# Direct impact of climate change on groundwater levels in the Iberian Peninsula

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**Correction Notice**: This is the accepted manuscript with the Figures in the correct order, which unfortunately were shuffled around in the published online version available at Science of the Total Environment Journal making it difficult to read.

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# Abstract

The Iberian Peninsula is a water-scarce region that is increasingly reliant on groundwater. Climate change is expected to exacerbate this situation due to projected irregular precipitation patterns and frequent droughts. Here, we utilised convolutional neural networks (CNNs) to assess the direct effect of climate change on groundwater levels, using monthly meteorological data and historical groundwater levels from 3829 wells. We considered temperature and antecedent cumulative precipitation over 3, 6, 12, 18, 24, and 36 months to account for the recharge time lag between precipitation and groundwater level changes. Based on CNN performance, 92 location-specific models were retained for further analysis, representing wells spatially distributed throughout the peninsula. The CNNs were used to assess the influence of climate change on future groundwater levels, considering an ensemble of eight combinations of general and regional climate models under the RCP4.5 and RCP8.5 scenarios. Under RCP4.5, an average annual temperature increase of 1.7°C and a 5.2% decrease in annual precipitation will result in approximately 15% of wells experiencing > 1-m decline between the reference period [1986-2005] and the long-term period [2080-2100]. Under RCP8.5, with a 3.8°C increase in temperature and a 20.2% decrease in annual precipitation between the same time periods, 40% of wells are expected to experience a water level drop of > 1 m. Notably, for 72% of the wells, temperature is the main driver, implying that evaporation has a greater impact on groundwater levels. Effective management strategies should be implemented to limit overexploitation of groundwater reserves and improve resilience to future climate changes.

# Keywords

water table depth, groundwater management, water scarcity, Mediterranean, groundwater sustainability, convolutional neural networks

# Highlights

- Data-driven assessment of climate change on groundwater in the Iberian Peninsula
- Deep learning (CNN) was used to create site-specific groundwater models
- Evaporation has a major influence on shallow groundwater levels
- Resilient groundwater management essential to mitigate climate change impacts

# 1. Introduction

Groundwater accounts for 99% of the planet's total liquid fresh water, serving as a strategic resource for multiple sectors, including drinking water, agriculture, and ecosystem services. Groundwater is the main source of fresh water for more than two billion people worldwide (Adams et al., 2022; Alley et al., 2002; Gleeson et al., 2012), making up more than 20% of global water usage and 43% of irrigation water (Earman and Dettinger, 2011; Zektser and Everett, 2004). With continued growth of the global population and projected changing climate, it is anticipated that groundwater’s contribution will rise as surface water resources become less dependable (Adams et al., 2022; Burchi and Mechlem, 2005; UN World Water Development Report., 2020)).

In the Iberian Peninsula, groundwater plays a vital role in supporting domestic and agricultural needs. Spain relies on an estimated 131 m³ of annual per capita extraction, with 30 m³ used for domestic purposes and 94 m³ for irrigation, while Portugal exhibits one of the highest global extraction rates at 474 m³ per capita, including 33 m³ for domestic use and over 420 m³ for irrigation (Margat and Gun, 2013). Groundwater has sustained essential water supplies, such as Porto's Paranhos spring system, in use since 1120 AD (Chaminé et al., 2010). The region's agri-food sector is critical to Europe's food security, with exports of olive oil, wine, and fresh products valued at €15 billion in 2022 (Eurostat and Cook, 2024; Moral-Pajares et al., 2024). These factors underscore the need for sustainable groundwater management amidst growing environmental challenges.

The hydrogeological conditions of the Iberian Peninsula are shaped by its diverse geological formations, variable climate, and historical fluctuations in precipitation and temperature. Groundwater is a vital resource for ecosystems, agriculture, and domestic supply in the region, with aquifers playing a crucial role in storing and regulating water. The peninsula features both shallow and deep aquifers, with shallow systems averaging 36 m in depth, making them particularly vulnerable to climatic variability. Deeper aquifers, often semi-confined, provide more stable freshwater reserves, capable of buffering against short-term climatic changes. However, they are susceptible to long-term anthropogenic and climatic pressures (Diodato et al., 2024; Estrela et al., 2024).

The geological diversity of the peninsula includes porous, fractured, and karstic aquifer systems, each with distinct hydrogeological properties. In regions like Castile and León, the aquifer system consists of an unconfined upper layer and a semi-confined deeper layer, forming a complex 3D network. Recharge in these systems primarily occurs through meteoric infiltration, with rivers such as the Duero acting as major discharge outlets. Karstic aquifers, characterized by high permeability due to dissolution features in limestone and dolomitic formations, are critical for water storage and flow. These systems are particularly sensitive to variations in precipitation and anthropogenic extraction, which influence their recharge and discharge dynamics. Extensive groundwater pumping in many areas, such as Castile and León, has led to significant declines in water table levels, highlighting the challenges of balancing extraction with natural replenishment (Diodato et al., 2024; García-Valdecasas Ojeda et al., 2021).

The interplay of geological diversity, shallow aquifer vulnerability, and climatic variability underscores the complexity of groundwater dynamics in the Iberian Peninsula. Sustainable management efforts must account for the unique geological characteristics of these aquifers, along with their sensitivity to climatic influences, to ensure the resilience of water systems that are critical for the region's ecosystems and human livelihoods (Estrela et al., 2024; García-Valdecasas Ojeda et al., 2021).Recent studies highlighted the increasing stress on groundwater resources caused by climate change, heatwaves, and human activity, affecting both groundwater quantity and quality. Due to climate change and water scarcity, Catalonia in the western Mediterranean region of the Iberian Peninsula is experiencing a severe drought and increased groundwater nitrate pollution (Mas-Pla and Menció, 2019). Groundwater in the peninsula is also important for various ecosystems, particularly in the Mediterranean area. Groundwater uptake predominates during the dry summer months, impacting different groundwater-dependent ecosystems. For instance, in Quercus suber forests, which cover substantial portions of the Iberian Peninsula, groundwater accounts for 73.2% of tree transpiration (Pinto et al., 2014). As climatic variability rises and water quality deteriorates, the need for sustainable water management grows, especially in semi-dry climate regions like the Iberian Peninsula (Grantham et al., 2008).

The southeastern corner of the Iberian Peninsula is expected to be one of the regions most affected by climate change in Europe (Carvalho et al., 2021). Model predictions indicate that the Mediterranean region, and particularly the Iberian Peninsula, will receive less precipitation while temperature distributions are expected to shift toward higher mean (+2°C) and maximum (+4°C) temperatures by the end of the century under the RCP8.5 scenario, along with increased drought frequency and duration (Pereira et al., 2021). Moreover, future climate change is predicted to worsen water stress and it's severity in the Mediterranean area (Strada et al., 2023). Climate change in Portugal is expected to significantly affect temperature and precipitation patterns, potentially severely impacting crops such as vineyards (Wunderlich et al., 2023).

Machine learning (ML) is a powerful prediction tool for modelling groundwater level fluctuations because of its ability to handle complex and nonlinear relationships between explanatory variables and groundwater changes. Furthermore, it can be used to assess the uncertainty of model outputs (Ahmadi et al., 2022; Seifi et al., 2020). In a study comparing ML and numerical models for simulating groundwater dynamics, it was shown that multilayer perceptron (MLP), radial basis function (RBF), and support vector machine (SVM) methods can perform as well or better than physically based numerical models, such as MODFLOW (Chen et al., 2020). Also, artificial neural networks (ANN) are effective tools for forecasting changes in groundwater levels (Guzman et al., 2017; Jeong and Park, 2019; Müller et al., 2021; Wunsch et al., 2021; Zhang et al., 2020). Wunsch et al. (2021) recently showed that 1D-convolutional neural networks (CNNs) outperform long short-term memory (LSTM) models in terms of accuracy and calculation speed for simulating groundwater levels. CNNs exhibited superior adaptability and consistency compared to nonlinear autoregressive models with exogenous inputs (NARX) models. Because of their demonstrated precision, efficiency, reliability, and versatility in handling diverse temporal patterns, CNNs were selected for the present study. They excel at capturing both short-term fluctuations and long-term seasonal trends, making them well-suited to model the direct effects of climatic factors on groundwater systems. Their ability to efficiently process large datasets, identify complex hierarchical features, and adapt to various temporal scales enhances their reliability for tasks involving spatially and temporally distributed data across the Iberian Peninsula. Additionally, CNNs' computational efficiency, stemming from their weight-sharing mechanism, minimizes overfitting risks while optimizing resource usage on modern GPUs, further justifying their selection for this extensive regional-scale analysis.

