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Research Article

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Posted Date: October 15th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11116863/v1>

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Additional Declarations: No competing interests reported.

From Hours to Daily Extremes: Evaluating ERA5 and ERA5-Land Biases Across Morocco's Diverse Climates

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ABSTRACT

Reanalysis products increasingly serve as ground-truth references and training/verification data for statistical and machine-learning applications in regions with sparse in-situ networks. This study evaluates ERA5 and ERA5-Land against 36 quality controlled synoptic stations over Morocco, across hourly, seasonal, Köppen-climate, and daily-extreme timescales, from 2016 to 2024. Both reanalysis reproduce the mean diurnal and seasonal cycle of near-surface variables with high fidelity (Pearson r frequently > 0.9 for temperature), and the two reanalysis products are broadly interchangeable for climatological applications, with small, systematic differences per variable (ERA5 ahead for temperature, humidity and wind bias; ERA5-Land ahead for wind-speed RMSE in complex terrain). Categorical verification of daily extremes reveals a threshold-dependent, rather than uniformly poor, skill: moderate warm/cold/wind thresholds are detected well by both products, but skill collapses specifically at the most extreme, rarest thresholds (POD falling from ~ 0.85 to ~ 0.4 for the hottest T2M_MAX class; near-zero

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for the strongest WS_MAX class), a pattern consistent with the known degeneracy of traditional contingency-table scores for rare events rather than with a specific flaw of either reanalysis. We additionally document a structural ERA5-Land limitation: its land-only grid leaves no valid nearest-neighbour match at some coastal/island-adjacent stations (e.g. Dakhla), a gap that is easily mistaken for missing observations if not checked explicitly. The results argue for anomaly- or percentile-based extreme definitions, and for explicit reporting of land-mask coverage, when ERA5/ERA5-Land are used for impact studies or as an AI-model verification baseline over Morocco's complex, station-sparse terrain.

Key words: ERA5 Reanalysis, ERA5-Land Reanalysis, Validation, Morocco, Extreme Weather, Climates.

Article Highlights:

- Filling an important benchmark gap, this study provides the first station-dense, multi-variable assessment of ERA5 and ERA5-Land across Morocco's diverse Köppen climate zones and throughout the complete diurnal cycle.
- The study systematically assesses reanalysis performance across a wide range of geographic and meteorological situations using high-resolution hourly observations from 36 synoptic stations between 2016 and 2024.

- The study creates a solid reference for evaluating the dependability of reanalysis in out-of-sample AI model evaluation by rigorously validating daily temperature, wind speed, and precipitation extremes.

1. Introduction

The fifth-generation ECMWF reanalysis, ERA5 (Hersbach et al. 2020), and its land-surface companion, ERA5-Land (Muñoz-Sabater et al. 2021), are now the default reference datasets for a wide range of downstream products: bias-correction of numerical weather prediction, hydrological and agrometeorological modelling, climate-service indicators, weather remote sensing validation, and the training and out-of-sample evaluation of data-driven (AI) weather models. This last use case raises the stakes of reanalysis quality assurance considerably, since biases and unresolved local processes in the reanalysis are silently inherited by any model trained on it. On global scale several research studies have been achieved in reanalysis validation or intercomparison. Mainly driven by climate monitoring such studies suggest generally three streams of validation: (1) a climate scale evaluation of the reanalysis quality and accuracy on daily basis, (2) a validation of reanalysis against satellite data and finally (3) a validation against extreme weather events. In recent years the ERA5 reanalysis played a key role in the development of weather fully data driven models. As they found the initial unique complete reliable input covering profound archive periods extending to 40 years. The majority of global weather foundation models (GraphCast (Lam et al. 2023), Aurora (Bodnar et al. 2024), Pangu (Bi et al. 2023), FourCastNet (Pathak et al. 2022) and AIFS (Lang et al. 2024) are commonly trained using ERA5 Reanalysis differing only in architectures with a set based on graphical neural networks and another based on transformers. These data-driven

models have matched state-of-the-art physics-based systems like the ECMWF's IFS HRES in deterministic medium-range forecasting across multiple lead times (Keisler 2022; Chen et al. 2023). Independent benchmark evaluations, such as WeatherBench 2, affirms that these models consistently achieve higher average skill across various parameters and metrics and provide competitive performances to classical NWP models (Rasp et al. 2024; Bouallègue et al. 2024; Bouallègue 2026; He and Chan 2025; Casati et al. 2026). Despite strong overall performance, existing assessments focus generally on average forecast skill rather than extreme events. This shortcoming known as the out of sample data driven models issue remain big challenge despite isolated case studies exist such as cyclone tracking (Charlton-Perez et al. 2024) and surface temperature extremes (Bouallègue et al. 2024) a global, systematic assessment is missing. Average forecast skill does not automatically guarantee strong performance in the tails of the distribution (Watson 2022; Olivetti and Messori 2024; Burgh-Day and Leeuwenburg 2023). Discrepancy between data driven models forecasts and extreme events are mainly due to three factors: (a) Sparsity of extreme events in training data mainly ERA5 Reanalysis (Watson 2022); (b) Inadequate symmetric loss functions that fail to weight extremes appropriately (Olivetti and Messori 2024) and (c) Architectural optimizations, such as multi-task and multi-step training (e.g.,(Bi et al. 2023; Lam et al. 2023)). Since ERA5 Reanalysis acts as the main ground truth baseline and training input for advanced data-driven weather models, it is essential to validate its accuracy and reliability against local observations in specific regions to detect any regional representation errors before they affect model predictions.

Reliable extreme weather forecasts are vital for disaster risk management (World Meteorological Organization 2023; Merz et al. 2020) and key socioeconomic sectors like energy and insurance (Kron et al. 2019). Consequently, validating extreme-weather performance is critical prior to operational adoption (Watson 2022). This imperative directly underlines the necessity of locally validating ERA5 and ERA5-Land, which serve as the primary inputs, training targets, and verification benchmarks for data-driven models. Because gridded reanalysis inherently smooth out hyper-local physical dynamics and peak values, an AI model that appears highly accurate against global ERA5 baseline data may still fail to capture severe, real-world local impacts. To guarantee reliable deployment in risk-critical decision-making, the ERA5 and ERA5-Land benchmarks themselves must be rigorously evaluated against local ground observations and extreme-quantile thresholds, ensuring that downstream AI predictions reflect true localized hazards rather than smoothed reanalysis artifacts. ERA5 and ERA5-Land reanalysis play a vital role in weather model verification and validation by serving as the primary benchmark. Numerous benchmark datasets spanning mesoscale to climate scales have been built on ERA5 data to act as ground truth for operational and fully data-driven forecasting models. This foundational role is crucial, as these reanalysis supply the core baseline needed to evaluate model performance, particularly at high altitudes and in data-sparse regions where observational coverage is sparse.

2. Literature Review

Many studies on global reanalysis validation generally categorize their evaluations into three main streams: assessing daily accuracy across climate scales, validating data against satellite observations, and testing reliability during extreme weather events. From global

validation perspective, authors in (Liu et al. 2024) conducted a global assessment of ERA5 temperature and precipitation accuracy on monthly scale over the past 70 years against Climatic Research Unit Time-Series version 4.04) gridded data using multiple statistical scores and detection metrics. Authors in (Liu et al. 2024) report overall good consistency of ERA5 reanalysis with gaps in accuracy of ERA5 between the two periods (1950–1979, 1979–2019) and generally a better performance of ERA5 temperature compared to precipitation. Results also show that mid- and low-latitude precipitation in both hemispheres follows a positive–negative pattern, while for temperatures an inverse distribution between the hemispheres, dominated by warmer conditions in the north and colder conditions in the south is noticed.

Correspondingly authors in (Molina et al. 2021) evaluated ERA5 datasets hourly wind speed 10m against HadISD observations across 245 European stations showing that ERA5 effectively captures regional wind characteristics. Authors also highlighted that ERA5 replicates accurately the annual cycle reproducing monthly wind speed cycle across Europe with slightly higher monthly medians in winter and lower medians in summer compared to observational data. Using a frequency distribution-based score ranging from 0 to 1, most stations record scores between 0.8 and 0.9. This indicates a high capability in mapping the full wind speed spectrum (from light to strong relative frequencies) across different European locations.

Regarding ERA5 validation against satellite data, authors in (Urraca et al. 2018) evaluated the global horizontal irradiance estimates from ERA5 and COSMO-REA6 reanalysis using ground and satellite-based data. Authors found that ERA5 and COSMO-REA6 reduce the quality gap between reanalysis and satellite data. ERA5 bias is like that

of satellite data for inland regions with few clouds. COSMO-REA6 is comparable to ERA5 for North and Central Europe. The absolute error of reanalysis is large due to a deficient cloud prediction. COSMO-REA6 underestimates due to the overestimation of aerosols. In similar context (Li et al. 2024) validated ERA5 reanalysis against cloud height (CHB) base from satellite images globally, the authors found that ERA5 underestimated globally CHB with strong bias in low latitudes, large bias on low latitudes depends mainly on separated type of cirrus clouds.

ERA5 Reanalysis helped also in monitoring several global weather and climate extremes, authors in (Dullaart et al. 2020) assessed how the improvement in ERA5 reanalysis can affect the accuracy of simulating storm surge events using the Global Tide and Surge Model. The authors find that the improved wind and pressure fields in ERA5 compared to ERA-Interim helps increase accuracy by reducing tropical cyclone wind speed errors by 58%, for the Irma use case authors stress out a matching between ERA5 and tide gauge observations compared to large under-estimation using ERA-Interim. This displays that model resolution markedly enhances global coastal flood hazard assessment in early warning systems.

