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Research

Evaluation of ERA5, ERA5-Land, CERRA and NEWA datasets in reproducing observed near-surface wind speeds across Spain

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Abstract

Near-surface wind speed (NSWS) is a key variable for climate and energy applications, yet it remains difficult to model because of its sensitivity to local conditions that are often inadequately represented in reanalysis and regional datasets. This study evaluates daily NSWS from four widely used gridded products, ERA5, ERA5-Land, CERRA, and NEWA, against homogenized observations from 748 stations of the Spanish Meteorological Agency for 1/Jan/1990−31/Dec/2018. Performance was quantified using correlation, bias, and error metrics, with results stratified by synoptic circulation types (Jenkinson−Collison classification) and station setting (inland, coastal, mountain). Among the datasets, CERRA showed the best agreement with observations (r = 0.77, cRMSE = 0.95 m/s), largely by reducing unrealistic elevation biases present in ERA5 and ERA5-Land. NEWA systematically overestimated NSWS (MBE = 1.56 m/s) but reproduced the observed elevation dependence more effectively than the other products. Across circulation regimes, all datasets performed best under westerly and south-westerly flows, and worst under weak or easterly conditions, especially in summer and in complex terrain. These findings identify CERRA as the most reliable product for NSWS studies in Spain and regions with similar geographical diversity, while highlighting important limitations of NEWA for applications requiring accurate NSWS.

Keywords: Near-surface wind speed; Evaluation; Reanalysis; Weather stations; Synoptic circulation; Complex terrain

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1. Introduction

Near-surface wind speed (NSWS, typically measured at 10 m above ground) is a key variable for multiple processes in nature and the consequent socioeconomic impacts, such as evapotranspiration estimation (McVicar et al., 2012), wildfire propagation (Pausas and Keeley, 2021), transport of air pollutants (Aguilera et al., 2020), and wind power generation (Gualtieri, 2019), to mention but a few. While weather station networks provide direct NSWS observations, their sparse spatial coverage and the need for quality control and homogenization procedures often limit their use in regional or long-term analyses (Brinckmann et al., 2016; Luo et al., 2008; Bengtsson et al., 2007). In contrast, reanalysis datasets and their dynamically downscaled versions offer spatially and temporally consistent NSWS products, openly accessible over extended periods (Bengtsson et al., 2007; Hersbach et al., 2020). As a result, the use of reanalysis as reference datasets in many fields has become widespread in science (Nakamura et al., 2025, references therein) still being a common benchmark in Artificial Intelligence applications (Rasp et al., 2020; McGovern et al., 2024).

Despite these advantages, reanalysis-based NSWS estimates are subject to systematic biases, especially in regions with complex terrain (Wu et al., 2024; Ramon et al., 2019; Zuo et al., 2025; Helbig et al., 2017). Model limitations include coarse resolution, which restricts the representation of sub-grid processes (e.g., convection, turbulence, local orographic effects), and reliance on planetary boundary layer parameterizations with simplified surface roughness values (Rose and Apt, 2016; Sandu et al., 2013). Consequently, evaluations against observations often reveal overestimation of weak winds and underestimation of extremes (e.g., Gutiérrez et al., 2024).

Among the available datasets, the fifth generation ECMWF atmospheric reanalysis of the global climate (ERA5, Hersbach et al., 2020) represents a notable advance over earlier reanalyses, with higher resolution, improved assimilation, and updated parameterizations, in particular for wind speed at turbine height (Ramon et al., 2019; Murcia et al., 2022, and references therein) and, although less studied, in NSWS as well (Minola et al., 2020, 2023; Molina et al., 2021). Nevertheless, its skill varies geographically: it tends to overestimate NSWS in flat or coastal areas and underestimate it in mountains (Molina et al., 2021; Laurila et al., 2021). The land component of ERA5, hereafter ERA5-Land (Muñoz-Sabater et al., 2021), despite its finer spatial resolution (0.1°; ~9 km grid spacing), derives NSWS from tricubic interpolation of ERA5 fields without additional physical constraints, which often results in only marginal improvements (Jourdier, 2020; Minola et al., 2023).

The new Copernicus European Regional Reanalysis (CERRA, Ridal et al., 2024) provides higher spatial resolution (5.5 km) and improved orographic representation, showing promising results in complex terrain, particularly in the Alps (Ridal et al., 2024) and in coastal regions (Galanaki et al., 2023). However, its added value for NSWS remains uncertain, although Pelosi (2023) has already shown larger deficiencies compared to other surface variables such as 2m-temperature and relative humidity. In contrast, the New European Wind Atlas (NEWA, 3 km resolution, Dörenkämper et al., 2020; Hahmann et al., 2020; Rodrigo et al., 2020), designed primarily for wind energy applications, has shown substantial biases, including mean overestimations and exaggerated diurnal cycles (Jourdier, 2020; Schicker et al., 2023). Yet, systematic evaluations of NEWA at 10 m height remain scarce and focus on offshore capacity (Soukissian et al., 2025).

From these studies, CERRA appears to be the most promising candidate for NSWS estimation, followed by ERA5. However, further evaluation in atmospheric conditions and heterogeneous spatial contexts is required. First, most studies have focused on hourly data, while daily mean NSWS remains underexplored in recent reanalysis. Second, the influence of large-scale circulation on NSWS model estimates has rarely been assessed, despite the fact that synoptic patterns strongly modulate local winds (Lorente-Plazas et al., 2015). Classifications of weather regimes have been widely used to analyze precipitation and temperature variability (e.g., Cortesi et al., 2014; Ramos et al., 2015) and wind gusts (Azorin-Molina et al., 2016), as well as to compare weather regimes in climate simulations (Otero et al., 2018; Fernández-Granja et al., 2021) and between reanalysis (Fernández-Granja et al., 2023), but their application to the evaluation of the modelled NSWS against observations remains limited. Finally, there has been little systematic analysis, sometimes with a very low number of stations, of how biases vary with geographical context, particularly elevation and proximity to the sea (e.g., Minola et al., 2020, 2023; Molina et al., 2021).