Before investigating the indirect effects caused by regional and local human activities, which certainly have a significant impact, it is crucial to first focus on the broader climate-driven influences. Only the wells that appear to be unaffected by human activities will be considered as the projections rely solely on meteorological variables. This approach is based on the expectation that future changes in temperature and precipitation will be primary drivers of groundwater behaviour. For example, on the Iberian Peninsula, significant fluctuations in precipitation and temperature have already influenced groundwater recharge and availability (Diodato et al., 2024), highlighting the importance of understanding climate-driven impacts for sustainable groundwater management. In this study, we investigate the impact of climate change on groundwater levels, using temperature and cumulative precipitation as explanatory variables, referred to hereafter as the direct impact of climate change. The direct impact of climate change on groundwater is evident through various mechanisms, such as increased temperatures leading to higher evaporation rates, reducing surface water availability, and subsequently decreasing groundwater recharge (Cuthbert et al., 2019). Climate change, characterized by rising temperatures, altered precipitation patterns, and increased frequency of extreme weather events, has a profound impact on the global hydrological cycle. Changes in precipitation patterns, with some areas experiencing prolonged droughts and others intense rainfall, can disrupt the natural replenishment of aquifers (Neidhardt and Shao, 2023). This disruption is particularly critical in regions like the Mediterranean, where future warming is expected to exceed global rates, significantly affecting water availability (Cramer et al., 2018).

Below, we use the CNN deep learning methodology of Wunsch et al. (2022) to forecast groundwater level changes. Our focus on understanding climate change impacts, so the models are driven by gridded meteorological data. We apply it at various locations within the Iberian Peninsula using an extensive database comprising 3829 wells with monitoring durations from 4 to 596 months. This approach allows us to evaluate how groundwater levels may evolve under different representative concentration pathway (RCP) scenarios. The specific objectives are to (i) evaluate the future direct climate change impact (without considering the local human activities) on groundwater under the RCP4.5 and 8.5 scenarios for three time periods: near- [2021-2040], mid- [2041-2060] and long-term [2081-2100], (ii) explore the best explanatory variables including temperature and cumulative precipitation computed for different antecedent time lags (3, 6, 9, 12, 18, 24, and 36 months), and (iii) identify the groundwater systems that are mainly controlled by climate forcing.

# 2. Materials and Methods

## 2.1. Data

We used a gridded dataset of daily precipitation and temperature over Iberia (Herrera et al., 2019, 2016) for historical climate data. Precipitation is considered a proxy for groundwater recharge, while temperature is a proxy for evapotranspiration. Furthermore, temperature has a distinct yearly cycle, which supplies the models with vital information on seasonality. This dataset (referred to as Iberia01), developed using data from 3156 monitoring stations, consists of daily precipitation and temperature data at a 0.1° regular resolution across the Iberian Peninsula from 1971 to 2015. The meteorological influence at each well location was determined as the average precipitation and temperature values from the nine surrounding grid cells of the Iberia01 dataset to reduce the uncertainty. Other weighting schemes were assessed but were found to have little influence on the results.

For historical groundwater data in Spain, we used data provided by the Ministry of Ecological Transition and Demographic Challenge, which hosts a piezometric monitoring network (https://sig.mapama.gob.es/redes-seguimiento/, last accessed 11 November 2024, data were downloaded with a web scraping code in early 2020). In Portugal, groundwater data is managed in a national hydrologic information system (https://snirh.apambiente.pt/, last accessed 11 November 2024). The data consist of records with variable durations, from 4 to 596 months and frequencies, from monthly to bimonthly water table depth (WTD) measurements in both country databases as meters below ground level (m b.g.l.). For consistency, data were downloaded in early 2020. The analysed data comprised 940 wells in Portugal and 2889 wells in Spain, giving a total of 3829 wells. **Figure 1** depicts the distribution of wells over the Iberian Peninsula along with their associated geological formations, with the Köppen climate classification (Cui et al., 2021) shown in the background.

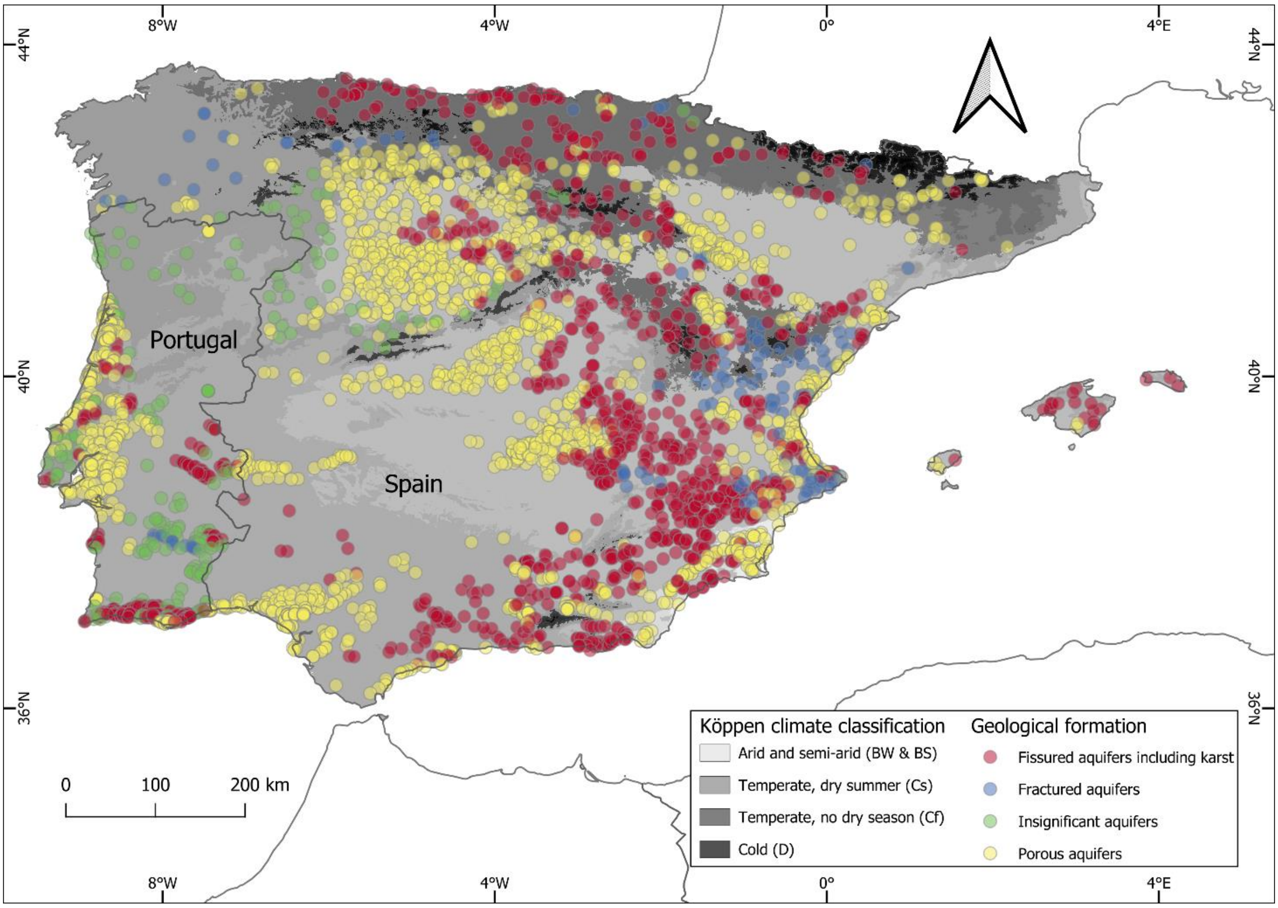


***Figure 1**. Spatial distribution and geological formation of the 3829 groundwater level wells in the Iberian Peninsula.*

## 2.2. Climate projections

For climate projections of daily precipitation and temperature, we utilised an ensemble of eight combinations of general circulation models (GCMs) and regional climate models (RCMs) from the Euro-Cordex initiative (Jacob et al., 2012), as delineated in **Table 1.** The spatial resolution of the climate model data is 0.1° (EUR-11 grid), closely resembling that of the historical dataset (Iberia01). These climate projections cover the period from 1950/1970 to 2100, comprising a historical simulation until 2005 and the model predictions from 2006 to 2100.