Over the Mediterranean region, authors in (Yavaslı and Erat 2024) applied ERA5-Land to long-term precipitation variability from 1950 to 2024, deriving high-resolution indices of precipitation frequency, intensity and persistence and testing them for trend with the Mann-Kendall test and Sen's slope estimator. The dataset resolves regional contrasts, including decreasing heavy precipitation frequencies in the western Mediterranean and increasing extremes in the northeastern basin, highlighting its capability to represent spatially heterogeneous climate signals. Likewise, authors in (Aragão and Porcù 2022)

displays that the high spatial and temporal resolution of ERA5 has proven valuable for atmospheric circulation studies, particularly for cyclone detection and climatology. By exploiting ERA5's enhanced resolution, a newly developed cyclone detection and tracking method identified approximately 40% more cyclones than previous datasets, especially sub-synoptic and baroclinic systems, while accurately reproducing known cyclogenesis regions and revealing previously underestimated areas such as the Aegean Sea and the Tunisian–Libyan coasts. Finally, authors in (Vannucchi et al. 2021) provided 29-year Mediterranean wind and wave hindcast driven by ERA5 atmospheric fields showed good agreement with buoy and coastal station observations, with significant wave height correlations ranging from 0.89 to 0.96 and improved representation of coastal wind and wave characteristics compared with the original ERA5 fields.

Over Africa, and Morocco in particular, the observation network is comparatively sparse and heterogeneous in exposure, which makes independent, station-based verification both more difficult and more necessary. Prior evaluations of ERA5 over the African continent have focused primarily on precipitation at seasonal-to-interannual scales (Nogueira et al. 2021), while Moroccan-focused studies have generally targeted a single basin or a handful of rain gauges for hydrological applications (El Khalki et al. 2023; Ait Dhmane et al. 2023; Chakri et al. 2025). Authors in (El Kihel et al. 2025) compared MERRA-2 and ERA5 reanalysis datasets for wind energy modeling and assess the technical and economic viability across 39 sites, the study displays that MERRA-2 outperformed ERA5.

Authors in (Rezkallah et al. 2026) reconstructed 44 years continuous monthly precipitation dataset over the Sebou basin in Morocco, spanning 11 stations (5 m to 1478

m elevation) using Quantile Mapping (QM) bias-corrected ERA5 data. The authors underlined ERA5 severe positive biases at high altitudes. Seasonal Quantile Mapping reduced mean bias from +8.9% down to -0.1% and improved mean Nash-Sutcliffe Efficiency (NSE from -0.32 to +0.68)

Authors in (Rasp et al. 2020, 2024) suggests two datasets Weather Bench and Weather Bench 2 both datasets are fundamentally based on ERA5 and ERA5-Land reanalysis. WeatherBench provides a standardized framework for evaluating data-driven weather forecasting methods. While physics-based numerical models excel at many tasks, key performance gaps remain. In contrast, artificial intelligence and deep learning leverage observational datasets directly, offering the potential to surpass traditional forecast accuracy. Standardized benchmarks such as WeatherBench and its second-generation iteration, WeatherBench 2 establishes unified evaluation metrics, open-source datasets, and code, with initial tasks focused on global pressure and temperature predictions across 3- to 5-day lead times. By setting these standards, the project aims to bridge AI and traditional numerical modeling, fostering interdisciplinary collaboration to accelerate progress in global weather prediction.

On the other hand, authors in (Sarpong and Nazemi 2025) proposed a benchmark on Snow Fields of ERA5-Land in the Northern Regions of North America. The authors, evaluates the accuracy of ERA5-Land snow cover, snow depth, and Snow Water Equivalent (SWE) across monthly, seasonal, and annual scales, within the ecological regions of Canada and Alaska, regions that are characterized by prolonged seasonal snow cover. By comparing ERA5-Land's snow data against MODIS satellite imagery and Canadian Meteorological Centre analyses, the authors found that ERA5-Land severely

overestimates historical averages and year-to-year variability while distorting multi-year trends. Raw values for both variables should not be used directly. However, ERA5-Land stays more reliable for snow cover and density but still requires local bias adjustments before use.

Together, these studies confirm that ERA5 and ERA5-Land provide a robust and physically consistent representation of Global, Mediterranean and Moroccan atmospheric and hydrological conditions in climatological scale, making them reliable benchmarking and training datasets for climate trend analyses, extreme event characterization and cyclone climatology, however a local fine-scale verification at the station level on an hourly basis is always a necessity to assess regional performance.

To our knowledge, a station-dense, multi-variable evaluation of ERA5 datasets across Morocco's full diurnal cycle, diverse Köppen climate classes (Beck et al. 2018), and daily extremes remains absent from the literature. This work addresses this benchmark gap, providing the rigorous baseline validation of the performance of both ERA5 and ERA5-Land in capturing hourly observations by climates space and extreme weather events over Morocco for 36 ground stations from 2016 to 2024. This work conducts a systematic, multi-variable, station-dense verification spanning the full diurnal cycle, the Köppen climate classes present in Morocco, along with daily temperature/wind/precipitation extremes. This is precisely required before ERA5/ERA5-Land can be trusted as a baseline for out-of-sample AI model verification over Morocco.

This work targets the following objectives:

• Hourly validation of ERA5 and ERA5-Land over different climate zones, several stations during 8 years against synoptic observations.

• Daily verification of the ERA5 and ERA5-Land in detecting extreme weather events of temperature, wind speed and precipitation.

This article is organized as follows: Following the introduction and literature review section that presents several works related to the global, local validation of reanalysis, their usage as inputs and benchmarks for data-driven models. The third section is dedicated to the studied domain, the used dataset, and the effect of nearest neighbor's grid point selection for our use case. The fourth part is devoted to methodology where the verification framework is presented along with the metrics used for continuous and binary validation. Results section covers two verification process: continuous verification using bias, RMSE, relative RMSE and correlation and a probabilistic verification process where occurrences of extreme wind, temperature and precipitation events are conducted using an operational set of thresholds. Finally, the conclusion and discussion where further perspectives and limitations of this work are highlighted.

3. Dataset and Study Domain

For this study the datasets used are ERA5 Reanalysis (Hersbach et al. 2020) and ERA5 Land Reanalysis (Muñoz-Sabater et al. 2021) provided by the European Center of Medium Range Weather Forecasts.

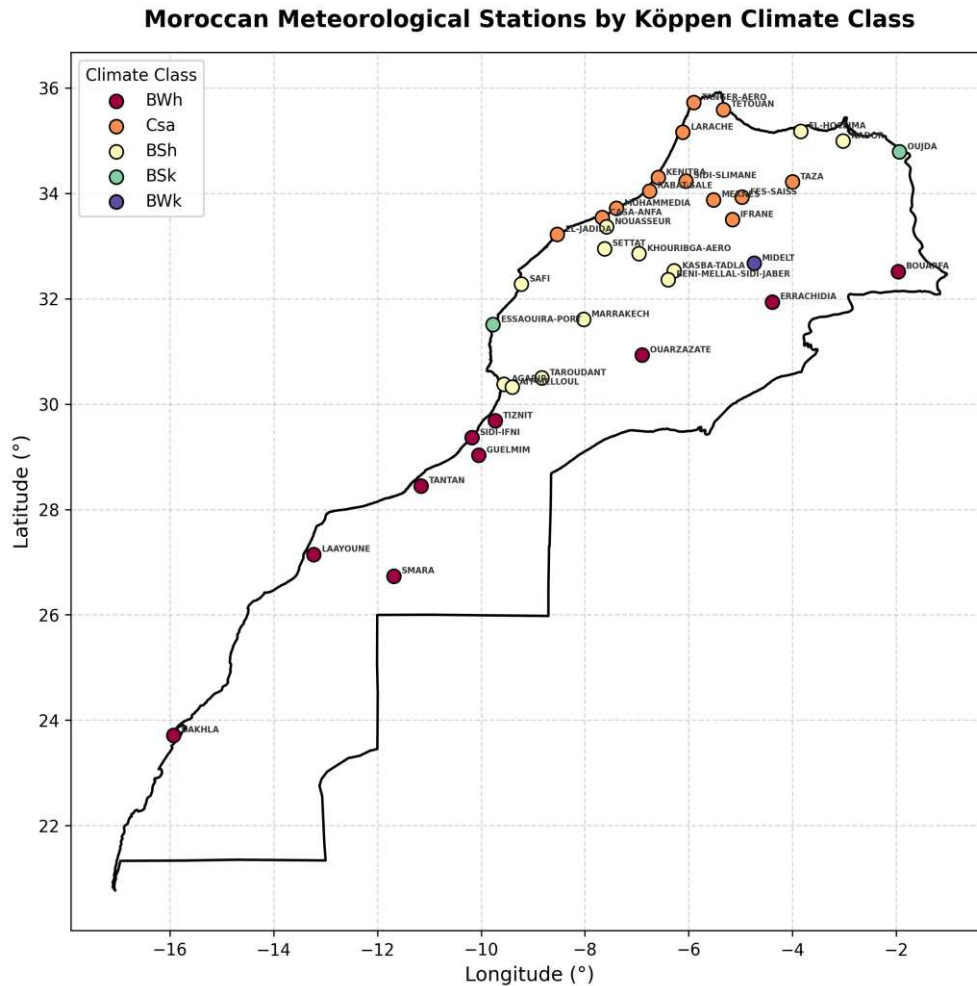


Fig. 1. Moroccan synoptic observation stations by Köppen climate class spatial distribution.

3.1 ERA5 Reanalysis

ERA5 is the fifth-generation ECMWF global atmospheric reanalysis delivered for the Copernicus Climate Change Service, operating on the Integrated Forecasting System (IFS Cycle 41r2) to produce a comprehensive multi-decadal climate record. Technically, these reanalysis offer a major upgrade compared to its predecessor by refining the global horizontal grid resolution from approximately 80 km down to 31 km (TCO639) and extending the vertical domain across 137 hybrid sigma-pressure levels from the surface

up to 0.01 hPa. Driven by twice-daily 12-hour 4D-Var data assimilation cycles (initialized at 06:00 and 18:00 UTC), ERA5 uniquely delivers hourly outputs for atmospheric, land-surface, and ocean-wave parameters (Hersbach et al. 2020). ERA5 has established itself as the indispensable foundation for a vast span of Earth-system applications, serving as the definitive baseline that bridges traditional Numerical Weather Prediction (NWP), multi-decadal climate monitoring, advanced satellite data assimilation, and the modern revolution of AI-driven weather forecasting models (Lam et al. 2023; Bi et al. 2023).

