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Assessing the Accuracy of ERA5-Land in Heatwave Monitoring

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***Abstract*—This study investigates the ability of reanalysis data to accurately identify heatwave events (HEs) in Greece from 1960 to 2022. High-resolution gridded reanalysis data from ERA5-Land, providing consistent land variables, namely maximum daily temperature over several decades, are utilized. In addition, HEs have been identified through high-quality homogenized meteorological data provided by the Hellenic National Meteorological Service (HNMS) from 1960 to 2022. The HEs are identified through a percentile-based threshold, calculated via a bootstrap resampling methodology to address artificial discontinuities in the reference period of 1961-1990. Furthermore, the HEs from both datasets are analyzed in terms of frequency, duration, and severity of events. Finally, the HEs calculated from the ERA5 dataset are assessed across five intensity classes derived from five percentile-based thresholds to evaluate their accuracy to capture these events. Expected results reveal the strengths and weaknesses of ERA5-Land data in capturing heatwave characteristics across different climate regions of Greece. This study will provide insights into the reliability of ERA5-Land as a tool for heatwave monitoring and risk assessment, informing the development of more effective heat-health action plans and climate adaptation strategies. The findings will be particularly relevant for regions with limited observational data, where ERA5-Land can serve as a valuable source of information.**

***Index Terms*—heatwave, Greece, severity, duration, frequency, reanalysis, climate.**

I. Introduction

GLOBALLY, heatwaves are expected to become more frequent and severe in the future [1, 2]. Subsequently, robust and accurate monitoring is required to mitigate socio-economic and environmental impacts [3, 4]. Europe has experienced numerous intense heatwaves in the 21st century which account for a substantial proportion of disaster-related fatalities and economic losses [3, 4]. Specifically, the Mediterranean basin has been identified as a hotspot for climate change impacts [5]. Projections indicate a significant increase in the number and intensity of heatwaves, particularly during summer months [6-8]. In Greece, utilizing various heatwave indices, HEs have increased in terms of both duration and frequency [8-10].

Reanalysis datasets, such as ERA5-Land, are often utilized to study HEs. Specifically, ERA5-Land provides high spatial (9 km) and temporal (hourly) resolution, integrating model data with observations to provide a robust set of data suitable for applications including the analysis of extreme temperature events [11]. Studies across Europe demonstrated the potential of this dataset for the analysis and monitoring of HEs [12, 13]. Researchers in [14] used ERA5-Land to investigate land-atmosphere interactions during HEs, reporting that dry soils reduce evaporation and increase surface heating, creating a positive feedback loop that intensifies the event. In [15] the same dataset is used to evaluate temperature extremes across the European continent. In Greece, the ERA5-Land dataset has been used to examine thermal bioclimatic conditions and assess heatwave intensity [9]. Furthermore, other reanalysis datasets have been employed to study compound events and atmospheric preconditions in Greece [16, 17]. This type of reanalysis data is particularly valuable for studying extreme events in data-sparse or mountainous regions with a small number of meteorological stations, assisting in filling observational gaps and providing a consistent view of land variables over several decades [18-22].

Taking into account the growing threat of HEs and the availability of reanalysis datasets, it is essential to conduct a thorough evaluation of ERA5-Land's ability to capture heatwave characteristics in Greece's complex climatology. Although reanalysis datasets provide valuable information for climate analysis, studies have highlighted the need to further evaluate their capacity to capture land-atmosphere interactions and extreme conditions such as heatwaves, especially in regions with sparse station distribution [12, 22]. In addition, the complex terrain of Greece poses challenges for reanalysis products to fully capture finer-scale atmospheric phenomena and small scale processes, leading to uncertainties in model-based products [23, 24]. This study aims to contribute to the development of robust monitoring systems by assessing ERA5-Land's accuracy for heatwave monitoring in Greece.

