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Advancing drought forecasting in Spain: Integration of meteorological indices and Random Forest algorythm for future projections

Gözde Nur Akşan* and **Fatih Dikbaş**

Pamukkale University,Faculty of Civil Engineering
Kınıklı, Kınıklı Campus, University St. 11, 20160 Pamukkale, Denizli, Turkey

**Corresponding author E-mail: gozdeaksann@gmail.com*

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Abstract— Drought is a serious environmental issue that negatively impacts water resources, agricultural production, ecosystems, and economic activities as a result of prolonged periods of low precipitation. In particular, the depletion of water resources and difficulties in accessing water pose significant threats to societies. In this context, developing effective forecasting systems in regions at risk of drought is critical for managing water resources more efficiently and taking timely measures. This study examines the potential of integrating various drought indices and machine learning techniques to improve the accuracy of meteorological drought predictions. Using data from 54 meteorological stations in Spain for the 1973–2023 period, drought analyses were conducted based on the standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI), and reconnaissance drought index (RDI). Future drought predictions were made using the Random Forest (RF) algorithm. The RF algorithm successfully analyzed historical climate data to understand the temporal and spatial dynamics of drought occurrences. Additionally, a newly developed drought mapping approach demonstrated that short-term droughts are more prevalent in northern Spain compared to the southern regions. The findings highlight the likelihood of increased drought severity in specific areas and its potential impacts on agricultural production and water management. This study serves as a crucial guide for policymakers aiming to develop drought management strategies and contributes to effective planning to mitigate future drought impacts. Furthermore, the developed software is provided as open source alongside the article.

Key-words: Spain, standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI), reconnaissance drought index (RDI), Random Forest algotythm, future drought prediction, climate change

1. Introduction

Climate change and drought analysis are of great importance for environmental and economic sustainability. Rising temperatures and changing precipitation patterns threaten agricultural production, drinking water resources, and the balance of ecosystems. Therefore, developing drought management strategies and preventive measures against these risks is critical for the efficient use of water resources and the success of climate adaptation policies.

Climate change significantly impacts water resources worldwide. Sustainable management of water resources is particularly vital for predicting and mitigating the effects of climatic risks such as droughts, extreme precipitation, and temperature increases. Studies on water resource management and drought prediction are indispensable for both short-term operational decisions and long-term strategic planning (*Wang et al.,* 2019; *Zhang et al.,* 2019; *Alivi et al.,* 2021).

Drought is one of the most significant and destructive consequences of climate change. Prolonged droughts can lead to declines in agricultural production, reductions in water reserves, losses in hydroelectric energy production, and challenges in meeting water demand. This situation necessitates continuous monitoring of water resources, along with conducting drought analyses and forecasts, to ensure sustainable management of water and make effective decisions.

Drought is a complex and multidimensional environmental issue characterized by prolonged water scarcity, threatening the sustainable use of natural resources. Often associated with low precipitation levels and high evaporation rates, drought can manifest differently depending on climatic conditions. Meteorological drought is defined as a prolonged period during which a region receives precipitation significantly below its normal levels. Agricultural drought occurs when insufficient soil moisture adversely impacts agricultural production, while hydrological drought arises from the depletion of surface and groundwater resources (*Wilhite* and *Glantz,* 1985; *Mishra* and *Singh,* 2010). Given the increasing severity of drought events, continuous monitoring, analysis, and forecasting are essential to developing effective strategies for water resource management.

Spain is one of the European countries most affected by drought due to its semi-arid and arid regions. In recent years, rising temperatures and changes in rainfall patterns have placed significant pressure on water resources, leading to more frequent and severe droughts. These changes have resulted in water shortages, agricultural yield losses, and reductions in hydroelectric energy production, particularly in the southern and eastern regions of the country (*Vicente-Serrano et al.,* 2014; *Lorenzo-Lacruz et al.,* 2013). Increased water demand further necessitates a reassessment of current water management policies to ensure sustainability.

Drought indices play a significant role in climate change studies. In this study, statistical and machine learning-based methods were employed to detect and predict long-term drought variations in Spain. For drought analysis, commonly used indices such as the standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI), and reconnaissance drought index (RDI) were evaluated. These indices serve as effective tools for identifying drought and its severity by utilizing water balance components such as precipitation, temperature, and evapotranspiration (*Sierra-Soler et al.,* 2016; *Zarch et al.,* 2015; *Zuo et al.,* 2018).

Long-term precipitation and temperature datasets from the meteorological stations included in the study were utilized to calculate drought indices. These indices are used to identify imbalances in the water budget and assess drought severity, considering climatic variables. Calculated over various time scales (1, 3, 6, 9, and 12 months), they provide insights into the intensity and duration of drought.

While SPI and SPEI analyze drought processes associated with precipitation and evapotranspiration, RDI better represents agricultural drought by also accounting for water demand. The use of these indices supports strategic decision-making in both agriculture and water resource management. Future drought values in Spain were predicted using the Random Forest algorithm, one of the Supervised Learning methods in machine learning. By forecasting future drought conditions in Spain, this study aims to support data-driven decision-making processes in water management and agriculture, ensuring the sustainability of vital resources amid the growing challenges of climate change.

2. Materials and methods

2.1. Study area

Spain, located in southwestern Europe, is a country distinguished by its diverse geographical and environmental features. It spans from 36°00’ to 43°47’ north latitude and 3°19’ west to 7°20’ east longitude. To the northeast, it shares borders with France and Andorra, to the west with Portugal, while it is surrounded by the Mediterranean Sea to the south and east, and the Atlantic Ocean to the northwest (*Fig. 1*).

The country is known for its varied landscapes, including vast mountain ranges such as the Pyrenees and Sierra Nevada, as well as large plateaus like the Meseta Central. With over 4,000 kilometers of coastline, Spain is also a significant maritime country. Its geographical diversity encompasses a range of climates, from the hot, dry summers and mild, rainy winters characteristic of the Mediterranean climate to the more temperate and oceanic climate of the north. Average temperatures vary from 10 °C in the northern regions to 25 °C in the south. Similarly, annual precipitation varies significantly; in the arid southeast, rainfall may be as low as 300 mm, while in the mountainous north, it can exceed 1,500 mm.

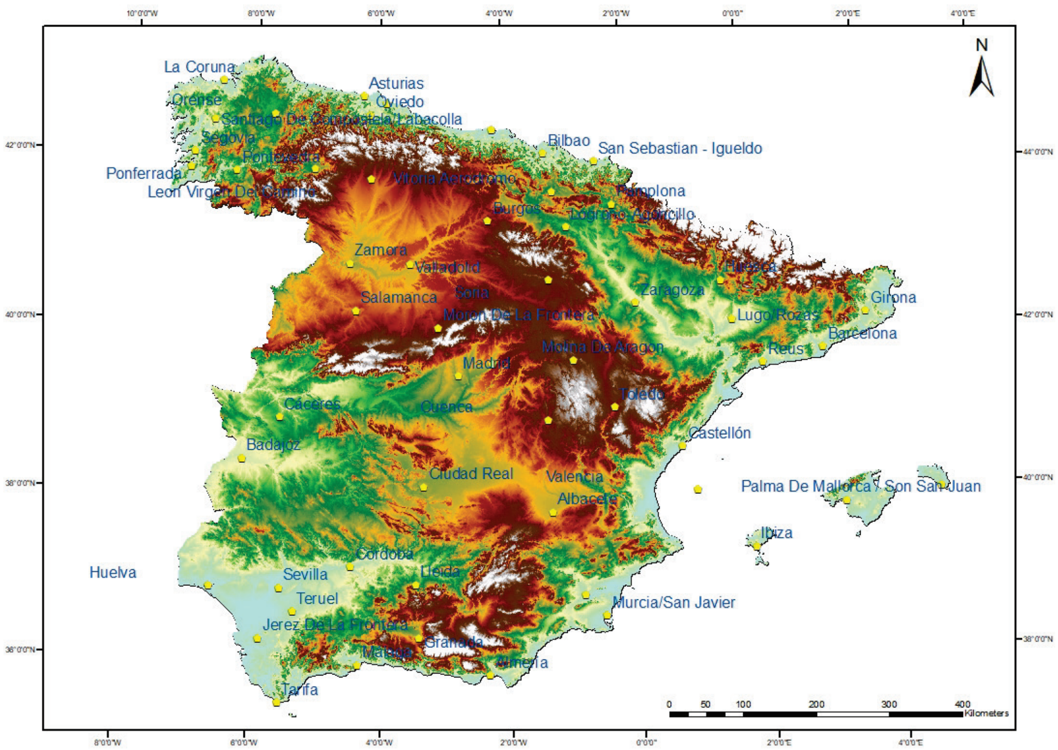


Fig. 1. A topographic map showing the locations of the meteorological stations examined in Spain. The authors used the administrative shapefile downloaded from the European Commission - Copernicus EU-DEM to create the map of Spain.

Spain's unique climate and topography have significant impacts on agriculture, the economy, and natural resource management. While some regions face challenges such as drought, others experience occasional flooding. This variability makes Spain a focal point for research on climate change, agriculture, water resource management, and disaster preparedness. These issues underscore the need for innovative solutions to protect livelihoods and promote sustainable development across the country.

Spain has faced increasing challenges related to drought due to climate change and the overexploitation of water resources. Recent studies highlight the intensifying drought conditions in Spain in terms of frequency and severity due to climate change-induced rising temperatures and reduced rainfall, which have significant implications for agriculture, water management, and public health. More than 60% of Spain's agricultural land has been affected by water shortages, with over 3.5 million hectares experiencing significant damage. Irrigated crops are particularly vulnerable. Urban water demand remains a high priority, with restrictions being implemented only during extreme *emergencies (García Galiano* and *Broekman,* 2023). *Jiménez-Donaire et al.* (2020) emphasize that future climatic changes will likely increase the frequency, duration, and intensity of agricultural droughts, necessitating the adoption of novel drought indices for better assessment. *Paneque* (2015) discusses the evolution of Spain's drought management strategies, advocating a shift from traditional infrastructure-based approaches to more sustainable, risk-based models. *Salvador et al.* (2020) quantify the impact of droughts on daily mortality rates in Spain, using indices like SPI and SPEI to reveal significant correlations. *García Galiano* and *Broekman* (2023) explore the dual impacts of rising temperatures and overexploitation of water resources, contributing to prolonged drought conditions. Additionally, the European Commission's Joint Research Centre (2024) underscores the critical impact of prolonged drought and record temperatures on the Mediterranean region, including Spain, affecting water availability, agriculture, and ecosystems. Projections indicate reduced precipitation and higher temperatures, leading to longer and more severe drought periods, and the findings collectively underline the urgent need for integrated and adaptive management strategies to mitigate the multifaceted impacts of drought in Spain.

2.2. Datasets

Climate records for 54 stations in Spain from 1973 to 2023 were collected from the European Climate Assessment and Dataset (ECAandD) and Wetter und Klima – Deutscher Wetterdienst – Startseite sources. The climatic variables obtained include daily precipitation (mm) and daily average temperature (°C). Using these data, potential evapotranspiration (PET) values were determined using the Thornthwaite method (*Thornthwaite,* 1948).

Table 1. The numbers of training and testing data

	SPAIN		
	SPI, SPEI, and RDI data		
	Training data (80%)	**Testing data (20%)**	**Total data**
1-month	491	120	611
3-month	489	120	609
6-month	487	119	606
9-month	484	119	603
12-month	482	118	600

The calculated drought indices were divided such that 80% of the data was used for training the machine learning model, and 20% was used for testing (see *Table 1*).

2.3. Standardized precipitation index (SPI)

The standardized precipitation index (SPI) is a commonly used index in drought analysis that expresses precipitation anomalies in terms of standard deviations. Developed by *McKee et al.* in 1993, SPI allows for determining the severity and duration of drought based solely on precipitation data. The SPI can be calculated for time scales ranging from one month to several years, capturing both short-term droughts (affecting agriculture) and long-term ones (affecting water resources and ecosystems) and therefore it is used in short, medium and long-term drought analysis.

2.3.1. SPI calculation steps

1. Data collection: A minimum of 30 years of precipitation data is required for SPI calculation. This data is used to determine the mean and standard deviation for each time period.
2. Normalization of precipitation: The precipitation data for a region is normalized by comparing it to the long-term average. SPI performs this normalization using the Gaussian distribution and calculates the degree of deviation from the long-term mean of precipitation (*Thom,* 1966; *McKee et al.,* 1993).
3. Interpretation of SPI Values: Positive SPI values indicate wet conditions, while negative values indicate dry conditions (*Sırdaş* and *Şen,* 2003). SPI values can be classified as follows (*Table 2*):

Table 2. Standardized precipitation index (SPI) values and classification (*Jain et al.,* 2015; *Adnan et al.,* 2018)

Classification	SPI value range
Extremely dry	SPI ≤ -2.0
Very dry	-2.0 < SPI ≤ -1.5
Moderately dry	-1.5 < SPI ≤ -1.0
Near normal	-1.0 < SPI < 1.0
Moderately wet	1.0 ≤ SPI < 1.5
Very wet	1.5 ≤ SPI < 2.0
Extremely wet	SPI ≥ 2.0

2.3.2. Features and advantages of SPI

The standardized precipitation index (SPI), with its flexible and simple structure, is a widely used index for meteorological drought detection and analysis. Its ability to be applied over different time scales makes SPI an ideal tool for agriculture, water management, and hydrological analysis. For instance, monthly SPI values can be used for short-term drought detection, while a 12-month SPI is more suitable for long-term assessments. Since SPI relies solely on precipitation data, it simplifies the calculation process and eliminates the need for large and complex datasets. Additionally, its normalized structure allows for spatial comparisons between different climatic regions and seasons. These characteristics make SPI suitable for a wide range of applications, from detecting sudden precipitation deficits to evaluating agricultural and hydrological droughts.

SPI offers diversity by being calculable over different time scales. The 1-month SPI represents short-term precipitation anomalies and provides information on sudden impacts such as crop loss. The 6-month SPI analyzes seasonal and medium-term precipitation trends, offering a more sensitive assessment compared to the Palmer drought severity index (PDSI). For long-term analysis, the 12-month SPI is associated with long-term hydrological processes such as reservoir levels, river flows, and groundwater levels. These variations of SPI provide flexible solutions tailored to different needs based on the time scale, offering high adaptability in drought analysis.

In this context, the convenience offered by SPI, its wide range of applications, and the ability to perform multi-scale analysis contribute to a better understanding of meteorological and hydrological drought processes. Especially with the increasing impacts of climate change, the use of SPI has become even more critical in environmental and economic decision-making processes.

2.4. Standardized precipitation evapotranspiration index (SPEI)

The standardized precipitation evapotranspiration index (SPEI) is a widely used index for drought detection that takes into account not only precipitation but also other climatic variables such as temperature. While SPEI is based on the fundamental principles of SPI, it provides a more climate-sensitive indicator by considering the effects of factors such as temperature increases and evaporation (evapotranspiration), recognizing that drought is influenced not only by a lack of precipitation but also by these additional factors (*Beguería et al.*, 2014; *Telesca et al.*, 2012; *Vicente-Serrano et al.*, 2010, 2011, 2012, 2014, 2020).

2.4.1. SPEI calculation steps

1. Data collection: The calculation of SPEI requires both precipitation and potential evapotranspiration (PET) data. PET is determined based on temperature and other meteorological factors. For PET calculation, the Thornthwaite (*Thornthwaite,* 1948) or Penman-Monteith (*Allen et al.,* 1998) methods are commonly used.
2. Water budget calculation: SPEI determines the water budget by calculating the difference between precipitation and PET for each time period (e.g., 1, 3, 6, 12 months). When this difference is positive, it indicates a water surplus, while a negative difference indicates a water deficit, representing drought conditions.

$$D_n^k = \sum_{i=0}^{k-1} (P_{n-i} - PET_{n-i}) \tag{1}$$

3. Probability distribution and standardization: The water budget differences are standardized to fit a normal probability distribution, which results in the calculation of the SPEI value. This standardization allows for the comparison of drought events across different time periods and spatial locations.

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}, \tag{2}$$

where C_0 = 2.515517, C_1 = 0.802853, C_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308 are constants.

If $P \leq 0.5$ then $W = \sqrt{-2In[P]}$

If $P > 0.5$ then $W = \sqrt{-2In[1-P]}$

P is the probability of exceeding a specific *D* value (*Wang et al.,* 2021).

4. Interpretation of SPEI values: Similar to SPI, the SPEI can have positive or negative values, and based on these values, drought or excessive rainfall conditions are classified in the same manner as shown in *Table 2*.

2.4.2. Features and advantages of SPEI

The standardized precipitation evapotranspiration index (SPEI) is a powerful tool for assessing the impact of climate change on drought by considering temperature increases. By incorporating factors such as precipitation, temperature, and evapotranspiration, SPEI becomes more sensitive to climate change. This comprehensive approach not only allows for a more accurate detection of drought severity but also provides a significant advantage for climate change studies. Like the SPI, the SPEI can be calculated over both short (e.g., 1 month) and long (e.g., 12 months or more) time scales, offering flexible applications for both meteorological and agricultural drought analyses.

The SPEI has a wide range of applications in meteorological, agricultural, and hydrological drought analyses. By considering not only precipitation deficits but also the effects of temperature and evaporation, it allows for a more accurate assessment of the impacts of drought on agricultural production and water resources. This feature makes the SPEI an ideal indicator, especially for climate change studies. Over the long term, the effect of temperature increases on drought severity can be effectively analyzed using the SPEI.

The different time scales of the SPEI provide an opportunity for detailed assessment according to specific needs. The one-month SPEI is ideal for detecting short-term precipitation and evaporation imbalances, highlighting immediate drought conditions. The six-month SPEI focuses on seasonal and medium-term water balance analyses, playing a crucial role in agricultural and irrigation planning. The twelve-month SPEI, on the other hand, analyzes long-term trends in precipitation and evapotranspiration, relating to long-term hydrological processes such as reservoir levels, river flows, and groundwater.

Overall, the versatile nature of the SPEI and its sensitivity to climate change make it a unique tool for drought analysis and resource management. By addressing the effects of temperature increases and changes in water balance, it provides valuable contributions to both scientific research and policy development processes.

2.5. Reconnaissance drought index (RDI)

The reconnaissance drought index (RDI) is an index used in drought analysis, based on the relationship between precipitation (P) and potential evapotranspiration (PET), which better represents situations where variables like temperature affect drought. RDI was developed to identify conditions like agricultural and hydrological drought, where water demand exceeds supply, and is one of the indices analyzing the water balance (precipitation – evapotranspiration difference) (*Tsakiris* and *Vangelis,* 2004, 2005*; Tsakiris et al.,* 2007). There are three different expressions of RDI: the RDI starting value (α_k), the Normalized RDI (RDI_n), and the Standardized RDI (RDI_{st}) (*Zarei et al.,* 2016).

2.5.1. RDI calculation steps

1. Data collection: To calculate the RDI, precipitation (P) and potential evapotranspiration (PET) data are required. PET data is typically calculated using meteorological variables such as temperature, wind speed, humidity, and solar radiation. These data can be obtained using models like Thornthwaite or Penman-Monteith.
2. Climatic water budget: The RDI calculates the water budget by dividing the total precipitation (P) by the total potential evapotranspiration (PET) for a specific time period. The basic formula is as follows:

$$\alpha_k^{(i)} = \frac{\sum_{j=1}^{j=k} P_{ij}}{\sum_{j=1}^{j=k} PET_{ij}}, \mathrm{i} = 1 \text{ to N} \tag{3}$$

The RDI initial value (α_k) is calculated in a time basis of k (months) as the following equation. where P_{ij} and PET_{ij} the precipitation and potential evapotranspiration of the jth month of the hydrological year and the precipitation and potential evapotranspiration of the ith year and N is total number of years. The hydrological year for the Mediterranean region starts in October, hence for October k=1. Here, RDI_n represents the RDI value for a specific time period. This formula measures the capacity of precipitation to meet evapotranspiration.

$$RDI_n^{(i)} = \frac{\alpha_k^{(i)}}{\alpha_k} - 1 \tag{4}$$

3. Gamma distribution and standardization: RDI values are standardized according to the Gamma distribution to analyze the anomalies in the water budget for a specific region and period (*Tigkas et al.,* 2013). This standardization process results in the calculation of the Standardized RDI (RDI_{st}). RDI_{st} allows for the comparison of drought events across different geographic regions and time periods (*Tsakiris* and *Vangelis,* 2005).
4.

$$RDI_{st}^{(i)} = \frac{y_k^{(i)} - \bar{y}_k}{\sigma_{yk}} = In\left(\alpha_k^{(i)}\right) \tag{5}$$

where y_k is the $In(\alpha_k)$, $\bar{y}_k$ is the arithmetic mean of y_k and σ_{yk} is its standard deviation.

5. Interpretation of RDI values: Like SPI and SPEI, RDI_{st} also has positive and negative values and uses the same classification (*Table 2*).

2.5.2. Features and advantages of RDI

The reconnaissance drought index (RDI) reflects drought severity in a more realistic manner by considering not only precipitation data but also meteorological variables such as temperature and evapotranspiration. Its ability to account for the increase in evapotranspiration caused by rising temperatures makes RDI a suitable tool for analyzing the impacts of climate change. Like SPI and SPEI, RDI can be used for both short-term (e.g., 1 month) and long-term (e.g., 12 months or longer) drought analyses. This flexibility provides a wide range of applications in meteorological and agricultural drought assessments. Furthermore, RDI's combined evaluation of water supply (precipitation) and water demand (evapotranspiration) offers a unique advantage, particularly in the context of agricultural and water resources management.

The RDI plays a critical role in agricultural and hydrological drought analyses. In terms of agricultural drought, it directly measures the water demand of plants, allowing for a detailed assessment of the impact of drought on agricultural production. In the context of hydrological drought, it serves as an important decision support tool in managing reservoirs, lakes, and groundwater resources. Additionally, in climate change studies, RDI stands out as an effective indicator for analyzing the long-term effects of rising temperatures and changing water budgets.

The different time scales of the RDI allow for a more detailed and scaled analysis of drought processes. A one-month RDI is used to assess short-term water imbalances, particularly effective in monitoring sudden impacts such as agricultural water stress. A six-month RDI reveals seasonal water imbalances, supporting critical decisions in agriculture and natural resource management. A twelve-month RDI analyzes long-term changes in the water balance, providing a foundation for strategic planning regarding reservoir levels, groundwater, and river flows.

Overall, the multidimensional structure of the RDI and its comprehensive approach, which incorporates climate variables, make it a valuable tool for the sustainable management of water resources and the mitigation of agricultural drought impacts. The flexibility it provides in both short-term and long-term applications makes the RDI a key component in drought analysis and management.

2.6. Machine learning

Machine learning is a field of technology capable of analyzing large amounts of data, discovering patterns, and predicting future events. In drought analysis and prediction, machine learning plays a crucial role, especially in the sustainable management of water resources. The machine learning models used in this field aim to predict future drought conditions by analyzing past trends in climate data. These predictions help develop strategies to reduce drought risk and manage water resources more effectively. In this study, the Random Forest algorithm has been chosen to make future drought predictions. The reason for this choice is its ability to handle complex and multivariable data. Primarily, it offers strong performance in regression problems, allowing for accurate predictions of drought intensity and duration based on drought indices. Additionally, this model stands out for its ability to identify important features in high-dimensional datasets, which helps select the most effective meteorological and environmental factors for analysis, thus improving the model's accuracy. Furthermore, since Random Forest can detect anomalies, it is effective in identifying extreme drought events and unusual climate conditions. With these capabilities, it emerges as a reliable and flexible method for drought analysis and prediction.

Random Forest is a powerful and flexible machine learning method used for both classification and regression problems within supervised learning algorithms. This algorithm is an ensemble model made up of multiple decision trees (*Breiman*, 2001). Random Forest aims to make more accurate and balanced predictions by reducing the weaknesses of individual decision trees. The term "random" refers to the model's process of making random selections between both data subsets and features, which helps reduce the risk of overfitting (*Pedregosa et al.,* 2011).

2.6.1. The basic features of the Random Forest algorithm

- Ensemble structure: Random Forest combines multiple independent decision trees. Each tree is trained on a randomly selected subset of data and a random subset of features. As a result, the trees make different predictions, which enhances the overall performance of the model.
- Bagging (bootstrap aggregating): Bagging is a technique where the model is trained on different subsets of data. In Random Forest, each decision tree is trained using random samples drawn from the original dataset. This method reduces the model's variance and helps achieve more generalized results.
- Random feature selection: When building each decision tree, a random subset of features is considered at each node, rather than using all features. This increases the diversity of the model, reduces the dependence between the trees, and enhances the overall performance.

2.6.2. Working steps of Random Forest algorithm

1. Creating trees with subsets of the dataset: Random Forest creates multiple decision trees using randomly selected subsets of the original dataset through the bootstrap method.
2. Training the trees: Each tree is trained independently based on these subsets. At each node of the tree, a random subset of features is selected, and the best feature for splitting is chosen.
3. Combining predictions: The model combines the outputs of each decision tree. In classification problems, the majority vote of the trees is considered. In regression problems, the average of the predictions made by all trees is taken.
4. Determining the final result: The model produces the final result by majority vote (for classification) or by averaging the predictions (for regression).

2.6.3. Advantages of Random Forest

- Prevention of overfitting: Decision trees are prone to overfitting, but Random Forest mitigates this issue. When multiple different trees are created, the model’s overall tendency prevents it from becoming overly sensitive to noise in the dataset.
- Low variance: Trees trained on different subsets of data through bagging reduce variance, which enhances the model’s ability to generalize.
- Feature importance ranking: Random Forest can measure the importance of each feature in the model. This is particularly useful for identifying key features as well as irrelevant ones in the dataset.

- Success with imbalanced datasets: Random Forest can yield effective results when working with imbalanced datasets. Some trees may give more weight to the rarer classes, improving performance on these classes.
- Parallel processing capability: Since the trees are trained independently, Random Forest can be run in parallel, which provides a time advantage when working with large datasets.

2.6.4. Disadvantages of Random Forest

- Slower predictions: Since Random Forest uses a large number of decision trees, the prediction time may be longer compared to individual decision trees.
- Memory usage: The creation of multiple trees requires more memory, which can be demanding, especially with large datasets.
- Interpretability: While a single decision tree is relatively simple and interpretable, the hundreds or even thousands of trees in a Random Forest model make it less interpretable.

