reanalysis dataset and the ground-based observations; RMSE, MAE, PBIAS and NRMSE refer to the root mean square error, the mean absolute error, the percent bias and the normalized root-mean-square error, respectively.

Italian region		Time-scale	Air temperature (T_{air})				Solar radiation (R_s)				Wind speed (u_{10})				Relative humidity (RH)			
			RMSE °C	MAE °C	PBIAS %	NRMSE	RMSE $W\ m^{-2}$	MAE $W\ m^{-2}$	PBIAS %	NRMSE	RMSE $m\ s^{-1}$	MAE $m\ s^{-1}$	PBIAS %	NRMSE	RMSE %	MAE %	PBIAS %	NRMSE
Lombardy		daily	1.62	1.20	-0.38	0.11	35.03	26.41	1.76	0.23	0.69	0.52	-15.69	0.45	8.62	6.70	-2.95	0.12
		winter	1.63	1.24	6.97	0.32	25.59	19.30	11.86	0.32	0.71	0.52	-14.35	0.46	8.96	6.93	-4.42	0.11
		spring	1.62	1.16	-2.58	0.10	42.82	33.49	1.25	0.20	0.78	0.60	-21.24	0.44	8.26	6.40	-2.25	0.12
		summer	1.74	1.27	-1.33	0.07	41.86	33.34	-3.22	0.17	0.64	0.50	-18.39	0.43	9.35	7.40	-1.96	0.14
		autumn	1.47	1.11	1.96	0.14	24.86	18.89	9.39	0.33	0.63	0.47	-6.37	0.47	7.80	6.04	-3.00	0.10
Emilia-Romagna		daily	1.78	1.38	6.62	0.13	29.83	21.99	-0.09	0.18	1.39	0.93	-34.72	0.57	8.93	7.06	4.58	0.13
		winter	1.85	1.44	17.74	0.37	22.42	16.52	5.39	0.26	1.50	0.95	-33.60	0.61	9.76	7.41	5.18	0.13
		spring	1.77	1.33	5.35	0.11	38.07	28.92	0.70	0.17	1.42	1.00	-35.60	0.54	8.32	6.78	3.61	0.13
		summer	1.78	1.40	4.19	0.08	32.84	25.38	-3.58	0.13	1.25	0.93	-37.16	0.53	8.77	7.13	3.73	0.15
		autumn	1.73	1.35	8.95	0.16	21.68	16.30	3.42	0.25	1.40	0.84	-31.95	0.63	8.88	6.94	5.60	0.12
Campania		daily	2.26	1.83	-9.22	0.14	33.54	24.75	4.61	0.20	0.82	0.56	-18.13	0.43	7.87	6.16	-0.39	0.10
		winter	2.09	1.65	-12.54	0.23	26.88	20.90	13.89	0.29	1.02	0.65	-16.70	0.47	8.53	6.64	-1.56	0.11
		spring	2.55	2.14	-11.66	0.15	41.16	31.50	3.59	0.18	0.81	0.57	-23.63	0.41	7.54	5.86	2.77	0.10
		summer	2.43	1.99	-7.51	0.10	32.09	23.57	-0.46	0.12	0.63	0.48	-23.32	0.35	7.09	5.59	1.20	0.10
		autumn	1.92	1.50	-7.20	0.13	32.23	22.87	12.89	0.34	0.80	0.53	-8.12	0.45	8.30	6.60	-3.57	0.10
Sicily	**Western**	daily	1.56	1.24	2.47	0.09	30.16	21.89	2.28	0.15	1.46	1.05	-7.75	0.45	11.13	8.50	8.78	0.17
		winter	1.64	1.31	9.37	0.15	28.20	21.97	4.73	0.23	1.71	1.24	-1.13	0.48	7.97	6.34	3.82	0.11
		spring	1.48	1.18	0.37	0.08	39.38	28.32	5.22	0.15	1.38	0.99	-12.95	0.40	12.46	9.71	11.86	0.20
		summer	1.57	1.26	-0.65	0.06	25.18	17.68	0.78	0.09	1.11	0.84	-17.11	0.37	14.08	10.87	15.30	0.24
		autumn	1.54	1.23	5.40	0.09	25.35	19.51	-2.71	0.19	1.61	1.14	0.01	0.51	8.52	6.85	5.46	0.12
	Eastern	daily	1.47	1.19	0.38	0.09	33.11	24.43	1.89	0.17	1.35	1.12	-35.75	0.48	9.63	7.75	7.55	0.15
		winter	1.56	1.29	2.16	0.16	29.12	22.33	1.60	0.23	1.40	1.12	-29.53	0.46	9.49	7.53	7.09	0.13
		spring	1.42	1.13	0.42	0.08	42.74	31.45	5.12	0.17	1.35	1.15	-36.10	0.46	9.10	7.28	5.54	0.15
		summer	1.39	1.10	-0.95	0.06	30.69	22.33	1.33	0.11	1.37	1.19	-45.24	0.54	10.42	8.53	10.21	0.19
		autumn	1.52	1.24	1.52	0.10	27.35	21.44	-3.12	0.21	1.26	1.02	-32.31	0.48	9.45	7.66	7.70	0.13
Apulia		daily	1.46	1.15	4.14	0.09	45.03	30.72	-5.21	0.24	1.57	1.17	-19.43	0.58	19.02	15.30	-18.46	0.24
		winter	1.41	1.13	7.13	0.17	37.27	26.24	-4.77	0.33	1.81	1.31	-20.48	0.59	16.31	13.70	-15.42	0.19
		spring	1.55	1.21	4.60	0.09	54.82	38.86	-2.64	0.22	1.37	1.07	-17.74	0.49	21.73	17.74	-22.18	0.28
		summer	1.35	1.08	2.31	0.05	51.29	34.70	-6.32	0.18	1.54	1.18	-24.97	0.57	20.59	15.65	-21.36	0.30
		autumn	1.50	1.20	5.23	0.11	32.71	23.01	-8.31	0.28	1.53	1.11	-13.39	0.65	16.81	14.11	-15.74	0.19

Table 4
Daily and seasonal performance obtained by comparing the predicted agrometeorological estimates from the ERA5-L reanalysis dataset and the ground-based observations; RMSE, MAE, PBIAS and NRMSE refer to the root mean square error, the mean absolute error, the percent bias and the normalized root-mean-square error, respectively.

