Climate Services 32 (2023) 100422

Contents lists available at ScienceDirect

Climate Services

journal homepage: www.elsevier.com/locate/cliser

Original research article

# Predicting precipitation on the decadal timescale: A prototype climate service for the hydropower sector

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ARTICLE INFO

*Keywords:*
Decadal predictions
Climate services
Hydropower
Hybrid forecasts

ABSTRACT

Decadal predictions present an emerging opportunity for various socio-economic sectors affected by climate variability. However, the development of associated climate services is still in an incipient stage. This study focuses on developing a prototype climate service for an end-user in the hydropower sector. The service aimed at predicting precipitation in three drainage basins (Guadalquivir, Ebro and Po) for the next ten years, and was developed in close collaboration with the user. In this paper we do not provide the real-time forecasts, but we focus on describing and evaluating the methods and the models used. Using a European multi-model ensemble, the predictive skill for precipitation is found to vary with the calendar season, the forecast range and the drainage basin considered, though it is generally low for the purposes of supporting such a climate service. To overcome this deficiency, a hybrid approach was developed making combined use of the good skill in predicting the North Atlantic Oscillation (NAO) and the observed dominant influence of the latter on the decadal variability of precipitation in the areas of interest. Implementing this hybrid approach, which combines predictive information from the dynamical models with statistical information from observations, brings significant skill improvements in all basins during the extended cold season (November-March) for the first 10 forecast years. The hybrid model outperforms the direct multi-model ensemble output, exhibiting statistically significant skill for all basins. Our results suggest that utilising large-scale predictors can significantly improve regional predictions, and provide usable information for the hydropower sector.

**Practical Implications**

Climate services have been rightly receiving increasing attention in recent years, since skilful climate forecasts are important for governments and businesses in various socio-economic sectors. Forecasts on different temporal horizons can be useful for assisting planning and decision-making in the energy sector. While sub-seasonal to seasonal forecasts (from weeks to a season ahead) can, for example, help in planning maintenance operations, identifying risks and preventing damages and power outages and/or anticipating energy prices, multi-year to decadal forecasts can be useful in assessing the available future resources and changes to the energy mix, integrating new infrastructure and storage capacity and in planning future investments and selecting new sites.

Decadal predictions have evolved rapidly in the last 15 years, and are now capable of skillfully predicting various aspects of the climate system. In addition, decadal predictions are now produced operationally by several institutions around the world, contributing to multi-model predictions of the next few years, updated annually and issued by the Lead Centre for Annual to Decadal Climate Predictions, established by the World Meteorological Organization (WMO) (Hermanson et al., 2022). Despite recent advances, and while information from sub-seasonal to seasonal forecasts and climate projections have been progressively incorporated into decision-making worldwide, the potential of climate services based on decadal predictions has not been adequately explored. On these grounds, the EU Copernicus Climate Change Service (C3S) aimed at revealing the potential benefits of decadal predictions for different industries, and to develop real-time prototype decadal prediction products. Under the C3S_34c project, four European institutions, each developed a prototype decadal climate service for four different

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https://doi.org/10.1016/j.cliser.2023.100422

Available online 5 November 2023

sectors (agriculture, energy, infrastructure and insurance), currently available on the C3S website[1].

In the present study, we focused on the development of the prototype climate service to assist decision-making of an energy company (ENEL Green Power), involved in this project as a stakeholder from the hydropower sector. Specifically, we provided 10-year mean precipitation forecasts for the extended cold season, for three drainage basins in Southern Europe. However, this paper aims to describe and evaluate the models used, rather than to provide the real-time forecasts.