II. Methodology

Greece is located between 34º and 42º N in latitude and 19º to 28º E in longitude, with the Aegean Sea to the east, the Ionian Sea to the west, and the eastern Mediterranean Sea to the south. Daily Maximum Air Temperature (TX) timeseries for the period 1960-2022 from 26 HNMS weather

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stations as illustrated in Figure 1 were used. The datasets underwent quality control and homogenization [25].

To investigate the suitability of ERA5-Land reanalysis data to monitor HEs, high-resolution gridded daily TX data were extracted for the period 1960-2022 from the Copernicus reanalysis dataset "ERA5-Land post-processed daily statistics from 1950 to present" [26]. The dataset's post-processed daily statistics are derived from the ERA5-Land global reanalysis, which provides land variables hourly at a 9-km spatial resolution and extends back to 1950.

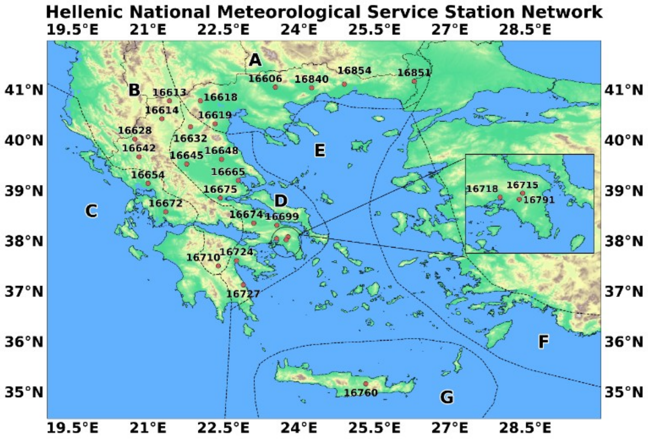


Fig. 1. HNMS weather station network and corresponding climate regions.

According to the World Meteorological Organization (WMO), there is no universally accepted definition of a heatwave, as its definition depends on the geographical and climatic context of the study area [27]. In general, the WMO defines a heatwave as a prolonged period of temperatures exceeding average values, often determined using a temperature-related threshold, lasting from two days to several months [28]. In this study, a heatwave day is defined as any day when the daily TX exceeds the climatological daily TX percentile-based threshold corresponding to the 95th percentile (TX95). A HE is defined as at least three consecutive heatwave days. The analysis is performed separately for each station and calendar day. Climatological TX percentile values were computed with respect to the 1961-1990 reference period. To mitigate inhomogeneity arising from artificial discontinuities at the edges of the reference period used for percentile calculations, the thresholds are determined using the bootstrap resampling procedure [29].

The Inverse Distance Weighting (IDW) spatial interpolation method is utilized to ensure a reliable comparison between weather station timeseries from HNMS and ERA5 data. The IDW is a technique that estimates variable values at unmeasured locations based on values from nearby measured locations [30]. Using this method, the two time series were compared using three climatological indices corresponding to Heatwave Frequency (HF), Heatwave Duration (HD), and Heatwave Severity (HS) of HEs and are represented by (1), (2), and (3), respectively.

$$HF=\sum_{i=1}^{n} D\left(HE_i\right) \tag{1}$$

$$HD=\frac{1}{m}\sum_{i=1}^{m} D\left(HE_i\right) \tag{2}$$

$$HS=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{D\left(HE_i\right)}\sum_{j=sd_i}^{ed_i} TX_{ij}-TX_{p,j} \tag{3}$$

with HE_i the i-th HE, n the total number of identified HEs (i=1, 2, …, n), $D(HE_i)$ the duration in days of HE_i, m the number of days per period, TX_{ij} the daily maximum temperature of the j-th day of HE_i, and $TX_{p,j}$ the climatological percentile-based threshold of the daily maximum temperature for percentile p, (p: the 75th, 80th, 85th, 90th, or 95th percentile) for the j-th calendar day.