2.6.5. Application areas of Random Forest

- Classification problems: It is commonly used in classification problems such as medical diagnosis, customer segmentation, and credit risk assessment.
- Regression problems: Random Forest is also highly successful in regression problems where predictions need to be made, such as in climate change studies, housing price forecasting, and agricultural productivity.
- Feature selection: Random Forest can be used to identify important features in high-dimensional datasets.
- Anomaly detection: It is an effective method for detecting anomalous data points.

2.6.6. Parameters of Random Forest

n_estimators: It specifies the number of decision trees to be used in the model.
Recommended value range:

- 5–30 (for small datasets).
- 10–100 (for large and complex datasets).

max_depth: It limits the maximum depth of each decision tree.
Suggested value range:

- 5–30 (for small datasets).
- 10–100 (for large and complex datasets).

random_state: It is a fixed seed value used in random number generation.
Recommended value range:

- It can be any fixed number.

In the modeling process with the Random Forest algorithm, the steps in the flowchart in *Fig. 2* have been followed.

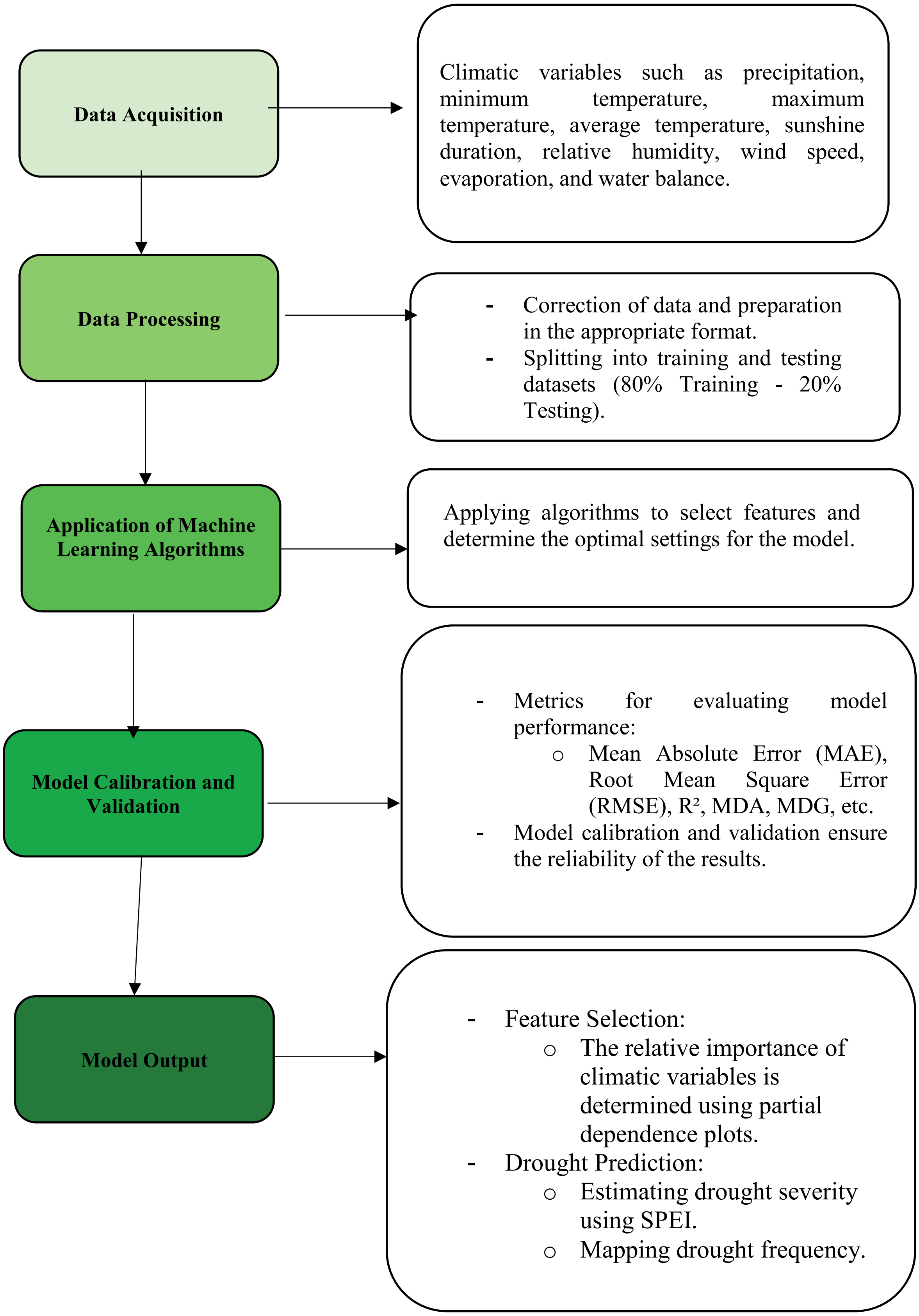


Fig. 2. Flowchart of the Random Forest algorithm implementation.

In this study, the Random Forest algorithm was applied using a Python-based code developed to model time series data and make future drought predictions (see *Appendix 1*). The model was designed to work with drought indices such as SPI (standardized precipitation index), SPEI (standardized precipitation evapotranspiration index), and RDI (reconnaissance drought index). In the first step, the datasets for these indices were scaled, and input (features) and target variables were created using 12 months of historical data. The dataset was split into 80% training and 20% testing subsets.

The regression variant of the Random Forest algorithm, the RandomForestRegressor, was configured as an ensemble model consisting of 10 decision trees (n_estimators=10). Each decision tree was trained on different subsets of the dataset and branched up to a maximum depth of 55 (max_depth=55) to enhance prediction performance. After the model training was completed, predictions were made on the test data and compared with the actual SPI, SPEI, and RDI values through inverse scaling. The predicted values were visualized along the time axis, generating graphs to understand drought trends in past and future periods.

The model generated monthly predictions covering a 50-year future period, presented as a continuous time series. In addition to the forecasts, the model's performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 metrics. For instance, the RMSE value was low on the training data, and the R^2 score exceeded 0.85, indicating the model's strong accuracy and predictive capability.

The obtained results provide a comprehensive evaluation for validating past drought trends and generating future projections. All predictions and analysis outcomes were saved in an Excel file along with graphical representations, enabling researchers to examine the data more conveniently. This approach once again highlights the effectiveness of the Random Forest algorithm in handling multidimensional climatic variables.

2.7. Model evaluation metrics

Model validation is an important step in testing the accuracy and reliability of machine learning models. In this process, researchers have utilized various statistical metrics (*Nabavi-Pelesaraei et al.,* 2018; *Chen et al.,* 2021). To evaluate the performance and reliability of the applied models, we used RMSE, MAE, and R^2 metrics:

- Root mean square error (RMSE): The square root of the average of the squared errors of prediction. A low RMSE value indicates that the model has more accurate predictions.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(Y_{obs} - Y_{pred}\right)^2}{N}} \tag{6}$$

- Mean absolute error (MAE): The average of the absolute differences between the actual and predicted values. A low MAE indicates better model accuracy.

$$MAE = \frac{\sum_{i=1}^{N}\left|Y_{obs} - Y_{pred}\right|}{N} \tag{7}$$

- R^2 (coefficient of determination): Represents how much of the variance in the data is explained by the model. The closer R^2 is to 1, the higher the accuracy of the model.

$$R^2 = \frac{\sum_{i=1}^{N}(Y_{obs} - \overline{Y_{obs}})\left(Y_{pred} - \overline{Y_{pred}}\right)}{\sqrt{\sum_{i=1}^{N}(Y_{obs} - \overline{Y_{obs}})^2}\sqrt{\sum_{i=1}^{N}\left(Y_{pred} - \overline{Y_{pred}}\right)^2}} \tag{8}$$

In the above equations, Y_{obs} represents the actual dependent variable, Y_{pred} represents the predicted dependent variable, and N denotes the number of observations. As a general rule, models with lower RMSE and MAE values, and higher R^2 values, are considered more accurate and reliable for prediction during the testing phase.

3. *Results and discussion*

3.1. *Frequency analysis of drought indices*

The frequency analysis results of SPI, SPEI, and RDI values for the selected time scales at the Spanish stations have been calculated, and the relative frequency results are presented in *Tables 3 to 19* of *Appendix 2*. The results have been classified according to the dry and wet categories. For all frequencies, considering dryness, the range of values has varied from 0% to 32% for SPI, 16% to 33% for SPEI, and 6% to 26% for RDI.

Upon detailed examination, according to the SPI analysis results, the highest relative frequency in the moderate dryness category is 12%, observed at the Huesca station on the 12-month timescale. Meanwhile, the highest relative frequency in the extreme dryness category is 8%, observed at the Barcelona and Sevilla stations, also on the 12-month timescale.

According to the SPEI results, the highest relative frequency in the moderate dryness category is 12%, observed at the Valladolid and Huesca stations on the 1-month and 3-month timescales, respectively. In the extreme dryness category, the highest relative frequency is 6%, observed at the Barcelona station on the 12-month timescale.

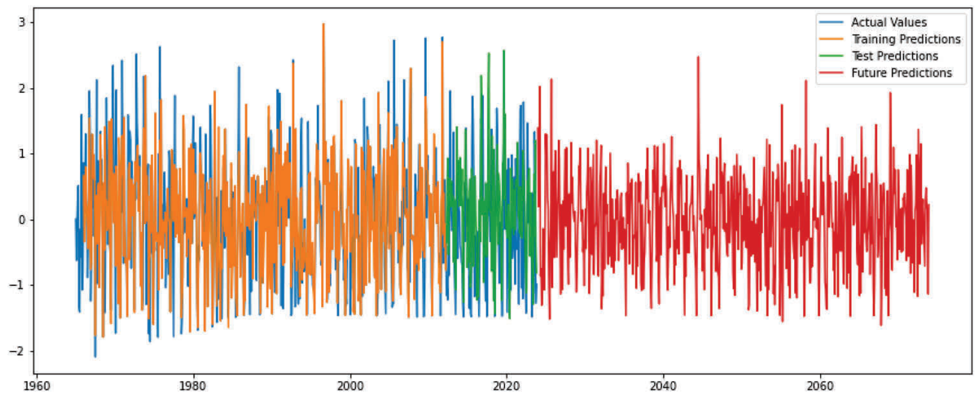
According to the RDI analysis results, the highest relative frequency in the moderate dryness category is 14%, observed at the Bilbao station on the 6-month timescale. In the extreme dryness category, the highest relative frequency is 6%, observed at different stations across all timescales.

3.2. The observed and future changes of meteorological drought events according to time series.

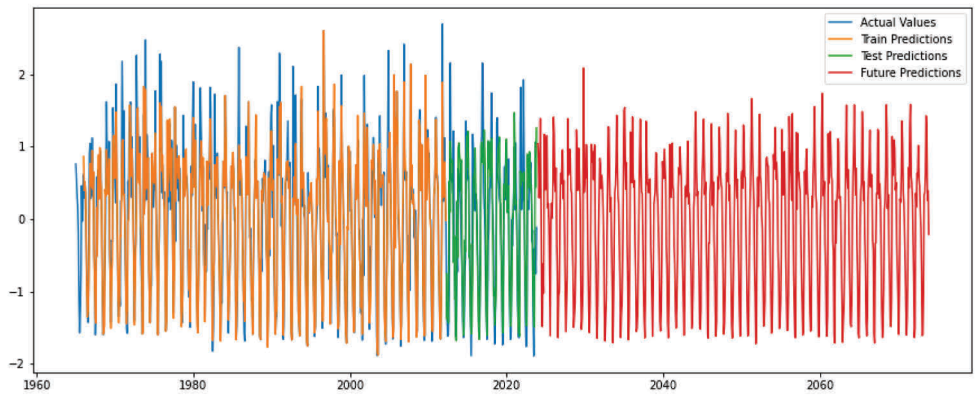
For each station examined in Spain, time series graphs containing observed data, training data, test data, and forecast values determined by the Random Forest method were generated for each 1, 3, 6, 9, and 12-month time period by the developed software (a total of 810 graphs for 54 stations). As an example, the SPI, SPEI, and RDI time series graphs for the 1-month calculation period at the Ibiza station are presented in *Fig. 3*. Upon examining the SPI, SPEI, and RDI outputs, it was observed that, as the time scale increased, the drought trend generally became more pronounced, the frequency of drought periods decreased, but there was a relative increase in the duration and severity of drought.

The wet and dry periods, which were relatively ambiguous at the one- and three-month time scales, began to become more distinct starting from the six-month time scale. When comparing the SPI, SPEI, and RDI values at the selected time scales, although the temporal development of both indices showed similarities, some small differences were observed in the characteristic features of drought periods (frequency, magnitude, and severity). The differences in the fluctuations and continuity characteristics of these indices representing drought features tend to decrease as the time scale increases.

a)



b)



c)

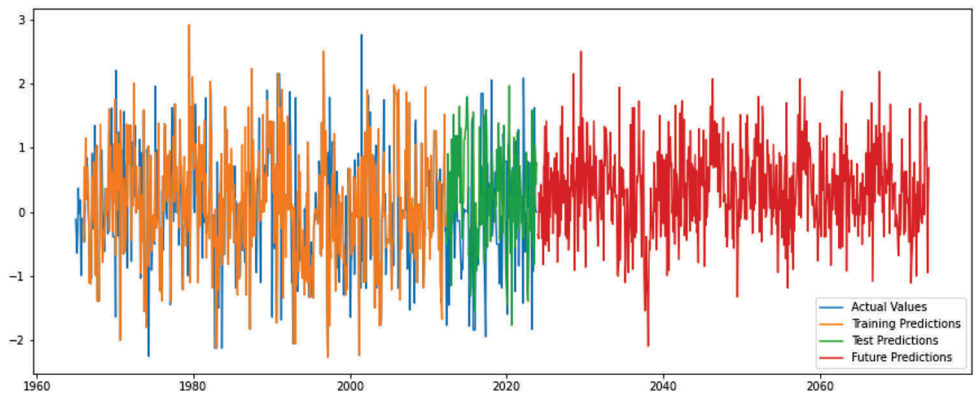


Fig. 3. Time series graphs for the Ibiza Station: a) 1-month SPI, b) 1-month SPEI, c) 1-month RDI.

3.3. The temporal and spatial pattern of drought intensity and frequency.

Using the selected model based on region-specific SPI, SPEI, and RDI, as well as the influential meteorological parameters, drought intensity was mapped for Spain from 1973 to 2023 based on observed data and from 2024 to 2073 based on predicted future data across different time scales (*Figs. 7, 8*, and *9*).

By summing the dryness values (SPI <= -1) experienced in the region and dividing by the total time, the SPI-based temporal drought values proposed in this study were determined. According to the SPI-based temporal drought values, spatially, it was found that short-term drought intensity occurred in the northern part of the country, while longer-term drought occurred in the central, eastern, and southern regions. For longer periods, the calculations indicated that drought shifted to the central and southern areas of Spain, and in future predictions, drought risks were observed to emerge particularly in the western regions. In the periodic evaluation, it was determined that the intensity of drought predicted to occur in the future would increase (*Fig 4*).

When looking at the SPEI-based temporal drought values, it has been determined that short-term drought observed spatially is more prominent in the central and southern parts of the country, while longer-term drought is more pronounced in the western and northern regions. Future predictions indicate that the intensity of drought is shifting from the southern part of the country towards the eastern and western regions. In the periodical assessment, the SPEI-based temporal drought value is expected to peak at -1.43 during the 12-month period (*Fig 5*).

Looking at the RDI-based temporal drought values, it has also been determined that short-term drought events are particularly impactful in the northern regions of the country, while longer-term drought, as seen in the maps, is more intense in the eastern and western regions, affecting the entire country. In the periodical assessment, it has been concluded that the intensity of future droughts is expected to increase compared to the observed drought intensity (*Fig 6*).

a) b)

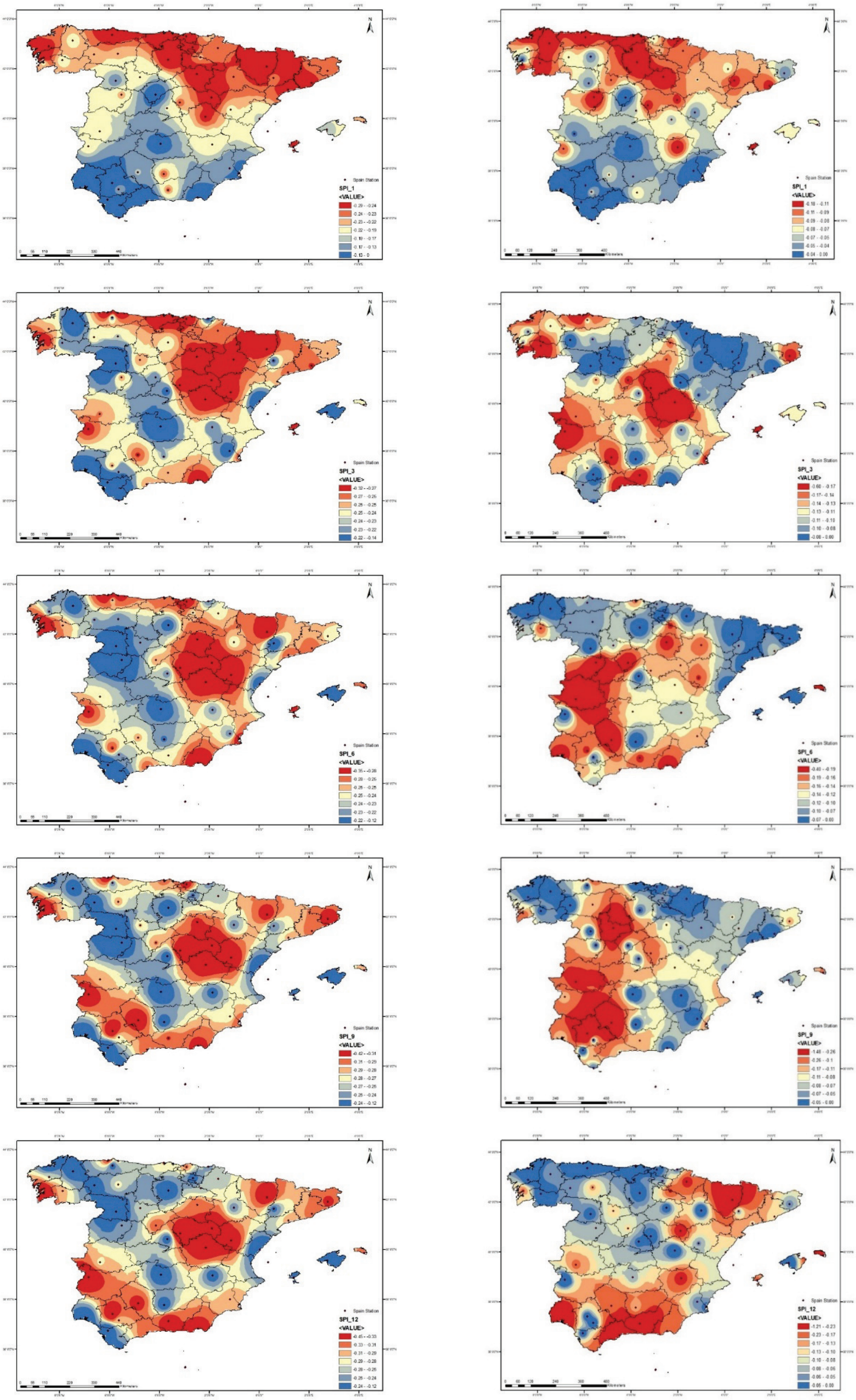


Fig. 4. Detection of drought over time based on SPI (a) observed (b) future

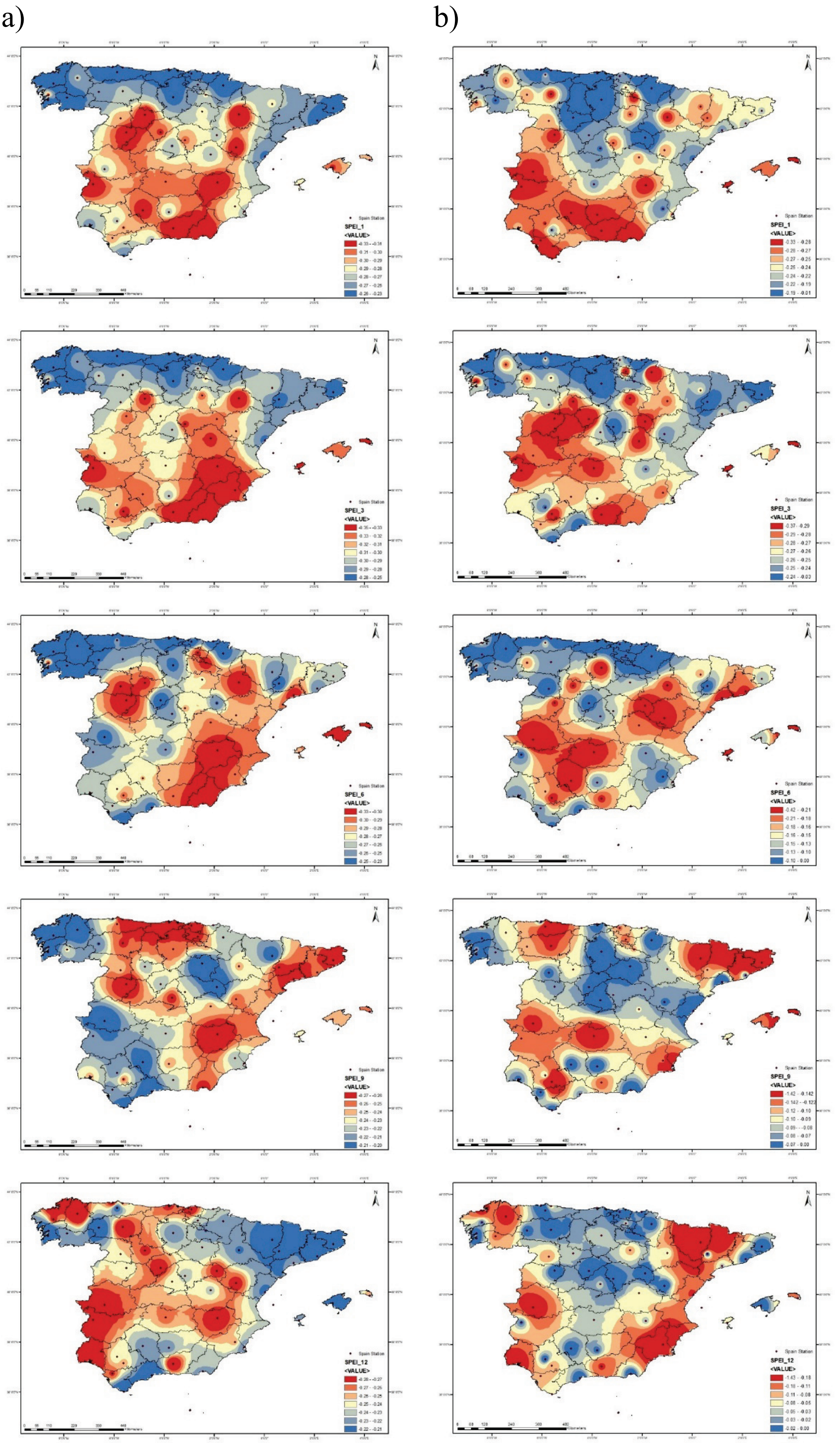


Fig. 5. Detection of drought over time based on SPEI (a) observed (b) future

a) b)

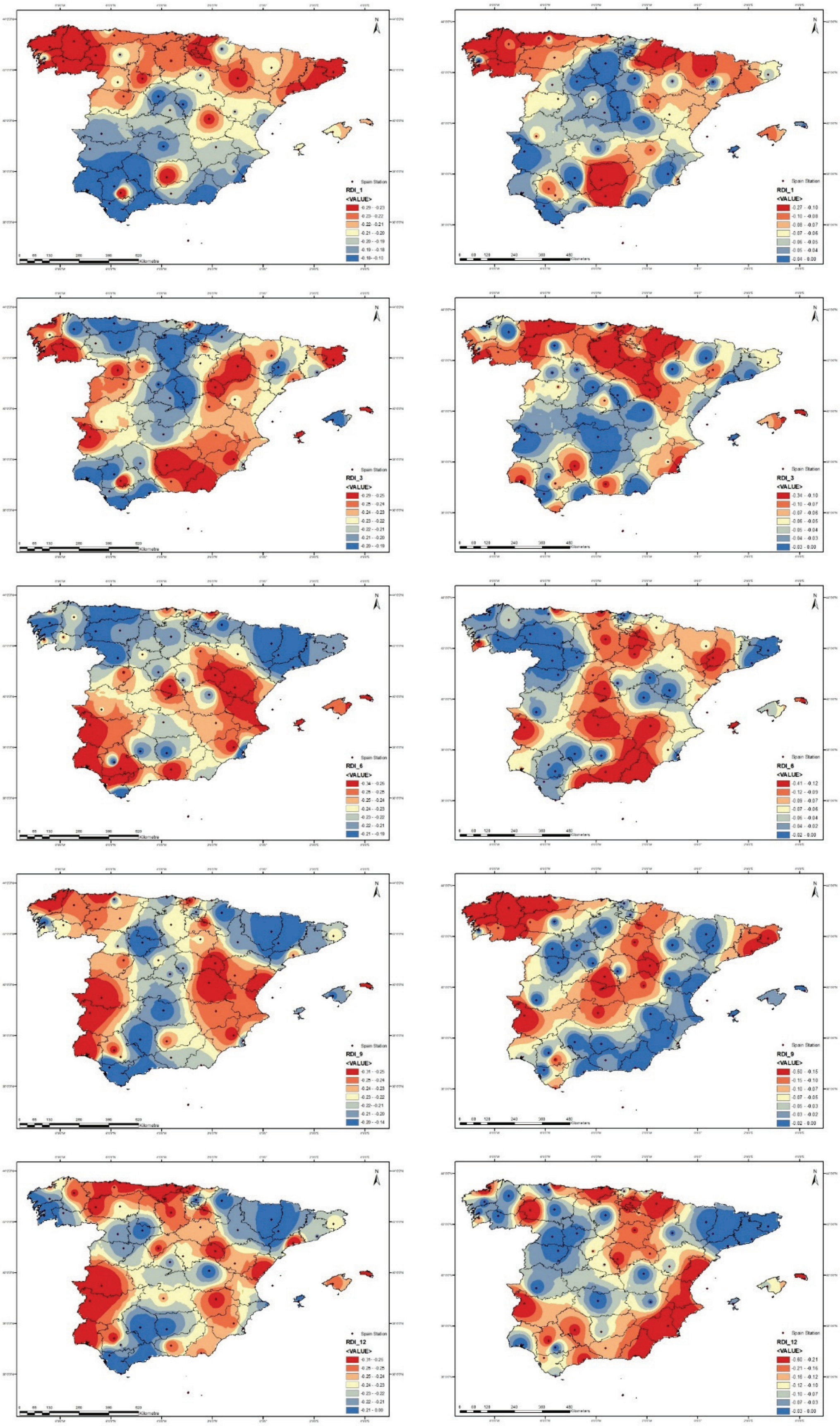


Fig. 6. Detection of drought over time based on RDI (a) observed (b) future.