3.2 ERA5-Land Reanalysis

Along with ERA5, ERA5-Land is a state-of-the-art global land reanalysis dataset designed to provide a highly consistent, multi-decadal record of the Earth's water and energy cycles near the surface. Technically, it is produced by running offline global numerical integrations of the ECMWF land surface model at a high native spatial resolution of 9 km ($0.1^\circ \times 0.1^\circ$)—a major refinement compared to the parent ERA5 atmospheric grid (31 km). Driven exclusively by ERA5 atmospheric forcing fields (such as air temperature, humidity, and surface pressure) corrected via lapse-rate adjustments for altitude differences, ERA5-Land outputs hourly variables that capture enhanced land-surface heterogeneity. It has become an indispensable baseline for hydrological studies, flood and drought forecasting, initializing regional NWP and climate models, and analyzing land-atmosphere feedback (Muñoz-Sabater et al. 2021). Because ERA5-Land is generated over a land-only mask, its nearest grid cell to a coastal or island-adjacent station can be undefined or hydrologically unrepresentative.

3.3 Observations

Hourly surface observations from 36 synoptic stations operated by DGM are used as ground truth, covering the full domain of the Moroccan Kingdom. Observations stations span over various climate zones and topographies (See Figure 1 and Table 1). The climate classification for the validation of reanalysis is driven by the Koppen classification where five classes are present in Morocco semi-arid (BSh) and cold semi-arid (BSk) in the interior; hot desert (BWh) and cold desert (BWk) in the Saharan and high-altitude zones; and hot-summer Mediterranean (Csa) along the coast and northern mountains. Standard quality-control procedures (range, internal-consistency and temporal-continuity checks, following WMO guidance in (World Meteorological Organization 2021)) are applied prior to matching.

Table 1. Station Metadata and Data Availability starting from 01-01-2016.

Wmoid	Station	Alt	Records	End_Date	T2m (%)	TP (%)	WS10m (%)	RH2m (%)
60033	LAAYOUNE	66.7	871476	2024-10-31	99.74	6.72	99.66	99.69
60060	SIDI-IFNI	49.5	817476	2024-09-30	95.91	31.12	91.92	94.37
60096	DAKHLA	11.0	788604	2024-10-31	76.69	0.15	62.19	76.68
60101	TANGER-AERO	16.0	871476	2023-12-31	99.87	5.14	98.51	99.86
60105	LARACHE	70.0	854148	2023-12-31	72.68	3.71	90.07	58.17
60107	EL-HOCEIMA	12.0	862236	2023-12-31	100.0	2.73	99.92	99.98
60115	Oujda	464.8	879564	2024-09-30	100.0	2.92	99.99	100.0
60120	KENITRA	1.9	862236	2023-12-31	100.0	4.61	99.85	99.98
60127	TAZA	509.2	644508	2021-12-31	99.87	4.96	54.15	97.13
60135	RABAT-SALE	74.7	871476	2023-12-31	100.0	4.28	99.84	100.0

60136	SIDI-SLIMANE	51.6	862236	2023-12-31	100.0	3.39	94.63	99.99
60141	FES-SAISS	571.0	953196	2024-09-30	100.0	4.01	99.96	100.0
60146	MOHAMMEDIA	4.3	843744	2024-09-30	66.62	2.68	99.15	66.55
60150	MEKNES	556.0	889380	2024-09-30	100.0	4.6	99.99	100.0
60155	CASA-ANFA	84.0	935004	2024-09-30	79.37	3.29	65.17	79.07
60156	NOUASSEUR	200.0	919128	2024-09-30	99.78	2.95	99.62	99.77
60160	IFRANE	1663.7	943956	2024-09-30	100.0	6.08	99.97	100.0
60165	EL-JADIDA	27.0	897744	2024-09-30	79.59	4.16	99.34	73.88
60177	SETTAT	407.5	907860	2024-09-30	61.05	6.12	60.45	60.75
60178	KHOURIBGA-AERO	772.4	548064	2024-09-30	67.83	1.98	67.73	67.82
60185	SAFI	43.0	925176	2024-09-30	71.65	2.5	97.7	71.65
60195	MIDELT	1507.4	661836	2024-09-30	73.62	2.07	99.45	73.54
60200	BOUARFA	1127.0	953196	2024-09-30	99.97	1.48	99.78	99.96
60210	ERRACHIDIA	1048.4	580116	2024-09-30	99.94	1.62	96.17	99.94
60220	ESSAOUIRA-PORT	7.1	862524	2024-09-30	78.72	0.81	78.53	51.84
60230	MARRAKECH	463.5	858768	2024-09-30	99.58	1.8	99.17	99.58
60250	AGADIR	17.0	826140	2024-09-30	70.4	0.52	65.21	65.29
60252	AIT-MELLOUL	74.0	835668	2024-09-30	100.0	1.09	99.64	100.0
60253	TAROUDANT	263.0	816624	2024-09-30	99.99	37.2	99.99	99.99
60265	OUARZAZATE	1131.0	543732	2024-09-30	99.99	1.12	58.91	99.97
60270	TIZNIT	264.6	825840	2024-09-30	96.32	29.86	94.72	94.93
60280	GUELMIM	332.0	844332	2024-09-30	79.94	0.96	79.07	79.9
60285	TANTAN	192.0	835092	2024-09-30	73.81	0.69	71.59	64.73

60318	TETOUAN	5.0	871476	2023-12-31	99.77	5.24	99.58	99.77
60335	SMARA	170.0	853572	2024-10-31	57.17	1.5	23.04	57.14
60340	NADOR	178.0	590508	2024-09-30	100.0	2.27	76.29	100.0

3.4 Nearest grid points representativeness

Figure 2 displays the spatial density of the minimal distance between each reanalysis grid point and the exact location of the ground station for ERA5 and ERA5-Land. Most of the stations nearest reanalysis grid points are in a less than 10km radius for both ERA5 and ERA5-Land, except for some interior stations (BENI-MELLAL and NOUACEUR) where this distance can climb up to 16km, which goes in line with WMO synoptic spatial representativeness. Figure 2 also highlights a structural ERA5-Land limitation: its land-only grid leaves no valid nearest-neighbor match at some coastal/island-adjacent stations (e.g. Dakhla see Zoom in Figure 2), a gap that is easily mistaken for missing observations if not checked explicitly, this displays a structural limitation of ERA5-Land compared to ERA5 despite the high-resolution advantage. It is to mention that elevation corrections for stations beyond 750m have been carried out for the studied variables.

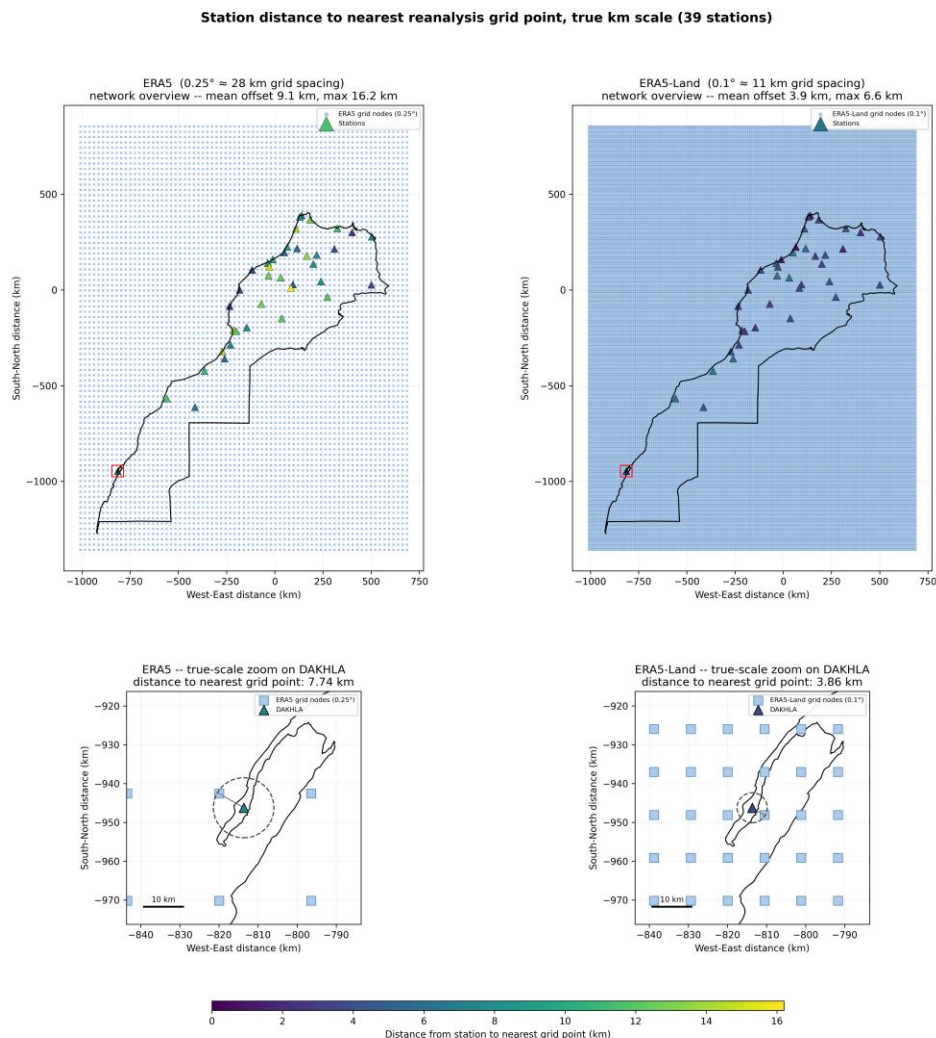


Fig. 2. Distance of nearest grid point from observation station's location for ERA5 and ERA5-Land reanalysis.