To assess the similarity between the measured and the reanalysis datasets during the different stages of the comparison, the two-sample Kolomogorov-Smirnov (KS) test was used. The KS test is a nonparametric statistical test used to determine whether two independent samples are drawn from the same underlying probability distribution [31]. It compares the empirical Cumulative Distribution Functions (CDFs) of the two samples to assess whether there is a statistically significant difference between them. This test does not require assumptions about the statistical distribution of the data, allowing for a robust comparison of the distributions of heatwave characteristics derived from both the weather station data and the ERA5 dataset. Finally, the occurrence of HEs within each time series from station measurements and ERA5 data was compared to determine the extent to which the latter dataset captures HNMS-derived Hes.

III. Results

The initial phase involved a comparative analysis between the spatially interpolated TX time series and their corresponding HNMS measurements. In Figure 2, a strong agreement between the ERA5-Land data and station measurements is observed as the distribution of the points closely aligned with the line of equality.

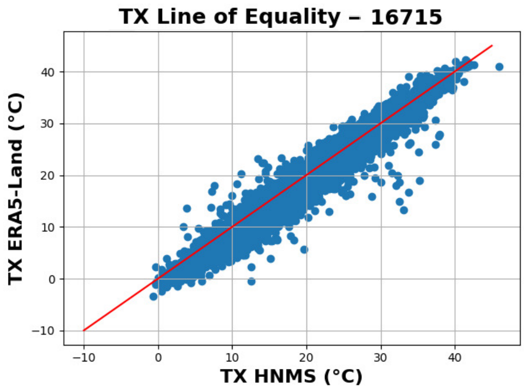


Fig. 2. Line of equality of the spatially interpolated, through IDW, ERA5-Land and HNMS weather station TX data for station 16715.

This alignment is further supported by Figure 3, which shows the CDFs of both datasets, displaying similar behavior. At high TX values, the reanalysis data exhibit stronger correlation than for lower TX values across all stations.

The small p-values across all stations, (Table I), indicate statistical significance for all cases. Furthermore, the KS statistic values ranging from 0.0560 to 0.2133 indicate a robust relationship between the interpolated values and observed measurements. At few stations stations (16619, 16628, 16654, 16675, 16727, 16840, and 16854) reanalysis TX values are underestimated, compared to measurements.

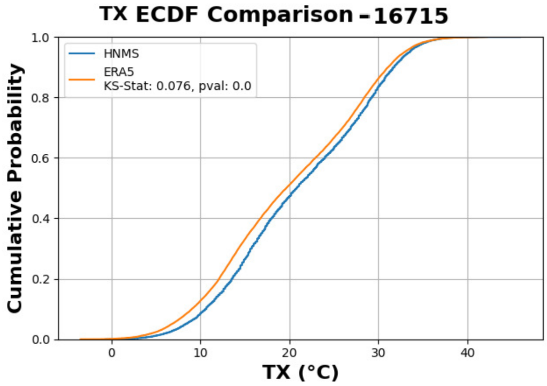


Fig. 3. CDF lines of the spatially interpolated ERA5-Land and HNMS weather station TX timeseries for station 16715.

TABLE I. KS TEST RESULTS BETWEEN ERA5 AND HNMS TX VALUES

Station Code	KS Statistic	p-value
16606	0.1449	0
16613	0.1521	0
16614	0.0971	0
16618	0.1063	0
16619	0.1985	0
16628	0.2492	0
16632	0.0560	0
16642	0.0993	0
16645	0.0881	0
16648	0.0623	0
16654	0.1890	0
16665	0.0631	0
16672	0.1432	0
16674	0.0944	0
16675	0.1714	0
16699	0.0601	0
16710	0.0862	0
16715	0.0763	0
16718	0.1328	0
16724	0.1581	0
16727	0.2133	0
16760	0.0548	0
16791	0.1159	0
16840	0.1769	0
16851	0.0884	0
16854	0.1936	0

TX95 thresholds were calculated for both measurements and the reanalysis data yielding two sets of TX95 values for each dataset per station: one for the reference period (1961–1990), referred to as the in-base period, and a second for the remaining years (1960 and 1991–2022), referred to as the out-of-base period. Figure 4 illustrates the comparison between the two datasets for station 16715. Most points from both periods lie below, but very close to, the line of equality, indicating a slight underestimation of TX95 station values by ERA5. This behavior is evident in most stations under study, except for stations 16632, 16648, 16665, 16674, 16699, 16715, 16718, 16724, 16760, and 16851, where values range between 15 °C and 25 °C.