Precipitation and temperature climate projections for each GCM/RCM combination were initially interpolated onto the Iberia01 grid and then subjected to bias correction, using a distribution mapping approach (D'Oria et al., 2017; Teutschbein and Seibert, 2012), based on the observed data from the period 1976-2005 (further details are given in **Supplementary Material**, Bias correction). The bias-corrected climate projections for the period 1976-2100 were obtained for RCP4.5 and 8.5.

***Table 1.** Ensemble of eight Euro-Cordex combinations of general circulation models (GCMs) and regional climate models (RCMs) (M1-8) used for climate projections.*

| Abbreviation | GCM-RCM combinations |
|---|---|
| M1 | CNRM_CERFACS_CNRM_CM5_CCLM4_8_17 |
| M2 | DMI_HIRHAM5_NorESM1-M |
| M3 | ICHEC_EC_EARTH_HIRHAM5 |
| M4 | IPSL-INERIS_WRF381P_IPSL-CM5A-MR |
| M5 | KNMI_CNRM-CM5 |
| M6 | MPI_M_MPI_ESM_LR_RCA4 |
| M7 | ICHEC-EC-EARTH_RACMO22E |
| M8 | IPSL_IPSL_CM5A_MR_RCA4 |

## 2.3. Data selection and outlier removal

The raw WTD data consisted of a total of 3829 time series. Inspection of the raw data revealed that 21 wells lacked valid measurements and were eliminated from the database. For the purpose of training the deep learning models, the datasets were first screened based on two criteria: the total number of measurements in each time series and the percentage of missing measurements. Specifically, we only included datasets with less than 50% missing data and at least 120 valid measurements, which yielded 1205 wells for analysis. This technique ensured that the models were trained on the most extensive datasets available.

Outlier detection approaches are classified into two types: test discordance methods and labelling methods (Muthukrishnan and Poonkuzhali, 2017). Most outlier detection systems consider extreme values to be outliers. In this work, outliers were identified using the generalised extreme studentized deviate (ESD) test (Rosner, 1983) and excluded from model training. Among the most common outlier removal methodologies, the ESD method was used because it only needs as input an upper bound for the suspected number of outliers (Heckert et al., 2002). We chose the value of 10 for the maximum number of outliers for each time series, as suggested in the guidance for the PyAstronomy (Czesla et al., 2019) Python package.

## 2.4. Model

We expanded on Wunsch et al. (2022), who only used temperature and precipitation as explanatory variables, by incorporating accumulated precipitation over various time periods (3, 6, 12, 18, 24, and 36 months) as additional variables. The convolutional neural networks (CNNs) used include layers designed to optimize model performance and prevent overfitting. We applied techniques like Monte-Carlo dropout, gradient clipping, and early stopping to improve model accuracy and robustness. Bayesian optimization was used to fine-tune the model's hyperparameters, and the entire process was built using Python and several key machine-learning libraries such as TensorFlow, Keras, and Scikit-Learn (further model description is given in **Supplementary Material**, Models setup).

## 2.5. Training and hyperparameter optimization

After finishing the pre-processing, we optimized key hyperparameters such as the number of filters, batch size, sequence length, and dense layer size. To do this, we used monthly WTD data from 1974 to 2015 and weather data, and split the time series into four sets: training, validation, optimization, and testing. The test period was always a four-year stretch, and adjustments were made when the data series ended early. The first 80% of the data before 2012 was used for training, and the rest was split evenly for validation and optimization during hyperparameter tuning. (**Figure 2a**) (Wunsch et al., 2022).

A maximum of 150 epochs was set for optimisation, stopping after 15 steps without improvement, provided at least 60 iterations had been performed. The data were scaled in the range [-1,1] and 10 different CNNs were built with randomly initialised weights. For each of the ten CNNs, we used Monte-Carlo dropout to estimate the model uncertainty from 100 realisations. The 95% confidence interval was then calculated using 1.96 times the standard deviation of the resultant distribution for each time step. To assess the model's accuracy, we computed various performance metrics, including the Nash-Sutcliffe efficiency (NSE), squared Pearson r ($R^2$), absolute and relative root mean squared error (RMSE, rRMSE), and absolute and relative Bias (Bias, rBias). The hyperparameters and test results are shown in **Figure 2c** for the well in the location indicated in **Figure 2b**.

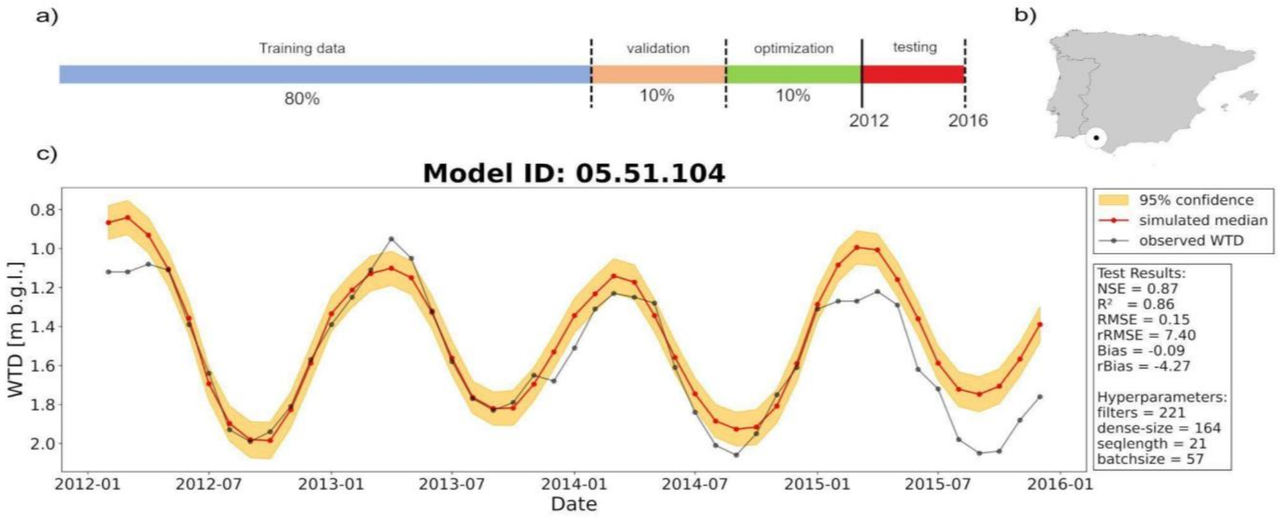


***Figure 2. a**) Time series splitting scheme for training (80%), validation (10%), optimization (10%), and testing (last four year) periods. **b**) Approximate location of the well in the region. **c**) Hyperparameters and model's performance using several statistical metrics for a random well (ID 05.51.104) during the test period [2012-2016].*

## 2.6. Filtering models based on test results

CNNs were constructed for 1205 wells and filtered based on $R^2$ and NSE. Aimed at retaining those wells that could really be explained with temperature and precipitation, only those CNNs with NSE $\geq 0$ and $R^2 \geq 0.5$ were retained, resulting in a final selection of 170 wells. **Figure S1** (**Supplementary Material**) presents a scatter plot showing the NSE and $R^2$ values for all locations, highlighting the selected ones.

## 2.7. Model evaluation

A plausibility test of the 170 CNN models was performed by analysing their behaviour for explanatory variable values outside the range of the training data. We retrained all models with hyperparameters from Section 2.6 and data until 2016. Data time series were divided into two parts: 80% for training and 20% for early stopping.

The retrained models were used to simulate well evolution assuming four times the precipitation and a uniform 5°C temperature rise with respect to the historical data in the training set (Duan et al., 2020) (**Figure 3a**). As expected, higher precipitation and temperatures produce larger oscillations in WTD. SHapley Additive exPlanations (SHAP) were used to identify how each explanatory variable contributes to the model's prediction for a specific instance. **Figure 3b** shows a SHAP summary plot for one of the wells (typical results shown). Each dot corresponds to one of the times over which the prediction is performed. A positive SHAP value indicates that a given feature drives the prediction above its average, and a negative one, the contrary. The larger the SHAP magnitude, the more important the feature is to explain the model prediction.

Thus, the results in **Figure 3b** show that elevated temperatures, which tend to induce larger evapotranspiration, result in a rise in WTD (i.e., depletion of groundwater levels), whereas high precipitation, which produces more recharge, drives WTD to decrease (groundwater recharge). The SHAP values are consistent with known aquifer responses to changes in meteorological forcing.