3.4. *Performance of machine learning models*

Among machine learning methods, Random Forest is highly successful in modeling multiple variables and complex relationships. In this study, the Random Forest algorithm was used to predict drought indices and make future drought predictions. 80% of the data was used for training, while 20% was reserved for testing. The performance of the obtained test data was evaluated. To assess the model's performance, the R^2, MAE, and RMSE performance metrics were used. The results obtained are shown in *Figs. 10, 11,* and *12*. It was found that the R^2 values for the 1-month results were lower compared to other time scales.

a)

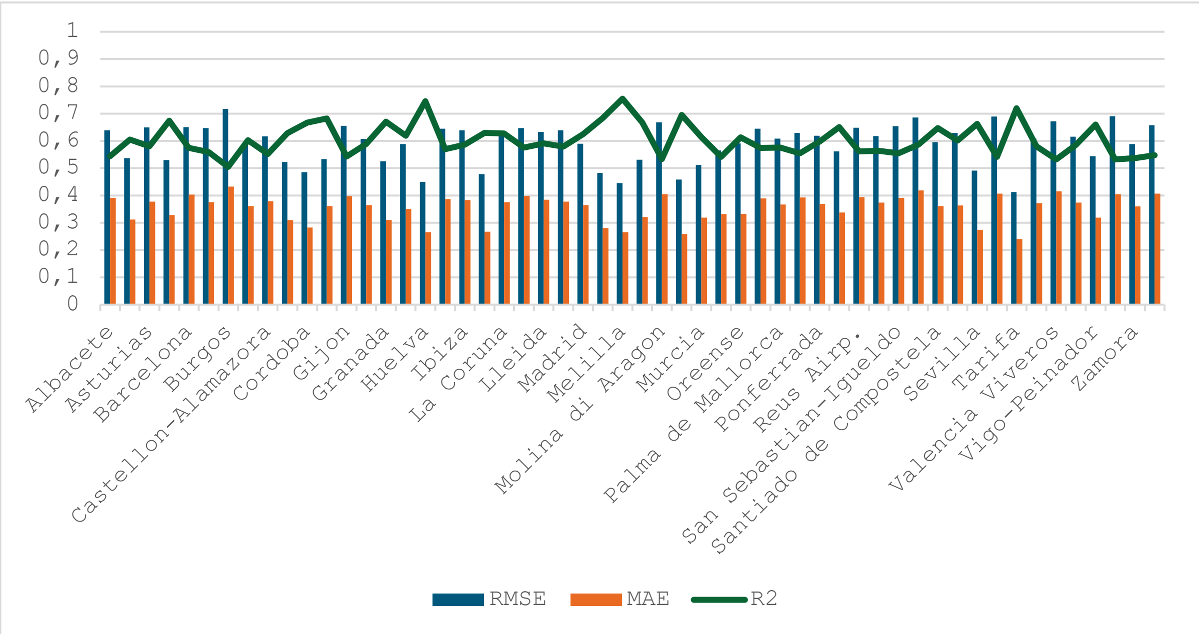
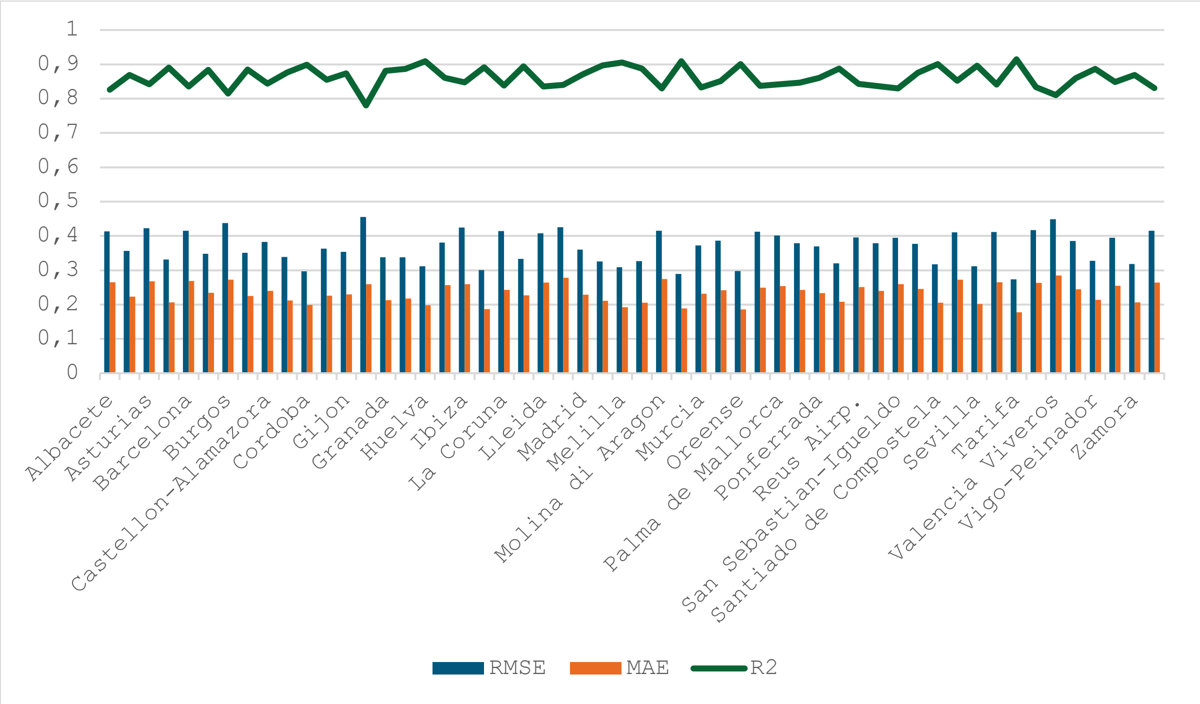


Fig. 7. Evaluation metrics for stations a) evaluation for 1-month SPI, b) evaluation for 3-month SPI, c) evaluation for 6-month SPI, d) evaluation for 9-month SPI, e) evaluation for 12-month SPI

b)



c)

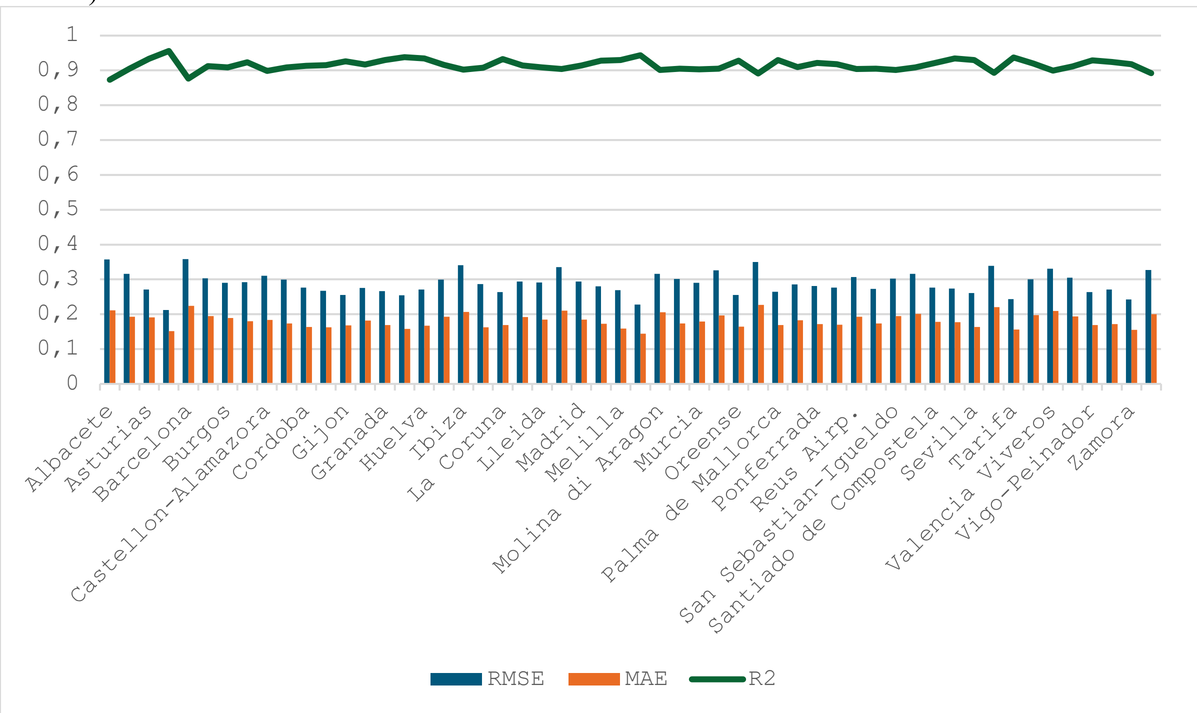
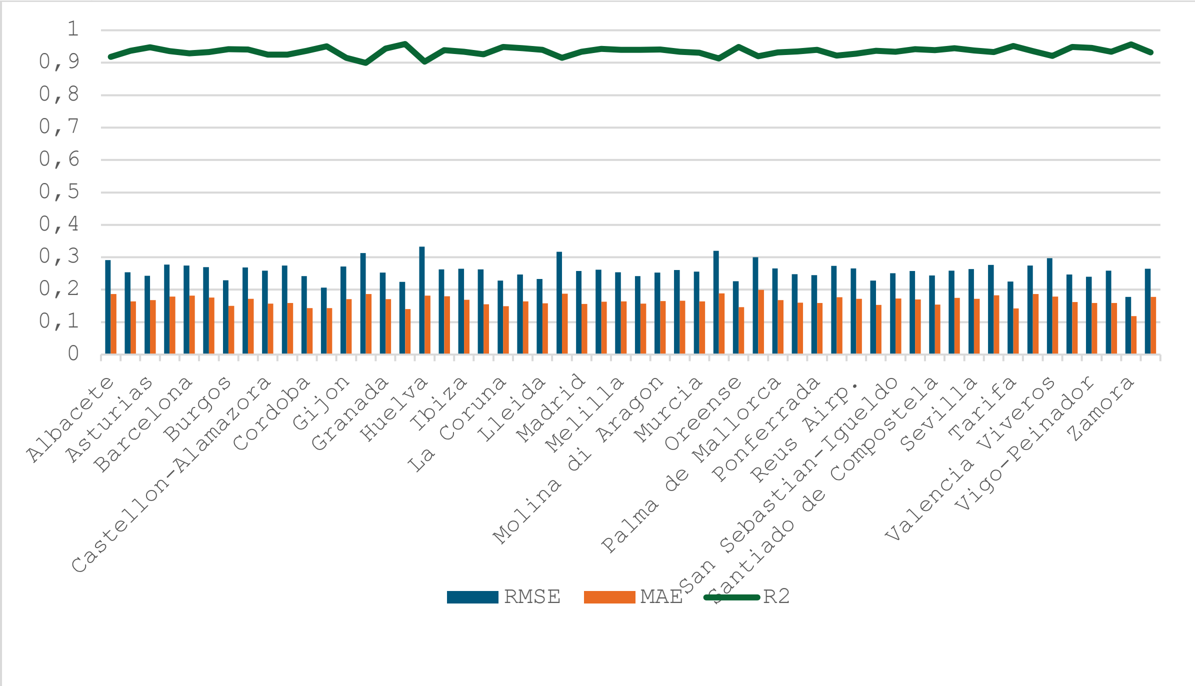


Fig. 7. Continued

d)



e)

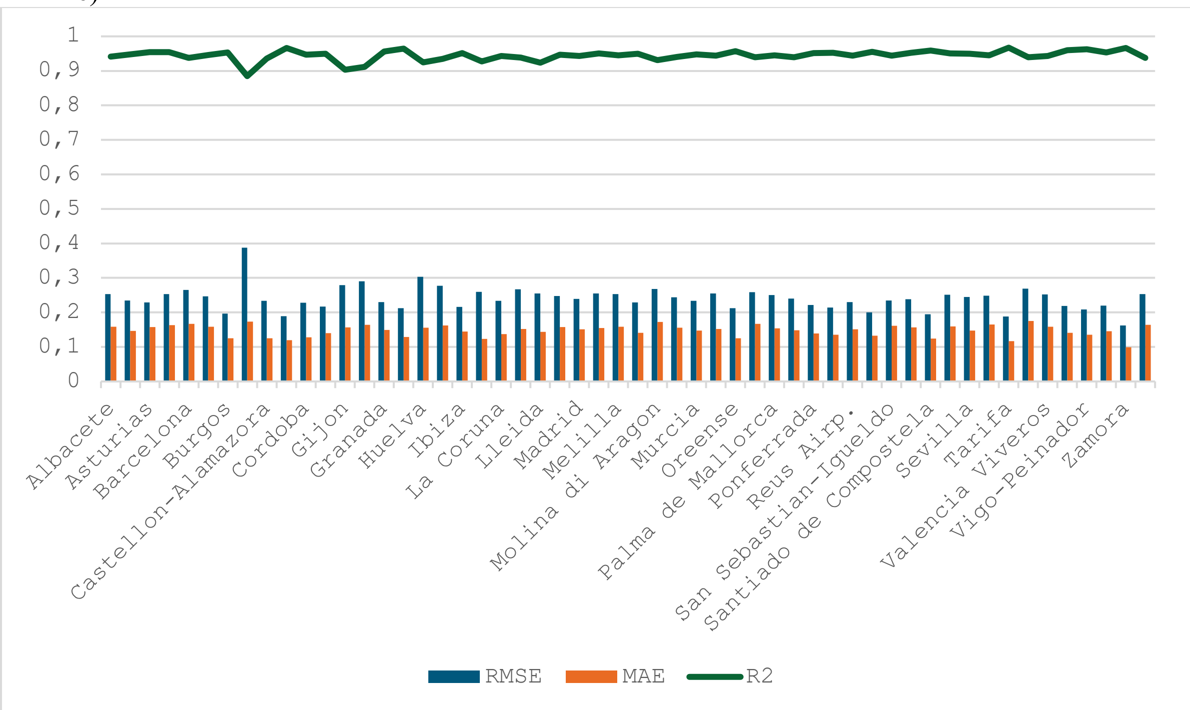
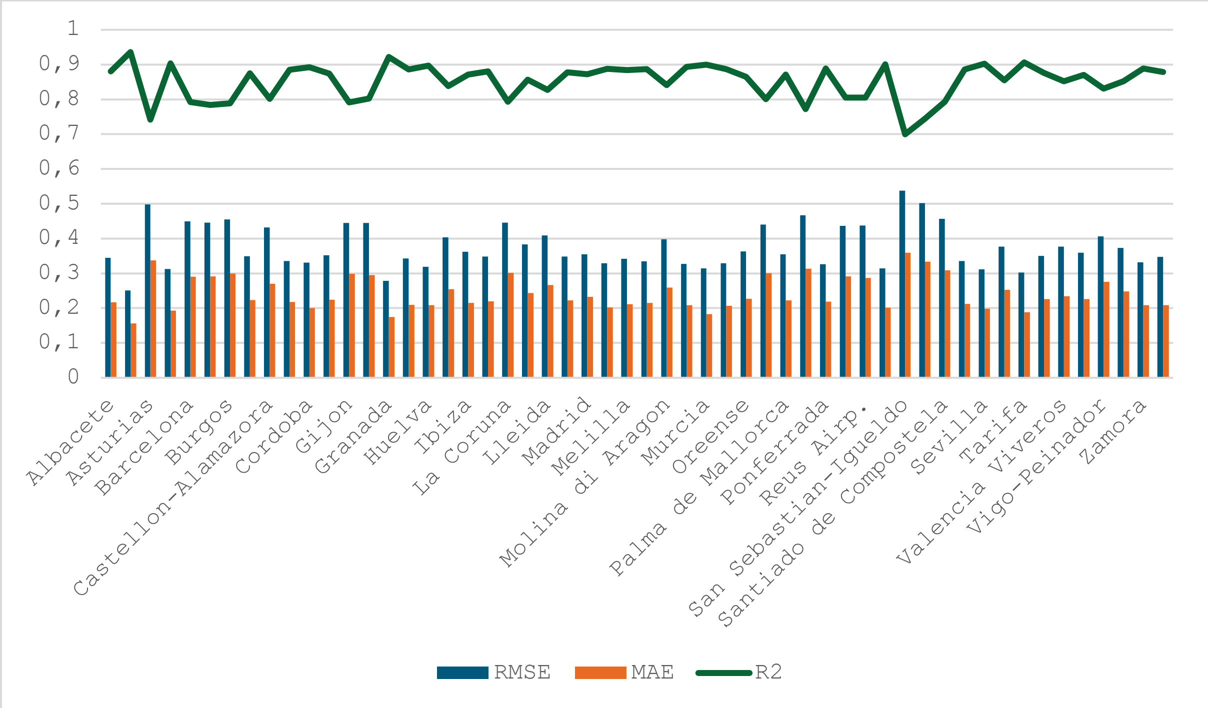


Fig. 7. Evaluation metrics for stations a) evaluation for 1-month SPI, b) evaluation for 3-month SPI, c) evaluation for 6-month SPI, d) evaluation for 9-month SPI, e) evaluation for 12-month SPI (continued)

a)



b)

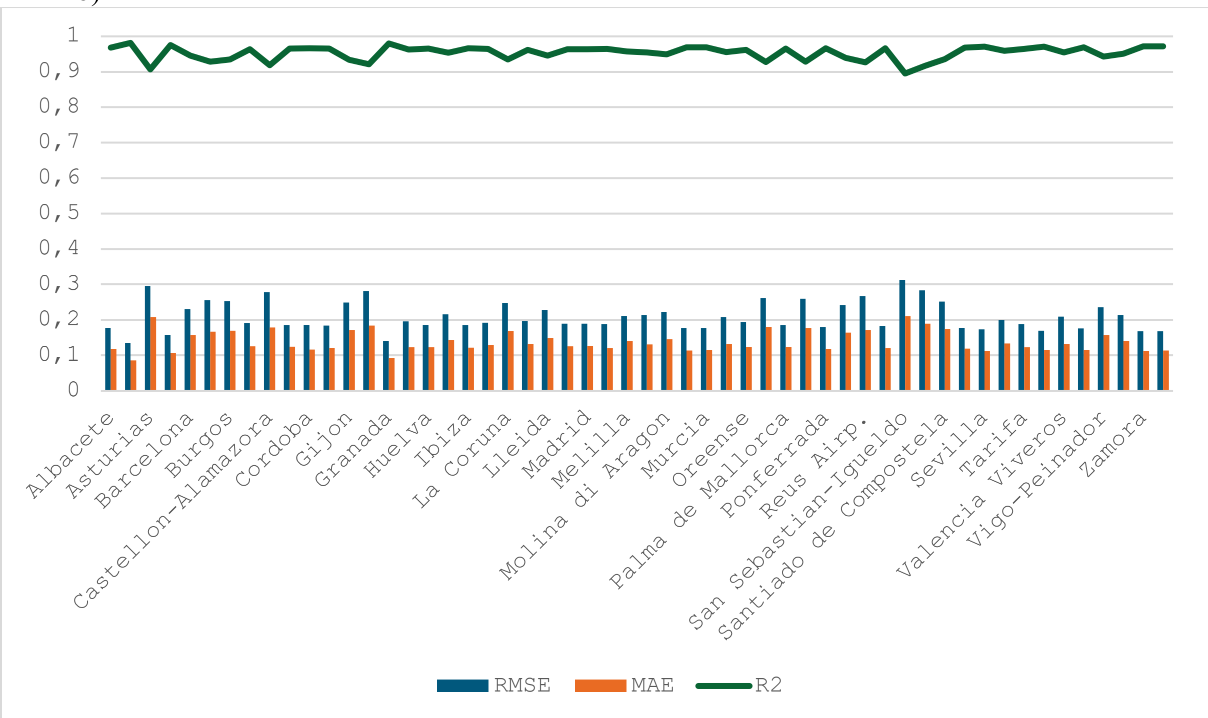
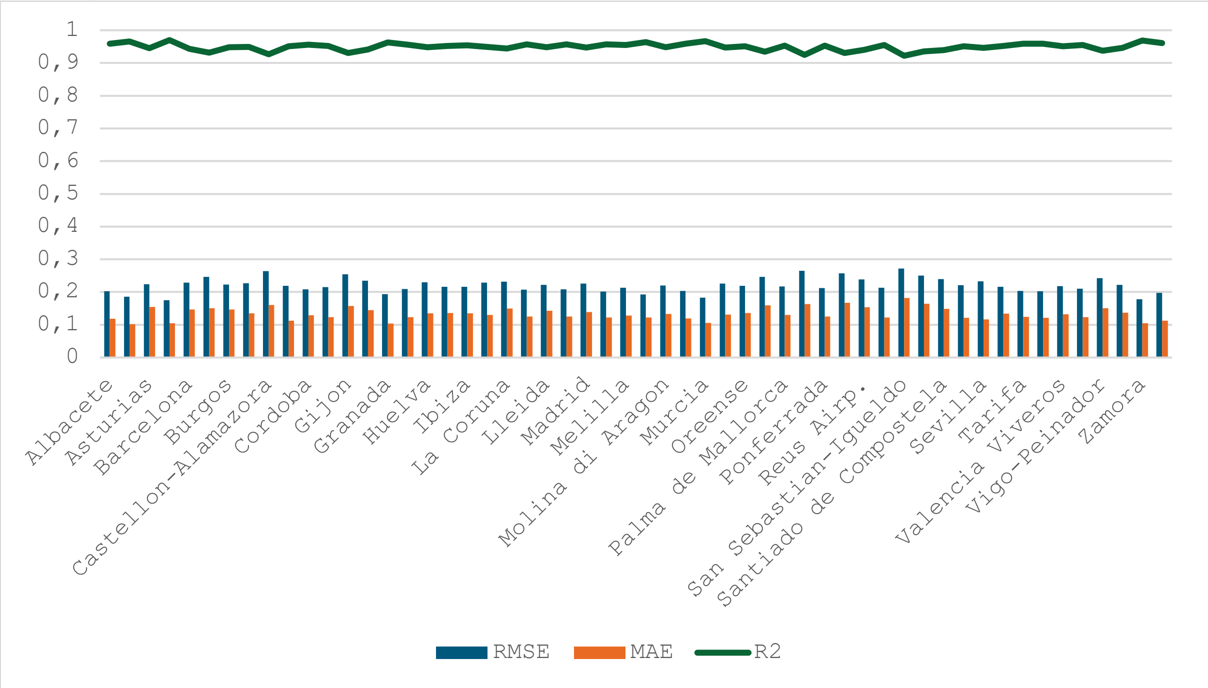


Fig. 8. Evaluation metrics for stations a) evaluation for 1-month SPEI, b) evaluation for 3-month SPEI, c) evaluation for 6-month SPEI, d) evaluation for 9-month SPEI, e) evaluation for 12-month SPEI

c)



d)

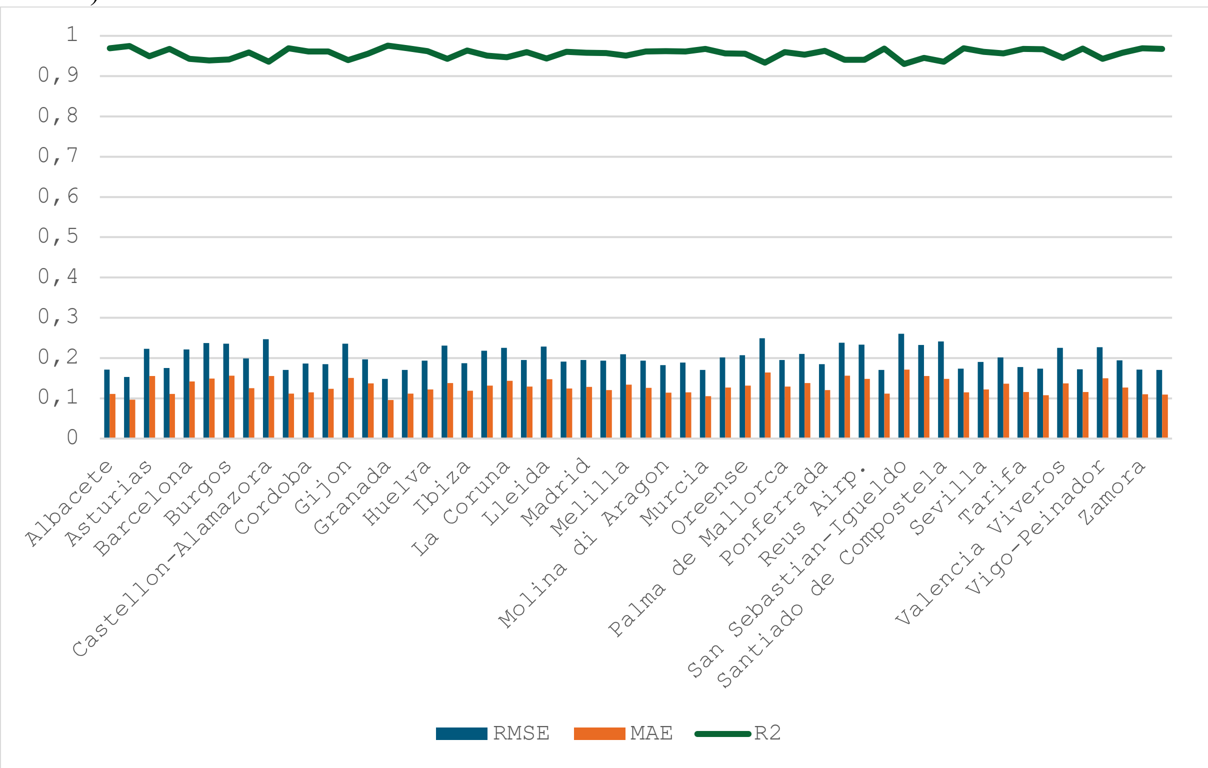


Fig. 8. Continued

e)