We adopted a hybrid approach based on the observed variability of a skillfully predicted large-scale circulation pattern and the local precipitation. Our results show that exploiting the current skill of large-scale information and their empirical relationship with regional climate variables, can be key in overcoming the deficiency of the current generation of decadal prediction systems to skillfully predict local meteorological variables, such as precipitation. However, further development and effort is needed to improve this prototype climate service in terms of skill and accuracy, predicting other variables and statistics (e.g. frequency and average intensity of extremes) relevant to the needs of the end-user, providing forecasts of different temporal horizons and other calendar seasons. Similar hybrid approaches can be potentially extended and applied to other regions in Europe, while similar products can be developed to provide information for other renewable energy sources, such as wind and solar power. Last but not least, in order to ensure the development of useful climate services with an impact on the end-user decision-making, we should involve the end-users more interactively in the design and the development of such services so as to provide tailored information matching their needs.

## 1. Introduction

Decadal predictions aim to provide valuable information of the climate system evolution over the next few years and up to a decade ahead. In contrast to long-term climate projections, which mainly provide an estimate of the climate system response to the external forcings by prescribing greenhouse gases, aerosol concentrations and natural radiative forcing changes, decadal predictions are additionally benefiting from simulating the predictable component of internal variability through realistic initialization. Initializing the model simulations (predictions) by providing a best estimate of the respective observed climate state provides the model with the correct “phase” of internal variability (Meehl et al., 2014; Boer et al., 2016; Kushnir et al., 2019; Meehl et al., 2021). At multi-annual to decadal timescales, the impact of the internally generated climate variability on the climate forecasts is comparable to the externally forced signal (Branstator and Teng, 2012; Boer et al., 2016; Meehl et al., 2021). Therefore, decadal predictions can improve the predictive skill by encompassing both sources of predictability, the internal climate variability and the external forcing (Doblas-Reyes et al., 2013; Boer et al., 2016; Yeager et al., 2018; Smith et al., 2019). Consequently, they present an emerging opportunity for the development of climate services to assist planning and decision making by governments and businesses in various socio-economic sectors.

Decadal predictions are now produced operationally worldwide, bridging the gap between seasonal predictions and climate projections. However, despite their rapid evolution in the last decade (Borchert et al., 2021; Delgado-Torres et al., 2022) and the increasing interest from end-users, climate services based on decadal predictions are limited and still in incipient stage. On these grounds, the EU Copernicus Climate Change Service (C3S) aimed at revealing the potential benefits of decadal predictions for different industries, and to develop real-time, sector-specific prototype decadal prediction products. Under the C3S_34c project, four European institutions — the Deutscher Wetterdienst (DWD, Germany), the Barcelona Supercomputing Center (BSC, Spain), the Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC, Italy) and the Met Office (UK) — each developed a prototype climate service, respectively for infrastructure, agriculture, energy and insurance, in close collaboration with interested end-users operating in these sectors. The four forecast products are now available on the C3S website[2], while details on the case studies are provided in Solaraju-Murali et al. (2021) (agriculture), Paxian et al. (2022) (infrastructure), Lockwood et al. (2023) (insurance). The co-development with the end-users, along with the main challenges to exploit the current predictive skill and tailor the climate information to real-world applications are also discussed in Dunstone et al. (2022).

Here, we focus on the development of the prototype climate service for the energy sector led by CMCC. The energy sector is very broad, encompassing power generation from different energy sources, power-grid management, distribution and retail. Weather and climate related information has always been relevant to the energy industry, as the power needs are strongly altered by the synergy of climate change and internal climate variability (Bloomfield et al., 2016; Van Ruijven et al., 2019; Larsen et al., 2020). Nowadays, it gains even more importance all along the energy value chain, due to the transition towards decarbonisation. The accelerating integration of renewable energy into the power grid renders the energy supply more climate dependent (Ravestein et al., 2018; Shu et al., 012126, 2018,; Jerez et al., 2019; Wohland et al., 2019).

However, climate information is not important only to anticipate supply and demand, but also to plan the operation and maintenance, and secure the energy infrastructure. At the same time, identifying future climate variations provides a useful tool to assess the available resources, understand possible changes in the energy mix, and integrate new infrastructure and storage capacity if needed (Ciscar and Dowling, 2014; Dubus et al., 2018).