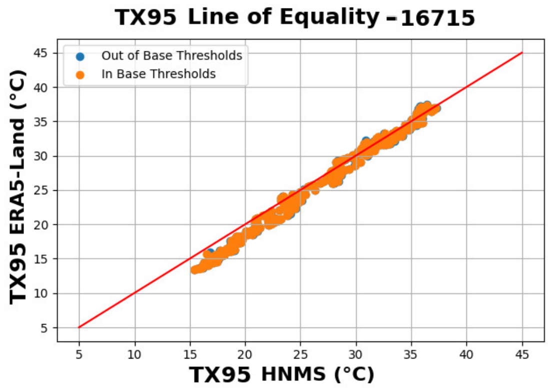


Fig. 4. Line of equality of the spatially interpolated, through IDW, ERA5-Land and HNMS weather station TX95 data for station 16715.

Figure 5 compares the CDFs of TX95 values for both in-base and out-of-base periods. The CDFs for ERA5 and HNMS closely follow one another in both periods, with only minor systematic deviations, mainly at lower values. The KS test indicates weak but statistically significant (p-value = 0.0) differences between the distributions across all stations. This suggests that while the datasets are not identical, they show a very high degree of similarity in representing the statistical distribution of TX95.

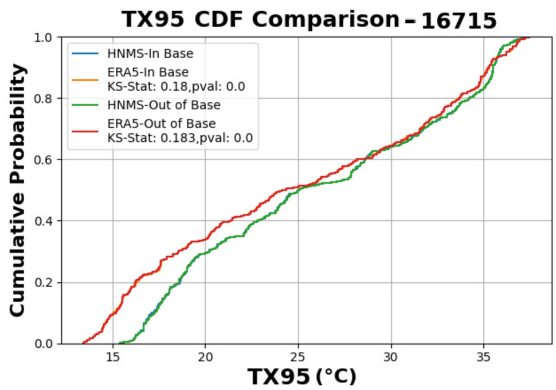


Fig. 5. CDF lines of the spatially interpolated, through IDW, ERA5-Land and HNMS weather station TX95 data for station 16715.

The summary of the KS test for all stations and both periods with respect to TX95 is shown in Table II. The KS statistic values range from 0.1530 to 0.3361 for the in-base years and from 0.1530 to 0.3388 for the out-of-base years, with all associated p-values very close to zero, indicating statistical significance. The maximum KS values (>0.3200) occur at stations 16619, 16628, and 16727, suggesting stronger discrepancies between ERA5 and HNMS data. Conversely, the minimum KS value (0.1038) occurs at station 16648, where the agreement between datasets is strongest. Similarly, after the calculation of the climatological indices, the comparison is performed and the results are presented in Table III.

For the indices HF and HD, the KS statistics are generally high (HF: 0.2600–0.4448 and HD: 0.2317–0.4390), with consistently small p-values. This indicates systematic and statistically significant differences between ERA5 and HNMS index distributions. In particular, several stations (HF: 16675, 16715, 16718, 16724, 16727; HD: 16760) exhibit KS statistics above 0.4000, suggesting stronger discrepancies. In contrast, the HS index showed mixed results, with only 9 out of 26 stations presenting statistically significant differences. These include stations 16606, 16672, 16674, 16699, 16710, 16727, 16760, 16851, and 16854, with relatively low KS statistic values (0.1423–0.2401).