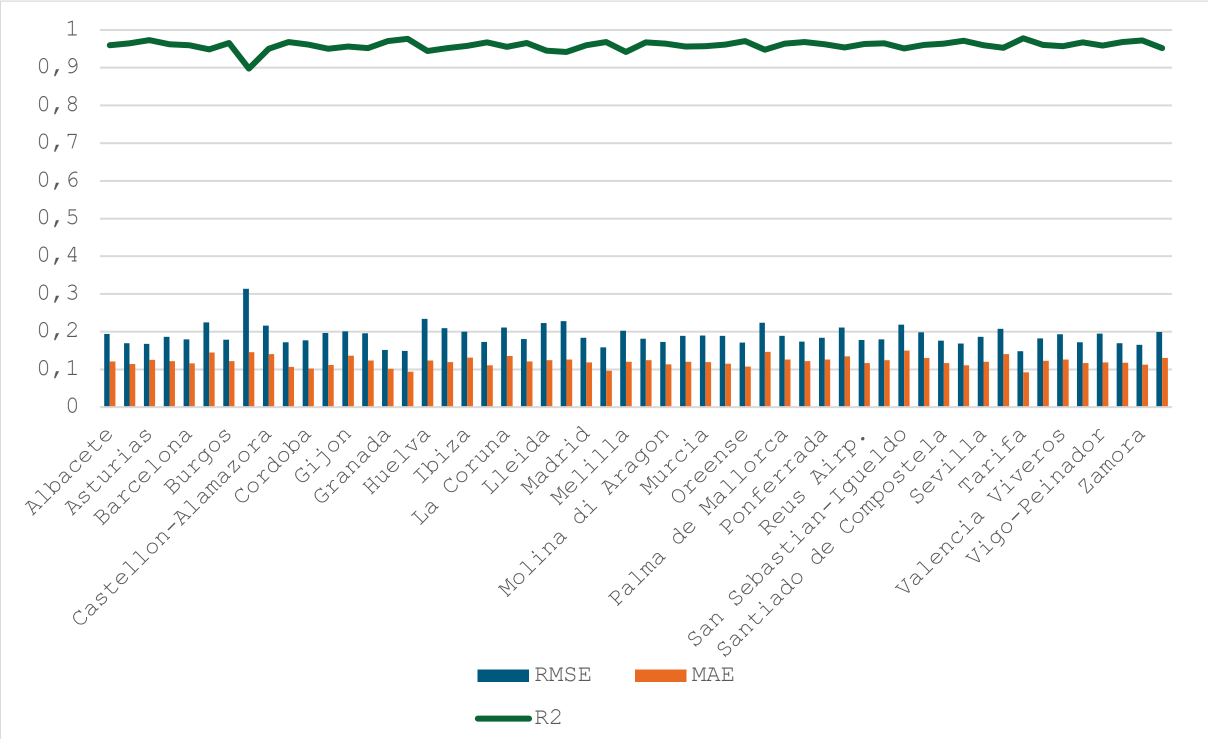


Fig. 8. Continued

a)

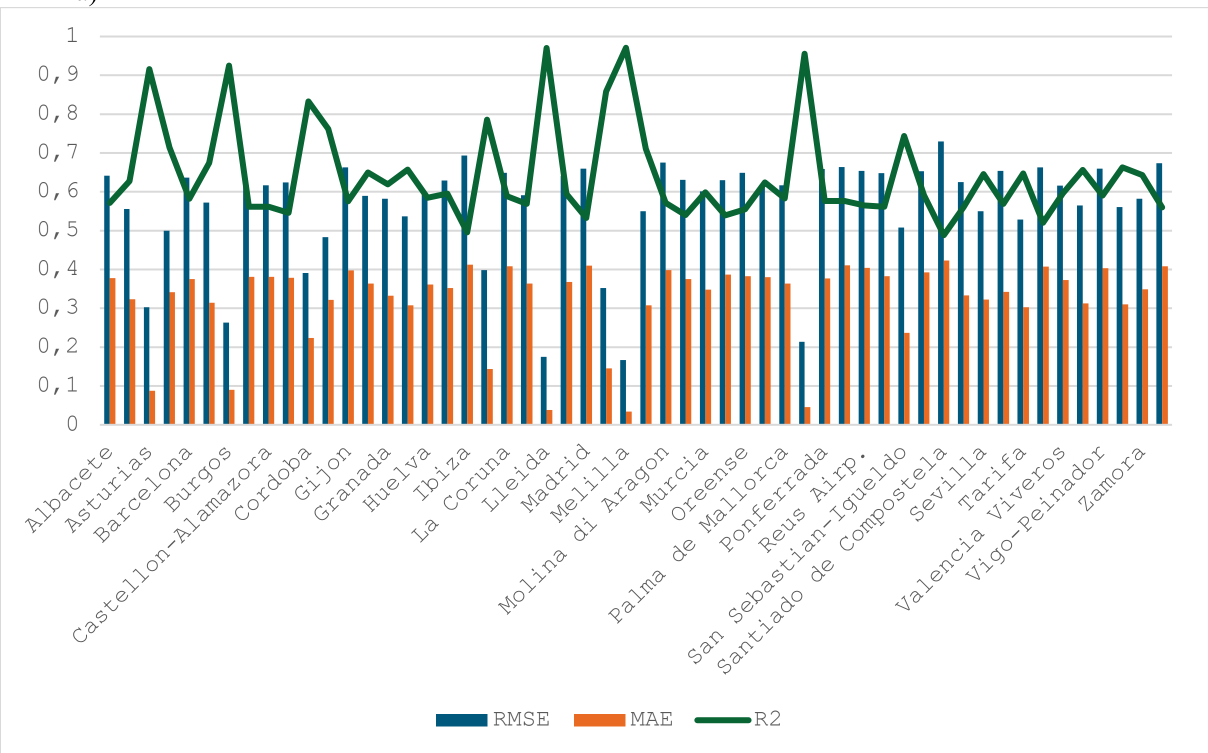
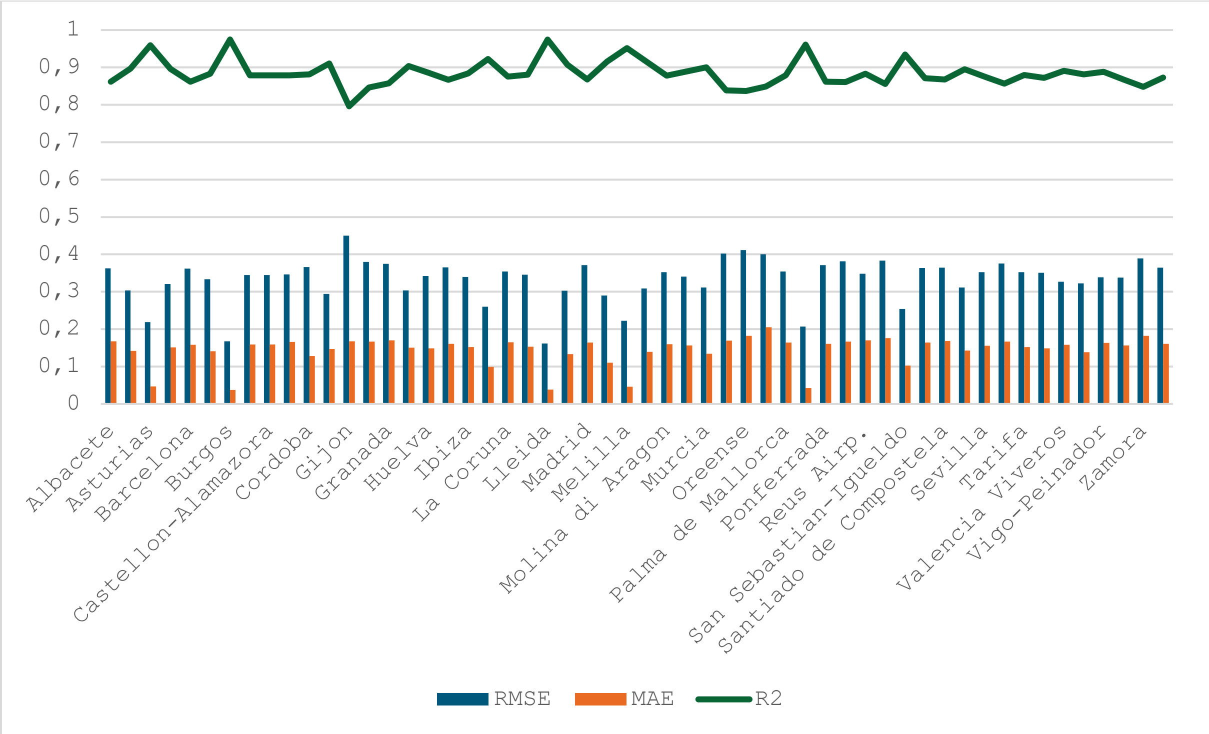


Fig. 9. Evaluation metrics for stations a) evaluation for 1-month RDI, b) evaluation for 3-month RDI, c) evaluation for 6-month RDI, d) evaluation for 9-month RDI, e) evaluation for 12-month RDI

b)



c)

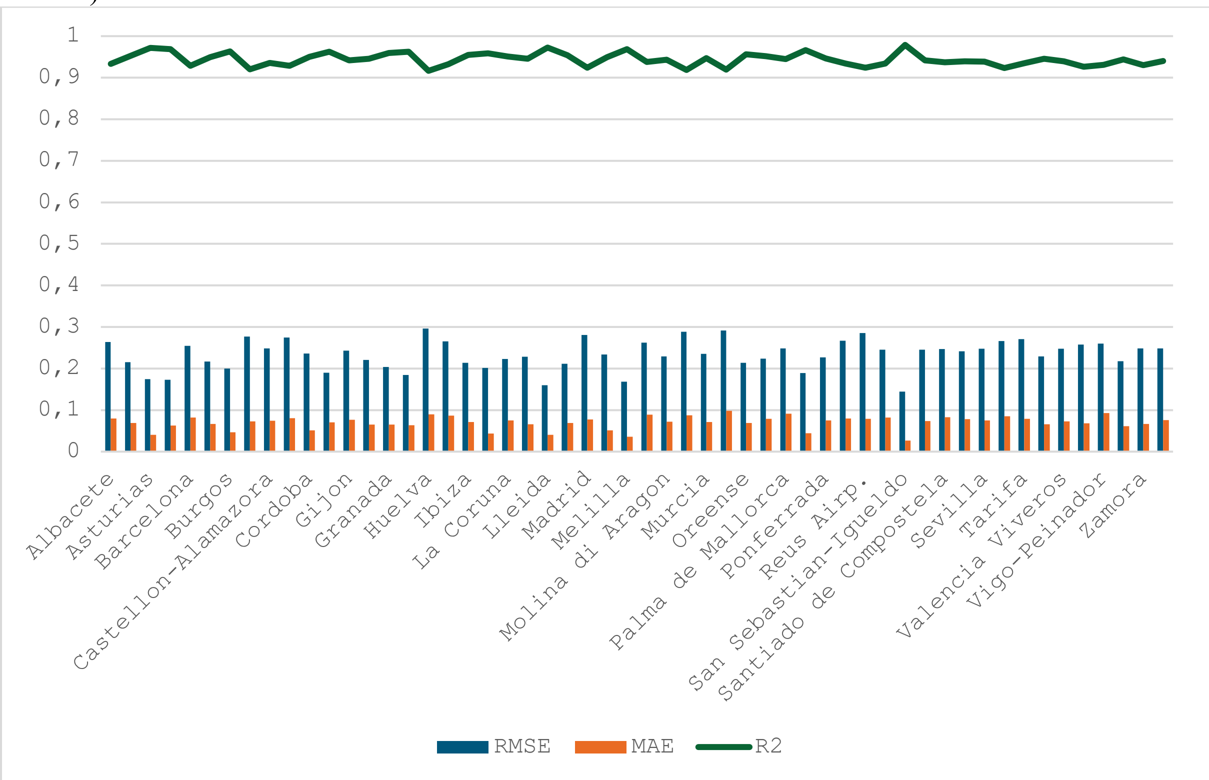
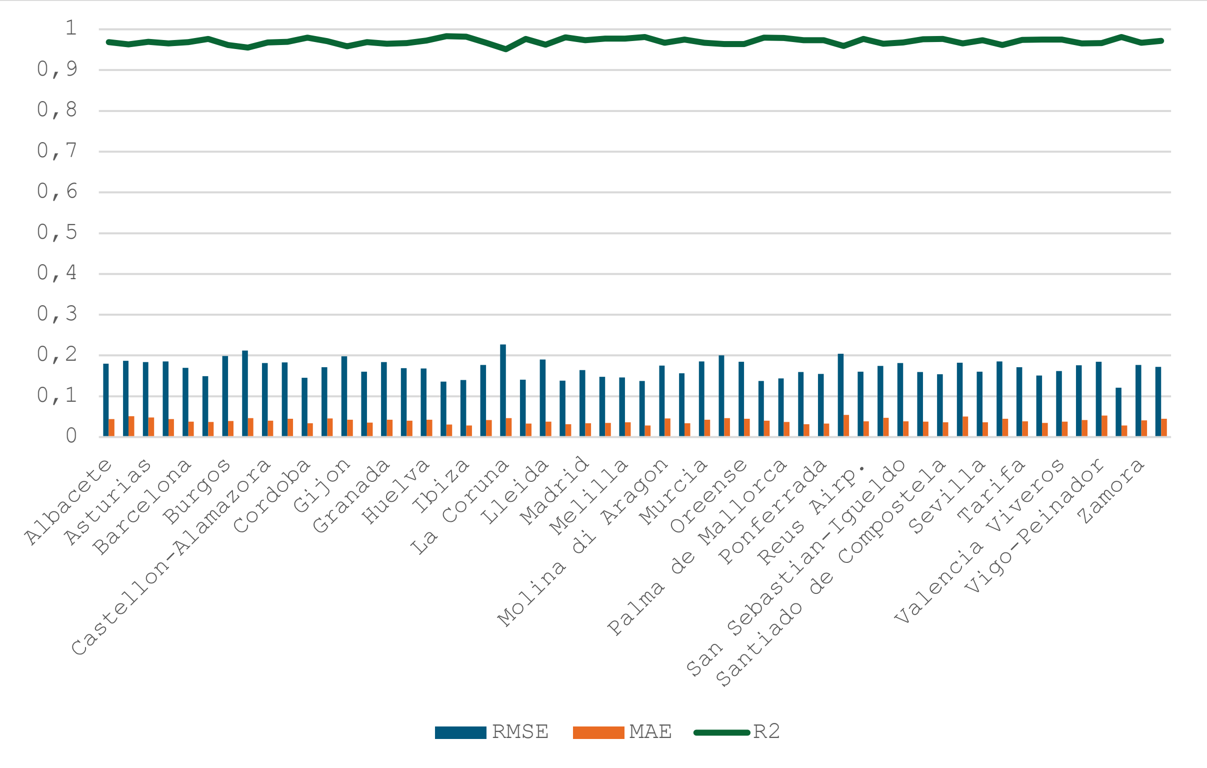


Fig. 9. Continued

d)



e)

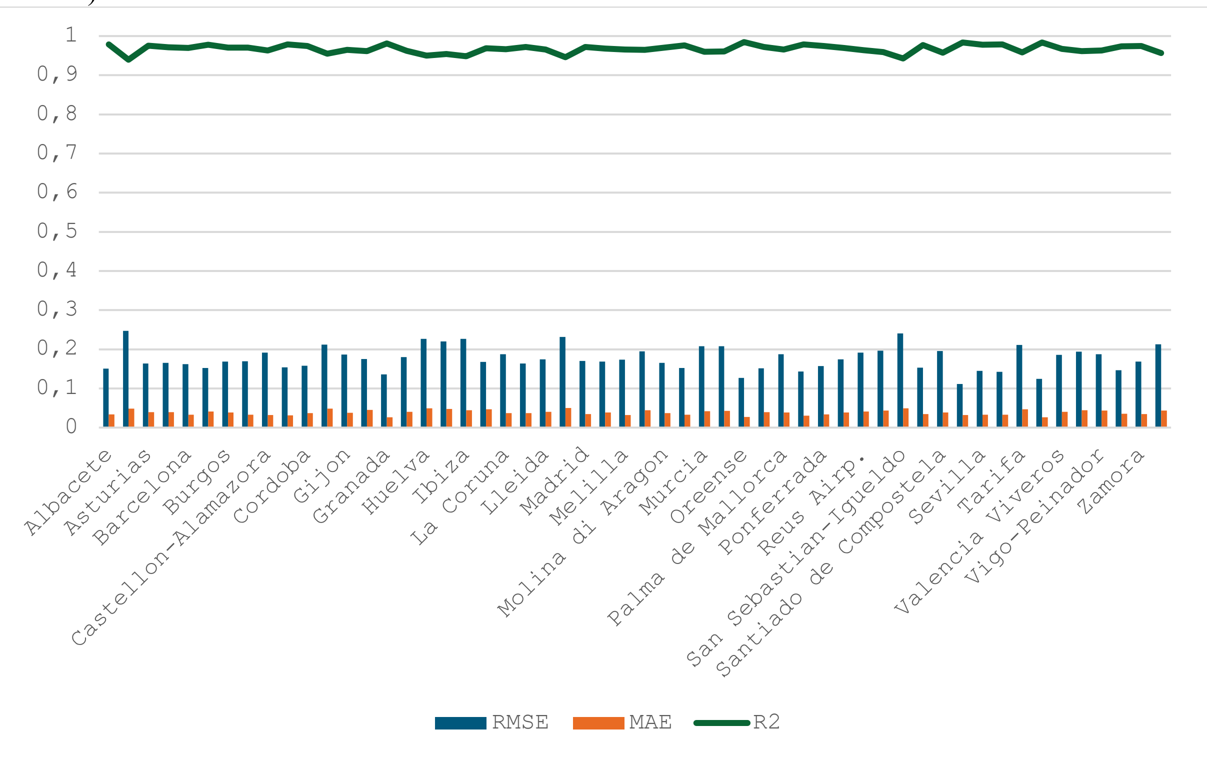


Fig. 9. Evaluation metrics for stations a) evaluation for 1-month RDI, b) evaluation for 3-month RDI, c) evaluation for 6-month RDI, d) evaluation for 9-month RDI, e) evaluation for 12-month RDI (*c*ontinued)

3.5. Correlation of stations

The correlation coefficients between the stations in Spain were calculated for SPI, SPEI, and RDI values across 1, 3, 6, 9, and 12-month time scales (*Appendix 3*, *Figs. 14, 15,* and *16*). The relationships between meteorological stations were examined across different time scales. The results show that many stations have very high correlation values in terms of drought behavior.

4. Summary and conclusions

This study combines SPI, SPEI, and RDI indices (*Zhou et al., 2013; Tao et al., 2014; Nandgude et al., 2020*) with the Random Forest machine learning algorithm to understand the meteorological drought dynamics in different regions of Spain and make future predictions. One of the most unique contributions of the study is the introduction of a new mapping approach applied for the first time in drought analysis. This method, by identifying the temporal and spatial patterns of drought with high accuracy, offers significant advantages both scientifically and practically.

The results indicate that drought intensity and duration will increase in different regions of Spain, particularly in the southern and central areas, where long-duration drought events will become increasingly severe. Additionally, the northern regions are found to be at a higher risk of short-term droughts. The new drought mapping method, by visualizing these spatial differences, has allowed for the development of region-specific intervention strategies for decision-makers. The maps provide more detailed information about drought intensity and frequency at the regional level, facilitating effective planning at the local scale. Based on time series, this method offers a powerful tool for understanding the temporal variations in drought trends and it can be adapted to different drought indices and time scales, creating a wide range of applications for various environmental and climatic scenarios.

The findings suggest that different regions of Spain should be classified based on their drought risk. With the new mapping method, the following recommendations can be made for developing short- and long-term water management strategies:

1. **Drought management strategies**: In southern regions, investments in water-saving technologies and sustainable agricultural practices should be prioritized to reduce the risk of prolonged droughts. In northern regions, early warning systems and crisis management plans can be developed to mitigate the impacts of short-term droughts.
2. **Guidance for policymakers**: The new mapping method provides concrete guidance for regional policymakers in the process of creating risk reduction

strategies. For example, the distribution and prioritization of water resources can be optimized based on these maps.

3. **Advancement of machine learning methods**: The success of the Random Forest algorithm could be enhanced by incorporating more complex models (e.g., Deep Learning) in the future. This would improve the accuracy of predictions and the reliability of regional forecasts.
4. **Addressing climate change**: The findings show that the drought mapping method is an effective tool for identifying the regional impacts of climate change and developing adaptation strategies for these impacts. It can serve as a fundamental data source for climate change adaptation plans.
5. **Future research**: The drought mapping method can be generalized by testing it in different geographical areas and drought conditions. Additionally, integrating this method with different meteorological datasets and modeling techniques will allow for more comprehensive results.

In conclusion, this study makes significant contributions to both scientific literature and practical policies. The newly developed drought mapping method provides a clearer representation of Spain's drought conditions and risks, aiding in the development of sustainable water management and agricultural policies. Such innovative approaches not only offer a strong model for Spain but also serve as a valuable tool for other regions facing similar climatic challenges.

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APPENDIX 1

```
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import os

# Load data
data = pd.read_csv('spi_data.csv')

# Convert to DateTime format
data['date'] = pd.to_datetime(data['date'])
data.set_index('date', inplace=True)

# Extract SPI values
spi_values = data['spi'].values.reshape(-1, 1)

# Scale data
scaler = MinMaxScaler(feature_range=(0, 1))
spi_scaled = scaler.fit_transform(spi_values)

# Prepare training and test data
def create_dataset(dataset, look_back=1):
    X, Y = [], []
    for i in range(len(dataset) - look_back):
        a = dataset[i:(i + look_back), 0]
        X.append(a)
        Y.append(dataset[i + look_back, 0])
    return np.array(X), np.array(Y)

look_back = 12  # 1 year
X, y = create_dataset(spi_scaled, look_back)

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
shuffle=False)
```

```
# Create and train the model
model = RandomForestRegressor(n_estimators=10, max_depth=55, random_state=900)
model.fit(X_train, y_train)

# Make predictions
train_predict = model.predict(X_train)
test_predict = model.predict(X_test)

# Inverse scale the predictions
train_predict = scaler.inverse_transform(train_predict.reshape(-1, 1))
y_train = scaler.inverse_transform(y_train.reshape(-1, 1))
test_predict = scaler.inverse_transform(test_predict.reshape(-1, 1))
y_test = scaler.inverse_transform(y_test.reshape(-1, 1))

# Add predictions to the time axis
train_predict_plot = np.empty_like(spi_values)
train_predict_plot[:, :] = np.nan
train_predict_plot[look_back:len(train_predict) + look_back, :] = train_predict

test_predict_plot = np.empty_like(spi_values)
test_predict_plot[:, :] = np.nan
test_predict_plot[len(train_predict) + look_back:len(test_predict) + len(train_predict) + look_back, :] = test_predict

# Plot the predictions
plt.figure(figsize=(15, 6))
plt.plot(data.index, spi_values, label='Actual Values')
plt.plot(data.index, train_predict_plot, label='Training Predictions')
plt.plot(data.index, test_predict_plot, label='Test Predictions')
plt.legend()
plt.savefig('prediction_results_spi.png')
plt.show()

# Create a list for future predictions
future_predictions = []
last_data = spi_scaled[-look_back:].reshape(1, look_back)

for _ in range(50 * 12):  # 50 years, monthly predictions
    future_pred = model.predict(last_data)
    future_predictions.append(future_pred[0])
    last_data = np.append(last_data[:, 1:], future_pred.reshape(1, -1), axis=1)
```

```
# Inverse scale future predictions
future_predictions =
scaler.inverse_transform(np.array(future_predictions).reshape(-1, 1))

# Combine future predictions with time series
future_dates = pd.date_range(start=data.index[-1] + pd.DateOffset(months=1),
periods=50*12, freq='M')
future_spi = pd.DataFrame(data=future_predictions, index=future_dates,
columns=['spi'])

# Create a new DataFrame to show results from 2023 onward
start_date = '2023-12-01'
result_index = data.index.append(future_spi.index)
results = pd.DataFrame(index=result_index)

# Add actual values
results['Actual Values'] = np.nan
results['Actual Values'].loc[data.index] = data['spi']

# Add training and test predictions
results['Training Predictions'] = np.nan
results['Test Predictions'] = np.nan

train_predict_index = data.index[look_back:len(train_predict) + look_back]
test_predict_index = data.index[len(train_predict) +
look_back:len(train_predict) + look_back + len(test_predict)]

results.loc[train_predict_index, 'Training Predictions'] = train_predict.flatten()
results.loc[test_predict_index, 'Test Predictions'] = test_predict.flatten()

# Add future predictions
results['Future Predictions'] = np.nan
results.loc[future_spi.index, 'Future Predictions'] = future_predictions.flatten()

# Save results to Excel
results.to_excel('spi_prediction_results_1.xlsx')

# Plot future predictions separately
plt.figure(figsize=(15, 6))
plt.plot(future_spi.index, future_spi['spi'], label='Future Predictions',
color='red')
plt.title('Future Predictions')
```

```
plt.xlabel('Date')
plt.ylabel('SPI Value')
plt.legend()
plt.savefig('future_predictions_spi.png')
plt.show()

# Plot combined results
plt.figure(figsize=(15, 6))
plt.plot(results.index, results['Actual Values'], label='Actual Values')
plt.plot(results.index, results['Training Predictions'], label='Training Predictions')
plt.plot(results.index, results['Test Predictions'], label='Test Predictions')
plt.plot(results.index, results['Future Predictions'], label='Future Predictions')
plt.legend()
plt.savefig('SPI_1.png')
plt.show()

# Calculate performance metrics
train_rmse = np.sqrt(mean_squared_error(y_train, train_predict))
train_mae = mean_absolute_error(y_train, train_predict)
train_r2 = r2_score(y_train, train_predict)

print(f"Training RMSE: {train_rmse}")
print(f"Training MAE: {train_mae}")
print(f"Training R2: {train_r2}")

# Create folder for saving plots
os.makedirs('plots_spi', exist_ok=True)

# Save plots to folder
plt.figure(figsize=(15, 6))
plt.plot(data.index, spi_values, label='Actual Values')
plt.plot(data.index, train_predict_plot, label='Training Predictions')
plt.plot(data.index, test_predict_plot, label='Test Predictions')
plt.legend()
plt.savefig('plots_spi/prediction_results_spi.png')
plt.show()

plt.figure(figsize=(15, 6))
plt.plot(results.index, results['Future Predictions'], label='Future Predictions')
plt.legend()
plt.savefig('plots_spi/future_predictions_spi.png')
plt.show()
```

```
plt.figure(figsize=(15, 6))
plt.plot(results.index, results['Actual Values'], label='Actual Values')
plt.plot(results.index, results['Training Predictions'], label='Training Predictions')
plt.plot(results.index, results['Test Predictions'], label='Test Predictions')
plt.plot(results.index, results['Future Predictions'], label='Future Predictions')
plt.legend()
plt.savefig('plots_spi/SPI_1.png')
plt.show()
```