In this project, ENEL Green Power (hereafter, ENEL-GP), an Italian company active in the international market by generating and providing electricity from renewable sources, was involved as a stakeholder for the hydropower sector in southern Europe. The most important climatic factor affecting the hydropower system is precipitation, since it determines the water input in the reservoir’s catchment area, and is the main variable affecting river discharge. Lower precipitation leads to decreased river discharge and power generation, while increased precipitation enhances the discharge, and depending on the system capacity can contribute to higher power generation (Wei et al., 2020; Huangpeng et al., 2021). Temperature is also important, as it regulates the water losses through evapotranspiration (Coelho et al., 1, 2016,; Zhao et al., 2021; Materia et al., 2022), the partitioning between rain and snow, and the timing of snow melting (Berghuijs et al., 2014). Earth surface processes, such as soil and land cover properties, can also modulate the river discharge (Khare et al., 2017). Moreover, extreme weather events, such as torrential rain and floods, are crucial to the safety of the current infrastructure and the design criteria for building new dams and hydropower installations (Bowles et al., 2013; Fluixá-Sanmartín et al., 2018).

Among several needs, the amount of water available in the reservoir was of great interest for the end-user. After discussing with ENEL-GP team about their needs and different forecast possibilities, it was decided to proceed with predicting precipitation, the key attribute for the river discharge and the water storage volume, in three European drainage basins: Guadalquivir and Ebro in Spain and Po in Northern Italy. In decadal forecasts, even though significant skill has been documented for surface temperature, precipitation still exhibits lower predictability (Doblas-Reyes et al., 2013; Meehl et al., 2014; Bellucci et al., 2015; Smith et al., 2019). However, recent studies have reported significant predictive skill for Euro-Atlantic circulation regimes at the

[1] https://climate.copernicus.eu/sectoral-applications-decadal-predictions

[2] https://climate.copernicus.eu/sectoral-applications-decadal-predictions

decadal timescale, when a large ensemble is utilized (Smith et al., 2020; Athanasiadis et al., 2020). A potential impact of these regimes on the climatic conditions in the areas of interest, may result in increased predictability of the local climate. Through a close interaction with the end-user, we produced a real-time forecast product[3], providing 10-year mean precipitation forecast for each of the above-mentioned basins. This paper focuses on the development of this prototype climate service, providing information regarding the models used and their predictive skill and not the real-time forecasts. Further we discuss existing limitations and possible improvements, and we highlight the potential value of decadal predictions in climate services for the energy sector.

## 2. Material and methods

### 2.1. Study Area

We focus on three European river catchments where the end-user, ENEL-GP, is operating: Ebro and Guadalquivir in Spain and Po in Italy (Fig. 1). Ebro is located in the northeastern part of Spain and is the largest drainage basin of the country, comprising an area of about 85,000 $km^2$. It is delimited by the Pyrenees and Cantabrian Mountains to the north, the Catalan Coastal Range to the east, and the Iberian Range to the west and south. It has mainly continental Mediterranean climate with oceanic climate influences in the northern and northwestern sectors. The Guadalquivir basin is situated in southern Spain. It has an area of approximately 57,500 $km^2$, 90% of which lies in Andalusia and is enclosed by Sierra Morena to the north, the Betic Mountain Ranges to the south and the Atlantic ocean to the west. Its climate is characterized as typical Mediterranean, with mild and rainy winters and hot and dry summers. The Po river basin is mainly located in northern Italy with small areas (~5%) lying in France and Switzerland. It covers an area of about 74,000 $km^2$, bounded by the Alps to the west and north, the Apennines to the south and the Adriatic Sea to the east. The location and the heterogeneous topography of the basin leads to diverse climatic conditions with main influences of the Alpine and the Mediterranean climate. Here, in order to meet the end-user needs, we focus on a smaller area for each basin as shown in Fig. 1.