In this phase, we assessed all 170 models using results from extreme conditions to ensure the stability of the models and analysed SHAP summary plots to confirm that the direction of the explanatory variables aligned with physical understanding of the groundwater system. Additionally, we evaluated the models based on rBias and rRMSE, ensuring that both metrics fell within a ±25% range. Models that did not meet these criteria were eliminated. Following this comprehensive evaluation, 92 wells were selected for further analysis.

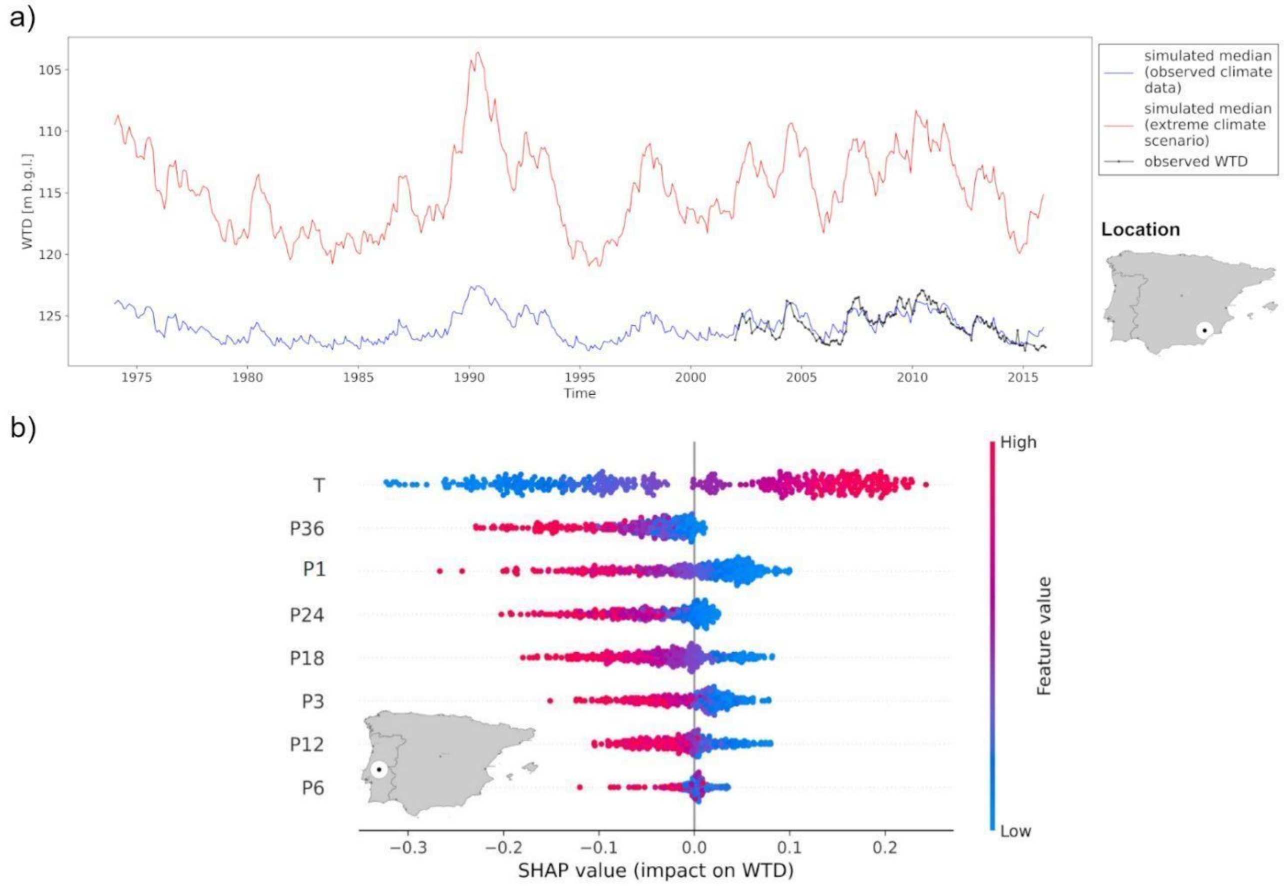


***Figure 3. a**) Plausibility Check under extreme conditions for a typical well (ID 07.26.001). Model output under an artificial extreme climate scenario in the past (1974 - 2015) along with the location of the well. **b**) SHAP summary plot for well (ID 331.89) and its approximate location. [P1, P3, ..., P36] are accumulated precipitation values for [1, 3, ..., 36] months and T is the average monthly temperature.*

## 2.8. Model selection

To analyse the impact of climate change on groundwater in the Iberian Peninsula, we focus on the 92 best-performing CNN models. These models are those for which the CNNs were able to predict groundwater fluctuations in response to temperature and precipitation data; this behaviour could be interpreted as that the 92 retained CNN wells were mainly controlled by climate variables. The **Supplementary Material** (**Figures S2-S93**) contains the results of the hyperparameter optimization test, extreme conditions, and SHAP summary plots for all 92 wells.

At the next step, we forecasted the WTD for each well using the eight Euro-Cordex models (M1-M8) in **Table 1** for two distinct climate change scenarios—RCP4.5 as the best-case scenario and RCP8.5 as the worst-case. This yields a total of 16 projection outcomes for each well (eight for each RCP scenario).

## 2.9. Evaluation of results

Following the projections for the 92 retained models, we examined changes in WTD along with a detailed analysis of their depths and historical trends. The changes were calculated using the following process: For each climate scenario, the annual median values from the eight models were first calculated. The average of these median values for both the 20-year reference period and the 20-year future projection period were computed, and the difference between these two averages represents the reported change. The equation used was:

$$\Delta WTD = \frac{1}{20}\sum_{y=1}^{20}\left(med\left(WTD_{y,M1},\dots,WTD_{y,M8}\right)\right)_{fut} - \frac{1}{20}\sum_{y=1}^{20}\left(med\left(WTD_{y,M1},\dots,WTD_{y,M8}\right)\right)_{ref}$$

where $\Delta WTD$ is the change displayed in the figure, $med(WTD_{y,M1}, \ldots, WTD_{y,M8})$ denotes the median WTD from the eight different models (M1-M8) for year *y,* and the summation refers to the averaging over the 20-year time period considered (*ref:* refers to the reference period [1986-2005], while *fut:* refers to the future periods [2021-2040], [2041-2060] or [2081-2100] which corresponds to short-, mid- and long-term, respectively).

Additionally, we examined the significance of aquifer depth on the climate change impact. We used the maximum historical water table depth for each well as an indicator to classify them considering a depth threshold of 50 m for shallow aquifers,

As previously stated, our models focus solely on climatic data, specifically the direct impact of climate change on groundwater levels, with precipitation and temperature being the primary direct drivers (Taylor et al., 2012; Wu et al., 2020). We used the Mann-Kendall test considering 5% significance level ($P < 0.05$) to evaluate trends in the historical groundwater level data for the same period as in model training. We performed the modified Mann-Kendall test with the Trend-Free Pre-Whitening method proposed by Yue and Wang (2002) to mitigate the effects of serial correlation.

# 3. Results

Analysis of yearly average temperature and precipitation data for the reference period [1986-2005] and the long-term period [2081-2100] reveals notable changes under both the RCP4.5 and RCP8.5 scenarios. The yearly average temperature under RCP4.5 is projected to increase from 15.0°C during the reference period to 16.7°C in the long-term period, a rise of 1.7°C. Under the more extreme RCP8.5 scenario, the yearly average temperature is projected to increase by 3.9°C from 15.0°C to 18.9°C (**Figure 4a**).

The yearly average precipitation is projected to decline for both scenarios. Under RCP4.5, the annual precipitation decreases from 624 mm in the reference period to 592 mm in the long-term period, with an absolute decrease of 32.8 mm, equivalent to a 5.2% reduction. The RCP8.5 scenario exhibits a more pronounced decline, with the annual precipitation decreasing from 624 mm to 498 mm, representing an absolute decrease of 126 mm, or 20.2% (**Figure 4b**).