TABLE II. KS TEST RESULTS BETWEEN ERA5 AND HNMS TX95 VALUES

Station Code	KS Statistic In-Base Years	p-value In-Base Years	KS Statistic Out-of-Base Years	p-value Out-of-Base Years
16606	0.2814	0.0000	0.2814	0.0000
16613	0.2623	0.0000	0.2650	0.0000
16614	0.1995	0.0000	0.2022	0.0000
16618	0.1913	0.0000	0.1940	0.0000
16619	0.3224	0.0000	0.3197	0.0000
16628	0.3279	0.0000	0.3279	0.0000
16632	0.1749	0.0000	0.1831	0.0000
16642	0.2077	0.0000	0.2104	0.0000
16645	0.1749	0.0000	0.1776	0.0000
16648	0.1038	0.0386	0.1038	0.0386
16654	0.2869	0.0000	0.2814	0.0000
16665	0.1858	0.0000	0.1913	0.0000
16672	0.2623	0.0000	0.2623	0.0000
16674	0.2104	0.0000	0.2131	0.0000
16675	0.2787	0.0000	0.2787	0.0000
16699	0.1776	0.0000	0.1803	0.0000
16710	0.1749	0.0000	0.1803	0.0000
16715	0.1803	0.0000	0.1831	0.0000
16718	0.2486	0.0000	0.2459	0.0000
16724	0.2596	0.0000	0.2568	0.0000
16727	0.3361	0.0000	0.3388	0.0000
16760	0.1530	0.0004	0.1530	0.0004
16791	0.2186	0.0000	0.2213	0.0000
16840	0.3169	0.0000	0.3169	0.0000
16851	0.1967	0.0000	0.1995	0.0000
16854	0.3060	0.0000	0.3060	0.0000

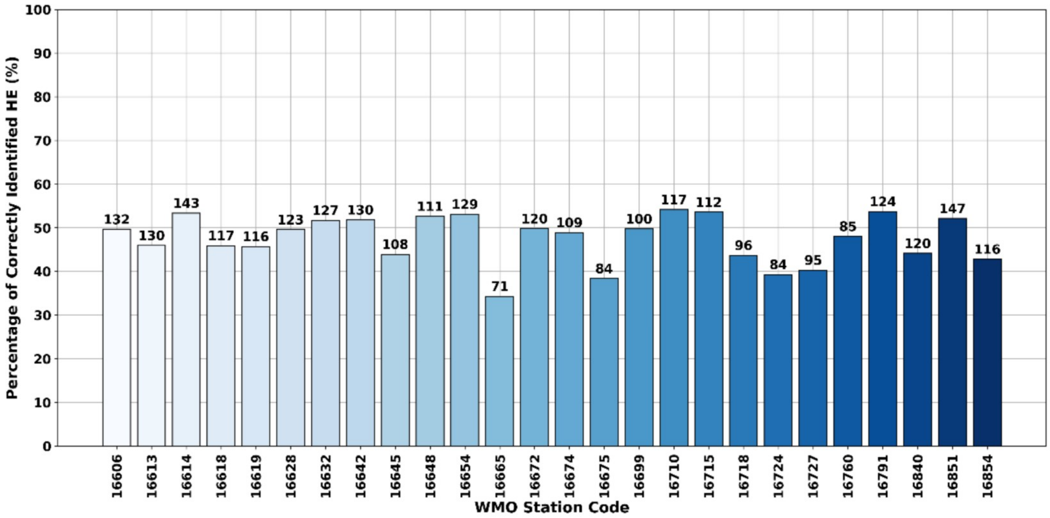
Figure 6a presents the percentage of correctly identified HEs by ERA5 per station. The percentages range between 34.30% and 54.17%. Some stations, such as 16614, 16654, 16710, and 16791, exhibit relatively higher precision, suggesting that ERA5 is more reliable in identifying HEs. On the other hand, stations 16665, 16675, and 16724 presented the lowest percentages. This variability highlights that while ERA5-Land data are moderately effective in distinguishing HEs also captured by HNMS stations, its effectiveness is not uniform across all stations. Furthermore, Figure 6b illustrates the percentage of HEs successfully captured by ERA5 per station, regardless of false alarms. These percentages range between 47.46% (16613) and 72.63% (16724). This behavior suggests that ERA5-Land data tend to capture the majority of HNMS-derived HEs, although they sometimes overestimate their occurrence. The overall trend indicates that the system prioritizes sensitivity (detecting most events) over precision (avoiding false positives).