The Iberian Peninsula is an ideal testbed for addressing these gaps due to its geographic diversity with plain elevated inlands enclosed by mountains, strong Atlantic and Mediterranean influences, and its exposure at mid-latitudes to both polar and tropical jet regimes (Azorin-Molina et al., 2014). In addition, it experiences strong seasonal variability, with winters more exposed to westerly synoptic-scale circulation and summers by local flow conditions related to the development of the thermal low (Hoinka and Castro, 2003). Under this context, the Iberian Peninsula exhibits a heterogeneous wind pattern, strongly modulated by complex orography and land−sea contrasts, which give rise to dominant regional winds such as the Cierzo, Levante and Poniente, posing a challenge for their accurate representation in gridded products (Ortega et al., 2023; Lorente-Plazas et al., 2015). Beyond its regional relevance, this complexity makes the Iberian Peninsula a robust test environment for NSWS assessment, with findings that are transferable to other extratropical regions characterized by intricate terrain and strong maritime influence. Using 748 quality controlled and homogenized stations from the

Spanish Meteorological Agency (AEMET), this study evaluates the performance of ERA5, ERA5-Land, CERRA, and NEWA in reproducing the mean daily NSWS in Spain (including the Balearic Islands) during 1/Jan/1990−31/Dec/2018. Specifically, we examine how model skill depends on i) synoptic weather types, using the Jenkinson−Collison classification, and ii) station location, categorized by elevation and coastal proximity.

2. Methods

2.1. NSWS daily observations

We used raw NSWS observations from AEMET stations recorded since 1961 till 2022. After quality control following Tomas-Burguera et al. (2016), daily means were computed by averaging the four subdaily timesteps (00, 07, 13 and 18 UTC); removing days with fewer than four records.

To correct for nonclimatic inhomogeneities (e.g., station relocations, instrumental changes), we applied the Climatol v4.1 homogenization R package (Guijarro, 2025), which identified 631 break points in the monthly aggregated datasets, and produced the corresponding adjustments in the daily series of the 338 stations affected. Missing values were not filled in to avoid introducing artificial variability. Finally, we must restrict the period of study used in this evaluation, as NEWA is only available from 1/Jan/1990 to 31/Dec/2018. For this period in which the four gridded products are available, the final dataset of AEMET comprises 748 stations with quality-controlled and homogenized daily NSWS records.

2.2. High-resolution gridded datasets: reanalysis and simulations

We evaluate four NSWS datasets (Table A1): ERA5 (31 km, Hersbach et al., 2020), ERA5-Land (9 km, Muñoz-Sabater et al., 2021), CERRA (5.5 km, Ridal et al., 2024) and NEWA (3 km, Hahmann et al., 2020; Dörenkämper et al., 2020). These products differ in spatial resolution, temporal frequency, and nature (global reanalyses vs. regional downscaling). None of them directly assimilates NSWS observations, although, for NEWA, validation studies have been conducted to optimize the configuration of the Weather Research and Forecasting model (WRF) accordingly (Witha et al., 2019), which is used for its production. The selection of these four products allows us to study the benefits of considering higher spatial resolutions to estimate the daily NSWS, although this implies a temporal limitation in our study as NEWA, the highest resolution dataset, is only available from 1/Jan/1990 to 31/Dec/2018. ERA5 and CERRA compute 10 m winds from boundary-layer parameterizations, while ERA5-Land derives them from ERA5 via interpolation. NEWA, based on the WRF downscaling of ERA5, has been tuned through targeted validation studies (Witha et al., 2019). Temporal availability varies: ERA5 and ERA5-Land (hourly), NEWA (30 min), and CERRA (3 h).

Daily NSWS means were derived consistently across the models. For each of them, we first computed the NSWS from the u and v wind components at 00, 07, 13, and 18 UTC (closest step available for CERRA), then averaged these four sub-daily values. This ensured alignment with the AEMET observation times. To compare with stations, we have extracted from the gridded products, the NSWS of the nearest gridpoint to each station, similar to Minola et al., (2023), and restricted the study to the common period of 1/Jan/1990−31/Dec/2018 for which we have daily NSWS in all datasets.

2.3. Jenkinson−Collison weather types

Large-scale circulation was characterized using the Jenkinson−Collison (JC) classification (Otero et al., 2018), implemented with the jcclass Python package (Herrera-Lormendez, 2022) and based on daily ERA5 mean sea-level pressure (MSLP). Each ERA5 grid point was classified according to their surrounding MSLP field and assigned a daily type, which was then mapped to the nearest station, rather than using a fixed regional domain. This approach ensures that synoptic weather patterns are locally representative at each station. Further details about the daily gridded JC classification are available in Otero et al., (2018).

The 27 original JC types were merged into 11 categories: anticyclonic (A), cyclonic (C), eight directional types (N, NE, E, SE, S, SW, W, NW), and an 'unclassified' (U) low-flow group.

2.4. Classification of stations based on their geographical context

Following Azorin-Molina et al. (2018) and Minola et al. (2020), we have classified AEMET stations according to their elevation above sea level (a.s.l.) and distance to the sea into three categories: coastal, those with a distance to the sea less than 20 km; mountain, those places with elevations exceeding 900 m a.s.l, and inland the remaining stations (Fig. 1a). As a result of this classification, we obtained 220 coastal, 125 mountain, and 403 inland stations. The three geographical contexts have benefited from the installation of new weather stations performed by AEMET in 2010, covering large unobserved areas such as the southern Mediterranean coast, central Pyrenees, and flat central inland regions (Fig. 1b).

2.5. Verification metrics

The evaluation was conducted over the common simulation period 1/Jan/1990−31/Dec/2018, during which all datasets overlap with observations, avoiding dates with