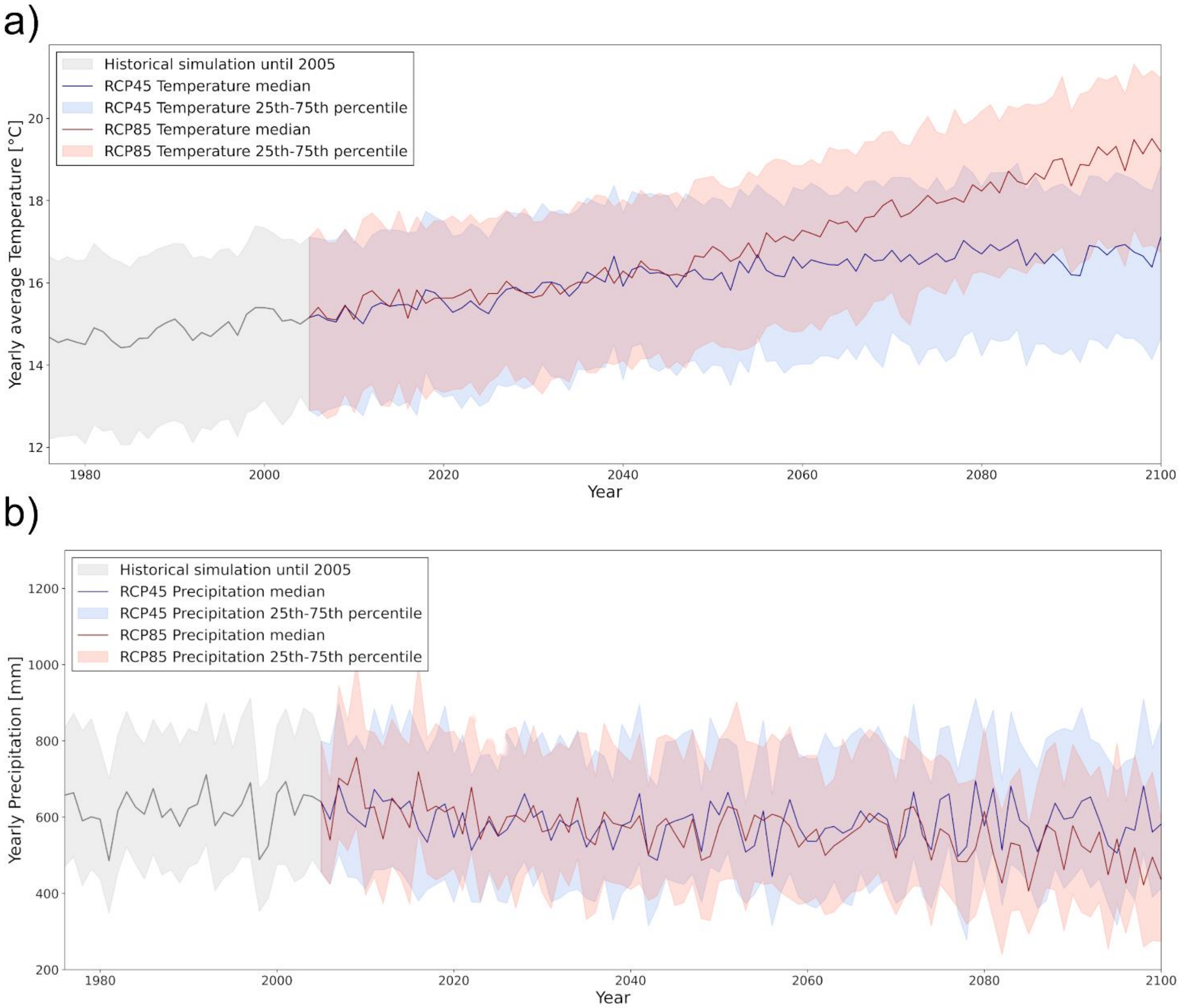


***Figure 4.*** *a) Median line and uncertainty band of temperature projection data of 92 well locations and eight ensemble climate projection models under the RCP 4.5 and 8.5 scenarios. b) The same results for annual precipitation.*

**Figure 5a** presents a heatmap of the projected WTD for a typical well (ID: 594.34) from 2020 to 2100. This figure compares predictions from eight different climate models under two RCP scenarios. The top row corresponds to the RCP4.5 scenario, and the various model predictions while the lower row corresponds to the RCP8.5 scenario. Under the RCP4.5 it is observed that most models indicate a relatively stable condition by not showing intense red tones in the long-term period [2080-2100] in water levels, except model M2 that shows a more extreme drop in groundwater levels towards the end of the century. The difference in model simulations (M1-M8) underscores the uncertainty level associated with climate change projection.

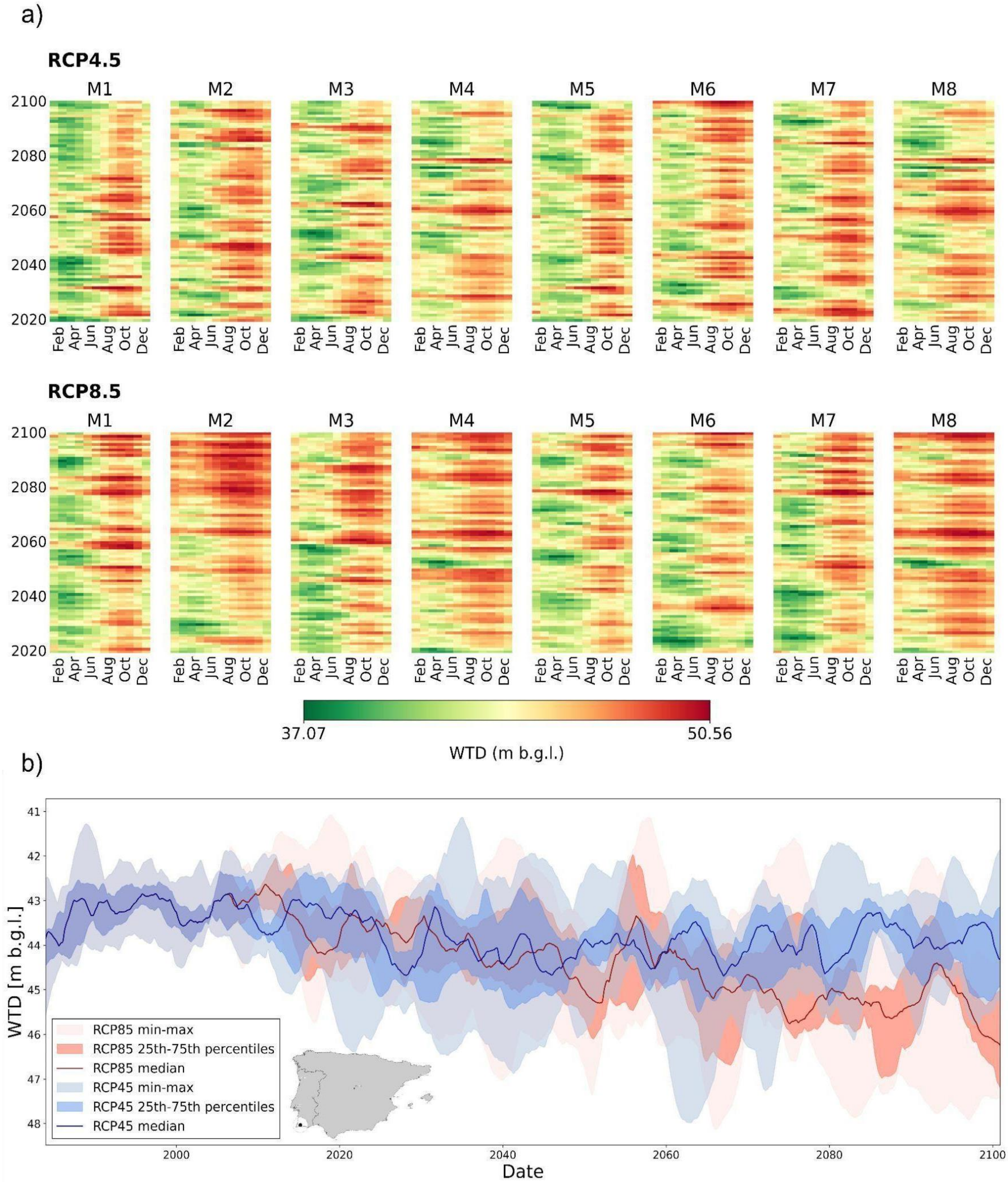


***Figure 5. a****) Heatmaps of water table depth (WTD) for a typical well (ID 594.34) under different climate scenarios (see Table 1). The top row represents RCP4.5, and the second row represents RCP8.5. The heatmaps cover the simulation period from 2020 to 2100 for each climate model projection within the respective scenario.* ***b****) Projections of WTD until 2100, showing the 5-y moving average, 25th-75th percentile range, and min-max range of the median values from eight models for both RCP4.5 and RCP8.5. The approximate location of the well is indicated in the map next to the legend.*

Unsurprisingly, under RCP8.5 (second row in **Figure 5a**), the influence of climate change on groundwater levels is more pronounced than for RCP4.5. The deviation between the RCP4.5 and RCP8.5 predictions begin in the mid-term period [2041-2060] and intensifies as the long-term period [2081-2100] approaches. It is evident that the M2 model shows the greatest decline in groundwater levels compared to other models, which is also observed for RCP4.5 scenario in the long run. As might be expected, all models exhibit the most significant impact during the long-term period [2081-

2100]. To assess the uncertainty associated with future scenarios and model predictions, **Figure 5b** presents the median, 25th-75th percentile interval, and min-max range obtained from the ensemble of climate models for both scenarios. To smooth the results, we computed all these statistics based on a 5-y moving average of the predictions. **Figure 5b** indicates that, despite variations, the medians of the two scenarios are comparable and relatively stable between 2006 and 2060, after which they begin to diverge from each other with the largest differences toward the end of the century. In the **Supplementary Material** (**Figures S94–S185**), heatmaps and predictions for all 92 wells are provided.