Italian region		Time-scale	Air temperature (T_{air})				Solar radiation (R_s)				Wind speed (u_{10})				Relative humidity (RH)			
			RMSE	MAE	PBIAS	NRMSE	RMSE	MAE	PBIAS	NRMSE	RMSE	MAE	PBIAS	NRMSE	RMSE	MAE	PBIAS	NRMSE
			°C	°C	%		W m^{-2}	W m^{-2}	%		m s^{-1}	m s^{-1}	%		%	%	%	
		daily	1.80	1.42	-6.10	0.13	34.68	26.13	1.83	0.22	0.90	0.71	-29.11	0.58	8.43	6.59	2.03	0.11
		winter	1.76	1.35	-8.77	0.34	25.46	19.21	11.58	0.32	0.86	0.67	-25.24	0.56	8.70	6.74	1.03	0.11
Lombardy		spring	2.07	1.68	-9.02	0.12	42.39	33.10	1.40	0.19	1.04	0.85	-36.42	0.58	8.38	6.54	4.58	0.12
		summer	1.86	1.48	-4.70	0.08	41.30	32.81	-3.06	0.17	0.90	0.73	-33.99	0.60	8.97	7.08	2.64	0.13
		autumn	1.47	1.14	-3.37	0.14	24.69	18.78	9.33	0.33	0.76	0.58	-17.58	0.57	7.58	5.97	0.30	0.09
		daily	1.84	1.36	1.35	0.13	33.99	23.99	0.08	0.20	1.61	1.21	-45.22	0.66	10.83	8.56	9.07	0.16
		winter	2.08	1.50	6.36	0.41	26.10	18.35	5.85	0.30	1.69	1.19	-42.70	0.68	12.55	9.76	10.08	0.17
Emilia-Romagna		spring	1.72	1.32	-1.37	0.11	44.33	31.97	0.89	0.19	1.66	1.30	-46.15	0.62	10.52	8.51	9.92	0.17
		summer	1.72	1.28	0.70	0.07	36.22	27.07	-3.51	0.14	1.53	1.24	-49.27	0.64	9.64	7.75	7.84	0.16
		autumn	1.83	1.35	4.68	0.17	24.26	17.74	3.63	0.28	1.57	1.08	-42.05	0.71	10.57	8.30	8.41	0.14
		daily	2.60	2.18	-11.75	0.16	33.81	24.97	4.64	0.20	1.03	0.8	-30.59	0.54	8.23	6.28	3.22	0.11
		winter	2.58	2.11	-19.73	0.28	27.02	21.03	13.70	0.29	1.14	0.82	-24.34	0.53	9.55	7.12	4.10	0.12
Campania		spring	2.95	2.59	-14.33	0.17	41.39	31.65	3.63	0.18	1.08	0.88	-39.80	0.54	8.52	6.59	6.46	0.12
		summer	2.53	2.16	-7.96	0.10	32.40	23.78	-0.37	0.12	0.95	0.79	-41.16	0.53	6.74	5.34	1.88	0.10
		autumn	2.28	1.85	-10.42	0.16	32.60	23.26	12.92	0.35	0.95	0.69	-16.33	0.53	7.96	6.13	0.64	0.10
		daily	1.37	1.09	-1.36	0.08	30.31	21.89	2.63	0.15	1.54	1.19	-7.19	0.47	9.72	7.99	9.32	0.15
		winter	1.44	1.13	-0.15	0.13	28.46	22.14	5.19	0.23	1.71	1.33	1.71	0.47	9.11	7.43	6.84	0.12
	Western	spring	1.36	1.08	-2.47	0.08	39.75	28.45	5.61	0.15	1.44	1.11	-13.21	0.42	10.27	8.49	11.58	0.16
		summer	1.33	1.06	-1.61	0.05	25.12	17.50	1.02	0.09	1.30	1.04	-18.87	0.44	9.82	8.02	11.43	0.17
Sicily		autumn	1.36	1.09	-0.52	0.08	25.28	19.41	-2.28	0.19	1.67	1.29	1.39	0.53	9.61	7.96	7.91	0.13
		daily	1.31	1.05	-1.51	0.08	33.47	24.76	2.00	0.17	1.54	1.3	-41.43	0.55	11.52	9.29	10.45	0.18
		winter	1.32	1.06	-4.68	0.14	29.11	22.38	1.56	0.23	1.50	1.22	-31.06	0.49	12.41	10.16	12.44	0.17
	Eastern	spring	1.28	1.03	-0.47	0.08	42.78	31.49	5.20	0.17	1.56	1.34	-42.29	0.53	9.67	7.79	7.93	0.16
		summer	1.36	1.08	-0.70	0.05	31.40	22.82	1.50	0.12	1.68	1.49	-56.64	0.66	11.57	9.28	10.08	0.21
		autumn	1.28	1.02	-2.16	0.08	28.19	22.16	-2.98	0.22	1.39	1.14	-35.86	0.53	12.30	10.03	11.09	0.17
		daily	1.97	1.44	-2.46	0.12	44.98	30.67	-5.29	0.24	1.75	1.34	-23.50	0.64	15.98	12.03	-11.92	0.20
		winter	1.86	1.38	-6.46	0.22	37.22	26.20	-4.99	0.33	1.95	1.45	-21.52	0.63	12.00	9.54	-7.37	0.14
Apulia		spring	2.20	1.58	-3.48	0.13	54.72	38.74	-2.66	0.22	1.59	1.27	-22.22	0.57	17.27	13.36	-13.46	0.22
		summer	1.90	1.40	-1.07	0.08	51.25	34.64	-6.34	0.18	1.76	1.39	-34.50	0.65	19.75	14.45	-17.89	0.29
		autumn	1.88	1.40	-1.49	0.13	32.71	23.03	-8.51	0.28	1.68	1.26	-14.31	0.71	13.41	10.63	-9.95	0.15

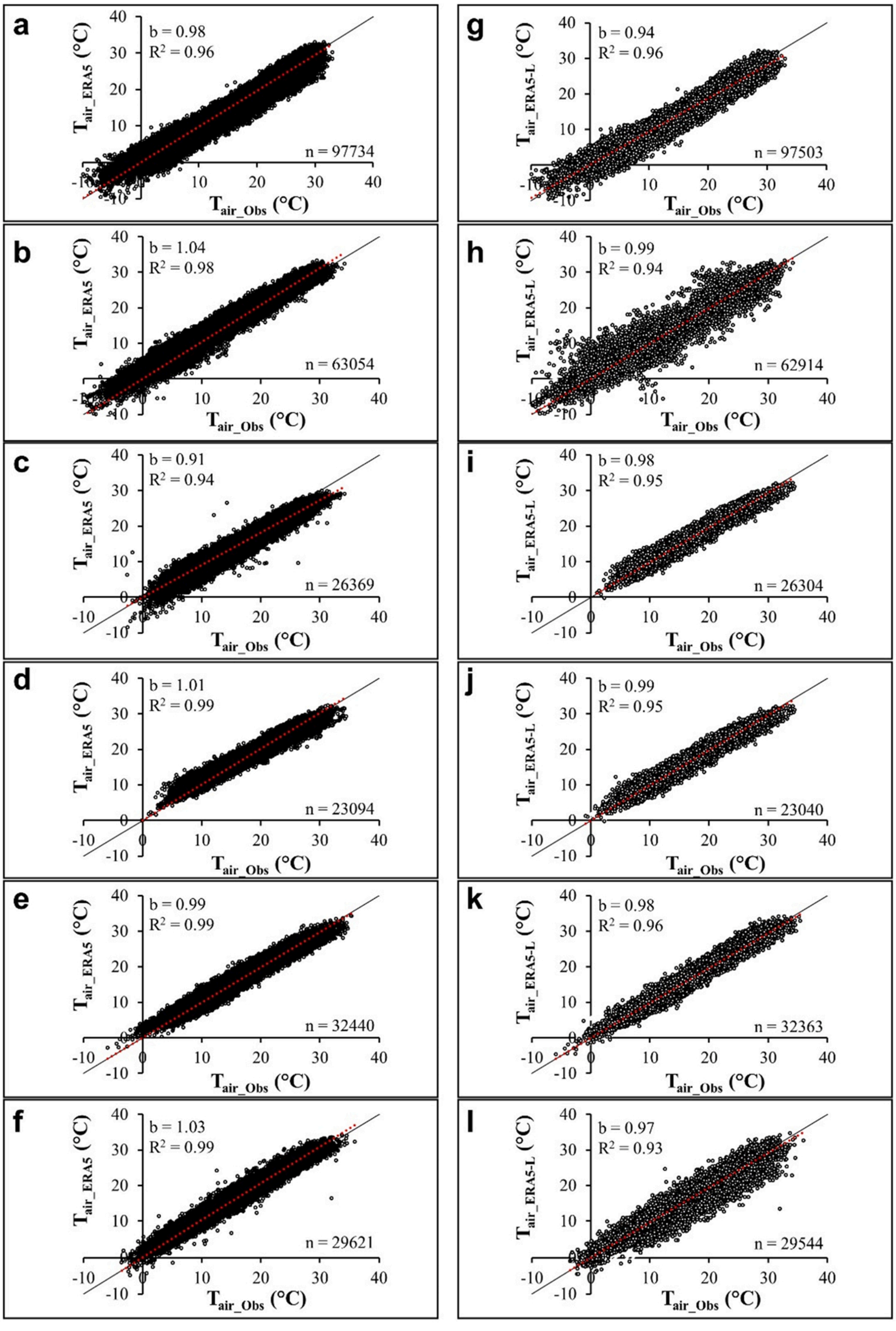

Fig. 2. Daily average predicted air temperature (T_{air_ERA5} and $T_{air\_ERA5\text{-}L}$, °C) *versus* observed (T_{air_Obs}, °C) values at the irrigation districts located in Lombardy (a, g), Emilia-Romagna (b, h); Campania (c, i), Western Sicily (d, j), Eastern Sicily (e, k) and Apulia (f, l) within the period 2008–2020. The black line and red line represent the 1:1 line and linear regression line, respectively. The terms b, R^2 and n refer to the slope of the regression equation through the origin, the coefficient of determination and the number of observations, respectively.