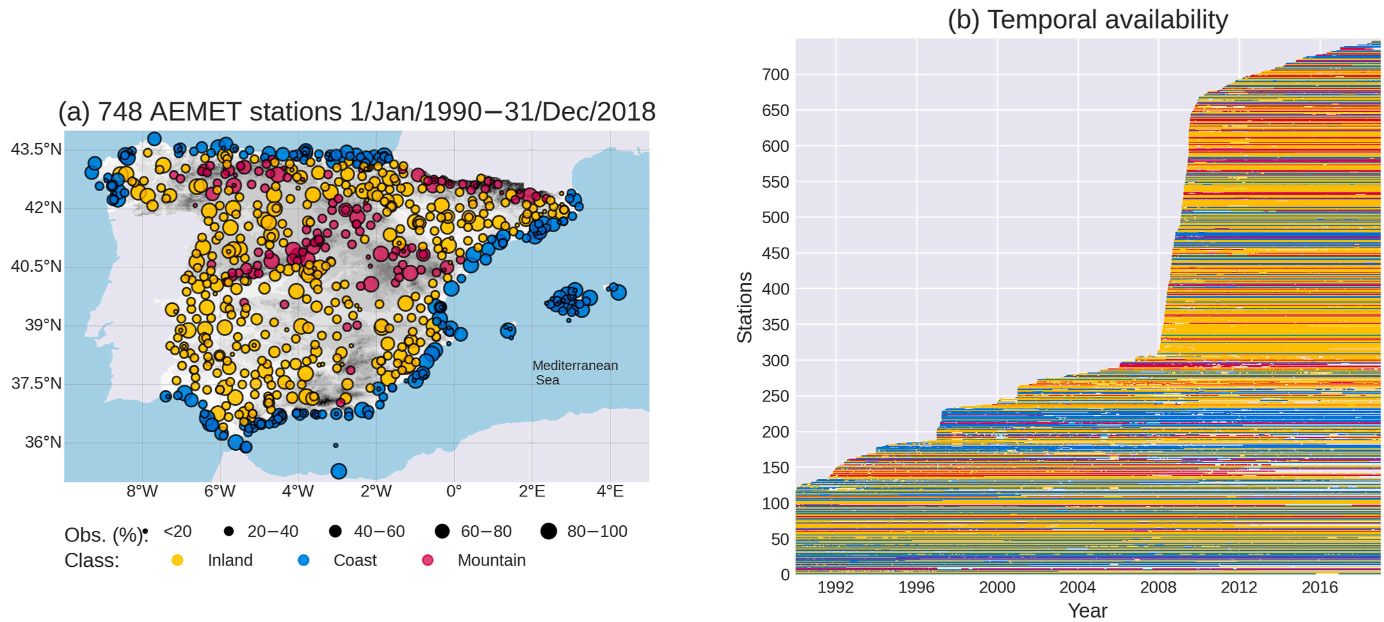

Fig. 1. Spatial and temporal characteristics of the 748 AEMET weather stations used here, (a) the geographic location, inland (403), coastal (220) and mountain (125), along with their percentage of daily observations between 1/Jan/1990 and 31/Dec/2018, and (b) temporal availability of daily NSWS averaged from observations at 00, 07, 13 and 18 UTC for each weather station, with colors representing the geographical class as in (a).

missing data. Model skill was assessed using a suite of complementary metrics. Temporal agreement between modelled and AEMET NSWS was quantified using Pearson's correlation coefficient, with statistical significance tested at the 95% confidence level ($p < 0.05$). In addition, the square of the Pearson correlation coefficient (r^2) was calculated to estimate the proportion of variance explained by synoptic and geographical factors. Because modelled data inherently differ from observations, we also evaluated systematic deviations using the Mean Bias Error (MBE) and their average magnitudes using the Mean Absolute Error (MAE). To further assess model performance in reproducing the variability of extreme NSWS, independent of mean biases captured by MBE and MAE, we employed the centered Root Mean Square Error (cRMSE), which compares anomalies respect to the mean NSWS between models and observations. Finally, linear regressions were performed with elevation and distance to the sea to quantify the linear relationships between these geographical factors and both observed and modelled NSWS.

3. Results

3.1. Comparison of gridded NSWS products against observations

CERRA provides the best overall performance, with a mean correlation of 0.77 ($p < 0.05$), MAE of 1.02 m/s, and cRMSE of 0.95 m/s (Fig. 2, Table 1). Its only notable limitation is the relatively high MBE (0.41 m/s), which exceeds the value obtained for ERA5-Land (0.10 m/s). In contrast, NEWA consistently performs worst, with a mean correlation of 0.73 ($p < 0.05$) and a MBE of 1.56 m/s, reflecting a systematic positive bias across all stations (Fig. 2h). Its MAE and RMSE distributions (Fig. 2l and p) are nearly identical, suggesting similar error magnitudes even in the presence of outliers. Among the ERA5 products, ERA5-Land performs slightly better across all metrics, standing out for its minimal bias. Excluding stations with less than 50% of daily NSWS leads to the same results (Fig. A1).

Beyond these overall results, Figs. A2−A5 reveal marked seasonal variability in performance. Winter (Fig. A2) shows the strongest correlations, with CERRA reaching 0.82 ($p < 0.05$) and the other models performing similarly well. At the same time, however, this season is also characterized by the largest MBE, MAE, and cRMSE. In summer (Fig. A4), correlations weaken across all models, although CERRA still achieves the highest value ($r = 0.64$, $p < 0.05$). This decline in performance is most evident in mountain regions such as the Eastern Pyrenees, the Central System, and the Sierra Nevada in the southeast, as well as along the Mediterranean coast. Despite these lower correlations, summer exhibits the smallest MBE, MAE, and cRMSE compared with the other seasons (Figs. A2, A3, A5). During this season, NEWA again performs the worst, with the lowest spatial mean correlation ($r = 0.61$, $p < 0.05$), although ERA5 and ERA5-Land only slightly outperform it ($r = 0.62$, $p < 0.05$).

In addition to these seasonal patterns, regional contrasts are also evident. The highest correlations and lowest errors are consistently found in the inland plains, while the lowest correlations occur in the northeast and southeast, coinciding with the areas of highest elevation in the Iberian Peninsula.