**Figure 6** illustrates the magnitude of the predicted changes during each of the three analysed periods under the two RCP scenarios. The results show that under the RCP8.5 scenario, changes are more pronounced than under RCP4.5. For the RCP8.5 scenario, the magnitude of the WTD changes tends to escalate as the century progresses, with the most significant changes occurring in the long-term period. On the other hand, for the RCP4.5 scenario, there is no clear trend, and for some wells, the long-term changes are even smaller than the mid- and short-term ones.

Each well in **Figure 6** is represented by a set of three bars, each indicating the absolute changes in WTD from the reference period [1986-2005] to the respective future time periods. The bars correspond to the short-term [2021-2040], mid-term [2041-2060], and long-term [2081-2100] periods.

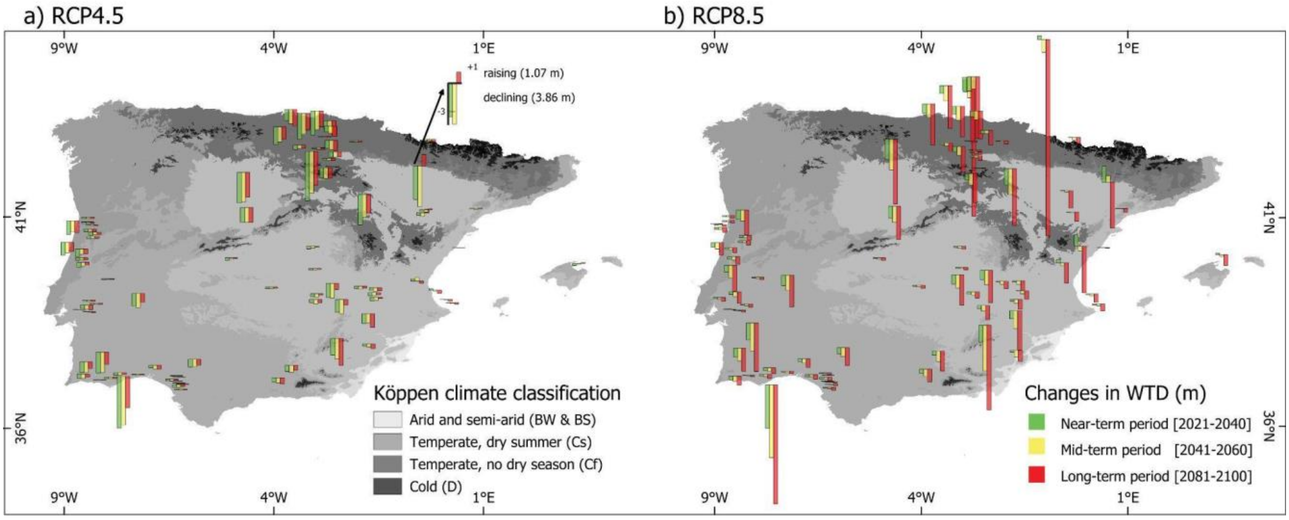


***Figure 6.*** *Bar charts of WTD changes under RCP4.5 (a) and RCP8.5 (b) during the near-term [2021-2040], mid-term [2041-2060] and long-term [2081-2100] periods compared to the reference period [1986-2005].*

Results in **Figure 7a, b** show changes only in the long-term period under both climate scenarios. Under the RCP4.5 scenario, 10.9% of the wells show a rise between 0 and 2 m (the highest rise is 1.5 m for well 09.821.002, see the location in the figure), while the rest of the wells display a decline. This decline is between 0 and 1 m for 73.9% of the wells, 15.2% of the wells show drops > 1 m with the highest predicted decline being 3.2 m for well 09.104.005. In comparison, under the RCP8.5 scenario, a smaller fraction of wells (5.0%) shows a rise (the highest rise is 0.7 m for well 09.106.004), while the rest display a decline. This decline is between 0 and 1 m for 55.0% of the wells, 40% shows drop > 1 m with the highest predicted decline being 18.8 m for well 09.801.003.

The histograms of the changes are shown in **Figure 7c** for both scenarios. The result clearly illustrates that the range of WTD changes under RCP4.5 is narrower than that for RCP8.5 and that the median for RCP4.5 is smaller than for RCP8.5, resulting in a more skewed distribution for RCP8.5 than for RCP4.5.

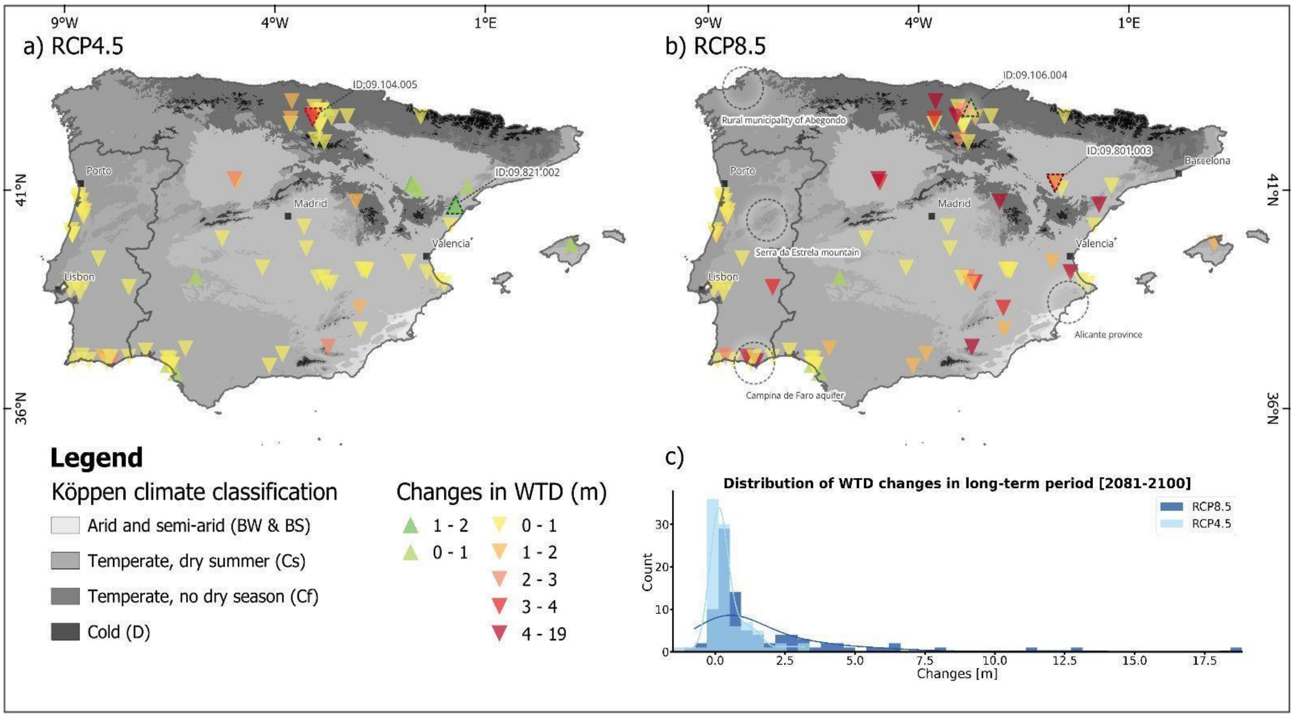


*__Figure 7.__ WTD changes in under RCP4.5 (__a__) and 8.5 (__b__) during the long-term period [2081-2100] compared to the reference period [1986-2005]. __c__) Comparison between RCP8.5 and RCP4.5 histogram of changes in both scenarios.*

As described in the methodology section, eight explanatory variables: temperature and cumulative precipitation over periods ranging from 1 to 36 months. Utilising SHAP values with each CNN model, we identified the dominant driver of groundwater level changes. In more than 70% of the models, temperature is the most influential driver, implying that evaporation has a greater impact on groundwater levels than precipitation.