4. Methodology

4.1 Verification workflow

The verification workflow is a two parts process (See Figure 3): continuous hourly verification in space, time, seasons and climate classes and daily categorical and continuous verification for extreme events based on operational local fixed thresholds. For the continuous hourly verification three parameters are assessed the temperature at

2m (T2m), wind speed at 10m (WS10m), relative humidity at 2m (RH2m). The choice of those parameters is justified by two main reasons: firstly, by their availability on profound archives of observations and in both reanalysis datasets, secondly those surface parameters characterize the main proprieties of the atmospheric conditions near the surface regarding heat, moisture and dynamics, they are also required for many applications and have impact in many strategic fields in Morocco such as agriculture, hydrology, aviation and marine traffic. The quality of those parameters in both datasets was evaluated daily and hourly using four key metrics: bias, RMSE, Pearson correlation and relative RMSE (see section 4.2 for more details). Regarding the daily categorical verification, 4 parameters are verified as the temperature at 2m daily minimum and maximum (T2m_Min, T2m_Max), wind speed at 10m daily maximum (WS10m_Max) and finally the total daily precipitation (TP). Categorical extreme-event verification employs standard 2×2 contingency-table metrics (Wilks 2001), including the probability of detection (POD), success ratio (SR=1-FAR), frequency bias, and critical success index (CSI), which are summarized using Roebber performance diagrams (Roebber 2009) alongside relative operating characteristic (ROC) curves and the area under the curve (AUC) for daily precipitation exceeding 10mm. Because these scores are known to degenerate toward trivial values as the verified event becomes rarer (Ferro and Stephenson 2011), results are evaluated across the full range of sampled thresholds rather than at a single nominal value, with the threshold-dependence itself treated as a primary finding. Daily extremes are evaluated using station-specific climatological thresholds across a spectrum of percentiles and absolute values.

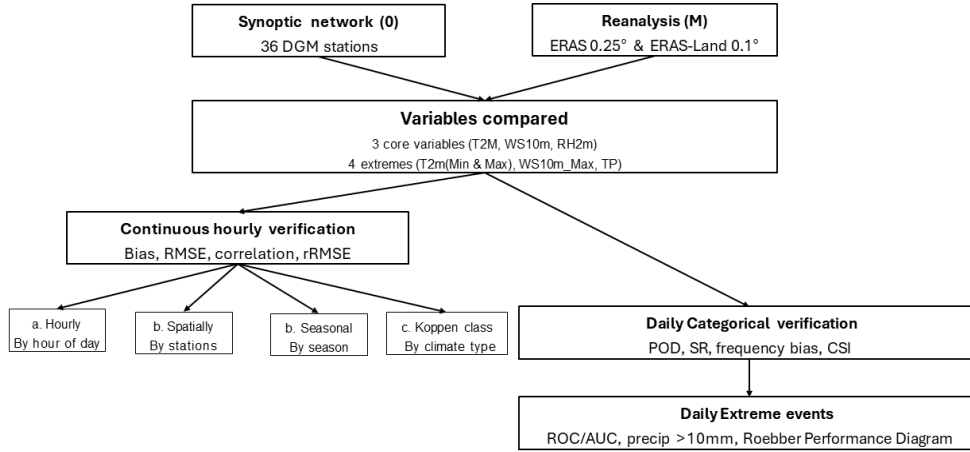


Fig. 3. The Verification Workflow.

4.2 Continuous verification

Continuous verification metrics evaluate the numerical error and linear association between continuous meteorological fields M_i and corresponding observations O_i .

4.2.1 Bias

Bias measures the average tendency of the reanalysis model to overestimate or underestimate observed values. A bias of zero indicates an unbiased system, whereas positive (negative) values denote systematic overestimation (underestimation).

$$Bias = \frac{1}{N} \sum_{i=1}^N (M_i - O_i)$$

Where N is the total number of evaluation pairs.

4.2.2 Root Mean Square Error (RMSE)

RMSE calculates the sample standard deviation of the differences between model forecasts and observations. It gives disproportionately high weight to large errors due to the squaring operation, making it sensitive to outliers and extreme values.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (M_i - O_i)^2}$$

4.2.3 Relative Root Mean Square Error (Relative RMSE)

Relative RMSE normalises RMSE by the mean or standard deviation of observations (or model values), facilitating dimensionless comparisons across variables with different units or magnitudes.

$$rRMSE(\%) = (RMSE / \bar{O}) * 100\%$$

Where $\bar{O}$ is the observation mean

4.2.4 Relative Root Mean Square Error (Relative RMSE)

Pearson correlation measures the strength and direction of the linear relationship between reanalysis estimates and observations, ranging from -1 to +1. It is insensitive to additive and multiplicative systematic biases.

$$R = \frac{\sum_1^N (M_i - \bar{M}) * (O_i - \bar{O})}{\sqrt{\sum_1^N (M_i - \bar{M})^2} * \sqrt{\sum_1^N (O_i - \bar{O})^2}}$$

4.3 Categorical (Binary) Verification & Contingency Tables

Categorical verification assesses how well a model predicts the occurrence or non-occurrence of discrete events (e.g., precipitation exceeding a specific threshold, frost, gale-force winds). Continuous or probabilistic fields are converted into binary outcomes using a defined threshold.

4.3.1 The 2×2 Contingency Table

The 2×2 contingency table is corner stone of categorical verification, which cross-classifies forecasts and observations into four distinct categories based on whether the event was forecasted and whether it occurred. From this verification tools one can extract a diversity of probabilistic verification scores (POD, FAR, CSI...)

Table 2. Contingency Matrix

Contingency Matrix	Observed Yes (O = 1)	Observed No (O = 0)
Forecast Yes (M = 1)	Hits (a)	False Alarms (b)
Forecast No (M = 0)	Misses (c)	Correct Negatives (d)

4.3.2 Probability of Detection (POD)

POD (Hit Rate) measures the fraction of observed events that were correctly forecasted by the model. Ranges from 0 to 1.

$$POD = \frac{a}{a + c}$$

4.3.3 False Alarm Ratio (FAR)

FAR measures the fraction of model-forecasted events that did not actually occur in observations. Optimal value is 0.

$$FAR = \frac{b}{a + b}$$

4.3.4 Success Ratio (SR)

SR represents the proportion of correct positive forecasts among all positive forecasts. It is the complement of the False Alarm Ratio.

$$SR = 1 - FAR = \frac{a}{a + b}$$

4.3.5 Critical Success Index (CSI) / Threat Score

CSI measures the overall fraction of observed and/or forecasted events correctly predicted, penalizing both false alarms and misses.

$$CSI = \frac{a}{a + b + c}$$

4.3.6 Frequency Bias

Frequency bias compares the total number of events forecasted to the total number observed, indicating systematic over-forecasting (>1) or under-forecasting (<1).

$$Frequency\ Bias = \frac{a + b}{a + c}$$

4.3.7 Relative Operating Characteristic (ROC) Curve

The ROC curve plots the Probability of Detection (POD) on the vertical axis against the Probability of False Detection (POFD) across various decision thresholds. POFD is defined as:

$$POFD = \frac{b}{b + d}$$

4.3.8 Area Under the ROC Curve (AUC)

AUC summarizes overall discriminative skill across all possible decision thresholds into a single scalar value from 0.5 (no skill) to 1.0 (perfect discrimination).

4.3.9 Roebber Performance Diagrams

Roebber performance diagrams provide an advanced geometric framework specifically engineered to visualize dichotomous forecast performance without the visual bias associated with rare events. By plotting Success Ratio ($SR=1-FAR$) on the x-axis against Probability of Detection (POD) on the y-axis, Roebber performance diagrams simultaneously display two critical diagnostic relationships:

- Critical Success Index (CSI): Represented as non-linear curved contours across the diagram, allowing direct reading of threat score skill levels.
- Frequency Bias: Represented as radial straight lines originating from the origin (0,0), enabling immediate identification of under forecasting or over forecasting tendencies.

Unlike traditional ROC space—where rare events can create an illusion of high performance due to the dominance of correct negatives (d)—Roebber performance diagrams omit correct negatives entirely. This makes them exceptionally powerful for evaluating high-impact extreme events (such as heavy daily precipitation thresholds > 10 mm) where traditional metrics degenerate.

5. Methodology

5.1 Hourly Validation

5.1.1 Hourly Bias and RMSE of ERA5 and ERA5-Land

Figure 4 displays hourly 24 hours mean bias and RMSE of surface weather parameters (T2m, RH2m, WS10m) for single level ERA5 and ERA5 Land reanalysis for 36 stations over Morocco. Regarding 2-meter temperature (T2m), the ERA5 single-levels reanalysis performs best, exhibiting a bias near 0°C (with a maximum magnitude of 0.5°C) at daytime hours. In contrast, ERA5-Land displays a mean bias of 0.5°C. In terms of RMSE, both configurations show a consistent value of approximately 2°C. For 2-meter relative humidity (RH2m), ERA5 single-levels show a near-zero mean bias for most hours, except for isolated peaks during daytime hours where bias magnitudes reach up to -4%. Conversely, ERA5-Land RH2m bias ranges between -6% and 2%. The

corresponding RMSE values vary from 10% for ERA5 single-levels to 12.5% for ERA5-Land. For 10-meter wind speed (WS10m), ERA5 exhibits a maximum mean bias of -0.5 m/s, outperforming ERA5-Land's -1.0 m/s. The highest WS10m biases for both datasets are concentrated during the evening and night. However, both configurations yield highly comparable RMSE values of up to 2 m/s.