APPENDIX 2

Table 3. Percentage classification values of drought based on 1-month SPI results (%)

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	1.1	1.3	1.6	2.0	2.1	2.8	2.1	2.3	1.5	2.6	2.0	1.1	1.3	2.8	2.8	1.5	1.6	1.5	2.6	1.0	2.0	2.6	2.1	1.8	2.5	2.1	1.3
Very Wet	1.5 – 2.0	3.9	4.1	3.1	3.4	4.1	5.9	5.7	4.9	3.6	4.3	4.4	4.6	4.1	5.1	4.4	3.4	4.6	2.6	3.8	2.8	4.9	5.2	2.8	3.9	4.9	4.9	4.3
Moderately Wet	1.0 – 1.5	9.2	7.9	8.0	9.8	9.5	8.0	8.0	9.2	6.2	8.2	7.7	8.2	9.0	8.3	7.0	7.5	9.5	8.8	9.3	8.2	8.0	8.8	8.8	7.2	8.2	7.7	10.3
Near Normal	-1.0 – 1.0	69.1	66.4	87.2	70.5	77.4	67.9	66.4	70.4	73.3	71.4	71.7	67.3	68.7	68.9	66.1	70.7	66.9	87.1	68.6	88.1	68.6	68.2	71.0	73.3	65.8	73.0	69.2
Moderately Dry	-1.5 – -1.0	10.8	12.9	0.0	14.2	6.9	9.3	11.0	9.0	9.2	7.7	8.0	11.8	11.1	9.2	12.4	9.7	10.6	0.0	8.0	0.0	10.1	7.7	9.0	6.9	9.0	10.5	8.5
Severely Dry	-2.0 – -1.5	5.9	5.9	0.0	0.0	0.0	5.6	4.9	4.3	5.9	3.8	4.6	7.0	5.7	3.8	4.7	5.2	6.7	0.0	5.2	0.0	6.4	7.4	6.2	5.4	7.4	1.8	4.6
Extremely Dry	< -2.0	0.0	1.5	0.0	0.0	0.0	0.5	1.8	0.0	0.3	2.1	1.6	0.0	0.0	2.0	2.5	2.0	0.0	0.0	2.5	0.0	0.0	0.0	0.0	1.5	2.3	0.0	1.8
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.6	1.6	1.8	2.6	2.3	2.6	1.8	3.4	2.8	2.0	1.5	1.5	2.3	2.0	2.0	0.7	2.5	1.3	2.0	1.5	2.3	2.1	2.3	2.0	2.1	1.6	1.8
Very Wet	1.5 – 2.0	4.7	4.9	5.1	2.6	5.1	4.1	3.6	3.8	4.4	3.8	2.9	2.8	3.6	3.6	3.9	3.6	3.3	3.9	4.1	4.6	6.1	4.1	4.3	5.9	4.3	4.1	4.3
Moderately Wet	1.0 – 1.5	9.0	6.7	8.8	7.0	8.3	8.2	7.7	10.1	10.1	6.7	8.2	8.3	10.0	8.7	5.7	8.7	9.3	6.7	8.7	7.4	8.5	7.4	9.0	8.5	6.2	8.3	8.3
Near Normal	-1.0 – 1.0	68.4	83.3	66.6	72.0	66.0	66.4	68.9	65.5	68.9	76.6	70.4	69.9	68.7	70.2	69.9	68.1	84.9	67.1	65.8	86.6	67.8	70.5	66.8	69.4	72.7	85.9	69.9
Moderately Dry	-1.5 – -1.0	9.5	3.4	10.8	15.7	10.8	12.3	8.8	17.2	8.7	11.0	17.0	11.0	10.8	7.5	18.5	16.2	0.0	11.9	16.9	0.0	8.2	10.0	11.8	8.2	10.0	0.0	15.7
Severely Dry	-2.0 – -1.5	5.7	0.0	4.6	0.0	5.2	4.3	5.7	0.0	5.1	0.0	0.0	6.5	3.3	6.4	0.0	2.8	0.0	8.7	2.6	0.0	4.9	5.4	4.9	3.8	4.7	0.0	0.0
Extremely Dry	< -2.0	0.0	0.0	2.3	0.0	2.3	2.1	3.4	0.0	0.0	0.0	0.0	0.0	1.3	1.6	0.0	0.0	0.0	0.3	0.0	0.0	2.3	0.5	1.0	2.3	0.0	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 4. Percentage classification values of drought based on 3-month SPI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.0	2.6	3.6	3.0	2.0	2.1	1.6	4.9	3.3	1.8	1.1	0.8	2.8	1.5	2.6	1.0	3.3	0.3	2.1	1.5	2.8	2.5	1.3	1.1	2.5	1.8	2.0
Very Wet	1.5 – 2.0	5.6	3.4	4.9	3.1	5.4	5.3	2.5	4.8	3.6	3.4	2.5	2.6	3.6	5.4	3.0	2.3	3.6	2.8	4.3	2.3	5.7	3.3	3.8	4.9	2.0	3.1	3.3
Moderately Wet	1.0 – 1.5	9.4	7.1	6.2	4.9	8.9	7.4	8.0	6.7	11.3	6.2	6.4	5.9	8.2	8.5	6.1	6.1	7.4	7.1	9.5	8.0	11.3	7.4	9.7	13.6	7.1	6.9	9.4
Near Normal	-1.0 – 1.0	66.3	67.3	64.4	70.0	63.2	62.4	71.6	67.2	69.8	75.0	71.9	71.4	65.5	68.0	71.6	70.1	71.6	66.7	63.5	73.9	63.5	68.5	65.8	63.2	73.4	70.0	68.1
Moderately Dry	-1.5 – -1.0	10.2	10.3	12.8	10.7	10.2	11.5	7.7	8.5	6.4	10.0	10.5	10.5	12.3	9.9	9.5	11.0	8.5	11.2	11.3	9.4	10.5	12.0	12.2	9.7	8.9	10.0	10.7
Severely Dry	-2.0 – -1.5	3.9	6.2	4.9	5.3	5.3	6.7	5.3	5.6	4.3	3.4	5.6	6.1	4.9	4.1	4.4	7.4	5.6	9.0	4.9	4.9	3.6	3.3	3.6	4.6	4.9	7.1	4.6
Extremely Dry	< -2.0	2.6	3.0	3.1	3.1	5.1	4.6	3.3	2.3	1.3	0.0	2.0	2.6	2.6	2.6	2.8	2.1	0.0	3.0	4.3	0.0	2.5	3.1	3.6	2.8	1.3	1.1	2.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.5	1.3	2.0	2.6	3.1	1.8	3.9	3.1	0.8	2.3	2.1	1.5	1.3	2.3	2.5	1.6	2.3	1.5	2.1	0.2	2.0	1.8	1.5	2.3	2.0	1.1	1.1
Very Wet	1.5 – 2.0	4.3	3.4	2.0	3.0	4.3	5.1	3.8	4.6	5.1	5.3	3.8	3.3	2.8	6.1	4.6	3.8	5.4	3.0	4.8	2.8	5.1	5.6	3.9	3.8	3.8	5.1	3.1
Moderately Wet	1.0 – 1.5	9.4	7.1	7.2	7.6	7.2	9.0	9.2	11.8	5.9	8.5	7.7	7.1	7.2	8.5	8.0	7.7	6.6	5.9	7.9	8.2	6.7	8.5	8.2	6.7	9.4	8.4	9.4
Near Normal	-1.0 – 1.0	70.4	67.0	72.6	72.2	67.3	71.1	67.5	68.5	68.8	68.1	70.8	70.1	70.4	66.7	62.6	69.5	67.2	71.4	67.7	73.9	66.8	68.5	67.3	69.1	64.5	74.7	70.0
Moderately Dry	-1.5 – -1.0	8.5	10.3	8.7	8.7	9.7	8.2	11.2	6.9	11.5	9.7	9.9	9.5	11.5	10.7	12.3	9.4	10.5	9.5	10.7	7.4	10.3	9.0	10.3	11.0	11.8	7.2	10.5
Severely Dry	-2.0 – -1.5	3.8	7.2	5.9	4.1	6.7	3.1	2.3	4.3	5.1	3.4	3.9	5.7	4.6	3.4	6.4	5.1	5.1	6.6	4.1	6.6	6.2	4.1	6.1	5.3	4.6	3.0	3.9
Extremely Dry	< -2.0	3.1	3.6	1.6	1.8	1.6	1.6	2.1	0.8	2.8	2.6	1.8	2.8	2.1	2.3	3.6	3.0	3.0	2.1	2.8	1.0	2.8	2.5	2.6	1.8	3.9	0.5	2.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 5. Percentage classification values of drought based on 6-month SPI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.1	2.3	3.0	2.5	0.8	1.8	0.3	5.4	1.3	1.5	0.7	0.3	2.1	2.0	2.3	0.8	4.3	0.0	1.5	1.7	3.0	2.5	0.7	1.7	0.8	2.1	1.7
Very Wet	1.5 – 2.0	3.8	3.5	4.3	2.5	7.3	4.5	3.3	4.5	5.9	2.1	3.1	1.2	4.5	4.5	3.8	1.0	2.5	0.8	2.6	2.1	4.6	2.8	2.8	4.3	3.1	3.5	4.0
Moderately Wet	1.0 – 1.5	9.7	6.9	7.3	5.3	9.9	6.8	6.6	8.3	8.9	8.6	5.6	4.8	6.9	10.2	5.6	5.8	7.3	4.6	5.9	6.1	13.2	7.6	9.9	10.7	6.6	5.8	7.6
Near Normal	-1.0 – 1.0	68.0	66.3	62.2	70.0	62.5	62.9	74.3	67.5	71.3	74.1	74.9	71.9	66.0	65.8	69.8	70.0	73.3	69.1	70.1	75.2	63.9	67.8	66.8	68.5	72.8	67.5	69.3
Moderately Dry	-1.5 – -1.0	9.6	11.4	13.0	11.1	10.1	10.9	10.1	6.9	6.4	10.9	7.6	14.4	10.9	10.7	11.6	12.7	7.6	13.7	10.4	10.4	9.6	10.9	12.4	6.1	11.7	12.9	10.4
Severely Dry	-2.0 – -1.5	5.1	5.3	6.1	5.4	4.6	7.4	3.8	4.1	4.5	2.8	5.8	5.0	6.1	5.1	4.3	5.6	4.1	8.1	5.4	3.5	4.0	5.8	4.6	4.8	4.3	6.1	4.5
Extremely Dry	< -2.0	1.7	4.3	4.1	3.3	4.8	5.8	1.7	3.3	1.7	0.0	2.3	2.5	3.5	1.7	2.6	4.1	1.0	3.6	4.0	1.0	1.8	2.6	2.8	4.0	0.7	2.1	2.6
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.2	0.3	1.3	1.5	1.3	1.7	4.3	3.5	1.2	1.8	1.5	1.0	1.2	2.5	1.2	1.8	1.2	1.5	2.0	0.0	1.3	3.0	1.0	1.8	1.7	0.7	1.8
Very Wet	1.5 – 2.0	2.6	2.3	2.6	5.3	5.9	4.3	5.8	5.3	1.7	5.3	3.3	3.3	1.8	4.3	3.3	2.6	3.6	2.1	3.5	1.3	3.6	4.1	3.0	2.6	2.3	4.0	3.8
Moderately Wet	1.0 – 1.5	8.3	5.6	7.4	8.3	9.9	10.4	9.1	10.4	5.3	10.7	9.2	4.1	6.4	7.9	8.4	8.7	8.3	6.8	8.3	10.2	8.1	11.1	7.8	9.2	9.1	8.1	7.3
Near Normal	-1.0 – 1.0	70.0	68.3	70.3	67.5	65.8	70.0	63.9	70.6	74.4	68.3	68.0	72.6	77.1	70.3	65.7	67.7	68.0	67.8	69.0	71.9	65.3	68.3	69.3	65.5	66.2	77.2	72.4
Moderately Dry	-1.5 – -1.0	10.4	12.4	11.4	12.4	10.1	10.1	9.6	6.1	9.1	7.9	10.4	10.9	7.3	8.4	10.6	11.1	10.2	12.5	10.4	10.6	12.7	7.4	10.6	11.4	10.1	8.1	9.6
Severely Dry	-2.0 – -1.5	6.4	5.8	4.5	4.3	4.6	2.3	5.8	3.5	4.1	4.3	4.6	5.1	4.0	5.0	7.9	5.1	5.3	6.4	3.1	4.8	6.1	3.8	4.3	5.3	5.9	1.8	4.3
Extremely Dry	< -2.0	2.1	5.3	2.5	0.8	2.3	1.3	1.7	0.7	4.3	1.7	3.0	3.0	2.3	1.7	3.0	3.0	3.5	2.8	3.8	1.2	2.8	2.3	4.1	4.1	4.8	0.2	0.8
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 6. Percentage Classification Values of Drought Based on 9-Month SPI Index Results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.7	3.2	3.2	2.7	0.3	1.7	0.3	5.5	1.7	1.0	0.0	0.2	1.5	2.3	2.8	0.8	4.6	0.0	1.3	1.3	2.0	2.2	0.3	1.7	1.0	2.5	2.2
Very Wet	1.5 – 2.0	5.3	1.8	1.2	2.8	6.3	1.8	1.5	6.3	5.3	3.5	3.6	1.0	3.3	4.5	3.3	1.0	4.5	0.2	2.0	2.0	4.6	3.3	2.3	4.8	2.7	2.7	2.8
Moderately Wet	1.0 – 1.5	8.8	5.1	6.8	5.6	11.9	6.8	6.6	9.6	12.6	6.6	4.5	4.1	11.3	8.6	5.8	4.6	5.8	4.0	7.1	5.8	11.9	7.5	10.9	10.9	6.8	7.1	8.1
Near Normal	-1.0 – 1.0	68.0	67.8	64.7	63.0	60.7	62.4	76.1	61.7	68.7	75.5	71.0	72.0	65.0	63.3	66.0	66.7	72.1	68.2	71.6	74.8	66.2	61.5	66.2	66.7	72.8	62.9	64.7
Moderately Dry	-1.5 – -1.0	8.6	10.4	13.4	12.8	9.1	11.9	9.5	9.8	6.8	10.9	10.9	13.1	9.5	11.4	10.3	15.8	7.6	15.6	10.9	11.3	9.0	15.1	10.8	7.6	12.6	12.4	13.8
Severely Dry	-2.0 – -1.5	4.5	7.0	6.1	8.1	6.6	9.3	4.1	4.1	2.7	2.5	6.3	6.8	5.5	8.0	7.6	6.6	3.3	6.6	4.1	4.0	4.5	6.6	7.1	4.5	3.5	8.0	5.0
Extremely Dry	< -2.0	2.2	4.6	4.6	5.0	5.0	6.1	1.8	3.0	2.3	0.0	3.6	2.8	4.0	1.8	4.1	4.5	2.0	5.5	2.8	0.8	1.8	3.8	2.3	3.8	0.7	4.5	3.5
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.0	0.2	2.3	1.3	1.2	1.7	4.6	4.3	1.3	2.0	1.0	0.0	0.5	1.7	1.2	2.0	1.8	0.5	1.8	0.0	3.0	1.5	0.5	1.7	1.5	0.8	1.5
Very Wet	1.5 – 2.0	1.8	0.8	0.7	4.6	4.3	4.8	5.8	5.6	1.8	5.0	3.5	2.3	1.3	5.0	3.0	2.2	3.8	2.8	2.7	0.7	2.8	8.5	2.5	2.3	2.8	2.8	4.1
Moderately Wet	1.0 – 1.5	9.5	6.8	6.3	7.8	11.3	9.1	9.3	9.1	3.2	9.3	9.0	6.6	6.6	9.3	7.0	6.8	5.6	6.5	10.4	5.3	5.3	8.0	7.1	8.0	4.6	8.3	7.8
Near Normal	-1.0 – 1.0	70.8	65.7	68.8	68.0	67.8	69.8	63.8	72.1	73.5	69.2	66.8	71.3	75.3	70.6	67.0	65.7	69.2	62.0	63.8	72.8	63.5	66.3	69.5	62.0	70.5	78.3	71.6
Moderately Dry	-1.5 – -1.0	8.1	11.8	12.8	11.9	9.6	10.0	10.0	5.3	10.1	8.8	10.3	11.9	9.8	8.1	11.8	13.3	10.9	16.1	11.8	12.9	14.3	10.1	10.6	14.1	9.3	6.6	9.1
Severely Dry	-2.0 – -1.5	5.8	7.5	7.0	5.1	3.8	3.8	4.1	2.3	5.6	4.1	6.1	5.0	3.8	3.2	6.1	6.1	5.1	7.3	7.0	6.8	7.0	3.6	5.8	8.0	6.3	3.2	4.1
Extremely Dry	< -2.0	4.0	7.3	2.2	1.2	2.0	0.8	2.3	1.2	4.5	1.7	3.3	2.8	2.7	2.2	4.0	4.0	3.5	4.8	2.5	1.5	4.1	2.0	4.0	4.0	5.0	0.0	1.7
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 7. Percentage classification values of drought based on 12-month SPI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.0	2.5	1.7	2.7	0.2	2.5	0.2	5.8	1.2	0.8	0.0	0.0	0.7	1.8	3.7	0.8	6.0	0.0	0.2	1.8	2.2	1.8	0.2	2.2	0.3	2.0	2.7
Very Wet	1.5 – 2.0	6.0	2.7	3.3	3.2	5.8	2.2	1.0	7.0	3.8	2.2	1.2	0.7	4.2	3.5	3.2	0.8	4.8	0.0	2.8	1.7	2.3	3.8	2.0	5.7	2.7	4.8	3.8
Moderately Wet	1.0 – 1.5	9.3	5.3	6.2	4.2	10.2	4.3	4.8	12.3	14.2	8.0	7.2	3.3	9.5	8.7	6.3	3.7	7.2	1.5	4.8	2.5	12.5	6.2	7.0	11.0	5.0	6.0	6.2
Near Normal	-1.0 – 1.0	66.8	64.5	67.3	63.7	65.0	65.5	78.3	59.3	70.7	75.2	73.5	72.3	67.7	64.8	59.2	64.7	69.2	66.2	74.3	76.2	69.8	65.0	70.3	66.2	75.2	59.5	61.3
Moderately Dry	-1.5 – -1.0	12.0	12.3	12.0	10.7	8.5	11.7	9.8	8.7	4.3	10.8	9.2	12.2	8.7	11.7	13.8	18.5	9.2	15.3	10.8	12.8	7.7	10.7	13.3	6.3	11.0	14.8	15.7
Severely Dry	-2.0 – -1.5	1.8	6.2	3.7	9.3	2.7	7.2	4.5	3.7	4.5	3.0	4.2	7.8	5.5	5.3	7.3	5.5	3.0	11.8	4.5	3.7	4.7	7.2	5.3	5.3	5.2	6.3	7.2
Extremely Dry	< -2.0	2.0	6.5	5.8	6.3	7.7	6.7	1.3	3.2	1.3	0.0	4.8	3.7	3.8	4.2	6.5	6.0	0.7	5.2	2.5	1.3	0.8	5.3	1.8	3.3	0.7	6.5	3.2
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.0	0.0	0.7	1.8	2.2	1.8	5.0	5.5	1.3	2.0	2.3	0.3	0.0	3.3	1.7	1.8	2.3	0.2	1.3	0.0	1.0	1.7	0.2	2.8	0.7	0.3	0.5
Very Wet	1.5 – 2.0	0.3	0.7	3.0	2.8	3.2	3.7	4.7	5.0	1.5	3.5	0.5	0.2	1.7	3.7	3.0	1.7	2.3	1.3	2.5	0.0	3.2	6.3	2.0	1.3	2.8	1.8	5.0
Moderately Wet	1.0 – 1.5	10.2	3.2	6.2	9.3	8.0	8.7	9.8	11.5	3.7	11.0	4.8	5.7	4.2	7.5	6.0	3.8	6.5	6.8	10.0	3.7	6.7	13.2	6.0	3.0	5.0	8.7	7.8
Near Normal	-1.0 – 1.0	70.2	67.7	64.8	68.8	70.3	73.5	66.2	67.7	71.8	67.3	72.0	72.0	75.3	72.8	68.8	67.8	69.5	61.7	64.8	75.5	63.2	64.5	72.3	69.2	71.7	79.5	72.3
Moderately Dry	-1.5 – -1.0	8.7	12.7	13.8	8.2	10.5	10.2	8.2	6.5	10.3	9.2	9.5	13.5	10.2	8.7	9.7	14.0	9.7	13.7	11.3	11.8	15.2	9.5	9.7	10.5	10.2	8.2	10.5
Severely Dry	-2.0 – -1.5	6.0	9.8	9.2	7.5	3.8	1.3	4.7	3.5	7.0	5.5	6.3	5.8	5.5	2.2	5.0	6.5	5.0	8.3	6.2	6.8	6.7	3.0	5.8	5.8	6.7	1.5	3.2
Extremely Dry	< -2.0	4.7	6.0	2.3	1.5	2.0	0.8	1.5	0.3	4.3	1.5	4.5	2.5	3.2	1.8	5.8	4.3	4.7	8.0	3.8	2.2	4.2	1.8	4.0	7.3	3.0	0.0	0.7
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 8. Percentage classification values of drought based on 1-month SPEI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	1.5	1.1	1.3	2.1	2.9	2.1	1.5	3.1	2.3	1.5	2.1	1.8	1.3	2.5	1.6	0.5	2.0	1.5	2.1	1.1	1.5	1.6	1.8	1.3	1.8	2.3	2.0
Very Wet	1.5 – 2.0	3.4	3.6	5.2	2.9	3.9	4.9	4.4	3.1	4.9	3.3	2.5	2.5	5.7	3.9	2.6	4.1	4.4	3.8	4.4	4.7	7.0	3.8	4.9	4.9	3.6	3.3	5.2
Moderately Wet	1.0 – 1.5	9.5	7.2	12.9	7.9	7.9	10.8	9.7	11.5	8.5	7.9	7.0	9.3	10.8	9.5	9.3	8.8	8.2	7.0	7.4	7.4	10.1	9.2	9.3	8.2	7.7	8.7	9.0
Near Normal	-1.0 – 1.0	62.4	64.0	61.0	62.5	66.0	61.5	64.8	60.1	64.6	63.8	65.0	65.1	61.2	66.1	62.2	65.0	63.2	65.1	64.6	65.0	60.2	64.5	61.2	63.8	63.0	63.2	61.4
Moderately Dry	-1.5 – -1.0	12.9	14.2	14.2	16.4	9.0	12.6	10.8	14.7	9.8	14.4	15.5	9.7	16.4	9.2	15.4	12.9	16.7	11.3	11.3	13.9	14.1	11.8	13.9	12.1	14.1	15.2	17.3
Severely Dry	-2.0 – -1.5	10.3	9.8	5.1	8.2	9.2	7.5	8.2	7.4	7.7	9.0	7.9	11.5	3.9	7.5	8.8	8.7	5.6	11.3	10.1	7.9	7.0	9.0	8.8	9.7	9.5	7.2	4.9
Extremely Dry	< -2.0	0.0	0.0	0.2	0.0	1.1	0.5	0.7	0.2	2.1	0.2	0.0	0.2	0.7	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.3	0.2	0.2
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	1.1	0.8	1.8	2.1	2.3	1.3	1.5	2.6	1.0	1.8	1.3	2.3	1.1	2.1	2.0	1.3	1.1	1.8	1.5	1.3	1.1	2.6	1.8	1.6	2.0	1.8	1.1
Very Wet	1.5 – 2.0	3.8	3.1	3.9	2.9	3.3	6.2	5.1	3.4	4.4	4.7	6.7	4.1	3.4	6.2	6.4	5.6	3.3	3.1	3.8	3.1	3.8	4.6	2.9	5.7	4.7	4.1	3.6
Moderately Wet	1.0 – 1.5	9.5	10.0	7.7	6.7	7.4	9.0	11.6	9.3	10.1	9.2	10.6	7.9	9.3	10.8	8.3	10.8	11.1	8.3	9.0	11.3	7.0	6.5	7.2	10.8	11.1	7.9	8.2
Near Normal	-1.0 – 1.0	63.5	65.0	63.0	66.4	64.5	62.0	62.2	62.7	66.4	63.8	62.4	65.1	63.2	64.0	60.4	62.5	61.5	63.8	64.6	64.5	63.5	64.0	63.5	62.4	60.6	63.0	63.0
Moderately Dry	-1.5 – -1.0	12.3	11.3	16.5	10.5	13.9	14.9	13.9	12.4	10.3	12.6	14.7	10.1	13.6	10.5	17.2	13.6	13.1	14.2	11.1	17.2	14.6	11.1	12.9	14.1	13.3	12.9	13.6
Severely Dry	-2.0 – -1.5	9.8	9.7	6.9	11.1	8.7	6.5	5.4	9.5	7.5	7.7	4.3	10.1	9.3	5.2	5.4	6.2	9.8	8.7	9.8	2.6	9.8	10.8	11.6	5.4	8.2	10.1	10.5
Extremely Dry	< -2.0	0.0	0.2	0.2	0.2	0.0	0.0	0.3	0.0	0.2	0.2	0.0	0.3	0.0	1.1	0.3	0.0	0.0	0.0	0.2	0.0	0.2	0.3	0.0	0.0	0.2	0.2	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 9. Percentage classification values of drought based on 3-month SPEI results (%)%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	0.7	0.3	1.6	1.1	1.6	1.5	1.0	1.8	1.5	0.8	1.3	0.7	1.6	1.8	1.1	0.3	1.8	0.8	0.7	1.5	1.1	1.5	0.8	0.5	0.8	1.6	1.1
Very Wet	1.5 – 2.0	2.0	2.5	5.1	3.3	3.9	4.8	3.6	6.6	4.9	3.3	3.3	3.0	5.9	3.8	2.5	3.0	5.3	2.6	4.1	2.8	7.4	3.8	3.1	3.3	3.6	2.8	4.1
Moderately Wet	1.0 – 1.5	10.8	13.0	10.2	9.0	10.2	11.0	9.5	7.4	10.3	8.7	5.7	10.7	10.2	10.2	11.3	9.5	8.9	8.9	11.7	9.2	12.0	8.2	13.3	13.6	8.5	8.7	12.3
Near Normal	-1.0 – 1.0	62.1	56.8	62.4	61.2	60.1	59.4	63.4	60.9	61.6	62.9	65.0	60.8	59.9	64.2	59.4	63.7	60.4	62.9	59.8	62.4	58.6	64.5	58.6	58.3	62.9	62.9	59.3
Moderately Dry	-1.5 – -1.0	14.3	19.4	14.6	16.9	13.5	13.6	13.6	15.9	13.1	14.0	16.7	16.6	15.9	12.6	18.4	15.6	17.7	13.1	15.6	18.1	13.1	14.3	14.6	16.6	14.8	16.9	19.2
Severely Dry	-2.0 – -1.5	10.2	8.0	5.1	8.4	10.2	9.5	8.2	7.4	8.0	10.2	7.9	8.2	6.4	7.1	7.2	7.9	5.9	11.7	8.2	6.1	7.1	7.7	9.4	7.6	8.9	7.1	3.9
Extremely Dry	< -2.0	0.0	0.0	1.0	0.0	0.5	0.2	0.7	0.0	0.5	0.2	0.0	0.2	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.0	0.2	0.2	0.5	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.0	0.5	1.3	1.0	1.3	1.5	1.3	1.1	0.5	2.0	1.0	1.8	0.5	1.8	0.7	1.3	0.3	1.3	0.8	0.5	0.5	1.8	0.5	1.3	1.0	0.5	0.3
Very Wet	1.5 – 2.0	3.3	2.5	3.8	2.1	4.8	4.1	4.6	3.6	4.3	3.4	6.1	3.0	2.3	5.9	6.9	5.6	3.8	3.4	3.6	3.4	3.3	3.4	3.6	6.7	4.8	3.4	2.3
Moderately Wet	1.0 – 1.5	13.1	11.2	9.5	11.8	9.0	11.7	12.2	11.7	10.7	12.5	12.3	9.7	13.0	10.2	10.0	10.8	12.5	8.0	9.5	12.3	10.3	10.3	8.2	9.4	13.0	10.5	12.8
Near Normal	-1.0 – 1.0	58.6	61.7	61.4	58.5	60.1	60.6	61.7	59.4	64.7	59.4	60.1	62.4	60.8	60.9	60.4	61.9	58.8	62.9	61.9	59.9	61.6	59.9	61.1	61.9	57.0	62.4	59.4
Moderately Dry	-1.5 – -1.0	17.4	14.3	17.1	16.1	16.1	15.6	13.5	15.1	12.0	16.3	13.8	13.3	15.6	13.8	13.6	13.6	15.6	16.4	16.1	21.5	13.6	14.3	15.6	14.3	16.4	13.8	16.4
Severely Dry	-2.0 – -1.5	7.6	9.9	6.9	10.5	8.7	6.6	6.7	9.0	7.6	6.4	6.7	9.9	7.9	6.2	8.2	6.7	9.0	7.9	7.7	2.3	10.5	10.2	11.0	6.4	7.7	9.4	8.7