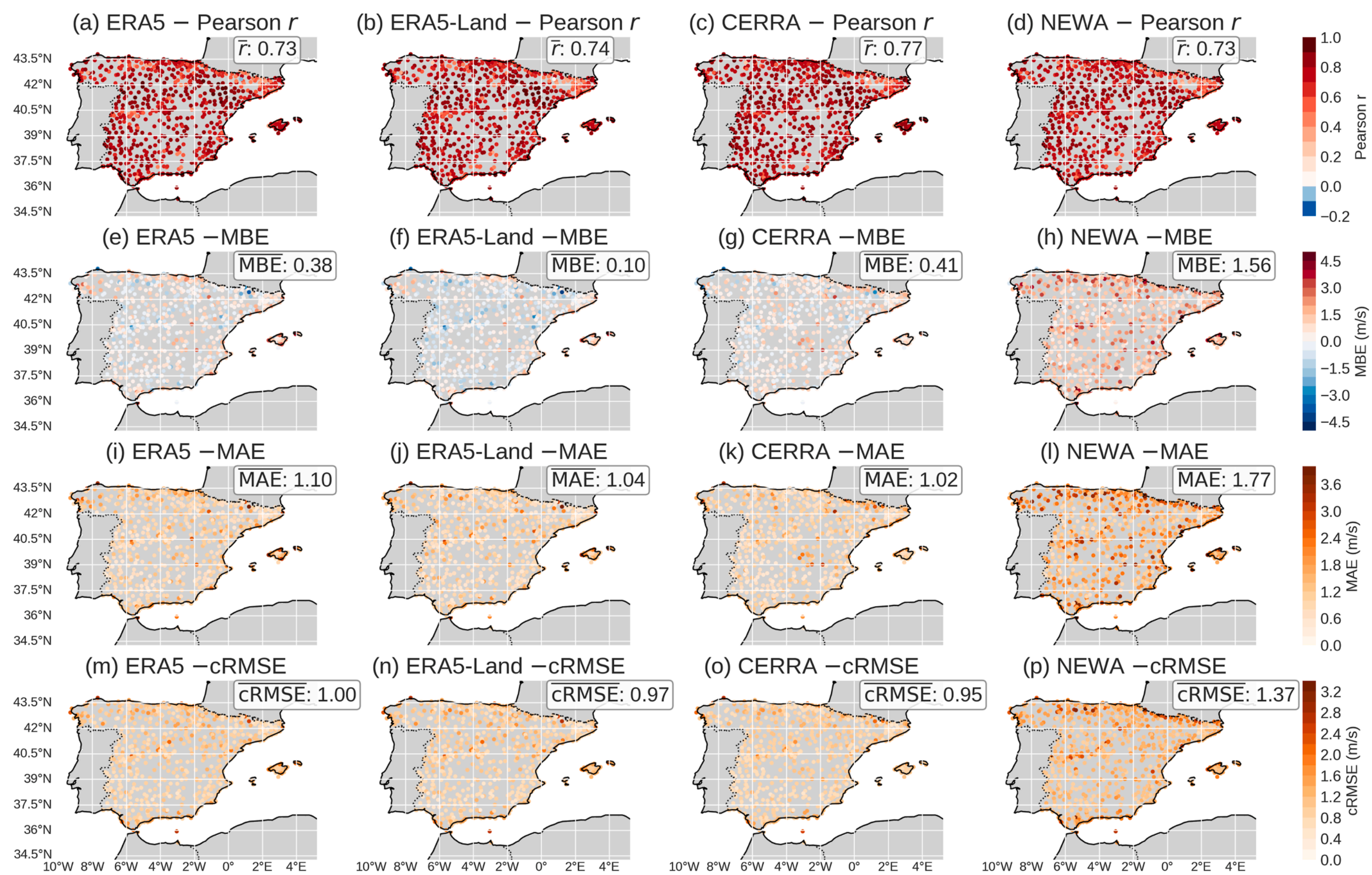

Fig. 2. Evaluation metrics of each gridded dataset against AEMET stations, (a–d) Pearson r correlations (only significant values with $p < 0.05$ are shown), (e–h) Mean Bias Errors, (i–l) Mean Absolute Errors, and (m–p) centered Root-Mean Square Errors, against AEMET NSWS for ERA5, ERA5-Land, CERRA and NEWA for 1/Jan/1990–31/Dec/2018.

Overall, the models achieve their strongest correlations, but also their largest deviations, in winter, and their weakest correlations, but smallest errors, in summer. Regional differences further modulate these patterns, with higher skill in plains and reduced skill in complex terrain. To explore the drivers of this seasonality, the following section examines the influence of weather types on model performance.

3.2. Sensitivity of modelled NSWS to weather types

For each model and weather type, we present the distributions of significant Pearson correlations ($p < 0.05$), MBE, MAE, and cRMSE against AEMET NSWS observations (Fig. 3). Overall, the models behave similarly across weather types, as the boxplots overlap considerably in all four metrics. The highest mean correlation values (Table 2) occur under conditions of SW, S, NW, and W, ranging from 0.78 to 0.79 for CERRA (best) to 0.73 to 0.75 for NEWA (worst). In contrast, the lowest mean correlations are found under NE, E, N, and U, where the values drop to 0.72–0.75 in CERRA and 0.70–0.72 in NEWA. These latter weather types also show the widest interquartile ranges, indicating greater spatial variability of the correlations and reduced model skill. ERA5 and ERA5-Land share the same behavior between weather types, with no differences coming from their different spatial resolution.

Regarding biases, MBEs do not differ markedly between weather types: all models tend to slightly overestimate NSWS at more than half of the stations, with NEWA showing the strongest bias. For S, SW, and W, the spread of positive and negative anomalies is noticeably larger. This is also found in the analysis of MAE and cRMSE, where these modes tend to have more outliers than the rest of weather types.

Because the frequency of the weather types varies in space and time, Figs. A6 and A7 display their seasonal distributions for winter and summer, respectively, to identify when and where the most challenging types dominate. In winter, A, W, and SW prevail; these types are

Table 1
Summary of metrics obtained in the evaluation of NSWS gridded datasets against AEMET (Best model is highlighted for each metric).

Dataset	Pearson r (↑)	MBE (↓)	MAE (↓)	cRMSE (↓)
ERA5	0.73	0.38	1.10	1.00
ERA5-land	0.74	**0.10**	1.04	0.97
CERRA	**0.77**	0.41	**1.02**	**0.95**
NEWA	0.73	1.56	1.77	1.37

Note: The model with the best metric is shown in bold.