TABLE III. KS TEST RESULTS BETWEEN INTERPOLATED AND MEASURED CLIMATOLOGICAL INDICES.

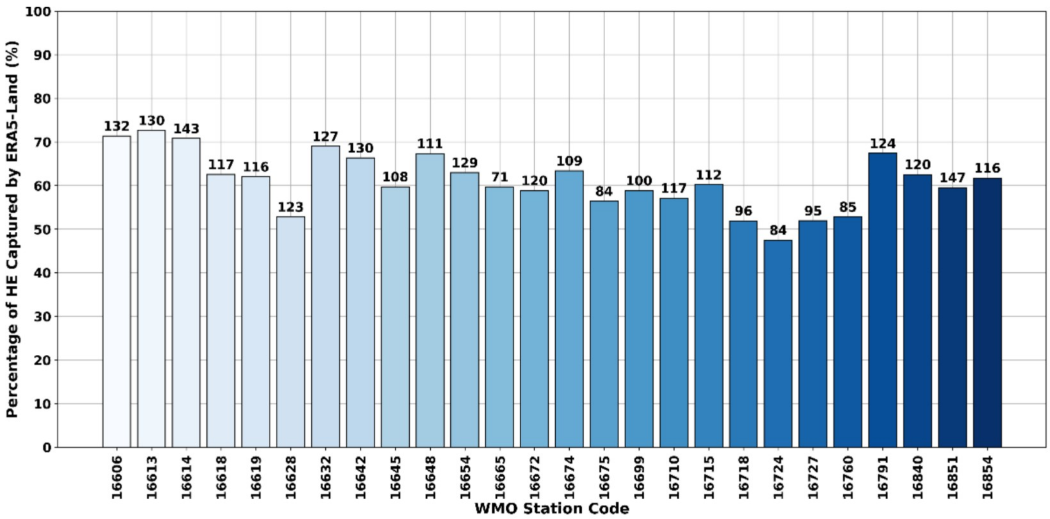
Station Code	HF KS Statistic	HD KS Statistic	HS KS Statistic	HS p-value
16606	0.2600	0.3293	0.1713	0.0280
16613	0.2788	0.2317	0.0769	0.7186
16614	0.2614	0.2770	0.0857	0.5570
16618	0.3274	0.2449	0.0776	0.7056
16619	0.3774	0.3198	0.1004	0.4232
16628	0.3423	0.2904	0.0698	0.7408
16632	0.3358	0.2578	0.1371	0.1279
16642	0.3206	0.3461	0.1189	0.1855
16645	0.3561	0.2578	0.1137	0.2924
16648	0.3859	0.3017	0.1070	0.3797
16654	0.3386	0.3037	0.0816	0.6169
16665	0.3965	0.3712	0.1282	0.4628
16672	0.3785	0.2642	0.1593	0.0296
16674	0.3882	0.3431	0.1715	0.0346
16675	0.4100	0.3492	0.0892	0.6616
16699	0.3424	0.3736	0.1565	0.0752
16710	0.3959	0.2783	0.2137	0.0012
16715	0.4176	0.3106	0.0733	0.8369
16718	0.4358	0.2704	0.1390	0.1531
16724	0.4448	0.3664	0.0693	0.8687
16727	0.4198	0.3448	0.2301	0.0012
16760	0.3214	0.4390	0.2262	0.0032
16791	0.3871	0.3288	0.1520	0.0564
16840	0.3430	0.2911	0.1161	0.1790
16851	0.3428	0.3647	0.1423	0.0413
16854	0.2639	0.3109	0.2401	0.0001