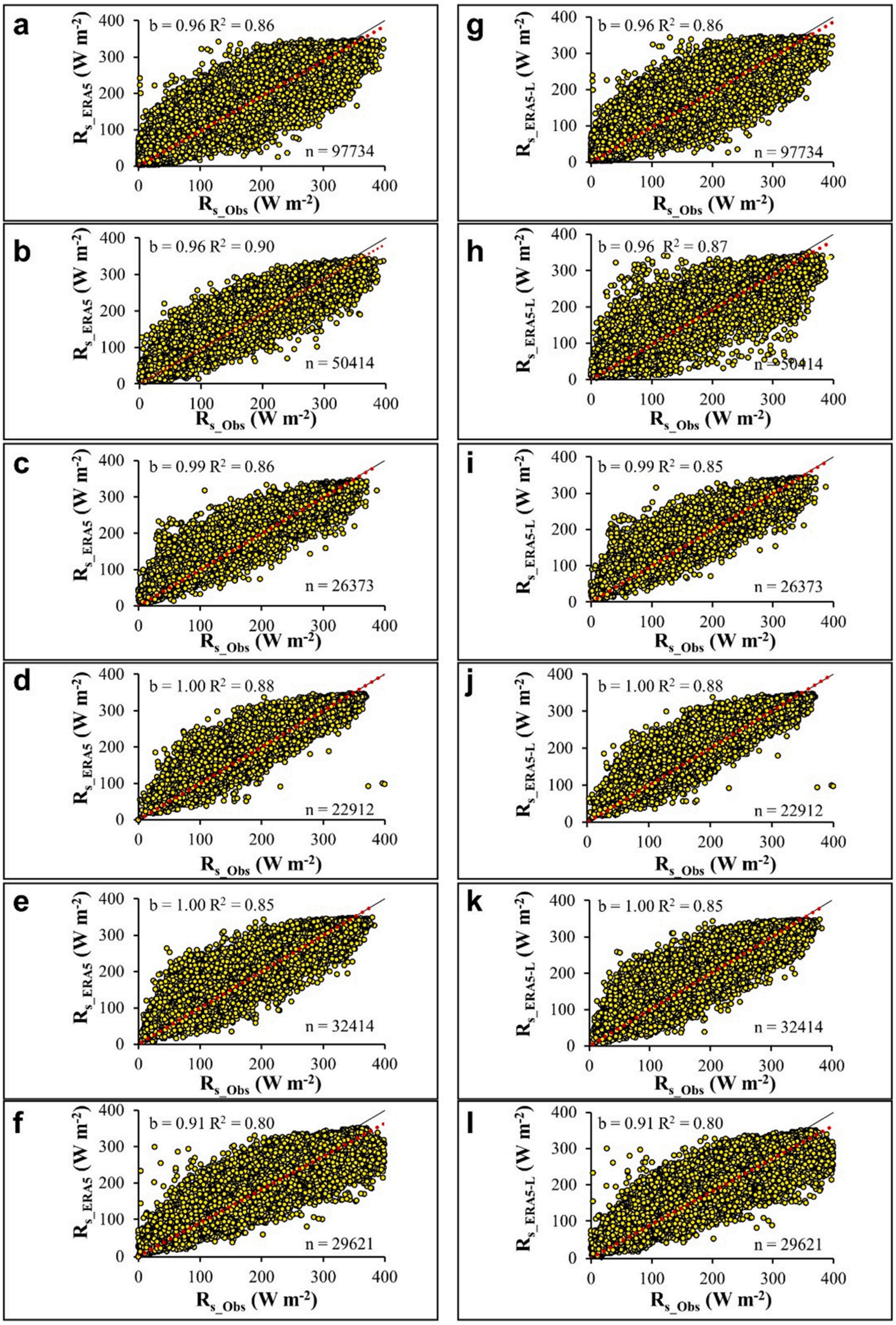

Fig. 3. Daily predicted solar radiation (R_{s_ERA5} and $R_{s\_ERA5\text{-}L}$, W m^{-2}) *versus* observed (R_{s_Obs}, W m^{-2}) values at the irrigation districts located in Lombardy (a, g), Emilia-Romagna (b, h); Campania (c, i), Western Sicily (d, j), Eastern Sicily (e, k) and Apulia (f, l) for the period 2008–2020. The black line and red line represent the 1:1 line and linear regression line, respectively. The terms b, R^2 and n refer to the slope of the regression equation through the origin, the coefficient of determination and the number of observations, respectively.

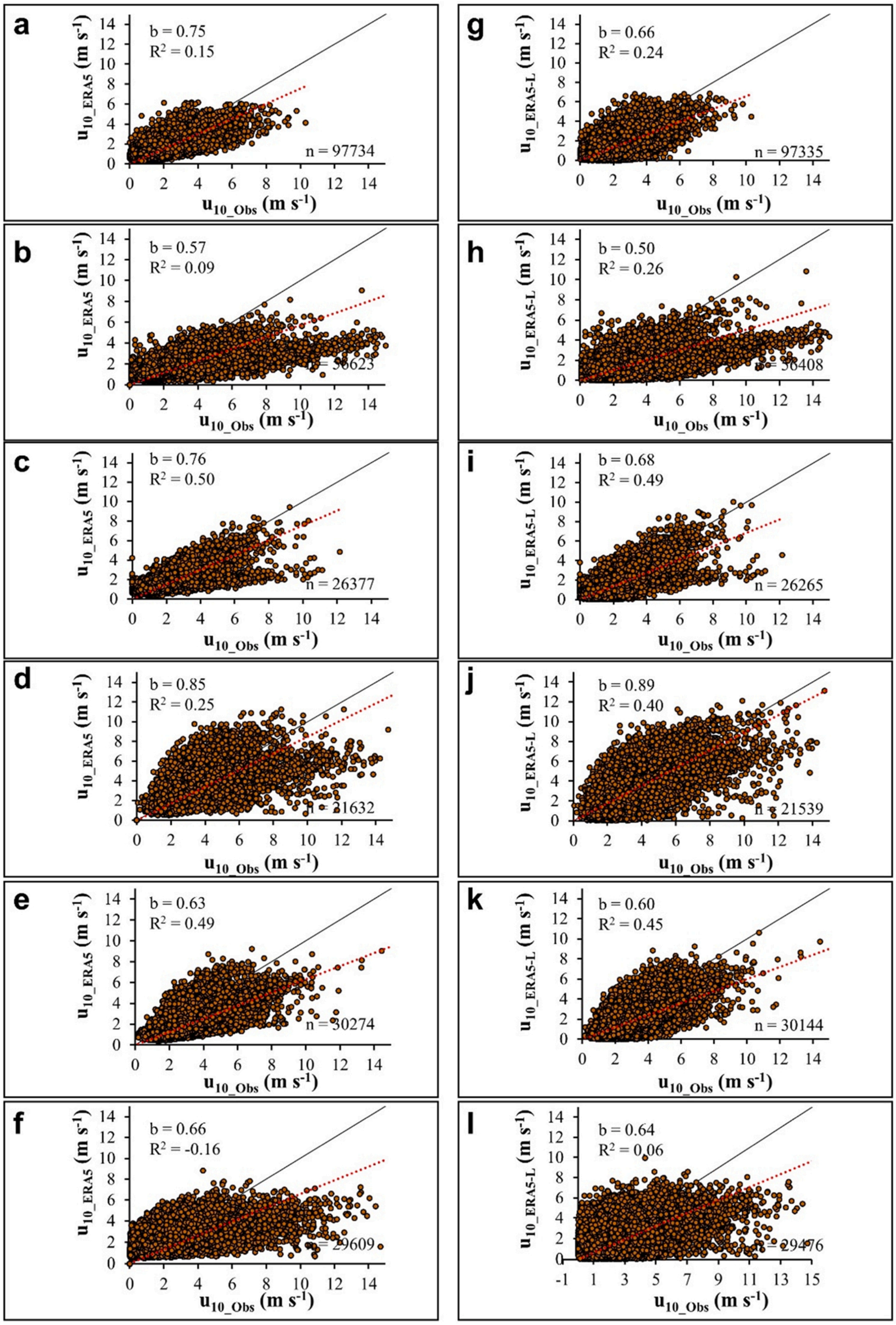

Fig. 4. Daily predicted wind speed ($u_{10\ \_ERA5}$ and $u_{10\ \_ERA5\text{-}L}$, m s^{-1}) *versus* observed (u_{10_Obs}, m s^{-1}) values at the irrigation districts located in Lombardy (a, g), Emilia-Romagna (b, h); Campania (c, i), Western Sicily (d, j), Eastern Sicily (e, k) and Apulia (f, l) within the period 2008–2020. The black line and red line represent the 1:1 line and linear regression line through the origin, respectively. The terms b, R^2 and n refer to the slope of the regression equation, the coefficient of determination and the number of observations, respectively.

agrometeorological information measured *in situ*.