The significance of aquifer depth was further examined in relation to climate change impacts. Among the 92 studied wells, 20 have depths greater than 50 m, with 7 of these exceeding 100 m. The average depth across all wells is 36 m, and the deepest water table reaches 290 m, based on historical records. This depth distribution may modulate how temperature and precipitation influence groundwater levels across varying depths (**Figure 8a, b**). Notably, almost 90% of the wells exhibited no trend during the training period considered (**Figure 8c, d**).

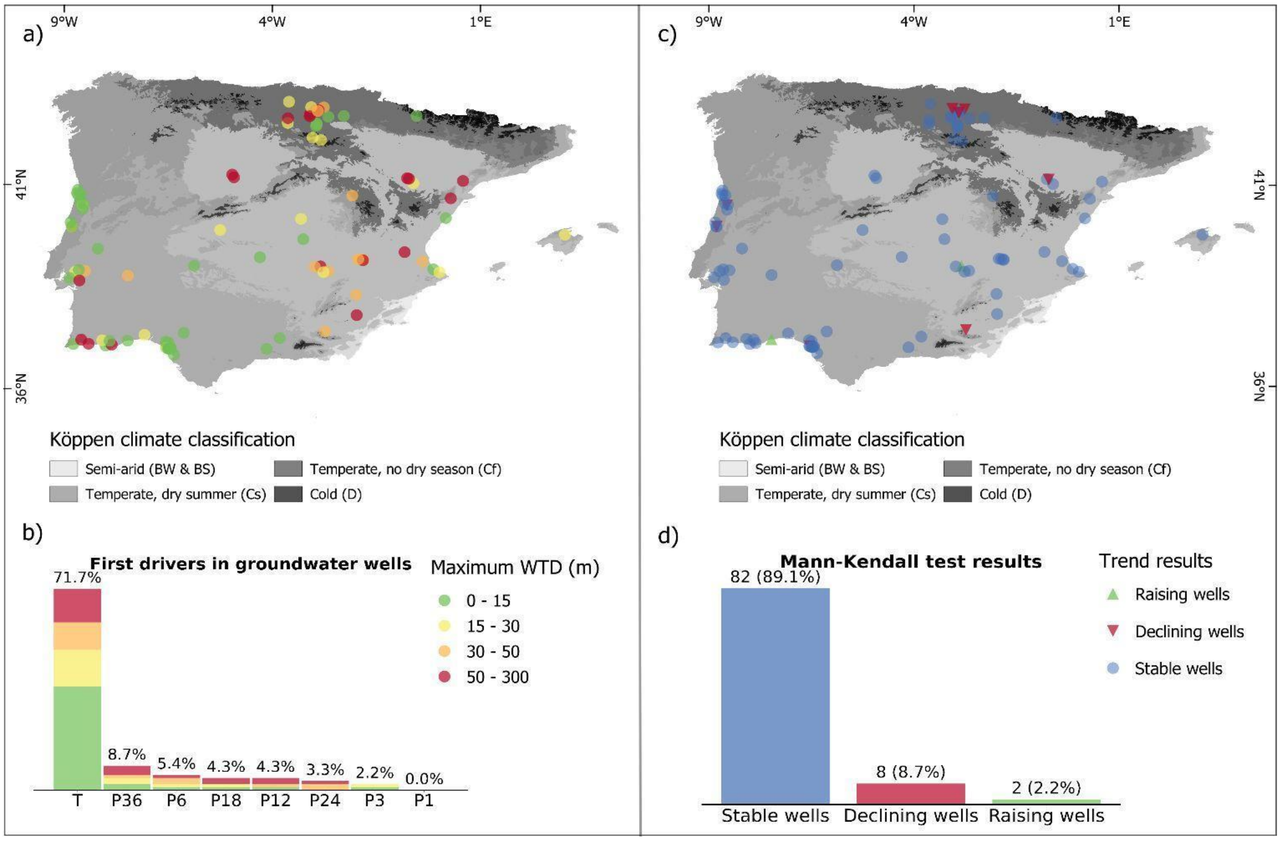


***Figure 8.*** ***a***) *Classification of 92 selected wells based on the maximum water table depth (WTD) during the historical period, with* ***b***) *the stacked bar chart representing the dominant explanatory variable (temperature) based on SHAP value results.* ***c***) *Modified Mann-Kendall test results based on the yearly historical data used for the training period.* ***d***) *Bar chart showing the trend analysis results.*

# 4. Discussion

Despite historically stable or increasing groundwater levels over recent decades (Chávez García Silva et al., 2024; Scanlon et al., 2023), projections from this study under the RCP4.5 and RCP8.5 climate scenarios suggest significant potential declines. These scenarios underscore the increased vulnerability of shallow groundwater to the impacts of climate change in the Iberian Peninsula (Barredo et al., 2018).

## 4.1. Importance of small changes

Although a groundwater decline of 1 m might not seem significant in a period of around 90 y, it is important to note that the models only consider the direct impact of climate change on groundwater levels. Climate change can directly impact groundwater levels through changes in precipitation patterns and intensity (Barredo et al., 2018), and a decrease in precipitation can lead to reduced groundwater recharge, resulting in lower groundwater levels. Similarly, lower levels are likely for temperature increases due to greater evapotranspiration and reduced soil moisture (Hunkeler et al., 2022; Odwori, 2022). Climate change can also indirectly affect groundwater levels through changes in land use and domestic as well as crop/vegetation water demand. As the climate changes, agricultural practices and water usage patterns may shift, potentially resulting in increased groundwater extraction for irrigation. This overexploitation of groundwater resources can lead to significant additional declines in groundwater levels (Davamani et al., 2024; Khoso et al., 2024). Changes in groundwater levels can greatly affect the ecological services provided by groundwater and its sustainable management. This is particularly true for ecosystems that rely on groundwater during low-flow conditions when it becomes scarce. Changes in groundwater depth can impact soil properties, which can subsequently alter surface vegetation characteristics (Dong et al., 2023;

Scanlon et al., 2023). In the Iberian Peninsula, groundwater depletion can significantly affect soil moisture dynamics and evapotranspiration fluxes, particularly in shallow water table regions where groundwater is hydraulically connected to the upper soil through upward capillary fluxes (Llamas et al., 2015). Although we consider only the direct impact of climate change on groundwater levels, it is important to recall that foreseen circumstances such as lengthy droughts (Gómez-Martínez et al., 2021) would potentially lead to over-pumping of groundwater to cope with water stress resulting in further drop in water levels (Taylor et al., 2012). In summary, the changes we forecast are the minimum ones, and they will be worsened by other actions induced by climate change.

## 4.2. Similar previous studies

Several studies have investigated the impact of climate change on groundwater levels within specific aquifers in the Iberian Peninsula, whereas our study examines the entire region. For instance, Samper et al. (2022) used a semi-distributed water balance model to assess changes in groundwater recharge in the municipality of Abegondo in Galicia, Spain (annotated in **Figure 7b**), projecting a reduction in recharge by 6-10% by the end of the century. Similarly, Costa et al. (2021) evaluated the Campina de Faro aquifer in southern Portugal using a 3D groundwater flow and nitrate transport model (FEFLOW), finding that climate change, along with agricultural practices, could lead to groundwater depletion and potential salinization. In another study, Moutahir et al. (2017) utilized the VISUAL-BALAN model in a Mediterranean region of southeastern Spain, forecasting decreases in groundwater recharge and streamflow, particularly under RCP8.5. Furthermore, Pisani et al. (2019) examined the Serra da Estrela region in central Portugal, predicting reductions in aquifer recharge and streamflow using water balance models.