The present study provides an overview of the ability of the ERA5-Land dataset to capture the occurrence of HEs. The agreement observed between ERA5-Land and station-based daily TX time series, as well as the reliable representation of TX95 values, is consistent with other studies that highlight ERA5-Land's accuracy in capturing general temperature patterns and extreme hot temperatures across Europe [12, 32]. Furthermore, the observation that ERA5-Land is valuable in areas with limited station coverage, particularly mountainous regions, is supported by other research highlighting the utility of reanalysis data in such data-sparse environments [20].

However, statistically significant discrepancies were identified in the HF and HD indices between the two datasets in all cases, despite good agreement in HS. Studies have indicated that while reanalysis products can accurately represent the magnitude of temperature extremes, they often struggle with the precise timing, frequency, and duration of HEs, especially in regions with complex or heterogeneous terrains [33]. The inherent smoothing effect of gridded datasets and the challenges in capturing finer-scale atmospheric phenomena in such diverse topographies, like those found in Greece, may lead to such discrepancies [23, 24, 34]. Despite these limitations, the strong temporal correspondence observed in



(a)



(b)

(a) Percentage of correctly identified HEs and (b) percentage of HEs captured by ERA5-Land dataset across different weather stations.Numbers above each bar indicate the exact number of HEs.

heatwave detection in this study reinforces the utility of ERA5-Land for identifying the occurrence and persistence of heatwaves.

IV. Conclusions

This study evaluated the ability of the spatially interpolated dataset, generated using the Inverse Distance Weighting (IDW) method, from the ERA5-Land reanalysis values from 1950 to present to replicate the measured daily Maximum Temperature (TX) and heatwave characteristics in Greece. The interpolated data were compared against measurements from the Hellenic National Meteorological Service (HNMS) weather station network.

The comparison of raw TX time series demonstrated strong agreement, with values distributed closely along the line of equality and Cumulative Distribution Functions (CDFs) exhibiting nearly identical shapes. In addition, Kolmogorov–Smirnov (KS) test statistics highlighted statistically significant results with low KS values (0.0560–0.2133) and near-zero p-values, indicating that ERA5-Land provides a robust reproduction of daily TX values across stations.

The assessment of daily 95th-percentile TX thresholds (TX95) further confirmed this reliability. ERA5-Land closely follows measurements, with only a few deviations, particularly at lower TX values. KS statistics indicated statistically significant but generally small discrepancies, consistent with the expected smoothing of localized extremes in gridded datasets. Similarly, the analysis of climatological indices highlighted systematic differences in HD and HF, with KS statistics often exceeding 0.3. These results suggest that ERA5-Land underestimates the temporal extent and recurrence of heatwaves, a limitation attributed to spatial averaging. In contrast, HS values showed far closer agreement, with small KS values but higher p-values.

Despite these systematic biases in HD and HF, the evaluation of HE detection revealed a moderate temporal correspondence between ERA5 and HNMS observations. The percentage of temporally correctly identified HEs ranged from 34.30% to 54.17%, while the percentage of HEs successfully captured by ERA5-Land ranged from 47.46% to 72.63%. This indicates that the ERA5-Land dataset can be utilized to identify the occurrence and persistence of heatwaves, but its limitations should be carefully considered. For precise temporal and recurrence analyses, however, the specific limitations of ERA5-Land concerning HF and HD should be acknowledged.

Overall, ERA5-Land is concluded to be a reliable dataset for assessing and identifying HEs in Greece, especially in areas with limited station coverage. While there are systematic biases in HD and HF , the dataset offers a reliable representation of extreme temperature intensity and a robust reproduction of heatwave occurrence. These findings highlight the suitability of ERA5-Land for climatological and risk assessment applications, while also underscoring the continued importance of station-based observations for capturing localized extremes.

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