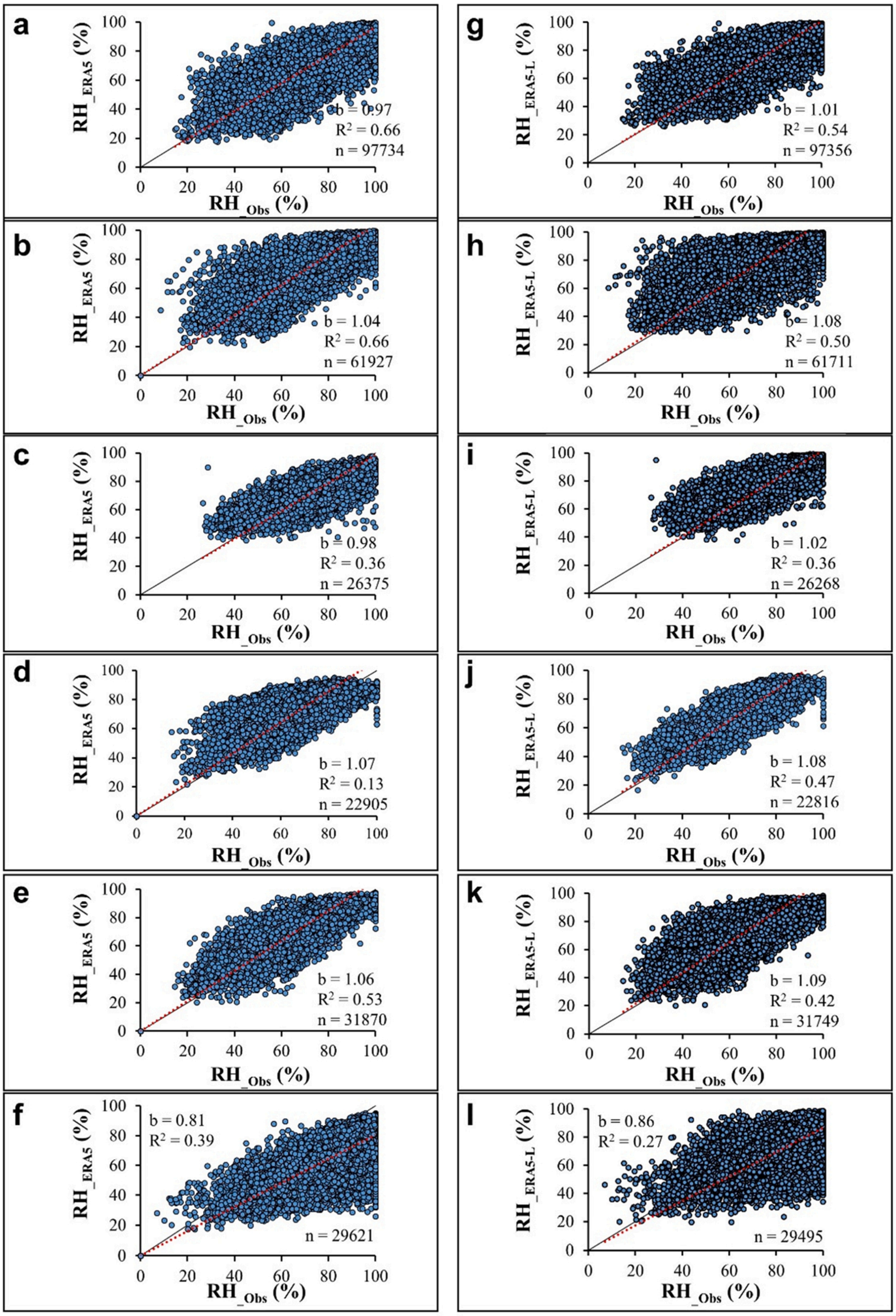

Fig. 5. Daily predicted relative air humidity ($RH_{\_ERA5}$ and $RH_{\_ERA5\text{-}L}$, %) *versus* observed ($RH_{\_Obs}$, %) values at the irrigation districts located in Lombardy (a, g), Emilia-Romagna (b, h); Campania (c, i), Western Sicily (d, j), Eastern Sicily (e, k) and Apulia (f, l) for the period 2008–2020. The black and red lines represent the 1:1 and the linear regression line through the origin, respectively. The terms b, R^2 and n refer to the slope of the regression equation, the coefficient of determination and the number of observations, respectively.

2.5. Statistical indicators

The comparisons between the reanalysis-based agrometeorological estimations, from ERA5 and ERA5-L, respectively, and the ground-based observations were assessed using different statistical metrics, such as the slope of the regression line forced by the origin; the coefficient of determination (R^2); the root-mean-square error (RMSE; Eq. 5); the mean bias error (BIAS; Eq. 6); the mean absolute error (MAE; Eq. 7), and the normalized root-mean-square error (NRMSE; Eq. 8); calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{n}\sum |S_i - O_i| \tag{6}$$

$$\mathrm{PBIAS} = \frac{\sum(\mathrm{S_i} - \mathrm{O_i})}{\sum \mathrm{O_i}} \cdot 100 \tag{7}$$

$$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{\widehat{O}} \tag{8}$$

where S_i is the simulated value by ERA5 and ERA5-L dataset, respectively, O_i is the observed value from the ground-based agrometeorological stations, where $\widehat{S}$ and $\widehat{O}$ are the averages of the data arrays of S_i and O_i, and n is the number of observations.

The difference in reproducing the agrometeorological variables by ERA5 and ERA5-L products, respectively, was assessed by applying the least-squares linear regression method and by comparing the outputs of the regression lines in terms of slope (for p-values < 0.05). This statistical analysis was conducted using the R software (R Core team, 2020).

The evaluation of the topographic effect on the agrometeorological variables obtained by the reanalysis datasets was assessed by comparing the elevation of the selected weather stations (Table 1) with the average elevation observed at the cell-size of the ERA5 single levels and ERA5-L datasets (30 and 9 km), respectively (see "Supplementary materials" section). In particular, the main zonal statistics (count, mean, minimum, maximum, standard deviation, and median values) of the elevation values were extracted at the level of the cell containing the weather stations (Table 1) from a digital elevation model, with a spatial resolution of 75 m, released by the Italian Ministry of the Environment and the Protection of the Territory and the Sea.

3. Results

3.1. Agrometeorological variable-by-variable comparisons

The description of the main results obtained by comparing the ERA5 and ERA5-L reanalysis agrometeorological estimates (T_{air}, R_s, u_2, RH and ET_0), respectively, and the relative ground-based variables are reported hereafter variable-by-variable for the irrigation districts under study (Table 1), referring to the period 2008–2020.

The overall performance (in terms of RMSE, MAE, PBIAS and NRMSE values) of the comparisons are given in Tables 3 and 4 at the different explored time scales (daily and seasonal). Note that Sardinia sites are not included in Tables 3 and 4 because no data was available. Figs. 2–6 report the scatterplots outputted by comparing the daily ERA5 and ERA5-L estimates, respectively, *versus* the observed variables for the irrigation districts under study, as well as the parameters of the regression analyses (b and R^2).