Extremely Dry	< -2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	1.1	0.2	0.0	0.0	0.0	0.3	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 10. Percentage classification values of drought based on 6-month SPEI results (%)%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	0.5	0.2	1.8	0.5	0.7	1.0	0.2	0.7	0.8	0.2	0.2	0.2	0.8	1.7	0.3	0.5	1.3	0.0	0.5	0.3	1.7	0.7	0.3	0.2	0.3	1.2	1.2
Very Wet	1.5 – 2.0	2.5	2.0	4.3	3.1	4.3	3.5	3.1	6.8	4.6	2.5	2.5	2.0	4.0	4.3	3.5	1.8	5.0	2.0	3.5	3.6	4.8	4.6	3.0	3.5	2.3	4.6	3.0
Moderately Wet	1.0 – 1.5	14.9	14.5	11.4	13.9	13.0	13.2	11.2	13.0	13.0	12.0	12.0	13.5	13.2	11.1	13.5	15.2	12.2	12.2	14.5	13.2	14.7	12.2	15.3	14.7	12.4	7.9	12.7
Near Normal	-1.0 – 1.0	54.6	50.3	61.4	57.1	57.6	57.9	63.5	59.2	59.2	60.1	59.9	59.7	59.1	63.0	56.8	59.4	57.4	59.1	58.1	60.1	58.4	61.1	59.7	56.3	58.1	61.6	59.6
Moderately Dry	-1.5 – -1.0	21.6	29.5	15.8	21.6	14.5	17.2	14.4	15.8	15.5	17.7	21.5	20.0	15.8	12.5	22.3	17.5	20.0	19.0	20.1	19.8	13.7	16.7	15.2	20.1	18.6	19.3	20.0
Severely Dry	-2.0 – -1.5	5.9	3.5	4.0	3.5	8.9	6.8	7.4	4.0	6.3	7.4	3.8	4.5	6.4	6.9	3.5	5.6	4.0	6.9	3.1	2.8	6.3	4.6	6.3	5.0	7.9	4.8	3.3
Extremely Dry	< -2.0	0.0	0.0	1.3	0.3	1.0	0.5	0.2	0.5	0.5	0.2	0.2	0.2	0.7	0.5	0.2	0.0	0.2	0.8	0.2	0.2	0.5	0.2	0.2	0.3	0.3	0.7	0.3
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.0	0.2	0.3	0.0	0.5	1.0	0.5	0.7	1.0	1.3	1.5	0.7	0.3	1.8	0.5	1.8	0.8	0.2	0.2	0.0	0.3	1.2	0.0	1.7	0.2	0.0	0.2
Very Wet	1.5 – 2.0	2.5	2.3	3.5	2.1	5.8	4.6	6.1	4.5	2.0	4.1	4.1	4.0	2.5	4.8	5.1	3.5	3.1	3.5	3.8	3.5	3.0	4.0	2.3	4.3	4.3	3.5	1.8
Moderately Wet	1.0 – 1.5	15.5	13.7	14.9	15.5	11.6	14.2	12.2	14.7	10.6	14.0	15.0	11.1	15.5	9.4	12.4	12.2	13.4	12.5	13.0	12.9	11.1	12.2	13.0	14.2	14.7	14.2	15.7
Near Normal	-1.0 – 1.0	56.9	61.7	58.7	53.5	56.4	58.7	60.6	56.4	65.7	59.6	61.4	59.1	56.3	64.4	57.6	61.9	57.1	57.3	58.7	65.3	57.8	55.4	53.8	60.7	55.1	56.1	54.1
Moderately Dry	-1.5 – -1.0	20.0	13.9	17.8	22.4	19.6	18.3	17.3	19.8	14.0	17.0	13.2	19.0	22.6	12.0	17.0	15.0	20.8	22.1	19.3	16.2	19.3	20.5	24.4	14.4	20.8	22.4	23.6
Severely Dry	-2.0 – -1.5	5.1	7.8	4.5	6.3	5.6	2.8	2.6	3.6	5.8	3.8	4.3	5.9	2.6	6.1	6.8	4.6	4.0	4.3	4.1	2.1	8.3	6.3	5.8	4.0	4.6	3.8	4.3
Extremely Dry	< -2.0	0.0	0.5	0.3	0.2	0.5	0.3	0.7	0.3	1.0	0.2	0.5	0.3	0.2	1.5	0.7	1.0	0.8	0.2	0.8	0.0	0.3	0.5	0.7	0.8	0.3	0.0	0.3
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 11. Percentage classification values of drought based on 9-month SPEI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	0.7	0.3	1.5	0.2	1.2	1.2	0.0	1.0	1.3	0.3	0.0	0.0	0.7	2.0	0.5	0.8	0.7	0.2	0.5	0.7	1.5	1.8	1.3	0.5	0.5	1.3	2.2
Very Wet	1.5 – 2.0	4.6	2.8	4.3	5.8	4.5	3.0	3.0	9.1	4.8	3.8	4.1	3.8	3.2	5.3	4.8	4.1	7.0	2.2	5.1	3.6	6.1	5.1	4.1	7.0	2.8	5.0	2.2
Moderately Wet	1.0 – 1.5	11.8	11.9	10.0	11.3	10.0	10.9	8.6	10.4	10.4	8.0	10.4	11.1	12.9	7.8	12.3	11.3	11.4	10.6	13.3	11.1	10.4	9.5	10.0	11.4	9.6	7.0	12.8
Near Normal	-1.0 – 1.0	58.7	60.2	65.5	60.2	61.2	60.2	67.2	61.9	67.2	65.2	63.5	64.2	61.7	67.2	60.9	63.8	60.5	64.7	62.0	64.8	62.2	63.3	66.5	60.4	61.9	65.3	64.3
Moderately Dry	-1.5 – -1.0	15.6	17.2	12.1	16.1	13.9	14.4	14.3	10.1	8.0	13.6	15.9	14.1	14.1	10.4	14.9	12.6	13.1	13.4	13.1	14.1	11.9	13.6	10.8	12.8	14.9	12.8	11.9
Severely Dry	-2.0 – -1.5	8.0	7.0	5.0	5.8	7.1	8.8	5.8	6.3	6.3	7.5	5.3	5.6	6.3	6.1	5.5	5.8	6.3	7.0	5.1	5.1	6.1	5.6	6.0	7.0	8.8	6.8	5.8
Extremely Dry	< -2.0	0.7	0.5	1.7	0.7	2.2	1.5	1.2	1.2	2.0	1.7	0.7	1.2	1.2	1.2	1.2	1.5	1.0	2.0	0.8	0.5	1.7	1.0	1.3	1.0	1.5	1.8	0.8
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.5	0.5	0.0	0.0	1.0	1.3	1.0	0.8	1.2	2.3	2.2	0.5	0.2	1.7	1.0	2.2	0.8	0.3	0.0	0.0	0.7	0.5	0.0	2.3	1.2	0.3	0.5
Very Wet	1.5 – 2.0	3.5	3.5	5.0	4.8	5.3	5.6	4.6	6.1	3.0	4.5	4.3	3.3	5.0	4.8	3.8	3.0	5.1	5.0	6.0	2.3	4.6	5.8	4.8	4.5	4.5	4.8	4.0
Moderately Wet	1.0 – 1.5	12.3	10.6	11.8	11.3	10.3	10.6	12.8	11.8	6.6	10.3	11.3	10.6	13.9	10.1	9.5	10.1	10.4	10.0	11.1	11.6	8.0	9.0	10.1	10.8	10.3	11.6	13.8
Near Normal	-1.0 – 1.0	63.5	66.7	62.9	60.4	62.9	64.0	63.5	62.5	70.3	65.5	64.5	64.7	60.5	64.2	61.0	65.3	62.9	61.9	62.9	69.7	61.7	60.9	60.5	63.0	63.8	61.7	59.7
Moderately Dry	-1.5 – -1.0	12.6	10.0	13.3	13.9	12.4	12.6	11.4	12.6	11.8	11.1	11.6	12.4	14.6	12.8	15.1	11.4	13.6	14.4	12.6	12.4	14.9	14.8	15.6	12.3	11.6	14.8	14.9
Severely Dry	-2.0 – -1.5	6.6	7.3	6.3	8.5	6.1	4.1	6.1	4.6	5.6	5.1	4.5	7.1	5.1	3.6	8.5	6.5	4.6	8.1	5.3	3.6	7.3	8.3	6.8	6.0	7.5	6.0	5.6
Extremely Dry	< -2.0	1.0	1.5	0.8	1.2	2.0	1.7	0.5	1.5	1.5	1.2	1.7	1.3	0.7	2.8	1.2	1.5	2.5	0.3	2.2	0.3	2.8	0.8	2.2	1.2	1.2	0.8	1.5
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 12. Percentage classification values of drought based on 12-month SPEI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	0.7	0.0	1.3	0.3	0.5	1.2	0.0	1.8	1.7	0.0	0.0	0.0	0.2	1.7	0.2	0.7	2.0	0.0	0.5	1.8	1.7	1.8	0.3	1.5	0.3	0.7	2.7
Very Wet	1.5 – 2.0	3.8	2.3	4.8	4.8	5.8	4.2	2.0	6.7	3.5	0.8	3.2	2.2	5.0	5.5	6.5	3.5	4.5	1.8	5.5	1.5	3.7	5.8	3.5	4.3	2.2	7.2	2.5
Moderately Wet	1.0 – 1.5	11.8	5.0	10.7	8.8	7.2	7.0	4.5	14.3	8.8	8.0	7.5	6.0	7.8	10.5	6.5	6.8	12.0	3.5	9.0	6.8	10.0	6.8	10.7	8.3	5.8	6.2	7.7
Near Normal	-1.0 – 1.0	59.0	68.2	63.3	61.0	66.0	62.3	74.0	58.7	70.3	66.5	67.3	70.5	67.0	66.7	62.5	68.8	59.7	73.2	67.5	70.7	64.7	63.3	69.3	64.3	65.2	64.0	72.7
Moderately Dry	-1.5 – -1.0	15.8	15.5	13.7	15.3	9.8	14.8	13.3	10.5	7.8	17.3	14.7	12.8	11.0	9.8	14.8	10.7	15.5	12.0	9.7	12.8	12.0	14.3	10.3	11.5	14.5	11.3	8.7
Severely Dry	-2.0 – -1.5	7.7	6.8	3.8	9.0	5.2	8.3	3.8	7.3	5.2	6.7	5.8	6.8	6.2	4.0	7.3	7.0	5.8	5.7	6.8	5.2	6.8	6.7	4.5	7.8	9.3	5.3	3.3
Extremely Dry	< -2.0	1.2	2.2	2.3	0.7	5.5	2.2	2.3	0.7	2.7	0.7	1.5	1.7	2.8	1.8	2.2	2.5	0.5	3.8	1.0	1.2	1.2	1.2	1.3	2.2	2.7	5.3	2.5
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.0	0.7	0.0	0.3	0.5	2.2	1.7	0.5	0.3	2.7	2.2	0.7	0.8	2.2	0.7	2.3	2.3	0.0	0.3	0.0	0.7	0.5	0.0	3.0	0.7	0.0	0.2
Very Wet	1.5 – 2.0	2.8	2.2	3.7	2.2	6.5	3.5	5.3	6.3	3.3	5.7	2.7	2.2	3.8	4.3	4.8	3.2	2.7	2.7	4.0	2.2	4.0	3.3	1.0	2.8	4.7	3.0	3.3
Moderately Wet	1.0 – 1.5	10.3	7.3	7.7	7.5	8.7	9.3	10.2	9.7	8.5	8.3	8.3	7.7	8.8	8.2	8.3	5.0	6.7	9.3	8.0	8.0	6.2	9.8	5.7	8.7	10.0	9.3	8.2
Near Normal	-1.0 – 1.0	65.2	68.2	66.8	63.3	60.7	64.3	66.8	67.0	67.8	69.0	71.5	70.3	67.3	67.3	61.7	68.3	69.7	64.0	65.0	77.0	60.7	60.5	66.2	66.2	65.2	65.5	67.2
Moderately Dry	-1.5 – -1.0	12.8	11.0	11.2	15.5	15.0	16.0	9.3	8.5	11.7	6.8	7.7	10.3	11.3	11.7	14.8	12.5	11.3	12.5	14.7	9.0	15.3	16.3	17.5	11.3	9.8	15.0	14.0
Severely Dry	-2.0 – -1.5	8.2	9.8	9.3	9.2	6.8	3.5	5.5	5.8	7.2	4.7	6.3	7.0	6.3	4.3	8.0	6.8	3.0	11.2	5.0	3.3	10.3	7.2	7.0	5.7	8.0	6.5	5.0
Extremely Dry	< -2.0	0.7	0.8	1.3	2.0	1.8	1.2	1.2	2.2	1.2	2.8	1.3	1.8	1.5	2.0	1.7	1.8	4.3	0.3	3.0	0.5	2.8	2.3	2.7	2.3	1.7	0.7	2.2
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 13. Percentage classification values of drought based on 1-month RDI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	1.3	2.3	5.4	2.0	3.3	2.3	1.8	2.6	2.6	1.6	2.0	1.6	2.5	1.8	1.6	1.5	2.6	1.8	1.8	1.1	1.3	1.0	2.0	2.0	1.8	1.1	2.0
Very Wet	1.5 – 2.0	3.1	4.1	2.3	2.8	2.8	6.1	2.3	3.3	3.3	3.6	6.9	2.0	3.1	5.4	3.4	3.3	3.6	2.9	6.1	6.5	3.8	3.3	7.9	3.8	3.1	4.3	3.9
Moderately Wet	1.0 – 1.5	9.7	7.7	8.0	9.0	8.3	4.4	8.7	9.8	9.8	8.0	3.6	7.0	8.5	10.1	8.3	9.3	9.7	6.1	8.5	9.0	10.0	7.2	7.9	8.5	8.2	6.2	9.8
Near Normal	-1.0 – 1.0	71.4	73.3	70.7	72.3	70.0	73.8	67.9	70.7	70.7	74.8	78.9	72.7	71.4	66.6	71.4	70.0	73.5	73.2	68.4	75.5	69.4	73.8	63.2	68.4	72.7	80.5	66.6
Moderately Dry	-1.5 – -1.0	9.0	8.0	9.0	8.0	9.7	8.7	7.7	7.7	7.7	8.7	5.1	9.7	8.0	8.0	7.9	14.4	5.2	11.0	9.3	7.9	7.9	9.5	13.3	10.8	8.5	5.2	11.8
Severely Dry	-2.0 – -1.5	5.1	4.6	2.6	5.2	4.4	2.6	11.5	4.1	4.1	3.3	0.3	5.4	4.6	5.9	6.5	1.5	3.6	4.3	3.9	0.0	4.9	4.7	3.9	5.4	4.7	2.6	5.9
Extremely Dry	< -2.0	0.5	0.0	2.0	0.7	1.5	2.1	0.2	1.8	1.8	0.0	3.3	1.6	2.0	2.1	0.8	0.0	1.8	0.8	2.0	0.0	2.8	0.5	2.0	1.1	1.0	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	1.8	1.1	1.3	2.9	3.4	1.6	2.8	2.9	0.0	2.3	1.1	1.5	1.0	6.1	3.1	1.5	2.1	1.8	2.8	1.3	1.8	3.3	2.5	0.7	3.4	1.1	2.1
Very Wet	1.5 – 2.0	3.9	3.3	3.8	4.4	3.8	3.9	4.1	4.1	2.0	3.9	4.4	4.1	5.1	5.4	2.5	2.8	1.8	3.9	1.6	2.5	3.3	4.7	3.1	4.4	3.4	3.4	4.7
Moderately Wet	1.0 – 1.5	11.6	9.3	7.5	9.2	7.4	7.4	9.0	8.0	7.9	10.6	11.0	11.3	7.7	3.1	9.2	8.3	6.4	7.4	7.7	6.7	8.0	10.6	5.6	8.0	8.7	10.8	8.2
Near Normal	-1.0 – 1.0	69.9	72.2	74.6	68.1	74.1	70.7	68.7	71.8	78.4	66.0	68.2	65.5	70.2	66.6	68.6	69.7	75.3	74.6	73.5	77.3	72.2	65.0	69.9	67.9	68.1	71.5	67.9
Moderately Dry	-1.5 – -1.0	6.5	8.8	6.9	12.6	8.5	9.2	9.2	9.3	3.9	10.8	8.0	12.3	9.5	15.4	9.7	10.8	8.8	6.2	8.8	6.1	8.2	11.6	10.8	12.3	9.0	8.2	10.0
Severely Dry	-2.0 – -1.5	4.7	2.1	5.7	2.5	2.6	6.4	4.3	3.4	2.0	4.1	3.8	4.3	3.3	2.3	4.3	4.4	5.6	5.6	4.7	6.2	5.6	4.3	6.7	4.6	5.4	4.1	5.6
Extremely Dry	< -2.0	1.5	3.1	0.2	0.3	0.2	0.8	2.0	0.3	5.9	2.3	3.4	1.1	3.3	1.1	2.8	2.5	0.0	0.5	0.8	0.0	1.0	0.5	1.5	2.1	2.0	0.8	1.5
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 14. Percentage classification values of drought based on 3-month RDI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.0	2.0	2.0	1.5	2.0	2.0	0.0	2.5	2.5	1.0	0.5	0.0	2.0	2.5	1.0	2.0	2.5	0.5	2.5	1.0	1.5	0.5	2.0	2.0	2.0	0.5	2.0
Very Wet	1.5 – 2.0	2.5	3.9	2.0	3.0	4.9	3.0	0.0	2.5	2.5	4.4	7.9	3.4	3.4	3.0	4.4	3.4	3.9	3.0	3.0	1.5	3.0	5.4	0.0	5.9	2.0	5.6	3.9
Moderately Wet	1.0 – 1.5	10.3	7.9	9.9	8.9	8.9	9.9	9.9	12.8	12.8	7.9	7.9	8.4	9.5	6.9	7.9	4.4	9.4	5.4	10.3	14.4	12.3	8.9	15.8	9.4	7.9	9.9	5.9
Near Normal	-1.0 – 1.0	67.5	64.0	76.4	67.0	64.4	63.5	76.4	67.8	67.8	73.9	69.0	70.4	68.8	69.3	68.5	73.9	73.4	71.9	64.0	64.9	63.5	67.5	65.4	63.9	73.4	67.3	71.3
Moderately Dry	-1.5 – -1.0	9.4	14.3	3.9	10.8	12.8	14.3	7.9	8.5	8.5	8.4	7.9	10.3	6.9	14.4	7.9	7.9	7.4	12.3	11.8	15.3	11.3	11.8	11.8	12.3	9.4	10.8	9.0
Severely Dry	-2.0 – -1.5	4.9	4.9	0.0	4.9	3.6	4.9	3.9	4.4	4.4	4.4	5.4	3.4	7.4	2.0	7.9	8.4	3.0	3.4	6.4	3.0	6.4	3.0	5.1	4.6	4.4	5.9	7.9
Extremely Dry	< -2.0	3.4	3.0	5.9	3.9	3.4	2.5	2.0	1.5	1.5	0.0	1.5	3.9	2.0	2.0	2.5	0.0	0.5	3.4	2.0	0.0	2.0	3.0	0.0	2.0	1.0	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.5	0.5	2.0	3.9	3.9	1.5	2.5	3.0	2.0	1.5	1.5	2.5	0.5	3.0	2.5	1.0	2.0	0.5	2.0	1.0	2.0	2.0	2.0	1.5	2.5	2.0	0.5
Very Wet	1.5 – 2.0	5.4	1.5	2.0	4.9	3.4	4.4	3.9	7.4	2.0	6.4	4.4	3.4	3.9	4.4	2.5	4.9	3.9	3.9	3.9	2.0	3.4	3.9	3.4	2.0	2.0	1.5	5.9
Moderately Wet	1.0 – 1.5	16.7	8.9	9.4	7.9	10.3	10.8	8.9	4.4	5.9	9.4	9.4	9.4	8.4	5.9	12.5	7.9	8.4	5.9	5.9	10.3	5.4	15.3	3.9	13.3	11.5	9.4	10.3
Near Normal	-1.0 – 1.0	61.9	69.5	70.6	65.5	67.0	70.4	70.0	72.4	70.4	66.5	66.8	66.8	66.0	69.5	62.4	68.5	64.0	72.4	70.4	73.4	72.4	63.5	69.0	64.0	66.3	69.5	66.3
Moderately Dry	-1.5 – -1.0	10.5	9.9	11.8	10.8	9.9	6.4	7.4	7.9	13.8	8.9	11.5	10.0	12.8	13.8	10.8	9.9	11.8	8.9	9.9	8.9	9.4	7.4	12.3	10.3	9.4	13.8	10.8
Severely Dry	-2.0 – -1.5	3.4	7.9	2.8	5.9	4.4	2.5	4.4	3.9	5.9	4.9	3.0	4.9	7.4	2.0	5.4	3.0	9.9	7.4	5.9	4.4	3.9	4.4	6.9	3.9	6.4	3.4	4.6
Extremely Dry	< -2.0	1.5	2.0	1.5	1.0	1.0	3.9	3.0	1.0	0.0	2.5	3.4	3.0	1.0	1.5	3.9	4.9	0.0	1.0	2.0	0.0	3.4	3.4	2.5	4.9	2.0	0.5	1.5
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 15. Percentage classification values of drought based on 6-month RDI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	1.0	1.0	2.0	1.0	2.0	4.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	4.0	1.0	1.0	2.0	0.0	2.0	0.0	1.0	2.0	0.0	3.0	0.0	0.0	2.0
Very Wet	1.5 – 2.0	4.0	5.0	0.0	3.0	3.0	0.0	2.0	5.0	5.0	3.0	5.9	0.0	3.0	4.0	4.0	4.0	5.0	2.0	5.0	0.0	3.0	2.0	4.0	6.9	3.0	0.0	2.0
Moderately Wet	1.0 – 1.5	8.9	3.0	11.9	6.9	9.9	5.6	11.9	11.9	11.9	5.0	5.9	10.9	6.9	9.9	5.9	8.9	11.9	6.6	5.0	15.8	11.9	9.9	9.9	5.9	8.9	13.9	9.9
Near Normal	-1.0 – 1.0	69.6	70.6	74.3	65.7	65.3	64.7	70.3	68.3	68.3	79.2	69.6	72.3	75.2	63.7	71.3	67.3	67.3	72.6	67.3	70.3	64.4	66.3	74.3	69.3	68.3	70.3	70.3
Moderately Dry	-1.5 – -1.0	10.9	11.6	4.0	13.5	12.9	17.8	7.9	4.0	4.0	11.9	10.6	9.9	5.0	16.5	8.9	9.9	10.9	9.9	11.9	9.9	8.9	11.9	5.9	6.9	13.9	5.9	7.9
Severely Dry	-2.0 – -1.5	4.6	5.0	2.0	5.0	4.0	6.9	5.9	5.9	5.9	1.0	4.0	4.0	4.0	1.0	4.0	8.9	3.0	7.9	5.9	2.0	9.9	6.9	5.9	5.0	4.0	4.0	7.9
Extremely Dry	< -2.0	1.0	4.0	5.9	5.0	3.0	1.0	2.0	4.0	4.0	0.0	4.0	3.0	5.0	1.0	5.0	0.0	0.0	1.0	3.0	2.0	1.0	1.0	0.0	3.0	2.0	5.9	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	1.0	1.0	0.0	2.0	4.0	3.0	3.0	3.0	0.0	4.0	2.0	0.0	1.0	0.0	1.0	2.0	2.0	0.0	2.0	1.0	1.0	2.0	0.0	2.0	2.0	1.0	0.0
Very Wet	1.5 – 2.0	4.0	3.0	2.0	3.0	4.0	5.0	5.9	5.0	2.0	5.0	3.0	5.9	5.9	9.9	2.0	5.0	6.9	2.0	5.0	2.0	2.0	7.9	4.0	4.0	4.0	3.0	5.9
Moderately Wet	1.0 – 1.5	12.9	7.9	10.9	11.9	10.9	8.9	6.9	7.9	4.0	5.9	12.9	7.9	6.9	5.9	10.6	3.0	6.9	7.9	7.9	5.9	8.9	6.9	5.9	5.9	9.6	9.9	7.9
Near Normal	-1.0 – 1.0	62.4	67.3	73.3	67.3	68.3	66.3	68.3	72.3	81.5	69.3	64.4	68.3	68.3	60.4	68.6	74.3	66.3	74.3	68.3	79.2	66.3	67.3	68.3	68.3	65.7	73.3	70.3
Moderately Dry	-1.5 – -1.0	11.9	11.9	5.9	12.9	7.9	10.9	10.9	5.0	2.6	9.9	11.9	9.9	11.9	9.9	7.9	5.9	11.9	3.0	9.9	5.9	12.9	10.9	9.9	9.9	9.9	10.9	11.9
Severely Dry	-2.0 – -1.5	5.9	5.9	3.0	3.0	3.0	5.9	5.0	6.9	5.9	5.0	5.9	7.9	2.0	9.9	5.0	7.9	5.9	9.9	4.0	5.0	5.9	2.0	9.9	8.9	5.9	2.0	4.0
Extremely Dry	< -2.0	2.0	3.0	5.0	0.0	2.0	0.0	0.0	0.0	4.0	1.0	0.0	0.0	4.0	4.0	5.0	2.0	0.0	3.0	3.0	1.0	3.0	3.0	2.0	1.0	3.0	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 16. Percentage classification values of drought based on 9-month RDI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.0	2.0	0.0	0.0	4.0	2.0	0.0	0.0	0.0	0.0	4.0	0.0	2.0	4.0	0.0	0.0	2.0	2.0	4.0	2.0	4.0	0.0	0.0	2.0	2.0	4.0	4.0
Very Wet	1.5 – 2.0	4.0	2.0	4.0	4.0	4.0	8.0	0.0	10.0	10.0	0.0	2.0	0.0	2.0	2.0	6.0	2.0	2.0	0.0	2.0	2.0	2.0	6.0	6.0	4.0	0.0	2.0	2.0
Moderately Wet	1.0 – 1.5	4.0	8.0	8.0	13.9	8.0	6.0	8.0	13.9	13.9	8.0	6.0	4.0	8.0	11.9	6.0	11.9	13.9	0.0	10.0	6.0	13.9	4.0	6.0	13.9	10.0	8.0	4.0
Near Normal	-1.0 – 1.0	72.0	72.1	68.2	58.2	64.2	58.2	76.1	56.2	56.2	82.1	72.1	72.1	70.1	64.0	74.1	68.2	66.2	82.1	70.1	84.1	58.2	70.1	74.1	60.2	74.1	68.2	74.1
Moderately Dry	-1.5 – -1.0	10.0	8.0	8.0	10.0	8.0	11.9	8.0	13.9	13.9	6.0	10.0	17.9	13.9	13.9	4.0	8.0	10.0	10.0	2.0	2.0	13.9	10.0	8.0	11.9	4.0	10.0	11.9
Severely Dry	-2.0 – -1.5	6.1	4.0	6.0	8.0	10.0	13.9	4.0	4.0	4.0	2.0	6.0	2.0	2.0	4.1	6.0	10.0	6.0	2.0	10.0	4.0	6.0	8.0	2.0	4.0	10.0	4.0	4.0
Extremely Dry	< -2.0	2.0	4.0	6.0	6.0	2.0	0.0	4.0	2.0	2.0	2.0	0.0	4.0	2.0	0.0	4.0	0.0	0.0	4.0	2.0	0.0	2.0	2.0	4.0	4.0	0.0	4.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.0	0.0	0.0	0.0	4.0	0.0	6.0	0.0	4.0	0.0	2.0	2.0	0.0	0.0	4.0	6.0	0.0	0.0	0.0	0.0	2.0	4.0	0.0	4.0	2.0	0.0	0.0
Very Wet	1.5 – 2.0	2.0	4.0	2.0	6.0	2.0	6.0	4.0	6.0	2.0	8.0	4.0	0.0	2.0	6.0	2.0	0.0	8.0	0.0	6.0	0.0	6.0	8.0	2.0	2.0	2.0	0.0	8.0
Moderately Wet	1.0 – 1.5	11.9	4.0	6.0	11.9	19.9	11.9	6.0	15.9	6.0	4.0	6.0	11.9	8.0	8.0	11.9	2.0	4.0	8.0	10.0	6.0	6.0	10.0	10.0	4.0	8.0	15.9	4.0
Near Normal	-1.0 – 1.0	64.0	68.2	78.1	68.2	60.2	66.2	70.1	68.2	72.1	72.1	74.1	70.0	72.1	70.1	62.2	72.1	70.1	70.1	66.2	82.1	66.2	62.2	76.1	72.1	72.1	70.1	76.1
Moderately Dry	-1.5 – -1.0	14.1	11.9	4.0	10.0	8.0	6.0	8.0	4.0	10.0	11.9	8.0	8.1	10.0	6.0	11.9	6.0	11.9	10.0	11.9	10.0	10.0	10.0	4.0	10.0	10.0	10.0	4.0
Severely Dry	-2.0 – -1.5	4.0	10.0	6.0	4.0	2.0	8.0	6.0	4.0	6.0	2.0	4.0	6.0	6.0	4.0	6.0	13.9	6.0	10.0	2.0	0.0	6.0	6.0	4.0	6.0	6.0	4.0	8.0
Extremely Dry	< -2.0	4.0	2.0	4.0	0.0	4.0	2.0	0.0	2.0	0.0	2.0	2.0	2.0	2.0	6.0	2.0	0.0	0.0	2.0	4.0	2.0	4.0	0.0	4.0	2.0	0.0	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