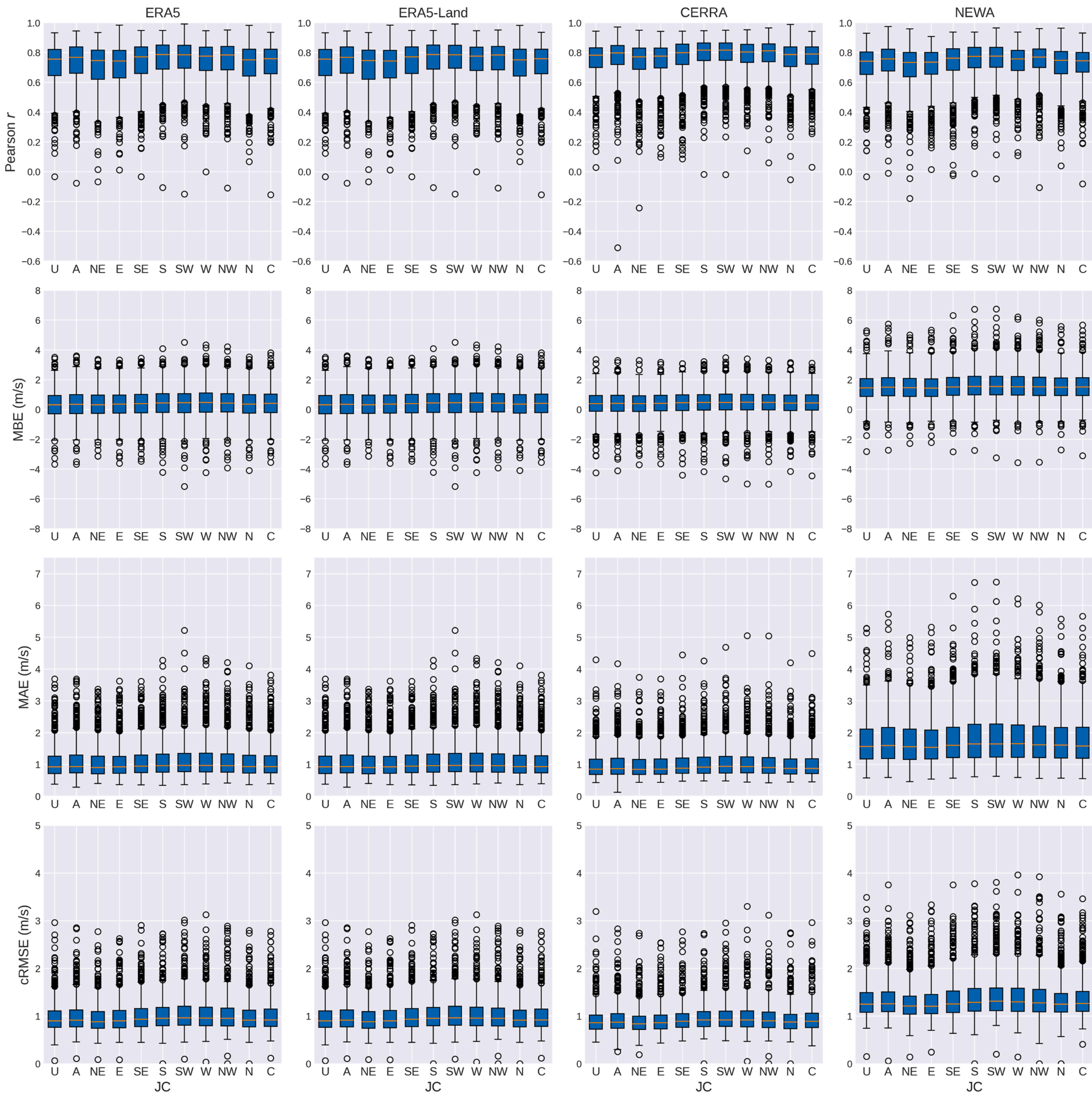

Fig. 3. Distribution of Pearson correlations, MBE, MAE and cRMSE between AEMET NSWS and ERA5, ERA5-Land, CERRA and NEWA considering days classified by each weather type, showing the effects of Jenkinson-Collison weather types on NSWS gridded datasets.

associated with moderate to best model performance, according to Table 2, and help explain the consistently high correlations observed across the Iberian Peninsula (Fig. A2). In contrast, summer is dominated by the U type, followed by E and NE, except in the northwest flank where A is most frequent. This seasonal dominance of less favourable types partially explains the performance drop in summer (Fig. A4), particularly in the Mediterranean region, where U, E, and NE occur more frequently.

Overall, the models reproduce temporal variability best under S, SW, W, and NW conditions, albeit with larger deviations, and lose skill under E, NE, U, and N. The seasonal prevalence of favourable (winter) versus unfavourable (summer) weather types therefore provides a clear

Table 2
Mean and Interquartile range (IQR) of aggregated Pearson correlations for each weather type (Sorted in ascending and descending order respectively, for ERA5, ERA5-Land, CERRA, and NEWA).

Weather type	ERA5		ERA5-Land		CERRA		NEWA	
	mean	IQR	mean	IQR	mean	IQR	mean	IQR
NE	0.71	0.20	0.71	0.20	0.74	0.14	0.70	0.16
E	0.71	0.18	0.71	0.18	0.75	0.13	0.71	0.15
U	0.72	0.18	0.72	0.18	0.75	0.13	0.72	0.15
N	0.72	0.18	0.72	0.18	0.75	0.13	0.72	0.15
C	0.73	0.16	0.73	0.16	0.76	0.11	0.72	0.13
SE	0.73	0.18	0.73	0.18	0.77	0.14	0.73	0.15
A	0.73	0.18	0.73	0.18	0.77	0.12	0.73	0.15
W	0.74	0.16	0.74	0.16	0.78	0.12	0.73	0.13
NW	0.75	0.16	0.75	0.16	0.78	0.12	0.74	0.12
S	0.75	0.16	0.75	0.16	0.79	0.12	0.75	0.14
SW	0.76	0.15	0.76	0.15	0.79	0.11	0.75	0.13

explanation for the observed seasonal artifacts in model performance.

3.3. Performance of ERA5, ERA5-Land, CERRA and NEWA according to sea distance and elevation

The mean NSWS at AEMET weather stations and model estimates from ERA5, ERA5-Land, CERRA, and NEWA, are plotted against their distance to the sea and their elevation above sea level in Fig. 4. In both cases, the observed NSWS exhibits clear dependence on these geographical features.

Mean NSWS increases at stations located closer to the sea (<20 km). This pattern is also present in the modelled NSWS. However, comparing the regression coefficients, R, for coastal stations (distance < 20 km), the models (dashed lines) tend to overestimate the coastal effect observed by AEMET (thick line), predicting a reduction in NSWS with distance from the sea that is nearly 1.5 times stronger. This overestimation is likely related to the use of smoothed orography and reduced surface roughness in the models, which increases NSWS values in coastal areas relative to observations. Indeed, most stations within 20 km of the sea have modelled NSWS above 2 m/s, while some AEMET stations record values below 1 m/s (Fig. 4). Interestingly, the slope for ERA5-Land ($R = -0.09 \pm 0.01$ m/(s km)) is steeper than for ERA5 ($R = -0.07 \pm 0.01$ m/(s km)), highlighting an unexpected effect of the interpolation scheme in ERA5-Land.