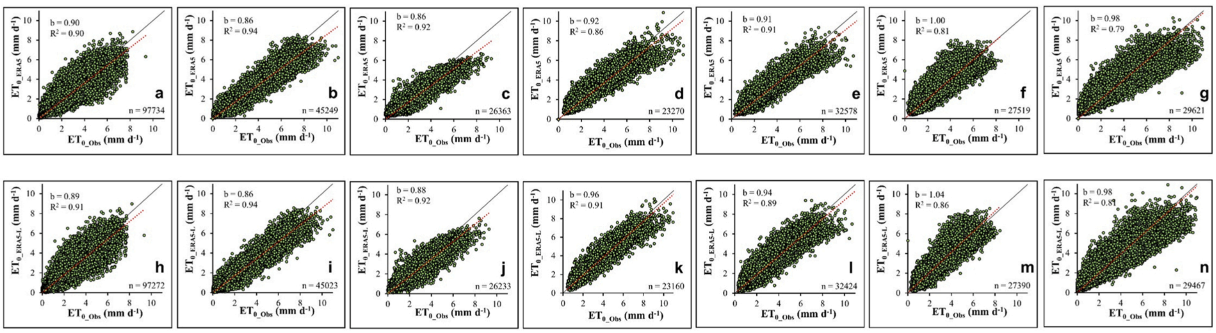

Fig. 6. Daily predicted crop reference evapotranspiration (ET_{0_ERA5} and $ET_{0\_ERA5\text{-}L}$, mm d^{-1}) *versus* observed (ET_{0_Obs}, mm d^{-1}) values at the irrigation districts located in Lombardy (a, h), Emilia-Romagna (b, i); Campania (c, j), Western Sicily (d, k), Eastern Sicily (e, l), Sardinia (f, m) and Apulia (g, n) for the period 2008–2020. The black and red lines represent the 1:1 and the linear regression line through the origin, respectively. The terms b, R^2 and n refer to the slope of the regression equation, the coefficient of determination and the number of observations, respectively.

In general, the results of the least-squares linear regression analysis carried out to compare the daily reanalysis datasets (*i.e.*, ERA5 and ERA5-L) *versus* the observed agrometeorological data showed significant differences in terms of slopes values for all the variables of interest also at the seasonal level.

3.1.1. Air temperature (T_{air})

3.1.1.1. T_{air}: ERA5 versus ground-observations. Daily average T_{air} values were estimated with good accuracy by the ERA5 reanalysis dataset at all the irrigation districts under study (Table 3), showing average RMSE values of 1.46 °C, 1.70 °C and 1.76 °C; and MAE values of 1.15 °C, 1.29 °C and 1.42 °C under Bsk, Cfa and Csa climate conditions, respectively. The average values of NRMSE varied between 0.09 and 0.14; reaching minimum and maximum values under Bsk and Csa-Cfa climate conditions, respectively. The PBIAS values varied from 0.38% (in Eastern Sicily study sites) to 6.62% (in Emilia-Romagna study sites) and − 9.22% (in Campania study sites); showing average values of − 2.12%, 3.12% and 4.14% under Csa, Cfa and Bsk climate conditions, respectively, with average R^2 values varying between 0.94 (Csa) and 0.97 (Bsk). The slope values (b) ranged from 0.91 to 1.04, indicating a site-specific underestimation of 9% and overestimation of 4% in Campania and Emilia-Romagna study sites, respectively (Fig. 2a-f).

On a seasonal basis, the best T_{air} performance was observed in autumn, showing average RMSE, MAE, PBIAS, b and R^2 values of 1.61 °C, 1.27 °C, 2.64%, 1.01 and 0.89, respectively. Similar performances were obtained in spring-summer seasons (with average RMSE, MAE, PBIAS, b and R^2 values of 1.72 °C, 1.35 °C, −0.62%, 0.99 and 0.79, respectively), while a slightly lower accuracy was observed in winter (with average RMSE, MAE, PBIAS, b and R^2 values of 1.70 °C, 1.34 °C, 5.14%, 1.00 and 0.72, respectively). The same trend was observed in terms of NRMSE values. Specifically, the T_{air} predictions reached the best performance in Apulia study sites during winter and summer (with RMSE and MAE values of 1.35 and 1.08 °C, respectively), followed by spring and autumn in Eastern Sicily and Lombardy study sites; whereas the lowest T_{air} performance was obtained in Campania study sites during all seasons (Table 3).

3.1.1.2. T_{air}: ERA5-L versus ground-observations. Daily average T_{air} values were predicted with acceptable accuracy by the ERA-L reanalysis dataset at all the irrigation districts under study (Table 4), resulting in average RMSE values of 1.76 °C, 1.82 °C and 1.97 °C; and MAE values of 1.44 °C, 1.39 °C and 1.44 °C under Csa, Cfa and Bsk climate conditions, respectively. The average NRMSE values varied between 0.08 and 0.16; with similar values under Csa, Cfa and Bsk climate conditions The PBIAS values ranged between 1.35% (in Emilia-Romagna study sites) to − 11.75% (in Campania study sites); showing average values of − 4.87%, − 2.38% and 2.46% in Csa, Cfa and Bsk climate conditions, respectively. The average R^2 values ranged from 0.93 (Csa) to 0.95 (Cfa and Bsk); and the slope values (b) ranged from 0.89 to 0.99, indicating a maximum and minimum underestimation of 11% and 1% in Campania and Emilia-Romagna study sites, respectively (Fig. 2g-l).

Seasonally greater T_{air} predictions were retrieved in summer and autumn seasons, resulting in average RMSE, MAE, PBIAS, b and R^2 values of 1.73 °C, 1.36 °C, − 2.39%, 0.97 and 0.81, respectively; whereas, slightly lower T_{air} performance were observed in spring and winter seasons, showing average RMSE, MAE, PBIAS, b and R^2 values of 1.89 °C, 1.48 °C, − 5.38%, 0.93 and 0.80, respectively. A similar trend was observed in terms of NRMSE values. Specifically, the T_{air} predictions reached the best performance at Eastern Sicily study sites during spring and autumn-winter periods (with average RMSE, MAE, PBIAS, b and R^2 values of 1.28 °C, 1.02 °C, −1.31%, 0.98 and 0.92, respectively) and in summer in Western Sicily study sites (Table 4); whereas the lowest T_{air} performance was obtained in Campania study sites during all seasons (Table 4).

3.1.2. Solar radiation (R_s)

3.1.2.1. R_s: ERA5 versus ground-observations. ERA5 dataset showed good performance in estimating daily R_s under all the examined climate conditions (Table 3), showing average RMSE values of 32.27 W m^{-2}, 32.43 W m^{-2}, and 45.03 W m^{-2}; MAE of 23.67 W m^{-2}, 24.20 W m^{-2} and 30.72 W m^{-2}, and NRMSE of 0.17, 0.21 and 0.24 in Csa, Cfa and Bsk, respectively. Average PBIAS values ranged between 0.83% (Cfa) to 2.93% (Csa) and − 5.21% (Bsk), corresponding to R^2 values of 0.88, 0.86 and 0.80, respectively. The slope terms (b) presented the same trend with values from 1.00 to 0.96 and 0.91 under Csa, Cfa and Bsk climate conditions, respectively.

Seasonally, the best R_s performance was retrieved in autumn (with average RMSE, MAE and PBIAS values of 27.36 W m^{-2}, 20.34 W m^{-2}, and 1.93%, respectively; and b and R^2 terms of 0.88 and 0.67, respectively) at all site locations (except for Campania locations), followed by winter and summer. Slightly lower R_s performance was obtained in spring, resulting in average RMSE, MAE, PBIAS, b and R^2 values of 43.17 W m^{-2}, 32.09 W m^{-2}, 2.20%, 0.96 and 0.48, respectively. In absolute terms, the best R_s predictions were reached in Western Sicily study sites during summer (also in terms of NRMSE values) and in Emilia-Romagna study sites for the other seasons (Table 3); whereas the lowest R_s performance was obtained in Bsk climate condition (Apulia study sites) during all seasons and in Campania sites for the autumn season in terms of NRMSE (Table 3).

3.1.2.2. R_s: ERA5-L versus ground-observations. Daily R_s values were predicted with good accuracy by the ERA5-L reanalysis dataset at all study sites (Table 4), resulting in average RMSE values of 32.53 W m^{-2}, 34.33 W m^{-2} and 44.98 W m^{-2}, and NRMSE values of 0.17, 0.21 and 0.24 under Csa, Cfa and Bsk climate conditions, respectively. Average MAE values ranged from 23.87 W m^{-2} (Csa) to 25.06 W m^{-2} (Cfa) and 30.67 W m^{-2} (Bsk); and PBIAS values varied between 0.96% (Cfa) to 3.09% (Csa) and − 5.29% (Bsk). The R^2 values and slope terms (b) varied from 0.80 to 0.86 and 0.87, and from 0.91 to 0.96 and 1.00, under Bsk, Csa and Cfa climate conditions, respectively (Fig. 3g-l).