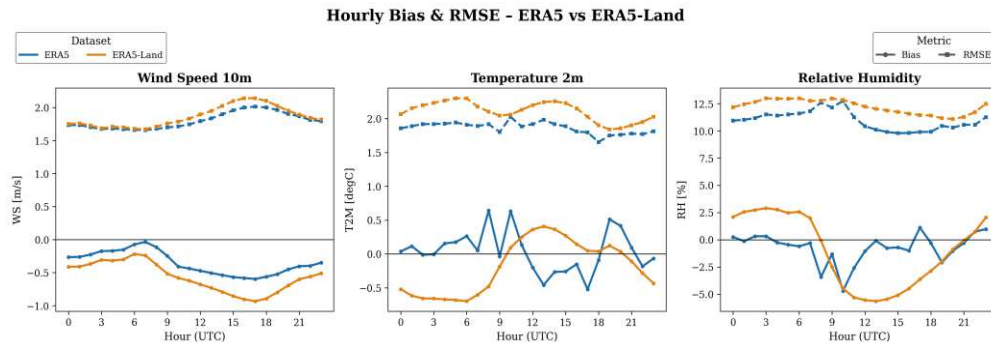


Fig. 4. Hourly (24h) Mean Bias (solid dotted lines) and RMSE (dashed dotted lines)

curves for 10m wind speed (WS10m), 2m temperature and humidity (T2m, RH2m) for ERA5 (blue) and ERA5-Land (orange).

5.1.2 Spatial verification of ERA5 and ERA5-Land

Figure 5 displays the spatial distribution of ERA5 and ERA5-Land bias and RMSE spatial distribution for RH2m and T2m across the 36 study stations. For relative humidity (RH2m), both ERA5 and ERA5-Land exhibit extremely small biases and RMSE values, with nearly all stations falling within the $\pm 10\%$ range. Both reanalysis products exhibit negative bias along central Atlantic coast showing that reanalysis underestimate near surface moisture. This confirms that both reanalysis struggles capturing the sharp, microscale transition of the coastline boundary and daytime sea breezes. The models tend to underestimate the shallow, highly humid marine layer and its sharp boundary along the coastline. This localized dry bias is likely driven by the models' inability to fully resolve

449 the cold coastal ocean upwelling, coupled with an over-penetration of warm, dry inland
450 airmasses or a slight daytime warm bias in land-surface temperature within coastal grid
451 cells (Wang et al. 2026). The higher resolution of ERA5-Land does not confer any
452 tangible advantage for humidity. Moving inland towards the Atlas foothills and eastward
453 into continental/semi-arid zones, the bias shifts to a near-neutral or slight positive bias.
454 The reanalysis captures the dry, continental air mass characteristics reasonably well,
455 though it tends to slightly overestimate humidity in some interior pockets. The highest
456 RMSE values (exceeding 15% to 20%) align perfectly with the regions of high negative
457 bias along the Atlantic coast. The elevated error here points to strong diurnal or seasonal
458 phase mismatches in humidity, which can be driven by the complex local wind regimes
459 (sea/land breezes) and low-level marine stratus clouds that the reanalysis struggle to time
460 correctly (North et al. 2025). Interior stations show a more uniform, lower RMSE pattern
461 ranging between 7.5% and 12.5%. In these regions, atmospheric moisture could be
462 largely driven by larger-scale synoptic features rather than complex land-sea interfaces,
463 making it easier for the reanalysis systems to simulate accurately (Wood et al. 2025; Wei
464 et al. 2025). Although ERA5-Land boasts a higher spatial resolution (9 km vs. 31 km), it
465 does not fundamentally correct the coastal humidity biases or lower the RMSE at these
466 stations. This suggests that the errors are not purely a function of horizontal topography
467 resolution. Instead, they are likely rooted in shared boundary layer physics parameterized
468 in the driving model, soil-moisture-atmosphere coupling schemes, or the representation
469 of the cold Canary Current's marine boundary layer influences. For temperature, the
470 central Atlantic coast both reanalysis exhibit a noticeable positive temperature bias
471 (rising to 2°C). The models are systematically overestimating surface temperatures here.

472 Moving east of the Atlas chain and into the continental interior, the bias flips to negative
473 (from -3°C to -1°C), meaning the reanalysis underestimate heat in the interior. For
474 temperature RMSE the highest RMSE values (2.5°C to 3.5°C) are concentrated directly
475 along complex topography, and eastward interior flatlands. The Atlantic coast shows a
476 simultaneous warm bias (T2m overestimated) and dry bias (RH2m underestimated). This
477 strong negative correlation points to a structural issue in how the reanalysis handles the
478 marine-terrestrial boundary. For wind speed (WS10 m) (not shown): The maps show a
479 more complex and spatially structured picture. Bias patterns (color scale from -2 to $+2$
480 m/s) indicate that both ERA5 and ERA5-Land tend to under-estimate wind speed over
481 the interior and mountainous regions and over-estimate along coastal areas and the Strait
482 of Gibraltar. This dipole pattern is typical of reanalysis struggling to represent the
483 interplay between large-scale flow and local orography. Importantly, ERA5-Land shows
484 a clear improvement in RMSE over ERA5. While ERA5 exhibits RMSE values reaching
485 up to 5 m/s in the Atlas Mountains and along the Atlantic coast, ERA5-Land reduces the
486 RMSE to typically 4 m/s in the same regions. This reduction could be attributed to
487 ERA5-Land's higher spatial resolution (9 km vs. 31 km), which allows for a better
488 representation of wind with finer land grid and the sharp land-sea contrast. The bias
489 magnitude, however, remains similar between the two models – both display the same
490 sign and approximate amplitude of systematic error, suggesting that the improvement in
491 ERA5-Land lies mainly in better capturing the temporal variability (lower random error).
492 Co-occurring warm (T2m overestimated) and dry (RH2m underestimated) biases along
493 coastal margins—alongside anomalous 10-meter wind speeds—stem from grid-scale
494 blending of land-sea masks that poorly resolves steep marine-terrestrial boundaries

(Alkhalidi et al. 2025; Patra et al. 2025). This coarse spatial smoothing amplifies daytime land thermal responsiveness while diminishing adjacent water-vapor availability, elevating local temperatures and depressing relative humidity. Simultaneously, the muted surface roughness representation distorts coastal friction profiles, generating systematic errors in low-level wind speed behavior (Caton Harrison et al. 2024).

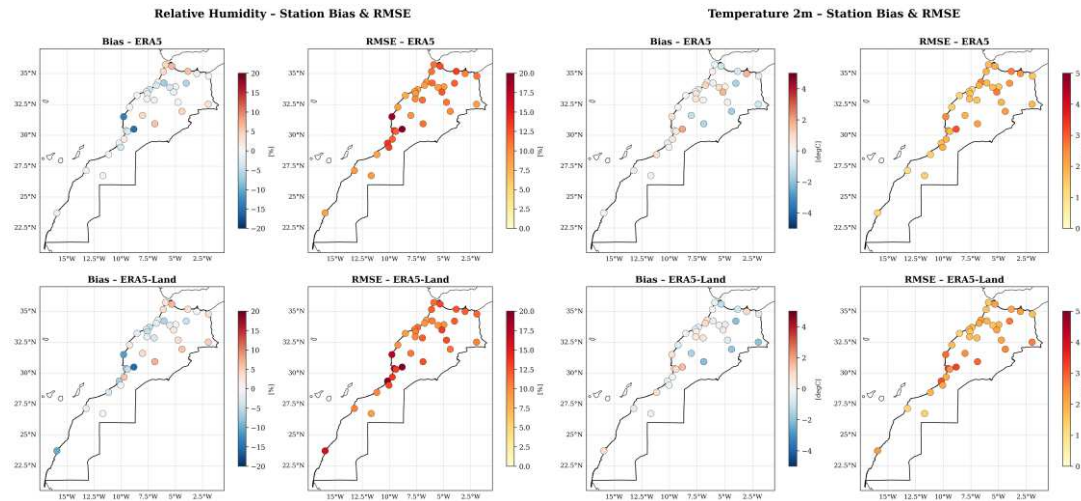


Fig. 5. Mean bias and RMSE spatial distribution for T2m and RH2m for ERA5 and ERA5-Land over the 36 stations of Morocco.

5.1.3 Diurnal verification by stations: *rRMSE* and Pearson Correlation

Figure 6 displays the hourly correlation and relative RMSE between ground observations and ERA5 and ERA5-Land reanalysis for all the stations studied. Regarding T2m correlation scores, most of the hours and stations display high values of correlation for both reanalysis with values exceeding 60%. The lowest values of correlation are displayed by central Atlantic coastline stations where there is a strong influence of sea land frontier micro-climates process. For relative RMSE scores values do not exceed 17.5% for both reanalysis, but high concentration of high relative RMSE values is concentrated within the night and early morning part of the day, with special focus of

high scores of rRMSE on mountainous and Atlantic coastline stations. It is worth mentioning that ERA5 reanalysis provides better scores than ERA5-Land. For RH2m (not shown), both reanalysis display high correlation values along all stations, with slightly better performance of ERA5 compared to ERA5-Land. When focusing on relative RMSE worst performances are of 35% observed only for isolated stations, the worst performances are shown during the day part from 12h to 18h, with better performance of ERA5. For WS10m (not shown), both reanalysis display very close moderate correlation values around 60%. Regarding relative RMSE scores, poor performances with up to 100% scores are illustrated during the night phase, moderate relative scores less than 50% are noticed during the day phase (12h-18h). The pronounced contrast in error metrics—where relative RMSE spikes up to 100% during stable nighttime phases but drops below 50% during afternoon convective periods (12–18h)—reflects structural NWP limitations in resolving stable boundary layers (Urraca et al. 2018). During the night, radiative cooling generates shallow, strongly stable regimes characterized by low absolute wind and turbulence values; minor absolute model mismatches in these decoupled layers are mathematically magnified into massive relative percentage errors (Cuxart et al. 2006). Conversely, daytime solar heating drives vigorous convective mixing that overrides micro-meteorological noise, allowing global models to track large-scale atmospheric dynamics with significantly higher accuracy and lower relative uncertainties. Approaching 100% rRMSE at some stations could be consequence of rRMSE's denominator, since nocturnal mean wind speeds at these stations are themselves small, so even modest absolute error translates into a large percentage.