These studies, although conducted on an aquifer scale, generally align with our findings, confirming that climate change significantly influences groundwater levels. However, these studies employed process-based models that require the incorporation of a large amount of data including: groundwater recharge, soil properties such as hydraulic conductivity, land use, agricultural practices, and abstraction rates, alongside climate variables like precipitation and temperature. The present study, in contrast, employs deep learning (CNN models) on a regional scale, using temperature and accumulated precipitation as the only explanatory variables to isolate the direct impact of climate change on groundwater levels. While aquifer-scale studies provide valuable localized insights and consider both climatic and anthropogenic factors, our approach offers a simpler data-driven approach that captures the spatial variability and climate-driven trends across the entire Iberian Peninsula.

Among the explanatory variables considered, temperature, which strongly influences evapotranspiration, has a greater impact than precipitation, confirming previous findings (Wunsch et al., 2022). Furthermore, we used cumulative precipitation data as explanatory variables to capture the time lag between precipitation events and groundwater response. While temperature was the dominant factor influencing groundwater levels, P36 (cumulative precipitation over 36 months) emerged as the main driver for 8.7% of the wells. This was followed by P6, P18, P12, P24, and P3, as shown in **Figures 8a, b**. As expected, P1 (precipitation over one month) was not identified as the main driver for any of the wells, indicating that long-term cumulative precipitation has a stronger influence on groundwater levels than short-term precipitation.

These results agree with numerous studies that emphasize the importance of accumulated long-term precipitation towards changes in groundwater levels. For instance, Jan et al. (2007) showed that groundwater level variations follow short-run and long-run cumulative rainfall, as evidenced in their work on the Donher well station in Central Taiwan. They found that the cumulated rainfall over 10 d was more influential in groundwater levels than shorter periods. They attributed this to the typically delayed response of groundwater to rainfall, wherein past rainfall contributes much to the current water table conditions. By using an exponential-decay weighting technique to determine

effective cumulative rainfall, they showed that older precipitation events continue to affect groundwater levels, although their influence becomes weaker over time (Jan et al., 2007).
Further, the Wisconsin study (Smail et al., 2019) trend of CDM60 (cumulative deviation from 5-y moving mean precipitation) indicated that groundwater levels are more correlated with long-term than short-term precipitation oscillations. This further reinforces the concept that groundwater systems take successive periods of surplus precipitation to alter their levels drastically. Thus, it is expected that P1 lacks influence, while more seasonable measures like P36 are responsible for groundwater responses to significant precipitation.
The deep learning algorithm identifies the relationship between input parameters, precipitation and temperature, and the output parameter, groundwater level. The 92 wells are those where groundwater levels can be described well using only these input parameters, thereby implying that the influence of external or anthropogenic pressures is minimal. As evidenced by the trend analysis, 90% of the wells exhibited no trend during the training period, indicating that they are naturally in a stable condition and not under heavy stress. Consequently, we can conclude that these wells are not subject to significant anthropogenic or any other pressure (**Figure 8c, d**).
A recent study examining groundwater level trends Chávez García Silva et al. (2024) covered the period from 1960 to 2020 across Spain, Portugal, France, and Italy, and similarly found that 68% of wells remained stable over this time, with an additional 20% showing rising levels. These findings underscore the resilience of many groundwater systems to external influences during the historical period, especially in temperate regions. However, the situation for groundwater wells in the future is projected to change significantly. While both studies highlight a period of relative stability in the past and near future, our future projections based on climate models and deep learning algorithms indicate that future conditions will likely shift towards declining groundwater levels. The anticipated reduction in precipitation and increased temperatures, which exacerbate evapotranspiration and soil moisture deficits, suggest that wells that are currently stable could experience depletion in the coming decades due to climate change.
Of the 92 wells, 72 have a depth of 50 m or less, indicating that approximately 78% are in shallow aquifers (**Figure 8b**). This distribution suggests that shallow aquifers are more influenced by climate variability and change, responding quickly to surface climatic conditions due to shorter lag times. A recent study by Gumuła-Kawęcka et al. (2023) supports this, demonstrating that shallow aquifers in northern Poland have shown significant responses to climate change over the past 70 y. In contrast, deeper aquifers exhibit greater resilience to climate impacts and serve as more stable, long-term freshwater storage due to their reduced sensitivity to surface conditions. This finding is consistent with Zhou et al. (2022), who studied the hydrochemical background levels and threshold values of phreatic groundwater in the Greater Xi'an Region, China, underscoring the importance of understanding aquifer characteristics for effective water quality management.

## 4.3. Challenges and perspectives

The Iberian Peninsula was chosen for its relatively dense and accessible groundwater data compared to other regions, yet only a few wells were retained for further analysis. Dropped wells were excluded primarily due to inconsistencies in regional monitoring strategies, including variability in frequency, duration, and completeness of the time series. Many historical groundwater time series suffer from short durations, irregular frequencies, and a lack of uniformity, all of which impact model training quality. Additionally, wells influenced by human activities, such as irrigation and domestic use, are unsuitable for our approach, which considers climate variables exclusively as controlling factors of groundwater changes. Comprehensive information of the effects of anthropogenic activities on groundwater levels remains challenging in the region due to fragmented monitoring of key drivers (Deines et al., 2019; Leduc et al., 2017). Furthermore, including more climate forcing parameters like soil moisture, surface net solar radiation and finding a suitable proxy parameter to capture the anthropogenic pressures on groundwater levels (such as groundwater abstraction) would also be highly beneficial. Numerous studies have utilized Earth Observation data to assess anthropogenic pressures on groundwater levels. Barron et al. (2014) used Sentinel-1 SAR data to identify groundwater-dependent vegetation. Similarly, numerous studies combined remote sensing data with hydrological and hydrogeological modelling results to capture human-induced groundwater depletion across scales (Abdelkareem et al., 2023; Döll et al., 2014; Guermazi et al., 2019). In the case of the Iberian Peninsula, similar methodologies have been applied, including the use of multispectral satellite imagery to map irrigated crops in Spain (Garrido-Rubio et al., 2018) as well as integration of global groundwater models with in situ observations for assessment of the status of groundwater resources and the impact of human activities on groundwater levels (Ben-Salem et al., 2023).

Future research could explore the use of multi-well training approaches alongside training individual models for each well. Multi-well training has gained popularity in recent years due to its potential advantages, such as predicting groundwater levels in areas with insufficient historical in situ data. However, these approaches do not consistently provide better accuracy compared to single-well training methods. As an example, Chidepudi et al. (2023) and Heudorfer et al. (2024) demonstrated that while deep learning models trained on multiple wells can effectively capture broader hydrological patterns, they do not always outperform models trained on individual wells in terms of predictive accuracy. By utilizing data from all available piezometric stations, multi-well models can identify relationships or events that might occur at a target location, even if not previously observed there.

# 5. Conclusions

In a future characterised by rising temperatures and decreasing precipitation (RCP8.5), groundwater resources will face significant stress. However, by limiting greenhouse gas emissions (RCP4.5), long term impacts of climate change on the depletion of groundwater levels are limited. Groundwater level changes under RCP8.5 intensify over time, with more severe impacts observed over the long term [2080–2100], while under RCP4.5, groundwater levels remain relatively stable, with occasional decreases.

Using deep learning, we developed CNN models with high computational speed irrespective of the availability of local geological or geophysical information. Only temperature and cumulated precipitation (the latter to account for the time lag between the actual precipitation event and the aquifer response), were used to identify the direct impact of climate change on groundwater levels. While the indirect impact related to human activities were not considered in our study, they could have even more severe consequences for groundwater. To address both climate and anthropogenic impacts and safeguard groundwater resources, effective management strategies must be implemented to optimize water consumption and enhance groundwater recharge. These include managed aquifer recharge techniques, adoption of water-saving irrigation practices, and prioritization of nature-based solutions. While groundwater aquifers will continue to be a vital and resilient resource, their long-term sustainability will depend on prompt and effective mitigation actions.

# CRediT authorship contribution statement

**Amir Rouhani**: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Nahed Ben-Salem**: Data curation, Investigation, Writing – review & editing. **Marco D'Oria**: Data curation, Methodology, Writing – review & editing. **Rafael Chávez García Silva**: Data curation, Writing – review & editing. **Alberto Viglione:** Writing – review & editing. **Nadim K. Copty**: Writing – review & editing. **Michael Rode**: Writing – review & editing. **David Andrew Barry:** Methodology, Writing – review & editing. **J. Jaime**

**Gómez-Hernández:** Methodology, Writing – review & editing. **Seifeddine Jomaa**: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

# Declaration of competing interest

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

# Data availability

All the data utilised in this study are freely accessible online.

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