At the seasonal level, the R_s predictions reached the best performance in autumn at all climate conditions (except for Campania locations also in terms of NRMSE), with average RMSE, MAE and PBIAS values of 27.96 W m^{-2}, 20.73 W m^{-2}, and 2.02%, respectively; and b and R^2 terms of 0.92 and 0.65. The lower performance was observed in spring under all climate conditions, with average RMSE, MAE and PBIAS values of 44.23 W m^{-2}, 32.57 W m^{-2}, and 2.35%, respectively; and b and R^2 terms of 0.98 and 0.46, respectively. (Table 4). Intermediate R_s performances were observed in winter and summer (Table 4). Partially different results were observed in terms of NRMSE showing greater performances in summer followed by spring and winter-autumn seasons. The R_s predictions reached the best performance in Western Sicily during spring and summer periods (Table 4) and in autumn and winter seasons under Cfa climate conditions (Lombardy and Emilia-Romagna study sites); whereas the lowest R_s performance was obtained under Bsk climate condition (Apulia study sites) during all seasons also in terms of NRMSE values (Table 4).

3.1.3. Wind speed (u_{10})

3.1.3.1. u_{10}: ERA5 versus ground-observations. The performances of the ERA5 dataset in predicting daily u_{10} values are shown in Table 3 and Fig. 4a-f. The ERA5 accuracy shows a specific pattern as a function of the climate conditions, resulting in average RMSE values of 1.04 m s^{-1}, 1.21 m s^{-1} and 1.57 m s^{-1} under Cfa, Csa, and Bsk climate conditions, respectively. Similar behaviour is observed in terms of average MAE values, ranging from 0.73 m s^{-1} (Cfa) to 0.91 m s^{-1} (Csa) and 1.17 m s^{-1} (Bsk). Inversely, PBIAS values were equal to − 19.43%, − 20.54%, and − 25.21% from Bsk to Csa and Cfa climate conditions, respectively. Lower R^2 values were obtained at all study sites, with b terms ranging from 0.66 and 0.74 in Cfa-Bsk and Csa climate conditions, respectively. A similar trend was observed in terms of NRMSE values.

ERA5 performance increased in summer-autumn/spring periods (with average RMSE, MAE, PBIAS, NRMSE, b and R^2 values of 1.16 m s^{-1}, 0.87 m s^{-1}, −22.53%, 0.46, 0.70 and 0.18, respectively). Lower performance was observed in winter, resulting in average RMSE, MAE, PBIAS, NRMSE, b and R^2 values of 1.36 m s^{-1}, 0.97 m s^{-1}, − 19.30%, 0.51, 0.71 and 0.22, respectively. In particular,

Table 5
Daily and seasonal (winter, spring, summer and autumn) performance obtained by the comparison between predicted crop reference evapotranspiration (ET_0) by ERA5 and ERA-L reanalysis dataset, respectively, and the ground-based observations; RMSE, MAE, PBIAS and NRMSE refer to the root mean square error, the mean absolute error, the percent bias and the normalized root-mean-square error, respectively.

Italian region		Time-scale	ERA5				ERA5-L			
			RMSE	MAE	PBIAS	NRMSE	RMSE	MAE	PBIAS	NRMSE
			mm d^{-1}		%		mm d^{-1}		%	
Lombardy		daily	0.62	0.42	-6.28	0.25	0.61	0.42	-7.92	0.25
		winter	0.29	0.19	-0.36	0.34	0.30	0.21	-9.45	0.35
		spring	0.75	0.58	-7.38	0.21	0.75	0.59	-8.68	0.21
		summer	0.88	0.69	-7.94	0.20	0.85	0.67	-7.55	0.19
		autumn	0.32	0.21	0.42	0.33	0.31	0.21	-5.45	0.32
Emilia-Romagna		daily	0.70	0.51	-13.00	0.24	0.70	0.52	-13.70	0.24
		winter	0.40	0.28	-15.04	0.37	0.44	0.31	-20.70	0.41
		spring	0.77	0.62	-11.67	0.20	0.79	0.64	-12.37	0.20
		summer	0.97	0.79	-13.33	0.19	0.94	0.76	-12.68	0.18
		autumn	0.44	0.31	-14.24	0.33	0.45	0.31	-16.92	0.34
Campania		daily	0.65	0.48	-11.25	0.23	0.62	0.45	-10.44	0.22
		winter	0.43	0.30	-9.95	0.35	0.47	0.32	-15.58	0.38
		spring	0.77	0.63	-12.57	0.21	0.73	0.59	-11.16	0.20
		summer	0.82	0.69	-12.39	0.17	0.73	0.58	-9.33	0.15
		autumn	0.43	0.29	-4.79	0.30	0.47	0.31	-8.08	0.33
Sicily	**Western**	daily	0.69	0.51	-3.32	0.20	0.57	0.43	-1.06	0.17
		winter	0.44	0.34	7.91	0.28	0.40	0.31	2.91	0.25
		spring	0.74	0.57	-5.57	0.17	0.59	0.45	-1.81	0.14
		summer	0.91	0.71	-7.55	0.16	0.71	0.54	-2.46	0.13
		autumn	0.56	0.42	4.90	0.28	0.53	0.39	1.49	0.26
	Eastern	daily	0.62	0.46	-6.62	0.19	0.57	0.42	-4.21	0.18
		winter	0.38	0.29	-5.20	0.25	0.37	0.28	-8.36	0.24
		spring	0.63	0.49	-3.49	0.16	0.60	0.46	0.55	0.15
		summer	0.87	0.68	-9.03	0.16	0.75	0.58	-4.98	0.14
		autumn	0.46	0.35	-7.47	0.25	0.46	0.34	-9.18	0.25
Sardinia		daily	0.71	0.52	4.20	0.26	0.68	0.50	5.60	0.24
		winter	0.56	0.41	16.80	0.47	0.45	0.33	5.91	0.37
		spring	0.74	0.57	0.83	0.21	0.74	0.58	4.94	0.21
		summer	0.90	0.67	1.54	0.19	0.92	0.71	6.74	0.20
		autumn	0.59	0.43	10.94	0.38	0.48	0.36	3.24	0.31
Apulia		daily	0.90	0.67	7.90	0.31	0.88	0.64	5.86	0.30
		winter	0.60	0.48	23.67	0.51	0.55	0.42	10.91	0.47
		spring	1.03	0.81	10.83	0.28	0.99	0.77	9.18	0.27
		summer	1.18	0.89	-0.37	0.22	1.18	0.90	1.04	0.22
		autumn	0.66	0.50	20.15	0.47	0.61	0.45	12.30	0.44

relatively better performance was observed in Campania (summer) and Lombardy study sites (for the rest of the seasons) (Table 3), whereas, lower performance was registered during winter and summer in Apulia study sites, during spring for Emilia-Romagna and autumn for Western Sicily study sites, respectively (Table 3).

3.1.3.2. u_{10}: ERA5-L versus ground-observations. The accuracy and performance indicators of the ERA5-L dataset in predicting daily u_{10} values are shown in Table 4 and Fig. 4g-l. Similarly to ERA5, the ERA5-L accuracy shows a specific pattern as a function of the climate conditions, resulting in average RMSE values of 1.26 m s^{-1}, 1.37 m s^{-1} and 1.75 m s^{-1} in Cfa, Csa, and Bsk climate conditions, respectively; showing similar trends in terms of average MAE values, that ranged from 0.96 m s^{-1} (Cfa) to 1.10 m s^{-1} (Csa) and 1.34 m s^{-1} (Bsk). Conversely, PBIAS values varying between − 23.50% (Bsk) to − 26.40% (Csa) and − 37.17% (Cfa); with R^2 and NRMSE values varying from 0.06 (Bsk) to 0.25 (Cfa) and 0.45 (Csa) and from 0.64 to 0.62 and 0.52, under Bsk, Cfa and Csa climate conditions, respectively. The slope terms (b) ranged from 0.58 (Cfa) to 0.64 (Bsk) and 0.72 (Csa), indicating an underestimation varying from 28% to 36% and 42%, under Csa, Bsk and Cfa climate conditions, respectively.