Regarding elevation, observed NSWS increases at AEMET stations above 900 m a.s.l., a pattern not captured by the models. At lower elevations, ERA5 and ERA5-Land generally agree with observations, but they exhibit decreasing NSWS with altitude, resulting in regression coefficients with opposite signs compared to AEMET. CERRA partially improves this behavior, showing a slightly positive slope (R= 0.2 ± 0.1 m/(s km)), though still

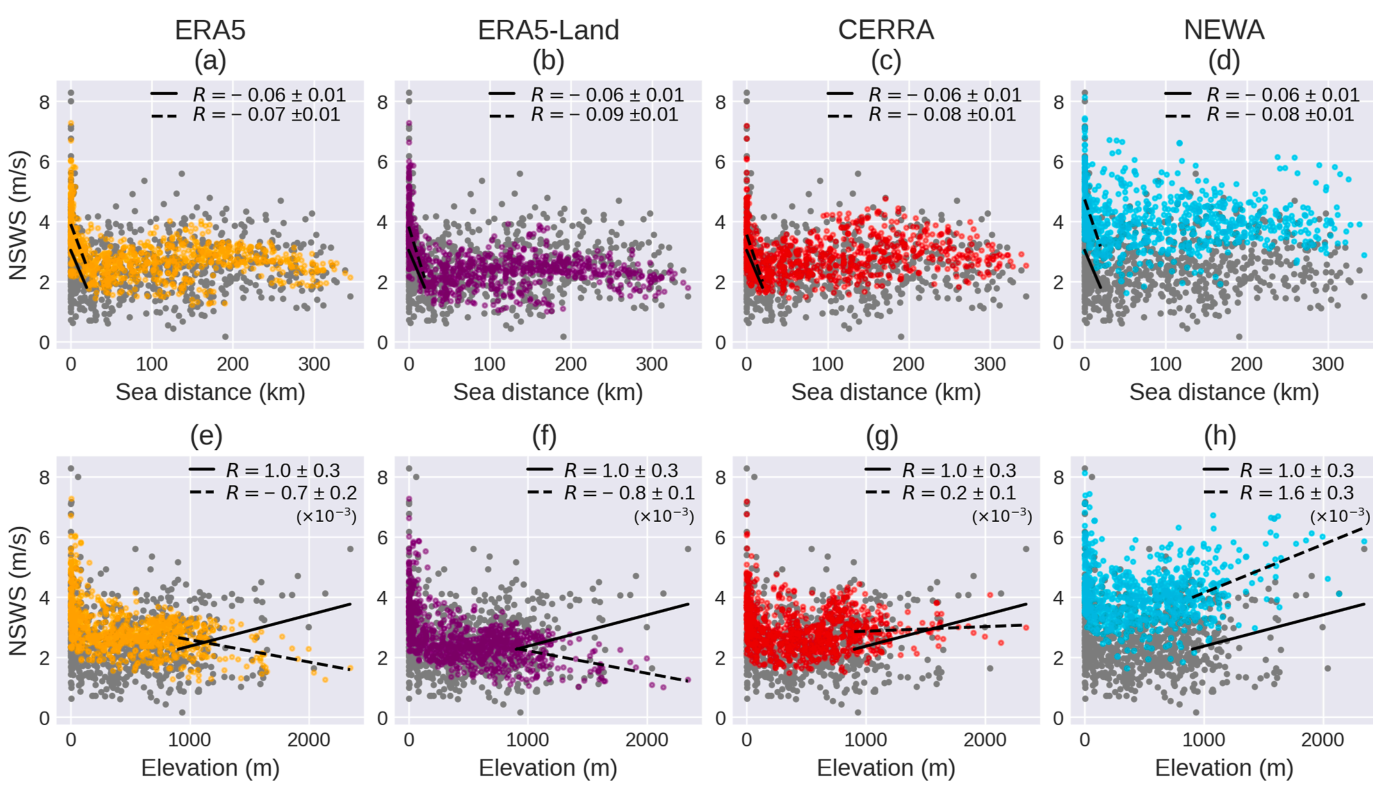

Fig. 4. Relationships between NSWS and sea distance and elevation, (a−d) mean NSWS of each weather station with respect to distance to the sea of (grey) weather stations and closest grid point in (yellow) ERA5, (purple) ERA5- Land, (red) CERRA and (blue) NEWA, (e−h) same as before but respect to the elevation. Straight/dashed black lines are linear regressions according to observations/grids from weather stations classified as (a-d) coastal and (e-h) mountain.

much smaller than observed (R = 1.0 ± 0.3 m/(s km)). Interestingly, NEWA is the only model that shows an increase in NSWS with elevation (R = 1.6 ± 0.3 m/(s km)), although it overestimates the effect and shows a clear positive offset relative to AEMET, even at stations above 900 m. This suggests that NEWA's higher resolution may better capture the orographic effect, enabling it to reproduce the increase of NSWS with altitude.

When evaluating model performance across station groups (inland, coastal, and mountain), the inland stations consistently have the highest mean correlations for all models, followed by the coastal stations and lastly the mountain stations (Fig. 5). Only in NEWA do mountain stations show slightly better correlations relative to other groups, with mean values close to those of coastal stations. However, the spread of correlations is greater for mountain stations than for coastal or inland sites, despite their smaller number. Regarding error metrics, ERA5 and ERA5-Land tend to overestimate NSWS in coastal and, to a lesser extent, inland stations, while underestimating NSWS in mountain regions. The largest mean MAE and cRMSE occur in coastal stations, although mountain stations show a larger dispersion of errors. In NEWA, the correlation distribution for mountain stations is closer to that of coastal sites, but the positive offset observed throughout the dataset also affects high-altitude stations, resulting in larger MAE and cRMSE distributions compared to the other models, despite the good regression coefficient (Fig. 4).

3.4. Combined effect of synoptic-circulation and geographical context

The combined influence of weather type and geographical context on model performance, quantified as the mean r^2 for each category, is shown in Fig. 6. Among the models, CERRA is the least affected by variations in orography and weather type, as reflected by the larger polygon areas. Inland stations in CERRA consistently achieve the highest performance, while mountain stations

Fig. 5. Significant Pearson correlation (p < 0.05), MBE, MAE and cRMSE between weather stations and ERA5, ERA5-Land, CERRA and NEWA according to their classification into coast (N= 220), inland (N = 403) and mountain (N = 125) for 1/Jan/1990−31/Dec/2018 (Each box shows the interquartile range (25th−75th percentiles), with horizontal lines representing the median (solid) and the mean (dashed). Whiskers indicate extreme NSWS (1.5xIQR), and circular markers highlight stations beyond this range).