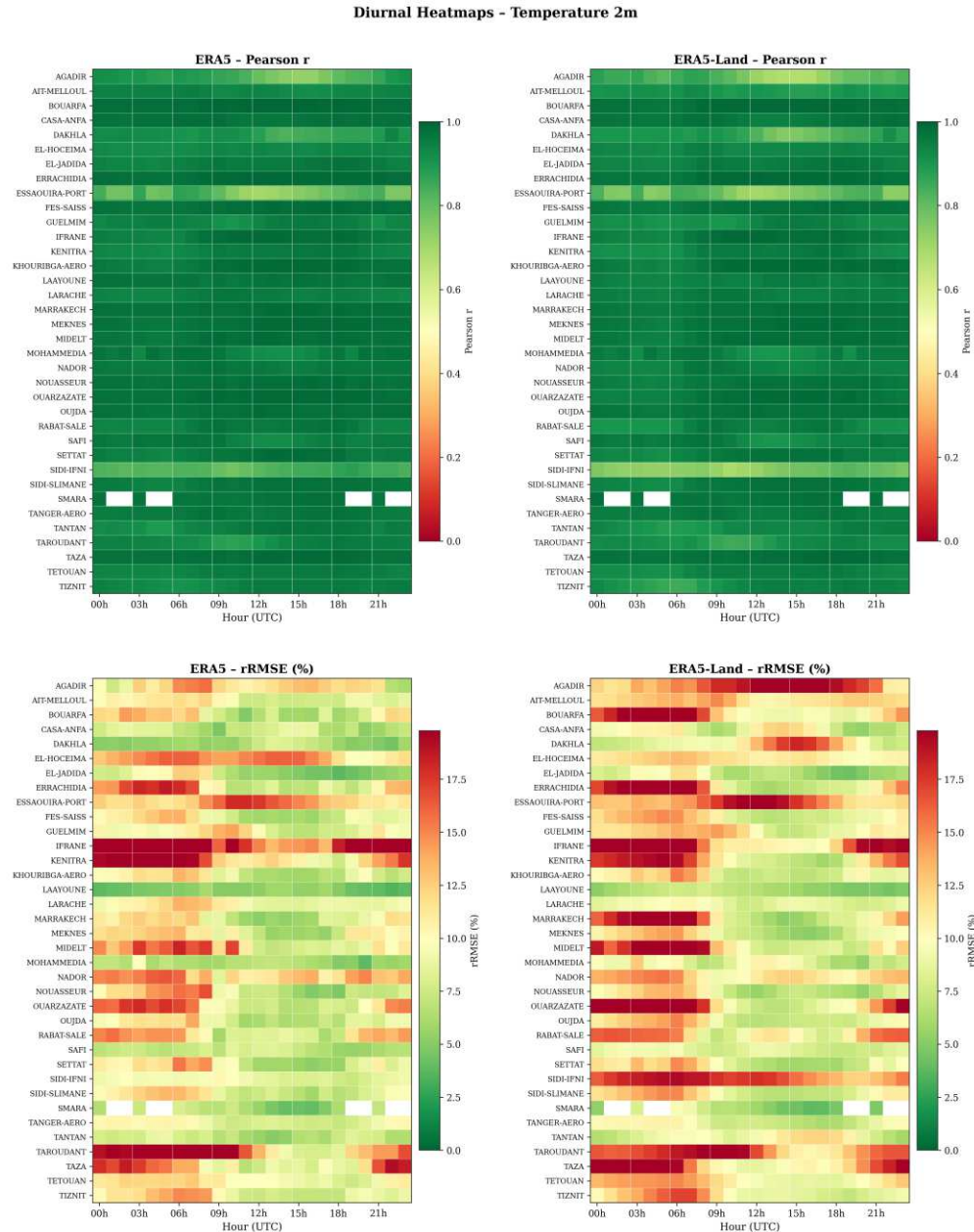


Fig. 6. Diurnal T2M Pearson Correlation and Relative RMSE of ERA5 and ERA5-

Land for all stations.

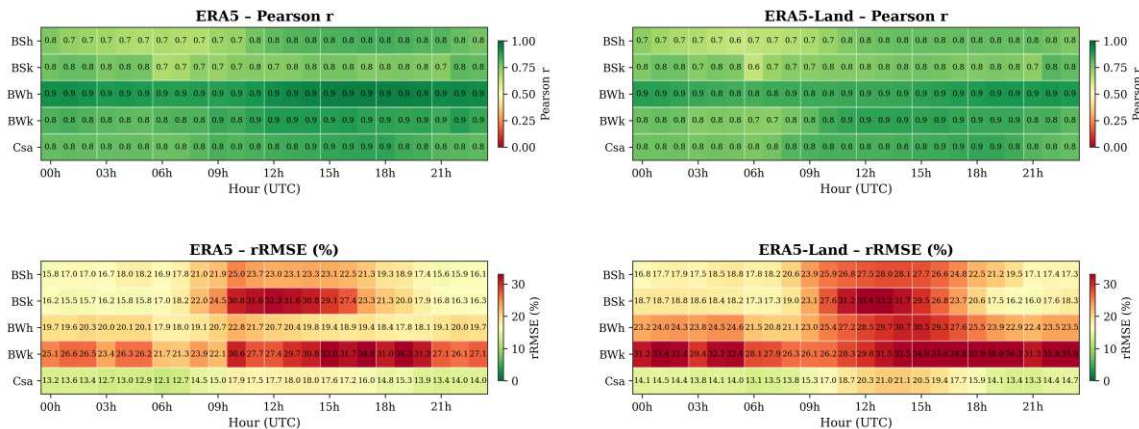
5.1.4 Diurnal Verification by Köppen Class

Figure 7 compares two reanalysis datasets—ERA5 and ERA5-Land—across five Köppen climate classes, evaluated at each hour of the day (UTC) using Pearson-r (correlation) and rRMSE % (relative error) metrics. Regarding relative humidity (RH2m),

performance is substantially stronger and more regular, particularly in desert environments where BWh and BWk maintain robust correlations of 0.88–0.95 and 0.80–0.89 in ERA5 respectively, though ERA5-Land drops slightly to 0.84–0.91 in BWh. Crucially, the afternoon breakdown for BSk does not manifest in RH2m where BSk, BSh, and Csa all perform solidly within the 0.64–0.84 range, proving that the midday issue is strictly isolated to dew point representation rather than a generalized afternoon modeling failure. Relative humidity error structures are significantly low with the Mediterranean Csa class yielding the lowest errors overall at 13–18%, followed by BSh at 15–25%, BWh at 18–23%, and the cold semi-arid and desert zones (BSk and BWk) experiencing the highest errors at 21–35%. Across all classes, relative humidity errors peak around solar noon due to daytime convective mixing and decline into the evening, with ERA5-Land consistently displaying higher rRMSE values than ERA5, such as a 35% error peak compared to 32% in BWk. A cross-variable synthesis including 2m air temperature T2m establishes a clear predictability hierarchy where T2m significantly outperforms RH2m. Temperature stands out as the best-predicted variable, with all five classes sitting in an exceptional Pearson-r range of 0.87–0.99 and a low ERA5 rRMSE range of 6–17%. While ERA5 temperature errors drop to a minimum of 6–8% during the well-mixed afternoon, they peak in the early morning hours (3h to 9h) this may be due to the turbulent complexity of the decoupled nocturnal boundary layer, an error that roughly doubles in ERA5-Land where morning spikes reach 20–25% in BWk climates. Furthermore, across all moisture and temperature fields within these arid, semi-arid, and Mediterranean zones, the higher spatial resolution of ERA5-Land consistently introduces additional noise during stable nocturnal boundary layer conditions rather than improving

565 near-surface atmospheric skill. For WS10m (not shown) the BSk and BSh zone
566 experiences a striking middle day collapse, with correlations plummeting to 0.2–0.4 for
567 ERA5 and ERA5-Land, suggesting a systematic failure to capture afternoon wind speed
568 variability in cold and hot semi-arid regions. In contrast, BWh, BWk and Csa climates
569 maintain moderate, stable correlations 0.65–0.8 across the day with no dramatic diurnal
570 breakdown. For relative RMSE both reanalysis display high relative RMSE values going
571 from 0.5 to 0.75% mainly concentrated during the early morning and night periods for
572 BSk and BWk climate classes, showing the limited ability of both reanalysis in
573 forecasting wind speed at 10m in cold arid and semi-arid zones. The best relative RMSE
574 performances for both reanalysis were concentrated in the middle of day period for the
575 BWh climate class.

Koeppen Diurnal Heatmaps - Relative Humidity



Koeppen Diurnal Heatmaps - Temperature 2m

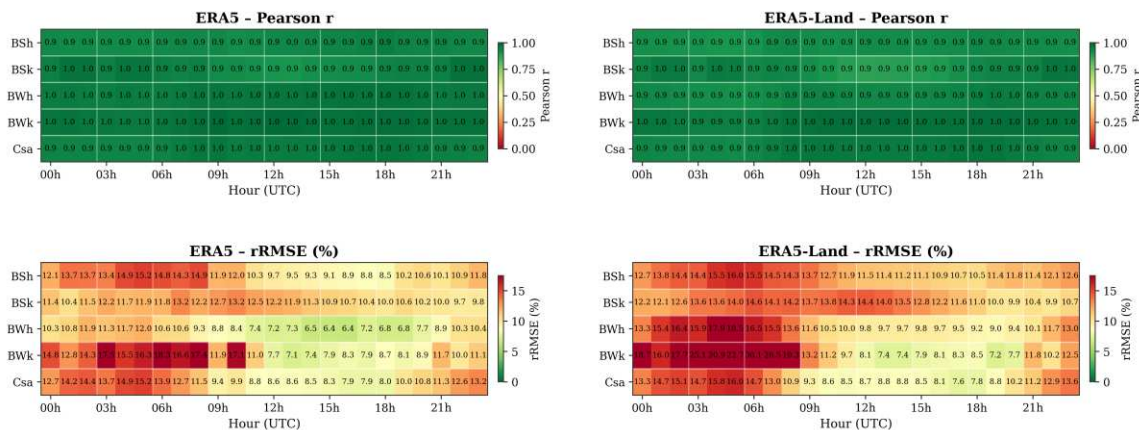


Fig. 7. Diurnal Pearson Correlation and Relative RMSE of T2m, RH2m across five Köppen climate classes.