At the seasonal level, the u_{10} predictions reached the best performance in autumn, with average RMSE, MAE and PBIAS values of 1.34 m s^{-1}, 1.01 m s^{-1}, and − 20.79%, respectively; and b and R^2 terms of 0.68 and 0.26, respectively. Lower performance was observed in winter, resulting in average RMSE, MAE, PBIAS, b and R^2 values of 1.47 m s^{-1}, 1.11 m s^{-1}, − 23.86%, 0.70 and 0.32, respectively. Moderate u_{10} performances were observed in the other seasons (Table 4). Slight differences were observed in terms of NRMSE values. Specifically, the u_{10} predictions reached the best and worst performance at Lombardy and Apulia study sites, respectively, during all seasons (Table 4).

3.1.4. Relative humidity (RH)

3.1.4.1. RH: ERA5 versus ground-observations. Good accuracy was observed in the estimation of daily RH values by ERA5 at all study sites (Table 3), resulting in a similar trend of RMSE and MAE, with values of these indicators ranging from 8.78% to 9.55% and 19.02%, and from 6.88% to 7.47% and 15.30% under Cfa, Csa and Bsk climate conditions, respectively. Similar behaviour was observed in terms of NRMSE, PBIAS and b values, showing better performances from Cfa to Csa and Bsk climates (Fig. 5a-f). The slope terms and R^2 values ranged from 0.81 to 1.04, and from 0.34 to 0.66, respectively.

On a seasonal basis, the ERA5 accuracy was better in autumn and winter (average RMSE, MAE and NMRSE values of 10.07%, 8.06% and 0.13), followed by spring and summer seasons (average RMSE, MAE and NMRSE values of 11.23%, 8.96% and 0.16, respectively). In particular, the best ERA5 performance was retrieved at Campania (spring-summer), Lombardy (autumn) and Western Sicily (winter) study sites. Lower accuracy was obtained at Apulia study sites for all seasons.

3.1.4.2. RH: ERA5-L versus ground-observations. The daily RH estimates predicted by ERA5-L in comparison to the ground-based measurements resulted in RMSE values ranging between 9.63% and 9.82% under Cfa and Csa climate conditions, respectively, reaching 15.98% in Bsk conditions (Fig. 5g-l). Similar trend was observed in terms of NRMSE values. This behaviour resulted in MAE and PBIAS values of 7.57%, 7.85%, 12.03% and 5.55%, 7.66%, − 11.92% under Cfa, Csa and Bsk conditions, respectively. Similar trends were observed for the b and R^2 terms, showing values of 1.04–1.06 and 0.86 and 0.41–0.52 and 0.27 under Cfa-Csa and Bsk conditions, with overestimation of 4–6% in Cfa and Csa and underestimation of 14% at Apulia study site (Bsk).

At the seasonal level, the overall best RH performance was observed in autumn (Table 4), with average RMSE, MAE, PBIAS and NRMSE values of 10.24%, 8.17%, 3.07% and 0.13, respectively. Similar performances were retrieved in winter and spring, with slightly lower ERA5-L accuracy during summer (Table 4). Specifically, the best performance was observed at Campania (in summer) and Lombardy study sites (in the other seasons); whereas lower performance at Emilia-Romagna (in winter) and Apulia study sites (in the other seasons) (Table 4).

3.1.5. Reference evapotranspiration (ET_0)

3.1.5.1. ET_0: ERA5 versus ground-observations. Daily ET_0 estimates obtained using as inputs the agrometeorological information provided by the ERA5 dataset showed good accuracy in comparison to the ground-based ET_0 estimates (Table 5 and Fig. 6a-m). In particular, the daily ET_0 estimates reached the best performance under Csa-Cfa climate conditions (with average RMSE, MAE and NRMSE values of 0.66 mm d^{-1}, 0.48 mm d^{-1}, and 0.23, respectively). Lower performance was observed at Bsk, resulting in average RMSE, MAE and NRMSE values of 0.90 mm d^{-1}, 0.67 mm d^{-1}, and 0.31, respectively. Positive average PBIAS values were obtained at Bsk (7.90%), whereas negative average PBIAS values of − 4.25% and − 9.64% resulted under Csa and Cfa climate conditions.

At the seasonal level, the ET_0 performance was greater during winter and autumn periods (with average RMSE, MAE, BIAS, b and R^2 values of 0.47 mm d^{-1}, 0.34 mm d^{-1}, 1.98%, 0.93 and 0.58, respectively), and lower, but still satisfactory, in spring and summer (with average RMSE, MAE, BIAS, b and R^2 values of 0.85 mm d^{-1}, 0.67 mm d^{-1}, −5.58%, 0.93 and 0.59, respectively). Similar values were observed in terms of NRMSE values among the seasons (Table 5). Better accuracy was obtained at Lombardy (winter-autumn seasons), Campania (summer) and Eastern Sicily (spring) study sites; whereas, lower accuracy was reached at Apulia study sites for all seasons (Table 5).

3.1.5.2. ET_0: ERA5-L versus ground-observations. Overall, ERA5-L provided daily ET_0 estimates with good accuracy (Table 5 and Fig. 6h-n). Specifically, the daily ET_0 estimates reached the best performance under Csa and Cfa conditions (with average RMSE, MAE and NRMSE values of 0.63 mm d^{-1}, 0.46 mm d^{-1} and 0.22, respectively) (Table 5 and Fig. 6h-n). The lower performance was observed at Bsk, with average RMSE, MAE and NRMSE values of 0.88 mm d^{-1}, 0.64 mm d^{-1} and 0.30, respectively. Positive average PBIAS values were obtained under Bsk (5.86%); whereas under Csa and Cfa climate conditions resulted in values ranging from − 2.53% to − 10.81%, respectively.

At the seasonal level, the ET_0 performance resulted better in winter and autumn (with average RMSE, MAE, BIAS, b and R^2 values of 0.50 mm d^{-1}, 0.36 mm d^{-1}, −3.84%, 0.90 and 0.64, respectively), and lower, but still quite satisfactory, in spring and summer (with average RMSE, MAE, BIAS, b and R^2 values of 0.77 mm d^{-1}, 0.60 mm d^{-1}, −3.53%, 0.94 and 0.63, respectively). As for the ERA5, similar values were observed in terms of NRMSE values among the seasons (Table 5). Greater accuracy was obtained at Lombardy (winter-autumn seasons) and Western Sicily (spring-summer seasons) study sites, while lower accuracy was obtained at Apulia study sites for all seasons (Table 5).

4. Discussion

Climate reanalysis data have been widely used for hydrological and meteorological applications. However, it is still difficult to quantitatively estimate their accuracy due to their variability both at spatial and temporal scales, especially under complex topography and pronounced climatic heterogeneity (*i.e.*, the rainfall) (Jiao et al., 2021). Often, ground variables are taken into account in the reanalysis process (such as air pressure, T_{air}, RH and u_{10}) to improve the reanalysis data quality. However, if the data assimilation approach can improve data accuracy, by adding physically meaningful information from the predictive model, this is still subject to uncertainty. The main sources of uncertainty are due to numerical simulations, assimilation schemes and errors associated with the observation systems (Dee et al., 2011). In this sense, some studies showed that it is difficult to completely replace observational data with reanalysis information for describing the true state of the atmosphere (Bengtsson et al., 2004), *e.g.*, for long-term climate trend studies (Liu et al., 2018) and/or for capturing seasonal and inter-annual changes (Jiao et al., 2021).

This study explored the potential of using the new released ECMWF climate reanalysis datasets (*i.e.*, ERA5 and ERA5-L) for proving daily and seasonal agrometeorological information (T_{air}, R_s, RH, u_{10} and ET_0) by determining their performance against measured ground-based observations within the Italian territory in the reference period 2008 – 2020. Moreover, since new user requirements are constantly emerging in society (Muñoz-Sabater et al., 2021), *ad hoc* user-interfaces GIS-based user-friendly tools have been developed in this study for supporting the needs of a diverse set of users, next to the climate and weather research motivations, within the reanalysis data pre-processing steps (Fig. 1.S-4. S).