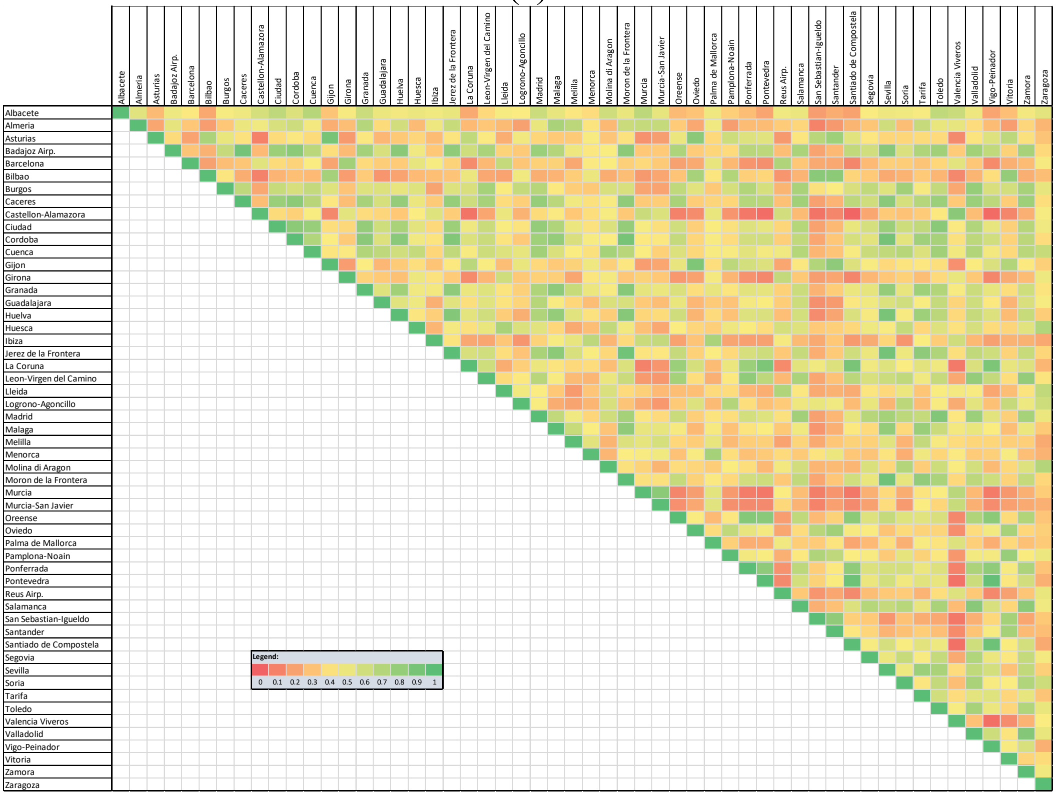
Table 17. Percentage classification values of drought based on 12-month RDI results (%)

		Albacete	Almeria	Asturias	Badajoz Airp.	Barcelona	Bilbao	Burgos	Caceres	Castellon-Alamazora	Ciudad	Cordoba	Cuenca	Gijon	Girona	Granada	Guadalajara	Huelva	Huesca	Ibiza	Jerez de la Frontera	La Coruna	Leon-Virgen del Camino	Lleida	Logrono-Agoncillo	Madrid	Malaga	Melilla
Extremely Wet	> 2.0	2.0	2.0	0.0	0.0	2.0	0.0	0.0	2.0	2.0	0.0	0.0	0.0	0.0	2.0	2.0	0.0	2.0	0.0	2.0	2.0	2.0	2.0	0.0	2.0	0.0	2.0	4.0
Very Wet	1.5 – 2.0	2.0	2.0	8.0	4.0	2.0	4.0	2.0	8.0	8.0	0.0	4.0	0.0	6.0	6.0	4.0	2.0	2.0	1.7	2.0	0.0	4.0	4.0	7.7	4.0	4.0	6.0	2.0
Moderately Wet	1.0 – 1.5	11.7	0.0	4.0	6.0	8.0	11.7	2.0	18.0	18.0	14.0	10.0	10.0	8.0	10.0	8.0	8.0	12.0	2.0	6.0	6.0	10.0	8.0	8.0	12.0	4.0	8.0	6.0
Near Normal	-1.0 – 1.0	66.3	70.3	68.0	68.0	68.0	58.3	76.0	50.3	50.3	74.0	68.0	76.0	68.0	64.0	64.3	70.0	68.0	76.3	70.0	78.0	70.0	68.0	70.3	64.0	76.0	64.0	68.0
Moderately Dry	-1.5 – -1.0	16.0	19.7	12.0	10.0	6.0	18.0	14.0	9.7	9.7	8.0	14.0	6.0	10.0	14.0	13.7	14.0	10.0	10.0	12.0	10.0	4.0	12.0	6.0	12.0	10.0	12.0	14.0
Severely Dry	-2.0 – -1.5	2.0	4.0	4.0	6.0	10.0	4.0	4.0	12.0	12.0	4.0	4.0	6.0	6.0	4.0	6.0	6.0	6.0	6.0	6.0	4.0	6.0	4.0	4.0	2.0	6.0	4.0	4.0
Extremely Dry	< -2.0	0.0	2.0	4.0	6.0	4.0	4.0	2.0	0.0	0.0	0.0	0.0	2.0	2.0	0.0	2.0	0.0	0.0	4.0	2.0	0.0	4.0	2.0	4.0	4.0	0.0	4.0	2.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

		Menorca	Molina di Aragon	Moron de la Frontera	Murcia	Murcia-San Javier	Oreense	Oviedo	Palma de Mallorca	Pamplona-Noain	Ponferrada	Pontevedra	Reus Airp.	Salamanca	San Sebastian-Igueldo	Santander	Santiado de Compostela	Segovia	Sevilla	Soria	Tarifa	Toledo	Valencia Viveros	Valladolid	Vigo-Peinador	Vitoria	Zamora	Zaragoza
Extremely Wet	> 2.0	0.0	0.0	0.0	0.0	1.7	0.0	2.0	0.0	2.0	2.0	2.0	0.0	0.0	2.0	0.0	6.0	2.0	0.0	2.0	0.0	0.0	2.0	0.0	4.0	2.0	0.0	0.0
Very Wet	1.5 – 2.0	6.0	0.0	0.0	0.0	6.0	2.0	6.0	6.0	3.7	2.0	4.0	4.0	2.0	6.0	6.0	0.0	0.0	6.0	2.0	2.0	2.0	4.0	4.0	2.0	4.0	0.0	4.0
Moderately Wet	1.0 – 1.5	2.0	12.0	10.0	9.7	2.0	6.0	6.0	8.0	6.0	10.0	4.0	2.0	6.0	6.0	6.0	0.0	10.0	4.0	8.0	6.0	16.0	8.0	10.0	1.7	6.0	10.0	9.7
Near Normal	-1.0 – 1.0	70.0	64.0	72.0	74.3	74.3	76.0	68.0	72.0	68.3	68.0	76.0	74.0	76.0	70.0	62.0	76.0	76.0	64.3	70.0	82.3	60.0	70.0	68.0	76.3	74.0	80.0	72.3
Moderately Dry	-1.5 – -1.0	12.0	16.0	8.0	10.0	10.0	12.0	12.0	8.0	14.0	12.0	4.0	10.0	10.0	10.0	18.0	8.0	6.0	17.7	10.0	9.7	12.0	12.0	12.0	8.0	4.0	8.0	4.0
Severely Dry	-2.0 – -1.5	8.0	2.0	4.0	6.0	2.0	2.0	6.0	2.0	6.0	4.0	6.0	10.0	4.0	2.0	6.0	6.0	2.0	8.0	6.0	0.0	6.0	2.0	2.0	4.0	10.0	2.0	10.0
Extremely Dry	< -2.0	2.0	6.0	6.0	0.0	4.0	2.0	0.0	4.0	0.0	2.0	4.0	0.0	2.0	4.0	2.0	4.0	4.0	0.0	2.0	0.0	4.0	2.0	4.0	4.0	0.0	0.0	0.0
	Total %	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

APPENDIX 3

(a)



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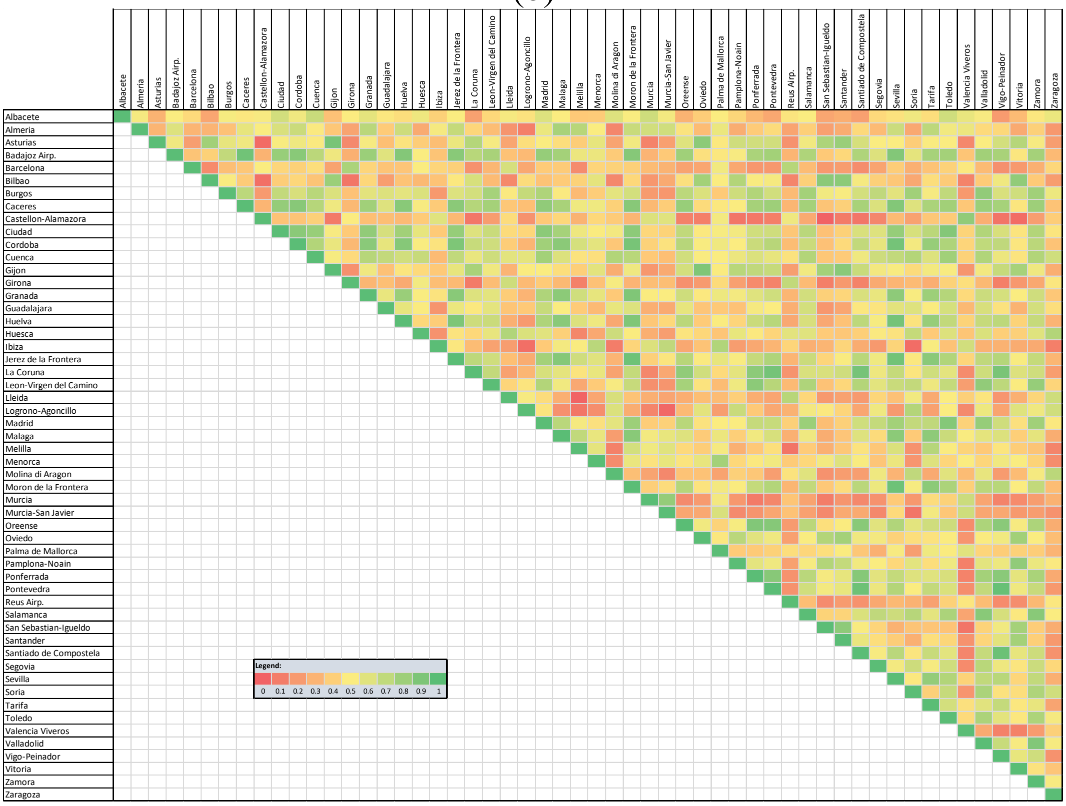

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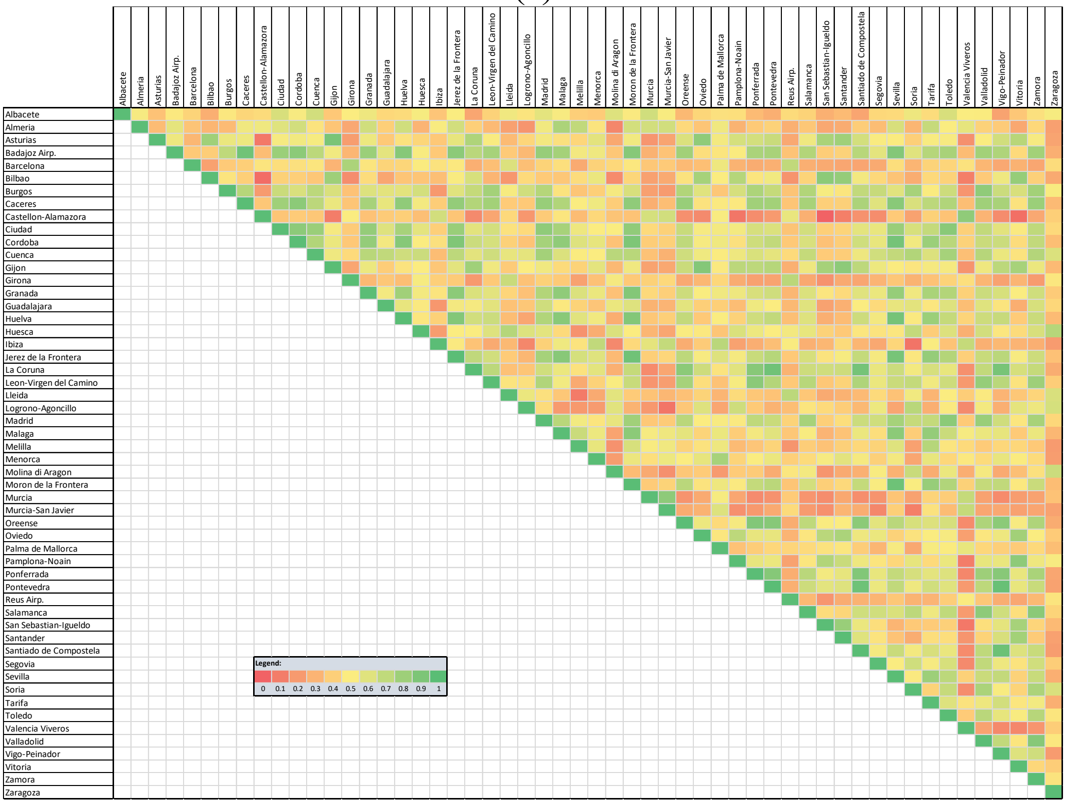
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Soria
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Toledo
Valencia Viveros
Valladolid
Vigo-Peinador
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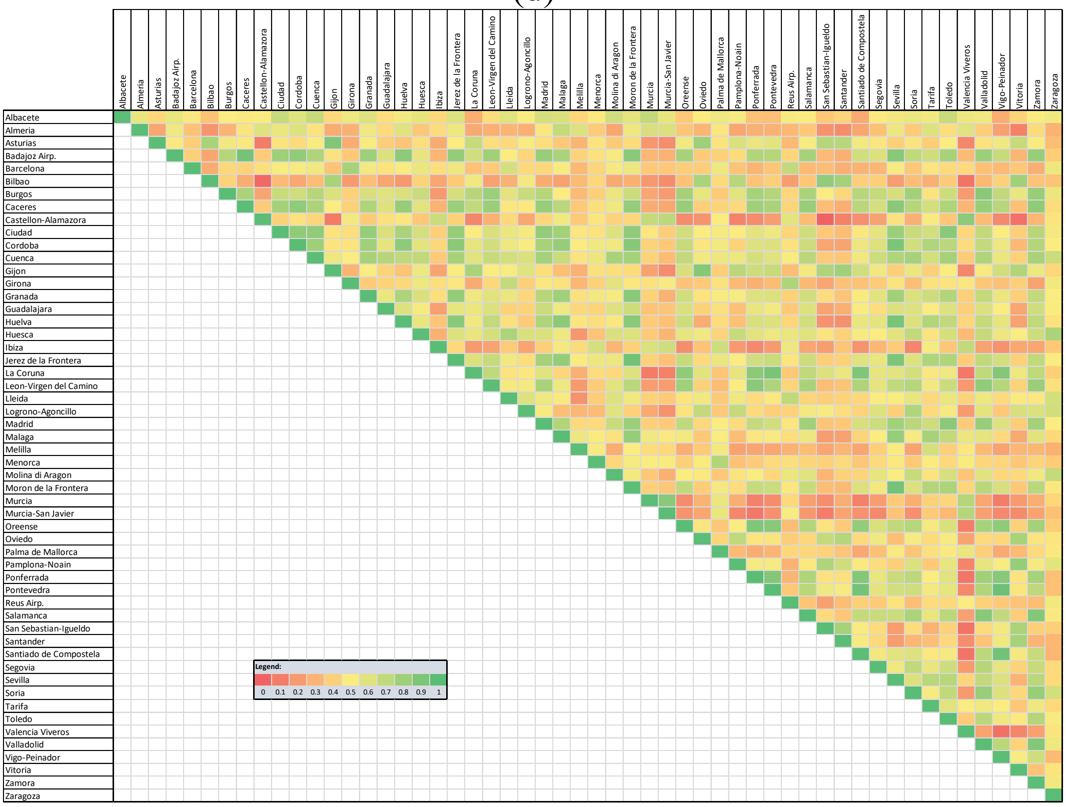
(d)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(e)

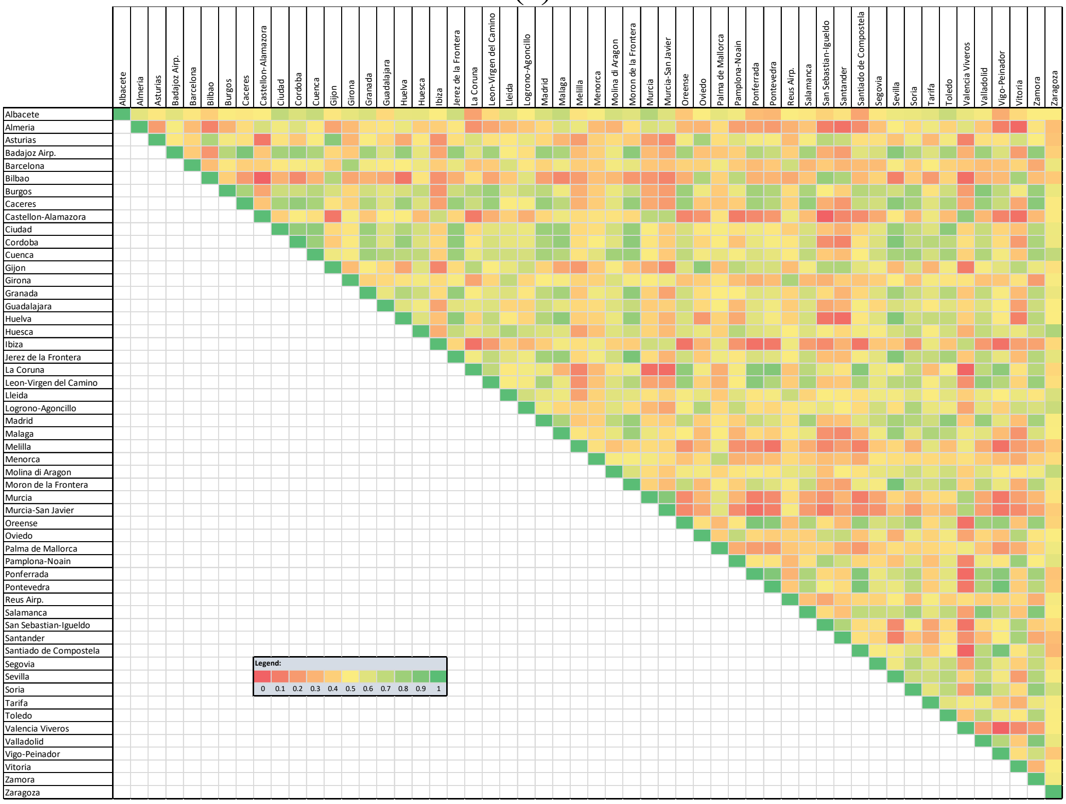
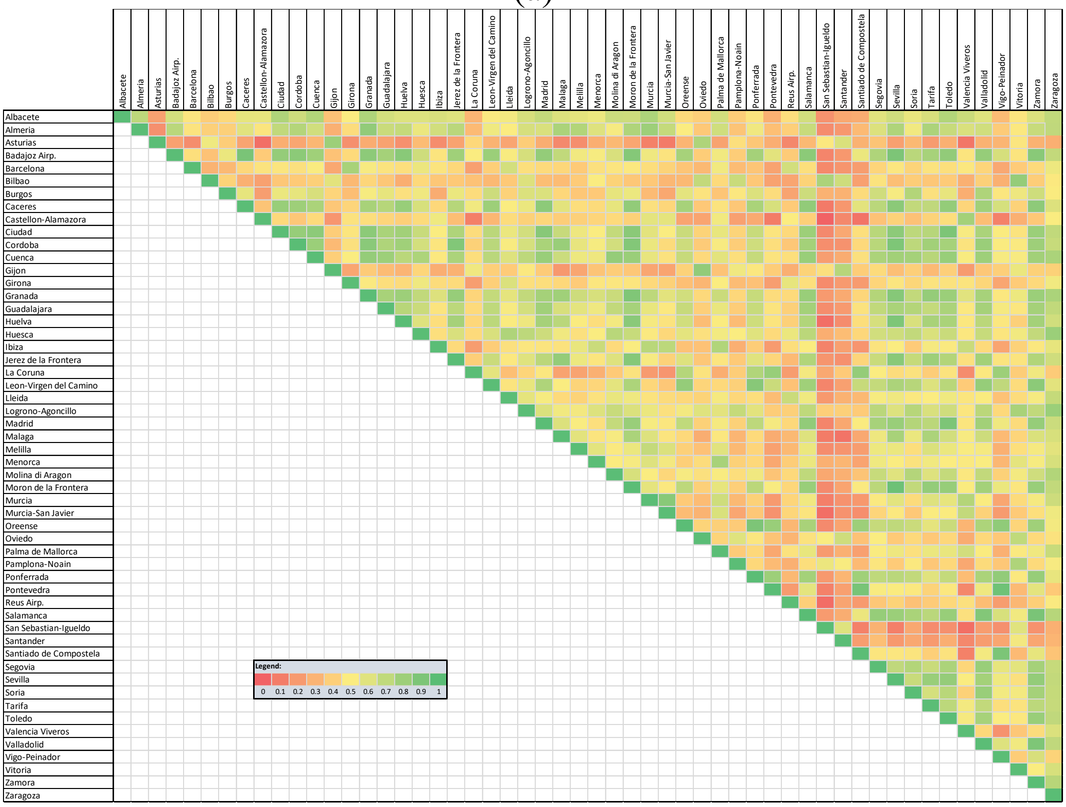