5.1.5 Seasonal Verification

Figure 8 displays the mean bias and RMSE by seasons for ERA5 (blue) and ERA5-Land (orange), for T2m, WS10m, and RH2m. Regarding WS10M, ERA5 shows the lowest bias distribution in Spring, Autumn and Winter with bias medians going from 0.2 to 0.3 m/s. For summer, ERA5 provides better performance compared to ERA5-Land with lowest bias median. It is to mention that ERA5-Land bias values are less dispersed compared to ERA5 showing longer ranges of bias values. For RMSE instead both

reanalysis display close distribution over all seasons for WS10m. For T2M ERA5 provides the lowest bias for spring and winter, while for summer both reanalysis display close bias values, ERA5-Land shows large, dispersed bias values for Autumn compared with ERA5 with values spanning from -0.25°C to 0.5°C , while ERA5 shows bias values around 0.5°C for the same season. Nevertheless, for RMSE values ERA5 shows the lowest errors values for all seasons with medians not exceeding 2°C . When considering moisture bias and RMSE distributions along seasons, generally ERA5 display lowest, well distributed values of bias and RMSE for all seasons compared to ERA5-Land.

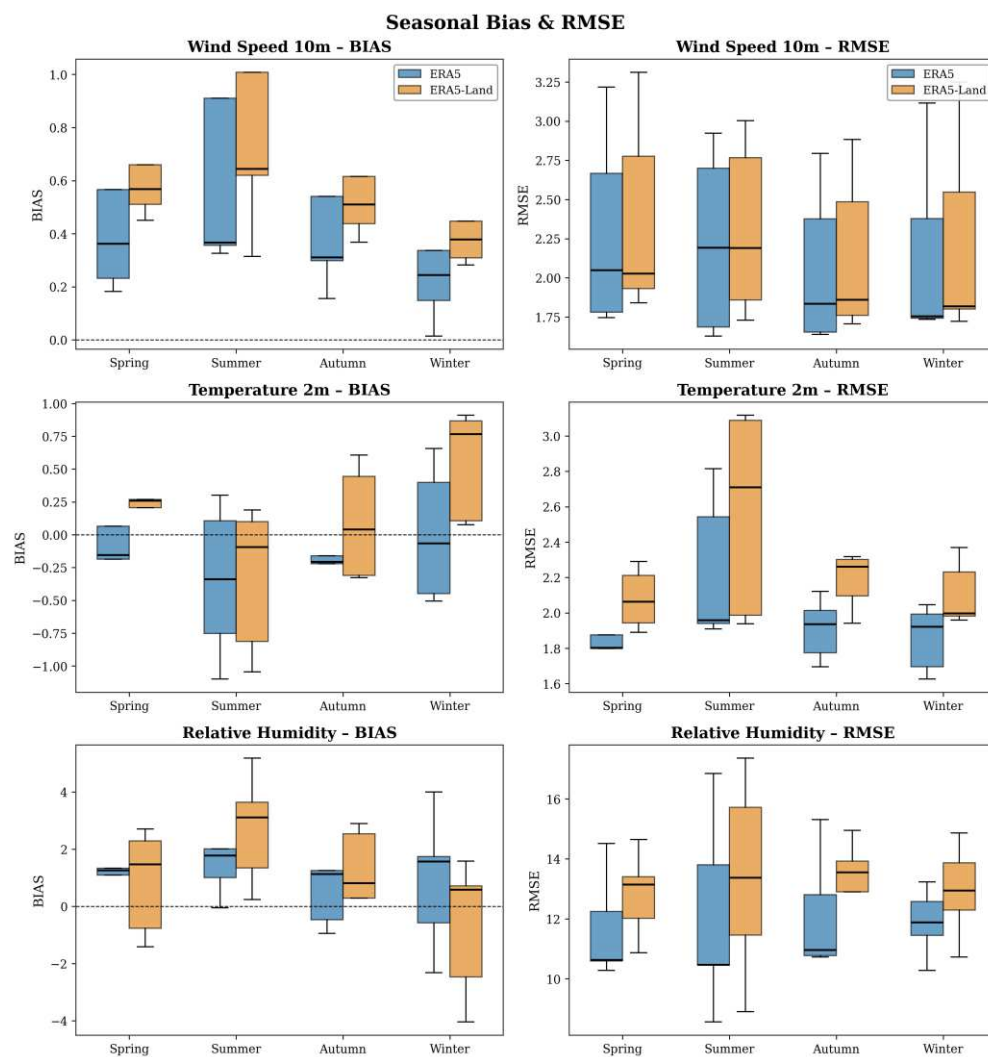
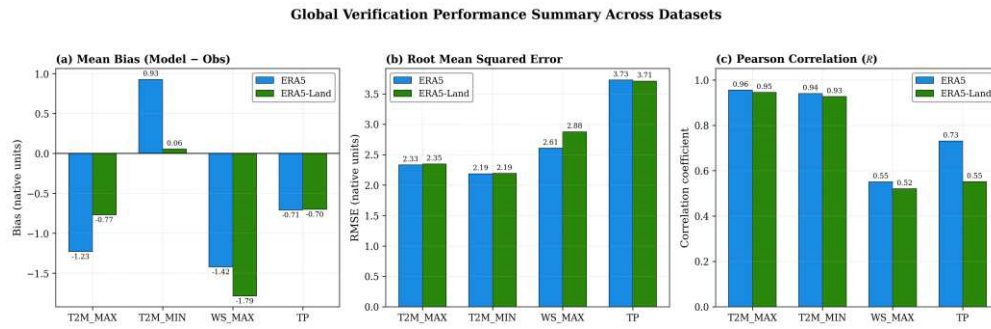


Fig. 8. Seasonal bias and RMSE boxplots of ERA5 (blue boxes) and ERA5-Land (orange boxes) for T2M, WS10M, and RH2M.

5.2 Daily Extreme events verification

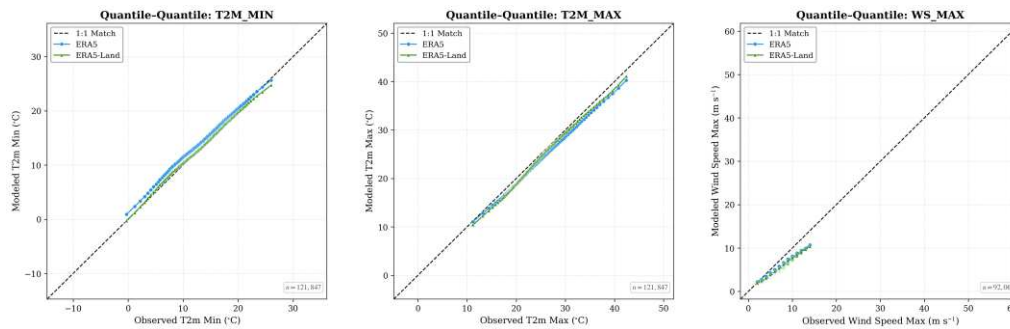
Figure 9 displays the global verifications scores of ERA5 and ERA5-Land for detecting extreme weather parameters including minimum and maximum temperature, max wind speed and total daily precipitation. Three scores are used: the mean daily bias, RMSE and Pearson Correlation. Both reanalysis show very close scores for most of the extreme parameters. RMSE values of ERA5 and ERA5 Land are very close with a max difference of magnitude 0.27 m/s for wind speed max, for other parameters this difference of errors is less than 0.02 unit. For correlations both ERA5 and ERA5-Land display very close and high correlations (>0.9) for T2m_MAX and T2m_MIN, performance remains close but with low correlation (0.5) for WS_MAX. For total precipitations, ERA5 displays higher values of correlation difference with up to 0.18 compared with ERA5-Land. Regarding the mean bias ERA5 and ERA5-Land shows very close bias values for TP near zero (0.7mm) and for WS_MAX with bias lower than -1.5m/s showing an underestimation of WS_MAX. For temperature extremes, ERA5-Land shows better bias with -0.77 and 0.06 for T2m_MAX and T2m_MIN respectively. This affirms that both reanalysis are under-estimating maximum temperature and slightly

614 over-estimates minimum temperatures.



615 **Fig. 9.** Overall verification barplots of ERA5 (blue bars) and ERA5-Land (green bars) for
616 T2M_MAX, T2M_MIN, WS_MAX and TP using mean bias, RMSE and Pearson
617 Correlation.

619 QQ-plots from Figure 10 confirms the previous findings, where ERA5-Land
620 provides the closest curve to perfect for T2m_MAX and T2m_MIN with slight over-
621 estimation of T2M_Min and under-estimation of T2m_MAX. Regarding maximum wind
622 speed both reanalysis are under-estimating deeply the wind speed max.