Herein, a generally good agreement was observed between the ability of ERA5 and ERA5-L products in reproducing the agrometeorological variables of interest (commonly used for ET calculation) in comparison to the ground-based observations collected at 66 study sites distributed over 7 irrigation districts. Specifically, the daily T_{air} estimates offered the most accurate reanalysis predictions, followed by the RH, R_s, and u_{10} variables, which still provided satisfactory results (Tables 3–4, Figs. 3–5). Similar (*i.e.*, for RH) or slightly improved statistical metrics were obtained by ERA5 in comparison to ERA5-L (*i.e.*, showing lower RMSE values than ERA5-L, for T_{air} and R_s, respectively, in 67% and 83% of the total number of the investigated irrigation districts). This can be attributed to the fact these variables are more homogeneous at the spatial scales provided by ERA5 products in comparison to ERA5-L (Fig. 5. S in Supplementary materials section). The u_{10} performance was always more consistent for ERA5 than ERA5-L in comparison to the observations at all irrigation districts, most likely because ERA5-L does not consider the influence of the sea surface in its products (Muñoz-Sabater, 2019). Altogether, the daily T_{air}, R_s, RH, and u_{10} estimates were more accurate during the autumn season for both reanalysis datasets (Tables 3–4).

The influence of topographic features on the accuracy of the reanalysis data was also investigated, following the evidence that it could be significant provided by previous studies. For example, Gao and Hao (2014) evaluated the relationship existing between the elevation of the climate reanalysis data from ERA-Interim and the observed station's elevation. These authors pointed out that differences in elevation can affect the accuracy of the reanalysis data, especially in areas with relatively higher altitudes. Analogous considerations are reported by Longo-Minnolo et al. (2022) for a Sicilian watershed, with elevation values ranging between 0 and 3313 m a.s.l., for which the highest RMSE values were observed in the ERA5-L cells with relatively higher variations in altitude. To overcome these shortcomings in mountainous areas, other authors suggest applying altitude correction procedures, especially for water vapour, precipitation and T_{air} estimates (Zhao et al., 2008; Feng et al., 2012; Hu et al., 2013; Negm et al., 2018). For altitudes below 1000 m (a.s.l.), however, Jiao et al. (2021) found a good agreement between climate reanalysis and observational data. Similar results emerged from this study, where no specific relationships were obtained between the elevation changes and the goodness of reanalysis datasets in reproducing the agrometeorological variables of interest, at the site-by-site scale, within the seven irrigation districts under investigation (Table 1). These findings show that the accuracy of the reanalyses products is strongly connected with the climatic conditions rather than the topographic distribution of the selected study sites. Due to the above-mentioned explanations and for maintaining the integrity of the reanalysis datasets, no topography corrections were applied in this study.

The performance of reanalysis data strongly depends on the different climate conditions characterizing the investigated sites, as shown by Tarek et al. (2020). Specifically, these authors observed that T_{air} and precipitation estimated by ERA5 are systematically more performant in comparison to ERA-Interim at all the 13 Northern America climate zones under study. In addition, they reported that *in situ* measurements are higher than ERA5 for Cfa and hot-summer humid continental (Dfa) climate zones; elsewhere, these differences are less pronounced. In this sense, they did not experience the difference in hydrological modelling performance using both ERA5 products and observations over 9 of the 13 climate zones. For the remaining regions (Bsk, Cfa, Dfa, and warm-summer humid continental climate, Dfb), the use of observations resulted in improved hydrological modelling performance. In agreement with Tarek et al. (2020), in our study site-specific performance depended on the different investigated climate conditions (Table 1). In particular, the major part of the variables of interest (R_s, RH, u_{10} and ET_0) resulted in greater and lower performance under Csa and Bks climate conditions, respectively, by both reanalysis datasets, except for T_{air} estimates provided by ERA5 that shows an inverted pattern due to the influence of the sea temperature in this product (Hersbach et al., 2020). Intermediate performance was observed under Cfa climate zones.

The good quality of the reanalysis data was translated into reliable daily and seasonal ET_0 estimates (with an underestimation from 2 up to 13% for the climate classes under study). Specifically, as for the other variables, ET_0 estimates were more accurate in autumn/winter than in spring/summer by both reanalysis datasets in terms of RMSE values (Table 5 and Fig. 6). In addition, ERA5-L reproduces with greater accuracy and higher spatial resolution the ET_0 observations at most of the study sites even under different climate conditions, *i.e.*, showing lower RMSE values than ERA5 in 86% of the total number of the irrigation districts under study. Thus, the high accuracy obtained in this study when estimating ET_0 by reanalysis products (resulting in RMSE and NRMSE values ranging between 0.57 and 0.90 mm d^{-1} and from 0.17 to 0.31, respectively) suggests the potential use of this information for calculating the daily crop evapotranspiration rates aiming at supporting the irrigation scheduling. In this sense, Rolle et al. (2021) have recently estimated the global irrigation requirement of 26 crops by implementing the Hargreaves-Samani method (Hargreaves and Samani, 1985) to calculate ET_0, by using information on T_{air} and R_s retrieved by the ERA5 dataset. Other studies assessed the use of a blended set of weather input data composed of ERA5-L outputs and different sources of climate data (*i.e.*, reanalysis data and satellite-based radiation data) to evaluate the ET_0 for the Campania region (Pelosi et al., 2020; Pelosi and Chirico, 2021). Pelosi et al. (2021) combined the ERA5-L products with multispectral satellite imagery for estimating the past crop evapotranspiration. Under this scenario, the results of the present study may contribute to the informed use of reanalysis data in water management applications in Italy and elsewhere.

5. Conclusion

This study explores the performance of the ERA5 single levels and ERA5-L in depicting the agrometeorological data from 2008 to 2020 in comparison to observational data measured at 66 sites distributed over 7 irrigation districts over the Italian territory. Specifically, the main findings that can be drawn from this study are the following:

– the daily average T_{air} estimates offered the most accurate reanalysis predictions, followed by RH, R_s, and u_{10} variables. This was translated into reliable daily ET_0 estimates resulting in RMSE and NRMSE values ranging between 0.57 and 0.90 mm d^{-1} and from 0.17 to 0.31, respectively;
– similar or slightly improved statistical metrics were obtained by ERA5 in comparison to ERA5-L in estimating RH, T_{air} and R_s; whereas the u_{10} and ET_0 performances were more consistent by ERA5 and ERA5-L, respectively, when compared to the observations at the majority of the irrigation districts under study;
– the R_s, RH, u_{10} and ET_0 estimates resulted in higher and lower performance under Csa and Bks climate conditions, respectively, by both reanalysis datasets; conversely, a reverse pattern was obtained for T_{air} estimates provided by ERA5, being more accurate under Bsk. Intermediate performance was observed under Cfa climate zones.

These results help to improve our understanding of the uncertain sources of reanalysis data under different climate conditions, the rational application of these datasets and the potential improvements for the next product generation. In addition, they open promising perspectives for the use of reanalysis data as an alternative data source to estimate ET_0 for irrigation water management in different climate contexts, overcoming the limited availability of observed agrometeorological data in many areas.

CRediT authorship contribution statement

Daniela Vanella: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Giuseppe Longo-Minnolo:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – review & editing, Visualization. **Oscar Rosario Belfiore:** Methodology, Software, Formal analysis, Investigation, Data curation. **Juan Miguel Ramírez-Cuesta:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation. **Salvatore Pappalardo:** Formal analysis, Investigation, Data curation. **Simona Consoli:** Conceptualization, Writing – review & editing, Funding acquisition. **Guido D'Urso:** Funding acquisition. **Giovanni Battista Chirico:** Investigation. **Antonio Coppola:** Funding acquisition. **Alessandro Comegna:** Investigation. **Attilio Toscano:** Funding acquisition. **Riccardo Quarta:** Investigation. **Giuseppe Provenzano:** Writing – review & editing. **Matteo Ippolito:** Investigation. **Alessandro Castagna:** Investigation. **Claudio Gandolfi:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2022.101182. These data include Google maps of the most important areas described in this article.

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