Fig. 10. Correlation coefficients between Spain stations for different time scales of SPI (1, 3, 6, 9, and 12 months) (a, b, c, d, and e)

(a)



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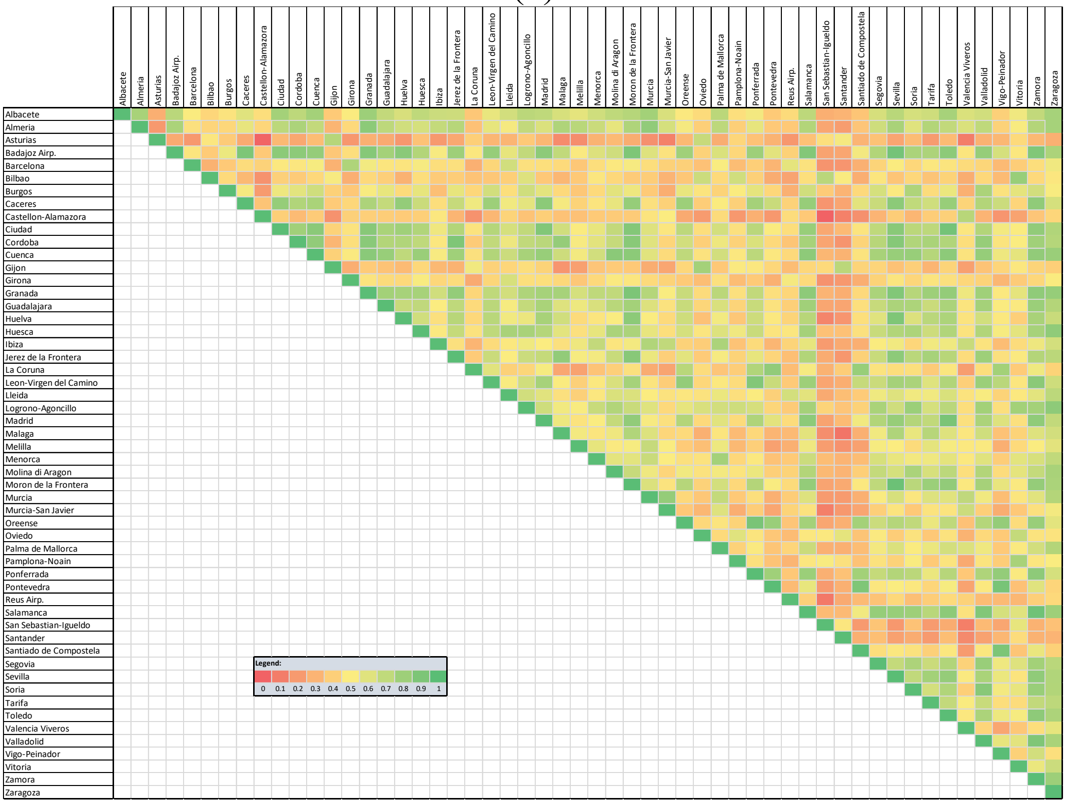
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Vigo-Peinador
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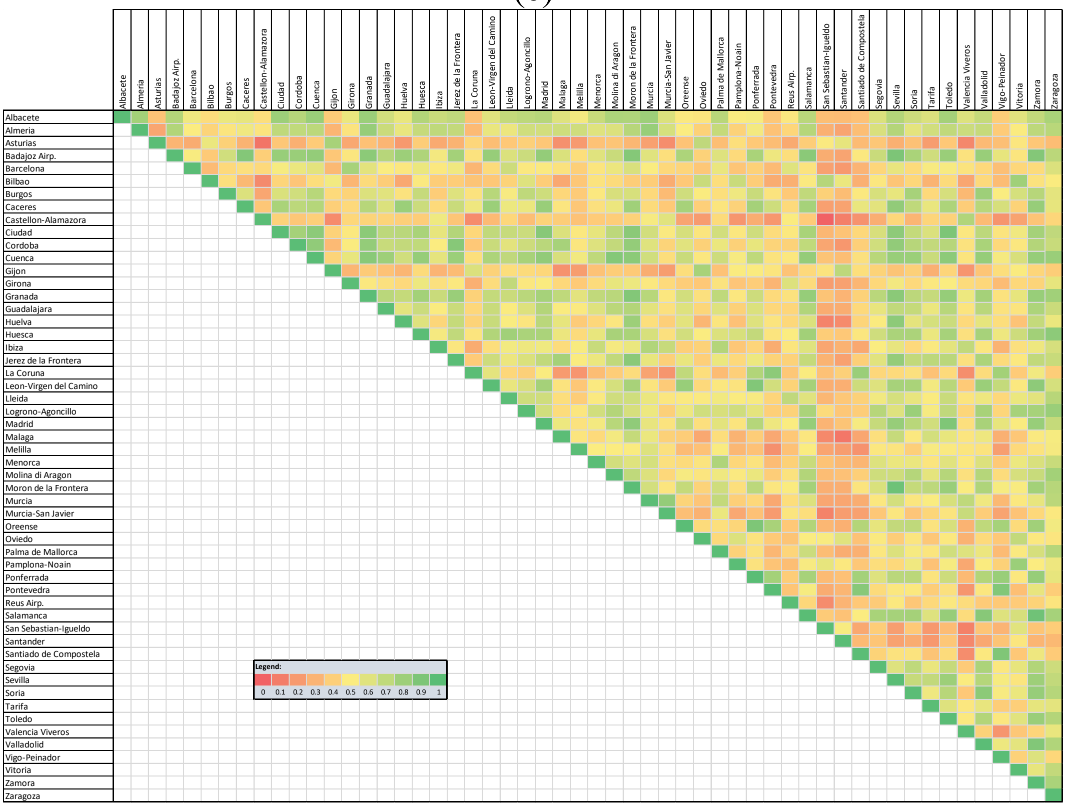
(c)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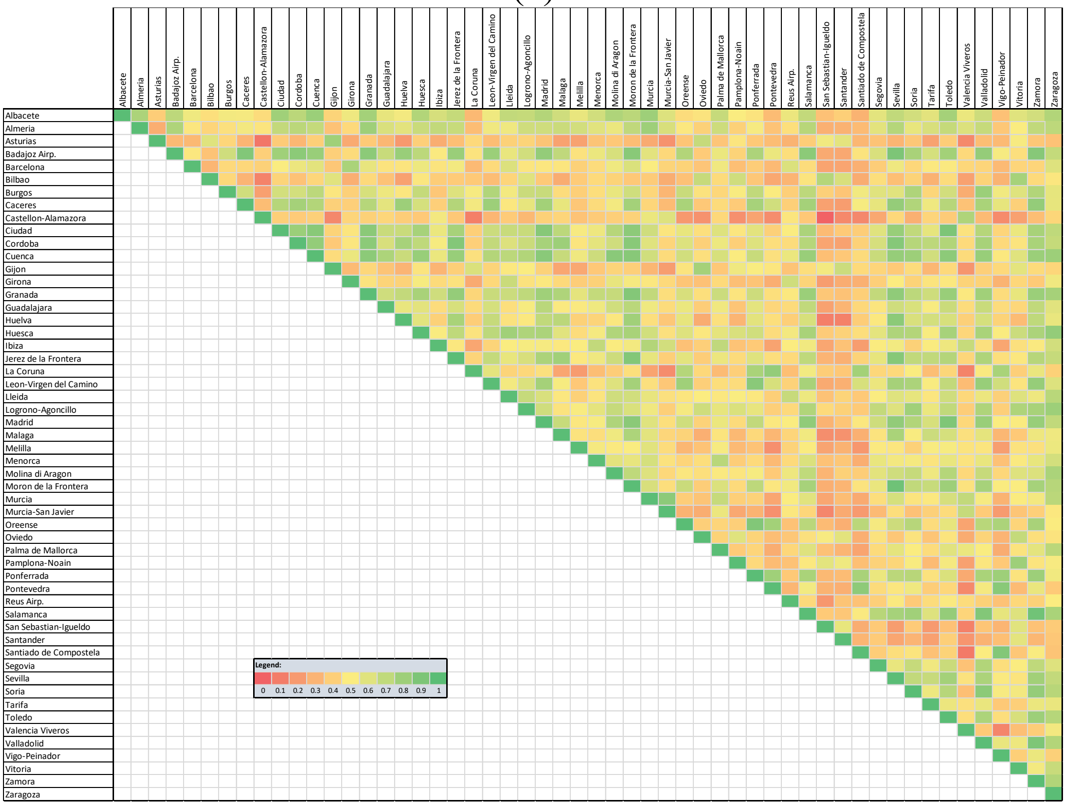
(d)



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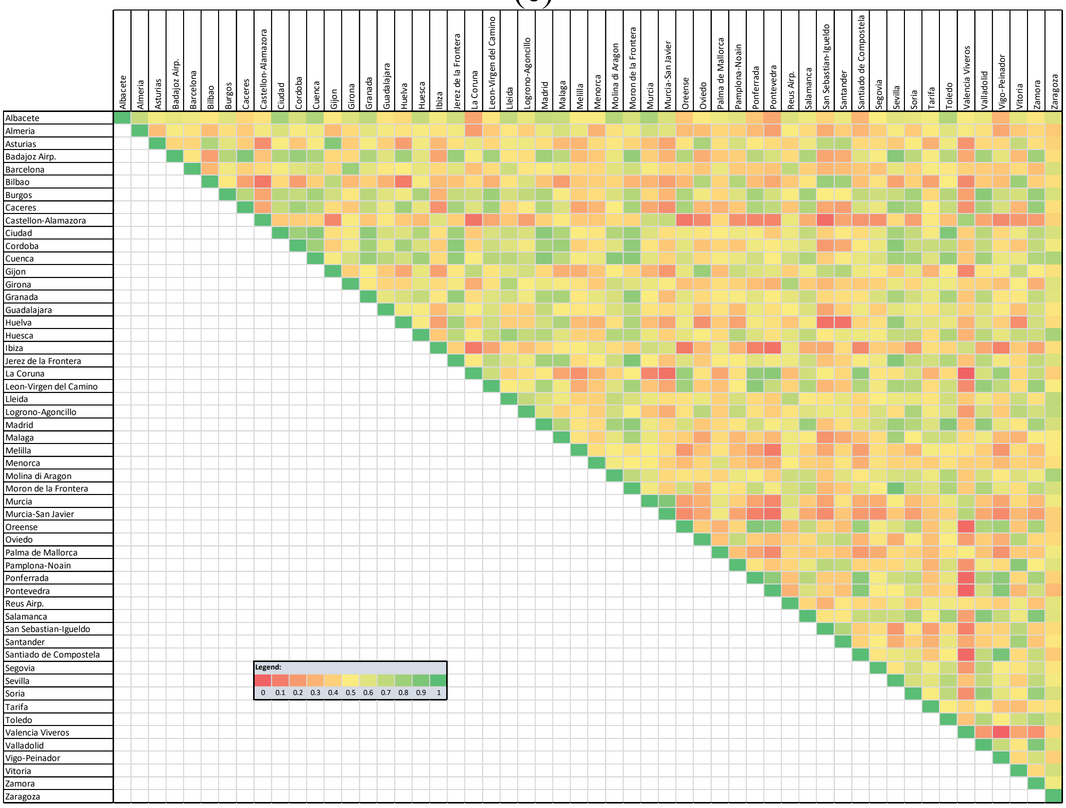
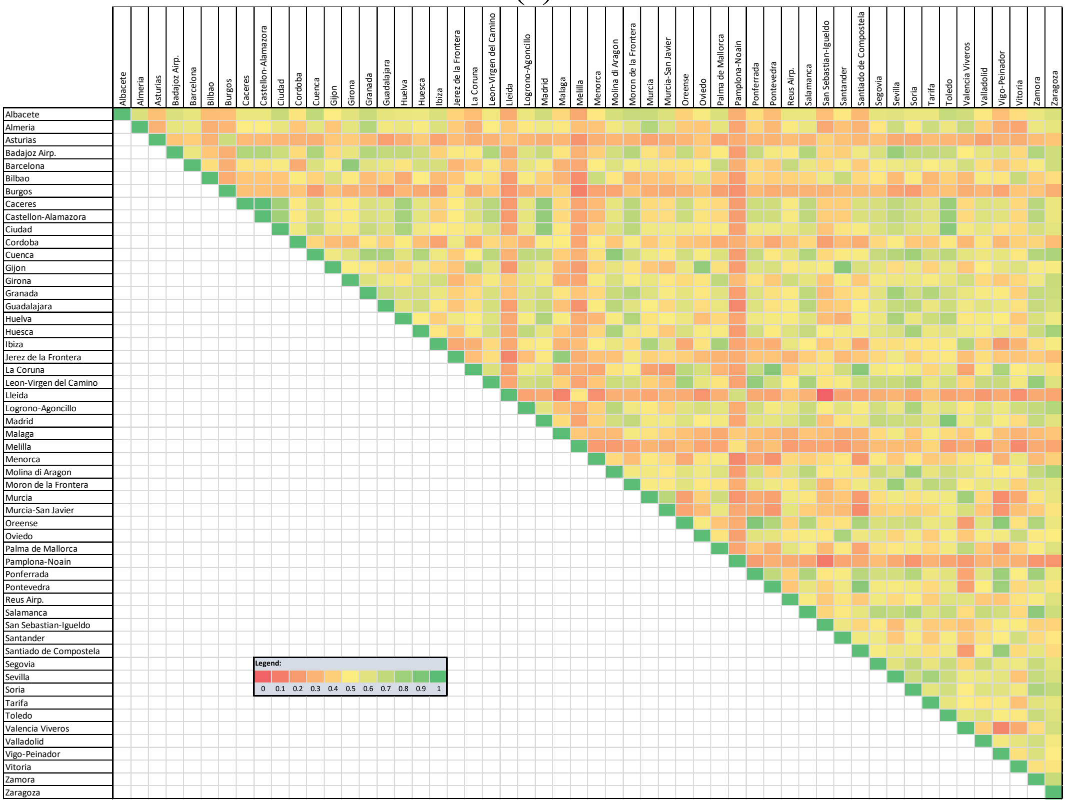


Fig. 11. Correlation coefficients between Spain stations for different time scales of SPEI (1, 3, 6, 9, and 12 months) (a, b, c, d, and e)

(a)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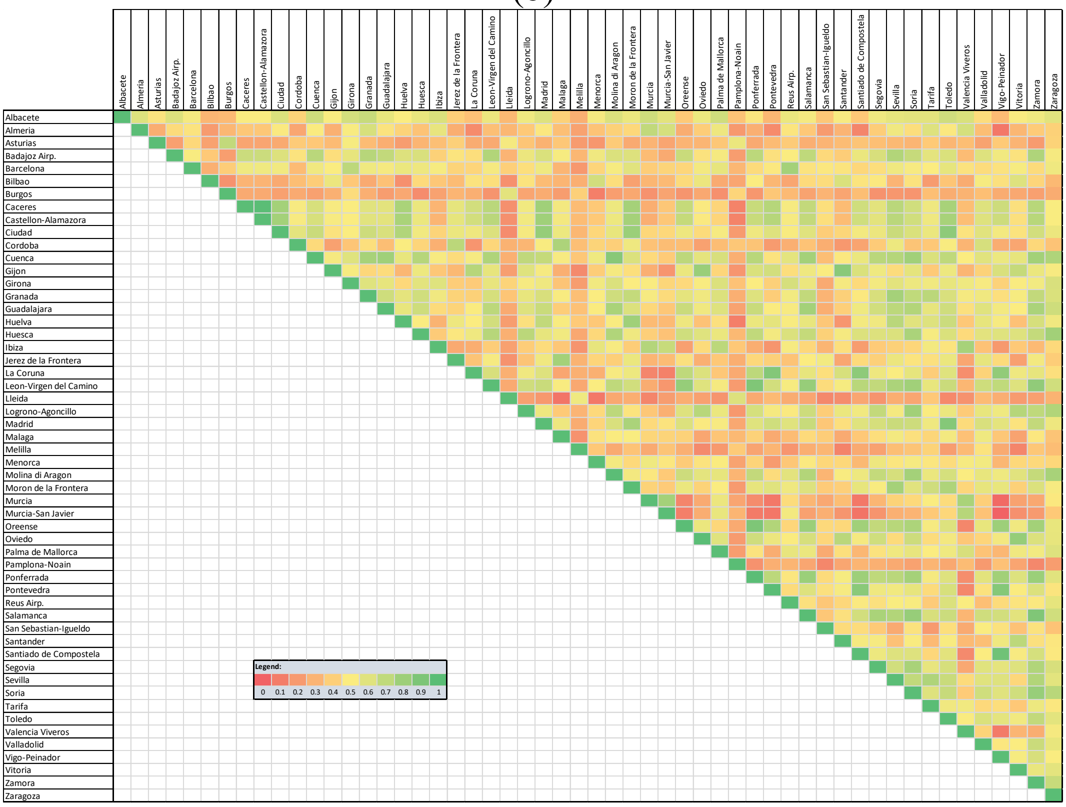
(b)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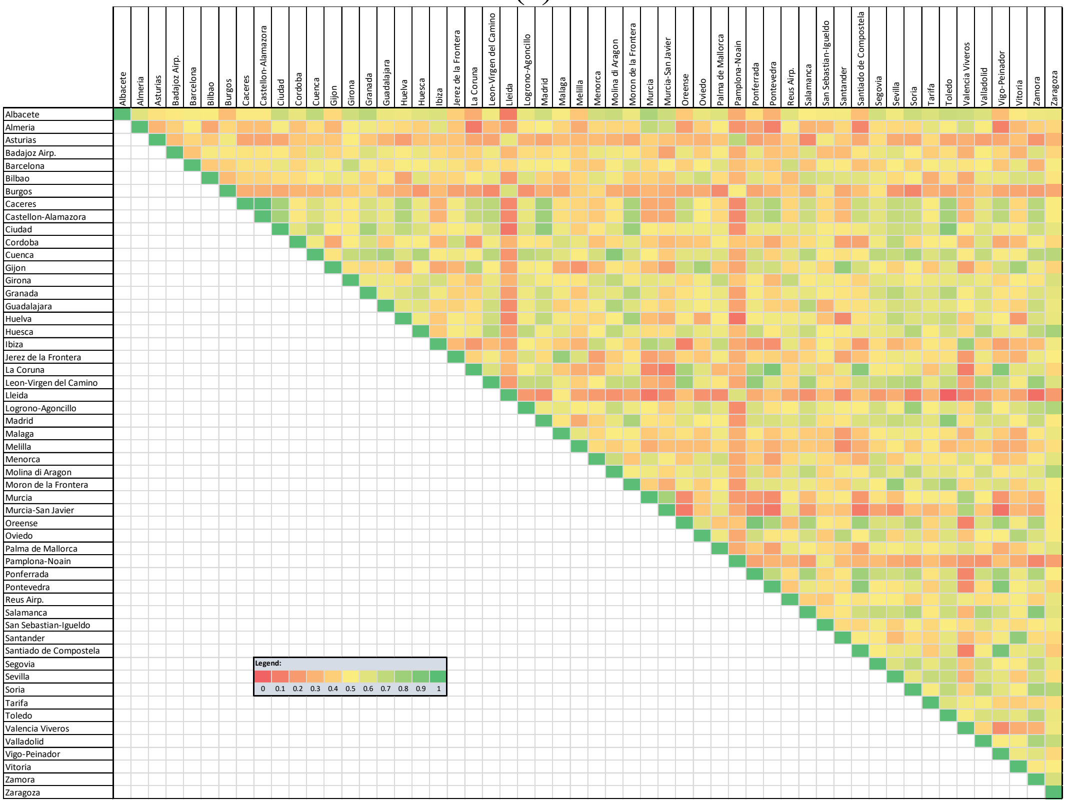
(c)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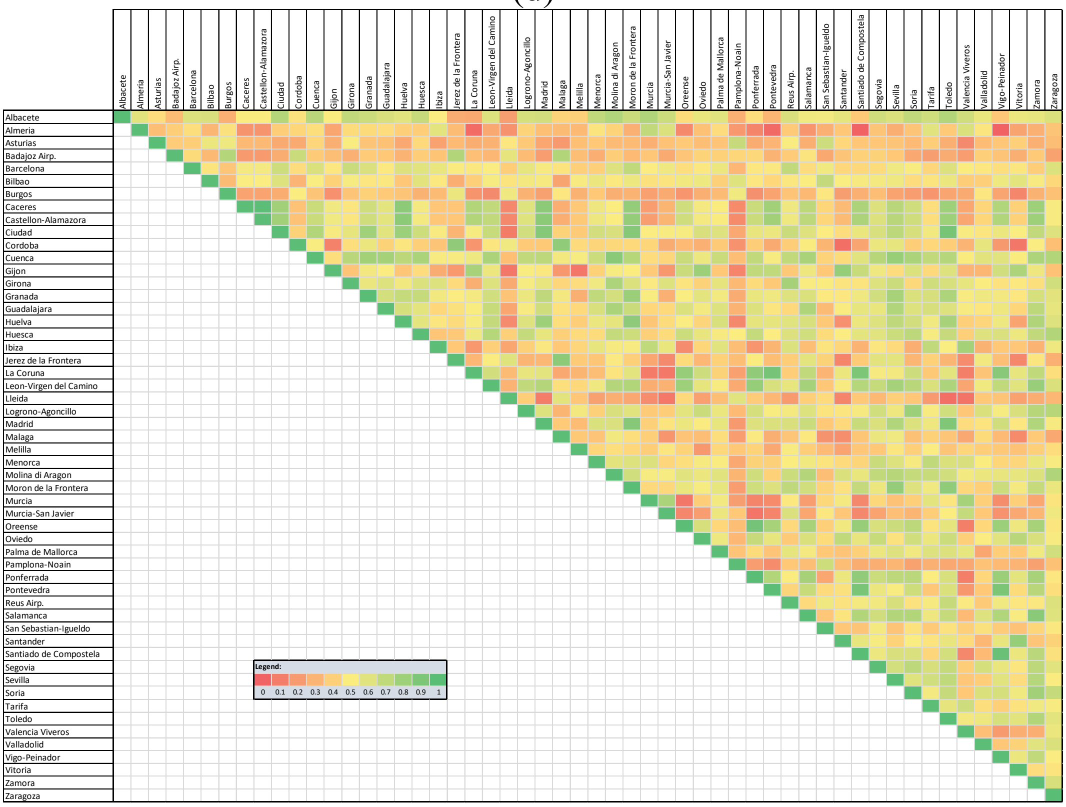
(d)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(e)

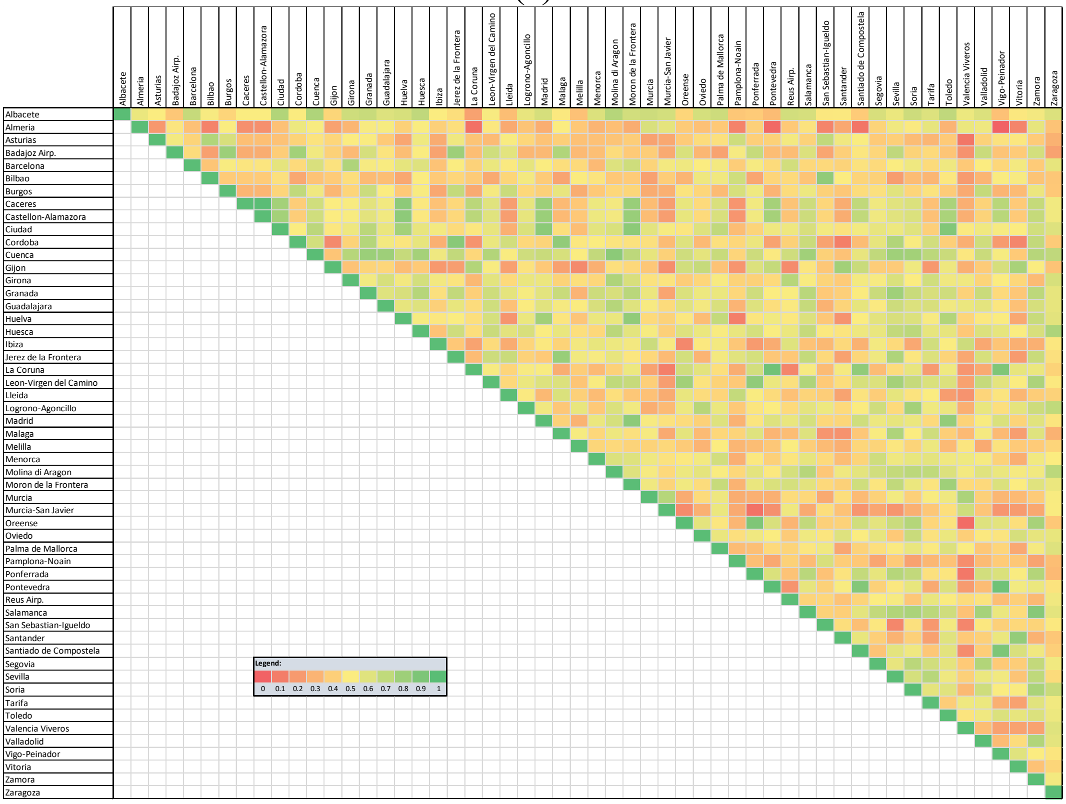

Fig. 12. Correlation coefficients between Spain stations for different time scales of RDI (1, 3, 6, 9, and 12 months) (a, b, c, d, and e)