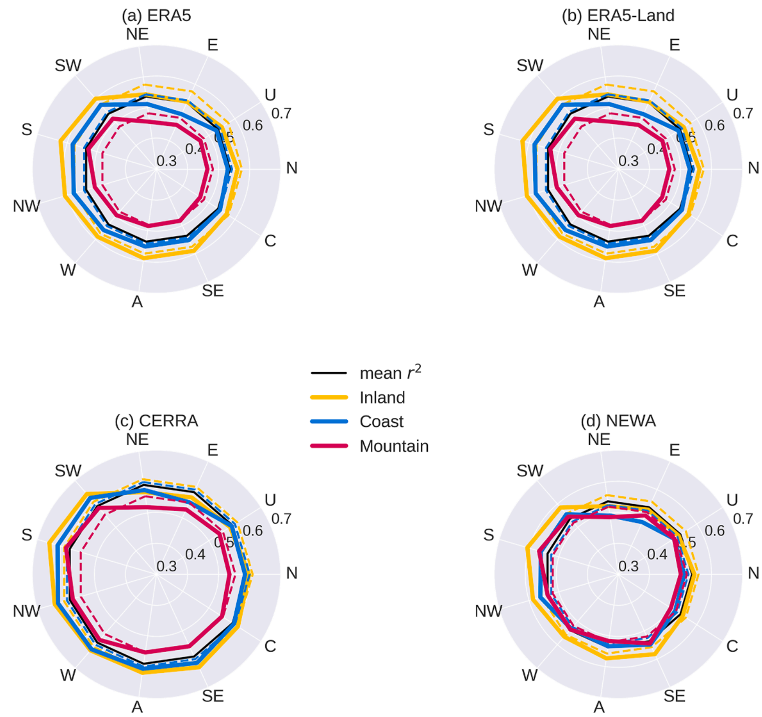

Fig. 6. Combined effect of weather types and geographical context on NSWS gridded datasets: mean r^2 obtained between models and observations considering stations aggregate depending on their geographical classification, inland, coastal and mountain, according to (thick lines) each JC and (dashed lines) the entire 28-year study period, compared to (black) the mean r^2 achieved by all stations independently of the JC.

perform the worst. Coastal stations generally match the performance of inland sites in most weather types, except for S circulation, where coastal performance declines.

This behavior is unique to CERRA. In the other models, coastal stations consistently perform poorly relative to inland sites but still outperform mountain stations. NEWA, on the contrary, exhibits smaller polygons overall, indicating more pronounced sensitivity to weather type and terrain. However, its r^2 values at mountain sites are comparable to those at coastal stations, except under E and SW circulations, where mountain and coastal stations, respectively, perform better. In particular, coastal sites experience the sharpest drop in performance under E-type circulation across all models, even more pronounced than under other challenging synoptic conditions.

4. Discussion

We evaluated NSWS from ERA5, ERA5-Land, CERRA, and NEWA against homogenized AEMET observations from 748 meteorological stations during 1/Jan/1990–31/Dec/2018. Our results identify CERRA as the most skillful dataset for Spain, performing best not only at annual and seasonal scales but also under different synoptic regimes and local contexts. This improvement is attributed to its higher spatial resolution, refined parameterizations, and the use of a larger observational database compared to ERA5 (Ridal et al., 2024; Galanaki et al., 2023). Compared with them, our results show a stronger seasonal cycle, with higher correlations in winter than in summer, and the opposite pattern in deviation errors. We explain these differences to the larger exposure of Spain to the extratropical circulation systems arriving unperturbed from the Atlantic Ocean than in the case of Greece. Another point is the generalized overestimation of NSWS in both CERRA and ERA5-Land reported by Galanaki et al. (2023), but in disagreement with the underestimation of NSWS by CERRA found by Pelosi (2023) in Sicily. The apparent discrepancy between the results of Pelosi (2023) and those presented here can be partly explained by differences in the region of interest. Their evaluation focuses on Sicily, a Mediterranean island where NSWS is strongly modulated by complex topography. Given that CERRA tends to underestimate the increase in NSWS with elevation (Fig. 4), assessments conducted over predominantly mountainous terrain are likely to yield an overall underestimation of NSWS by CERRA. By analyzing a much larger station network (748 vs. ∼40) and several geographical contexts, this study provides a broader perspective, showing that CERRA tends to slightly overestimate NSWS, while the sign of the deviations in ERA5-Land depends strongly on season and geographical features.

Regarding ERA5-Land, we generalize the findings of Minola et al. (2023) across diverse geographical settings, including complex orographic regions. Our results indicate that the increased spatial resolution does not provide added physical value for NSWS estimation respect to ERA5. Therefore, its use as a high-resolution NSWS dataset should be approached with caution. Finally, NEWA shows similar problems to those previously reported at turbine height (Jourdier, 2020; Murcia et al., 2022; Schicker et al., 2023): with a systematic overestimation of NSWS (Fig. 2d, h, i and p), likely related to boundary-layer schemes calibrated for Northern European wind regimes. However, in comparison to the ERA5 family, it better captures the temporal variability of NSWS over mountain regions. Overall, CERRA emerges as the most reliable dataset for estimating NSWS in regions without station coverage, despite its lower temporal resolution (3 h) compared to the hourly availability of ERA5. While this limits applications requiring sub-daily variability (e.g., gust analysis, short-term forecasting), our results support its use in climate and environmental studies, where accuracy at daily to seasonal scales is more critical than temporal detail.

By applying a gridded version of the JC classification, we assessed how synoptic-scale circulation modulates model skill. Unlike regional JC implementations that assign a single type to the whole domain (Lorente-Plazas et al., 2015), the gridpoint-centered approach by Otero et al. (2018) and Herrera-Lormendez (2022) revealed strong spatial heterogeneity in regional JC frequencies (Figs. A6 and A7). This methodology allowed us to detect the Mediterranean region as a recurrent challenge, especially in summer, when weak flow or easterly patterns dominate, likely as a result of the thermal low in the Iberian Peninsula (Hoinka and Castro, 2003) and the enhancement of local wind flows (Ortega et al., 2024). Under these conditions, models systematically underestimated temporal variability, likely explained by the difficulty of simulating thermally driven circulations (Lorente-Plazas et al., 2015). Contrary to our expectations, NEWA performs very similar to ERA5 family, but worse than CERRA, despite its higher resolution to solve these local flow phenomena. Across models, the best agreement with observations was found under westerly and southwesterly regimes, though these also produced higher deviations due to stronger observed winds. Similar regime-dependent behavior has been reported for wind gust by Azorin-Molina et al. (2016), suggesting a consistent role of synoptic forcing in modulating Iberian climate variability.