623 **Fig. 10.** QQ-plots for ERA5 (blue) and ERA5-Land (green) for T2M_MIN, T2M_MAX
624 and WS_MAX

626 Figure 11 displays the Roebber Performance Diagram evaluating the capability of
627 ERA5 (circles) and ERA5-Land (triangles) to detect minimum and maximum 2-meter
628 temperature (T2M_MIN, T2M_MAX) and maximum wind speed at 10m (WS10m)

629 events across various temperature and wind speed thresholds (indicated by the color
630 scale). A perfect model forecast would sit at the top-right corner (Probability of Detection
631 $POD = 1$, Success Ratio = 1). The dashed lines represent the Critical Success Index (CSI,
632 labeled 0.1 to 0.9), and the straight diagonal lines represent the Frequency Bias (Bias or
633 B, where $B=1$ is unbiased). The performance diagrams for maximum and minimum
634 temperature (T2M) and maximum wind speed (WS10m) provide a starkly different view
635 from the continuous metrics. Focusing on the most quantitatively robust data—the
636 T2M_max threshold of 35°C—both ERA5 and ERA5 Land exhibit nearly identical and
637 notably acceptable categorical skill. At this threshold, both reanalyses yielded a
638 Probability of Detection (POD) of 0.6 and a Success Ratio ($1 - \text{False Alarm Ratio}$) higher
639 than 0.8. This results in a Frequency Bias of 0.5, indicating a slight systematic under
640 forecasting of warm events (the models predict far fewer heat days than observed), and a
641 Critical Success Index (CSI) of 0.6—a value reflecting good predictive utility for
642 absolute station level extremes. The complete overlap of ERA5 and ERA5 Land points in
643 the low-skill quadrant of the diagram (low POD, low SR) for very extreme heat events
644 (above 45°C) is not an indictment of the reanalysis themselves, but rather a direct
645 consequence of representativeness error. The verification of 2-meter minimum
646 temperature over Morocco reveals a clear operational trade-off driven by the horizontal
647 resolution differences between ERA5 and ERA5-Land. Evaluation via a Roebber
648 performance diagram demonstrates that while both reanalysis products perform
649 exceptionally well for mild night and morning minimums (10°C to 15°C), their accuracy
650 significantly degrades for colder events near freezing (0°C to 5°C), where both
651 configurations systematically over-predict the frequency of sharp cold drops.

652 Intriguingly, the coarser 31 km ERA5 grid consistently achieves a higher Success Ratio
653 by minimizing false alarms. In contrast, the 9km ERA5-Land grid yields a higher
654 Probability of Detection (POD) across almost all temperature thresholds; however, this
655 aggressive capability to resolve localized microclimates and topographic cold-air pooling
656 comes at the expense of a lower Success Ratio, as the finer-scale drops generate a higher
657 rate of spatial or temporal false alarms when validated against ground observation
658 stations. Regarding wind speed maximum, ERA5 often shows low POD near zero for
659 extreme wind mean max thresholds 15m/s and moderate SR (0.2–0.4), placing it in the
660 lower left quadrant. Bias is usually < 1 (under forecasting extremes). For moderate wind
661 mean max, ERA5 often shows higher POD (0.3–0.4) but slightly higher SR (0.7–0.8),
662 placing it further up. Bias may be closer to 0.4. ERA5 is likely the better model for
663 maximum wind speed because it detects more moderate wind events without a
664 catastrophic increase in false alarms, leading to a higher CSI. Temperature and wind
665 extremes at individual stations are overwhelmingly dictated by local micro topography,
666 elevation, and land use contrast factors that cannot be resolved by either the 31 km ERA5
667 or even the higher resolution 9 km ERA5 Land grid. Crucially, this categorical deficiency
668 stands in direct contrast to the continuous verification shown earlier. Those analyses
669 demonstrated that ERA5 and ERA5 Land capture the mean state, diurnal cycles, and
670 spatial variability of temperature with high correlation (often >0.9) and low RMSE.
671 Regarding ROC curves of daily total precipitation (bottom left corner illustration), while
672 the ROC curve yields a high AUC score approaching 0.9 for both reanalysis, this strong
673 performance is largely driven by the high frequency of non-occurrence observations.
674 Because Morocco's climate during the study period was characterized by prolonged,

multi-year drought episodes, the overwhelming abundance of true negative events artificially inflates the AUC-ROC, masking the model's true skill in capturing distinct onset or termination transitions.

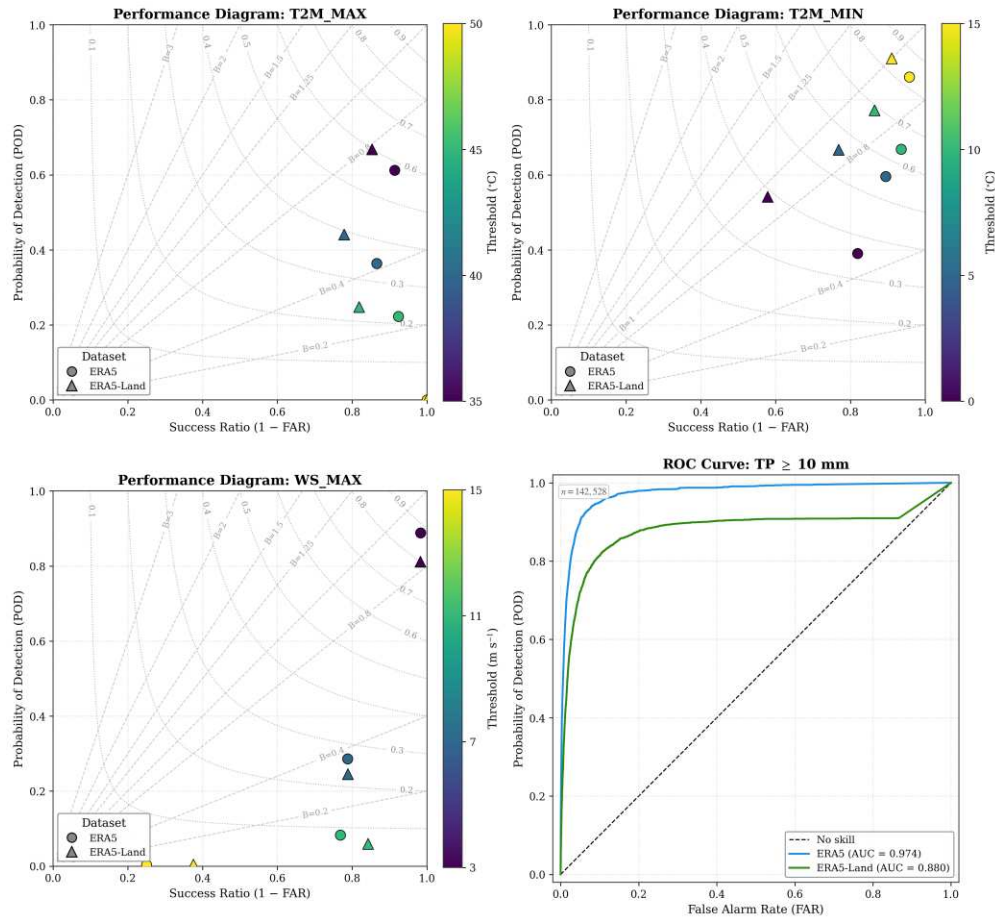


Fig. 11. Roebber Performance Diagram evaluating the capability of ERA5 (circles) and ERA5-Land (triangles) to detect minimum and maximum 2-meter temperature (T2M_MIN (up-right), T2M_MAX (up-left)) and maximum wind speed at 10m (WS10m_MAX (bottom-left)) events across various temperature and wind speed thresholds and ROC curve for total precipitation with 10mm threshold (bottom-right) (ERA5 (blue) and ERA-Land(green)).

687

688 In conclusion, while both reanalysis are equally robust for climatological and mean
689 state applications, they are structurally unsuitable for deterministic, absolute threshold
690 extreme event detection at the station scale over complex terrain. For such applications,
691 we strongly recommend either using anomaly-based thresholds (e.g., percentiles of the
692 local climatology) or relying solely on continuous error metrics to evaluate model skill.
693 Three threads run through the results above. First, resolution helps some variables and
694 not others: ERA5-Land's finer ~9km grid measurably reduces (WS10m RMSE over the
695 Atlas Mountains and the coast relative to ERA5's ~31km grid, but confers no
696 advantage—and in the cold-desert (BWk) class actively adds nocturnal noise—for T2m
697 and RH2m, whose dominant error is rooted in shared boundary-layer and soil-moisture-
698 coupling parametrisations rather than in horizontal grid spacing per se. Second, both
699 products are structurally limited, not by a flaw unique to either, but by station-scale
700 representativeness: individual stations at Ifrane, Taroudant, Errachidia and Midelt show
701 persistently high rRMSE across the whole diurnal cycle, and neither the coarse nor the
702 fine grid resolves the local micro-topography responsible. Third, and most consequential
703 for downstream use, categorical skill for daily extremes is not uniformly poor, it degrades
704 specifically and monotonically as the verified threshold becomes rarer, for T2M_MAX,
705 T2M_MIN and WS_MAX alike. This is the expected signature of traditional
706 POD/SR/CSI scores approaching their degenerate limits as the event frequency shrinks
707 (Ferro and Stephenson 2011), and it means that a single reported skill value at an
708 arbitrary threshold can be highly misleading about a reanalysis' fitness for genuinely
709 extreme-event applications; threshold-resolved reporting, as done here, or explicitly rare-

event-robust scores (e.g. the Extremal/Symmetric Extremal Dependence Index), should be preferred in future work (Ferro and Stephenson 2011).

6. Conclusion and Perspectives

ERA5 and ERA5-Land both reproduce the mean state, diurnal cycle and spatial structure of near-surface variables over Morocco with high skill, and are broadly interchangeable for climatological applications, with ERA5 marginally ahead for temperature, humidity and wind bias, and ERA5-Land ahead via its finer grid, for wind-speed RMSE in complex terrain. Categorical verification of daily extremes shows that skill is threshold-dependent: moderate warm, cold and wind extremes are captured reasonably well by both products, but skill collapses specifically at the rarest, most extreme thresholds, a pattern attributable to the intrinsic behavior of standard contingency-table scores for rare events as much as to any deficiency of either reanalysis. We recommend that downstream applications – including the use of ERA5/ERA5-Land as a verification baseline for out-of-sample AI weather models – (i) adopt anomaly- or local-percentile-based extreme definitions, or rare-event-robust scores, rather than reporting skill at a single absolute threshold; (ii) always report the mean-normalised rRMSE (Eq. 3) alongside the absolute bias/RMSE, particularly for **WS10m** at low-wind stations, where a small denominator can inflate the percentage without a proportional change in absolute error; and (iii) explicitly audit and report ERA5-Land’s land-mask coverage before using it as a station-matched baseline over Morocco’s coastline. Extensions include a weather-regime stratification of the verification and a comparison against the World Meteorological Organization’s WIGOS/GBON station-density targets

733 to quantify remaining representativeness gaps (World Meteorological Organization
734 2023).

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