Despite the influence of circulation, our results indicate that geographical context exerts a stronger control on model biases (Fig. 5). Inland low-elevation sites showed the best agreement, while coastal stations were prone to systematic overestimation, and mountain sites exhibited the poorest skill. This pattern is consistent with previous findings for ERA5 and ERA5-Land in complex terrain (Minola et al., 2023; Molina et al., 2021), but is here demonstrated across a substantially larger and more diverse set of stations. While CERRA mitigated elevation-related biases, it still underestimated NSWS at high-altitude sites, highlighting the persistent challenge of representing sub-grid orographic effects. Interestingly, NEWA was the only dataset to capture the observed positive relationship between NSWS and elevation, likely due to its very fine spatial resolution. Despite a mean overestimation of NSWS, consistent with turbine-height evaluations in France and Austria (Jourdier, 2020; Schicker et al., 2023), it outperformed other datasets in representing elevation-dependent patterns. This highlights the added value of high-resolution downscaled reanalysis in complex regions.

Our study highlights how the interaction between synoptic-scale forcing and geographical context modulates model skill both seasonally and regionally. For example, although several mountain regions across Spain were identified, the Eastern Pyrenees consistently show poorer performance across seasons, in contrast to other mountain areas. We associate this to the prevalence of more challenging weather types in this region compared with other high-elevation zones. A clearer pattern emerges in coastal stations. In our classification, these include sites along the Atlantic Ocean, the Cantabrian Sea, and the Mediterranean Sea. Coastal sites are more frequently exposed to easterly circulations, such as the Gulf of Valencia, the eastern Cantabrian coast, and the southeastern flank; prove especially challenging for models, explaining the spatial variation in skill observed (Figs. A2−A5). These results underline the importance of considering both synoptic-scale forcing, local geographical context and their interaction when evaluating model performance, as their combined influence strongly shapes seasonal and regional skill patterns. In this context, AI-based models trained on gridded datasets should also be evaluated with this approach, to ensure their performance is assessed across different synoptic conditions and geographical settings rather than only on overall metrics.

Last but not least, we must note the limitations. First, the restricted temporal coverage of NEWA (1/Jan/1990−31/Dec/2018) prevented comparisons over the longer historical periods available for ERA5, ERA5-Land, and CERRA, potentially biasing the frequency of certain synoptic patterns associated with specific phases of large-scale circulation modes and limiting the representation of climate variability. Future work should therefore prioritize NSWS gridded datasets with long temporal coverage. Second, although the selection of the gridded NSWS datasets evaluated here was motivated by their widespread use and the range of spatial resolutions they offer, future studies could benefit from including additional products. For instance, comparisons with E-OBS could help quantify uncertainties associated with NSWS observations used to generate gridded fields, while an evaluation of COSMO-REA6 (6 km resolution, 1995−2016) could clarify the added value of assimilating NSWS observations relative to datasets that do not. Third, the JC classification applied here relies solely on mean sea-level pressure. Extensions incorporating mid-tropospheric variables, such as 500 hPa geopotential height, have been shown to improve weather-type characterization and reduce the proportion of unclassified days (Miró et al., 2020), and could refine the synoptic-scale interpretation of NSWS variability. Finally, a more regional classification accounting not only for geographical features but also for the intrinsic temporal variability of each region may help better evaluate model performance across Spain, with a particular focus on regional wind regimes. In fact, further research on the interactions between synoptic-scale circulation and geographic features, particularly topography, which were not explicitly addressed in this study and are likely to vary between regions.

5. Conclusions

This study evaluated daily near-surface wind speed (NSWS) from ERA5, ERA5-Land, CERRA, and NEWA against homogenized observations from 748 AEMET stations across Spain during 1/Jan/1990–31/Dec/2018. Two perspectives were considered: the sensitivity of models to synoptic-scale circulation and geographical context. The main findings are:

(i) CERRA is the most reliable dataset for NSWS across seasons, synoptic regimes, and geographical contexts, compared to ERA5, ERA5-Land and NEWA.
(ii) Increasing spatial resolution is not straightforward related to an improvement of the skill of models, but can help to capture the dependency of NSWS with elevation.
(iii) Reanalysis and high-resolution model skill is modulated by synoptic forcing and local context: inland sites perform best, coastal sites overestimate, mountain regions pose the greatest challenges, and performance is the highest under weather types reflecting the general circulation (e.g., westerlies, southwesterlies; in the case of Spain) but the lowest under circulations more related to local flows.

Based on these conclusions, we recommend that future gridded datasets integrate, within their validation frameworks, evaluations that account for weather types and their interaction with geographical features. This would help identify systematic biases in NSWS variability and in NSWS trends under climate change.

Declaration of competing interest

The authors declare no conflict of interest.

CRediT authorship contribution statement

Nuria P. Plaza-Martin: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization. **Shalenys Bedoya-Valestt:** Writing – review & editing, Methodology, Conceptualization. **Marcos Martinez-Roig:** Writing – review & editing. **Kevin Monsalvez-Pozo:** Writing – review & editing. **Àngela Manrique-Alba:** Writing – review & editing. **Francisco Granell-Haro:** Data curation. **Miguel Andres-Martin:** Writing – review & editing. **Cesar Azorin-Molina:** Writing – review & editing, Supervision, Funding acquisition, Formal analysis, Conceptualization. **Juli G. Pausas:** Writing – review & editing, Funding acquisition. **Alejandro Royo-Aranda:** Writing – review & editing, Software, Methodology. **Marcos Gil Guallar:** Software, Methodology. **María del Mar Rondon Velasco:** Data curation. **Jorge Navarro:** Methodology. **J. Fidel Gonzalez-Rouco:** Writing – original draft, Methodology. **Elena Garcia-Bustamante:** Methodology. **Santiago Beguería:** Writing – review & editing. **Tim R. McVicar:** Writing – review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.accre.2026.04.011.

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