### 2.2. Data

In the current study we use initialized forecasts from four Decadal Prediction Systems (DPSs) following the Coupled Model Intercomparison Project phase 6 (CMIP6) protocol (Boer et al., 2016). These are 10-year-long retrospective forecasts (hindcasts) of 44 members in total, initialized every November from 1960 to 2009. The main characteristics of the models used to produce the forecasts are presented in Table 1. A detailed documentation of the DPSs (or the respective models) can be found in Nicolì et al. (2022) for CMCC-CM2-SR5, in Bilbao et al. (2021) for EC-Earth3, in Williams et al. (2018) for HadGEM3-GC3.1-MM and in Müller et al. (2018) for MPI-ESM-1–2-HR. We use monthly outputs of precipitation and sea level pressure (SLP).

For the evaluation of the hindcasts we use E-OBS (Cornes et al., 2018) for precipitation and the Hadley Centre Sea Level Pressure dataset (HadSLP2r) (Allan and Ansell, 2006) for SLP, for the period from November 1960 to December 2019. E-OBS is a daily, gridded dataset for Europe (25°N–71.5°N x 25°W–45°E) based on station observations from European Climate Assessment & Dataset (ECA&D). The data are available on 0.1° and 0.25° regular grids and cover the period from 1950 to date. For this analysis we use the 0.25° dataset. The HadSLP2r provides global, monthly, gridded data based on terrestrial and marine observations. The data cover the period from 1850 to present at a spatial resolution of 5°.

### 2.3. Methods

#### 2.3.1. Post-processing

First, the predicted precipitation is re-gridded to the observations' grid (0.5°x0.5°) using a first-order conservative method, while both predicted and observed SLP are bi-linearly interpolated to a 1°x1° regular grid. Monthly precipitation and SLP anomalies are computed for both hindcasts and observations with respect to the period 1981–2010. It should be noted that due to the models' tendency to drift towards their own climate state, the climatology of the models is computed for each forecast-year separately, using different initialization years so as to always obtain the reference period 1981–2010. For the computation of the multi-model ensemble mean anomalies we average all the members together (pooling method).

#### 2.3.2. NAO Index

We compute the NAO index as the difference of the zonally averaged, standardized SLP anomalies over the longitudes 80°W–30°E, between the latitudes 35°N and 65°N (Jianping et al., 2003). We follow this method in order to consider the longitudinal migration of the centers of action (Barnston et al., 1987) and best capture the large-scale impacts of the NAO variability.

#### 2.3.3. Variance Adjustment

After averaging over the ensemble members, the variance of the predicted NAO is much lower in comparison to the observed, due to the small signal-to-noise ratio (Scaife et al., 2018; Smith et al., 2019) of the models. Using a NAO index with reduced variance in the hybrid approach we implement in this study (see subSection 2.3.4), would result in unrealistically low absolute values of precipitation anomalies. In order to provide reliable forecasts we proceed with calibration of the model output. Following Eade et al. (2014), we adjust the variance of the multi-model ensemble mean so as to render it equal to the predictable component of the observed variance, while the spread of the ensemble members is adjusted to match the unpredictable component of the observations.

#### 2.3.4. Hybrid Approach

We use a hybrid approach which relies on the observed linear relationship between the North Atlantic Oscillation (NAO) and precipitation in each basin and the dynamically predicted NAO by the DPSs. The NAO is one of the leading modes of atmospheric variability in the Euro-Atlantic sector with dominant climatic impacts in Europe (Walker and Bliss, 1932; Van Loon and Rogers, 1978; Wallace and Gutzler, 1981), including a major influence on precipitation from interannual to mutltidecadal timescales (Hurrell, 1995; Thompson and Wallace, 2001; Woollings et al., 2015). During the positive phase of the NAO, when the pressure gradient between the subpolar low pressure system and the subtropical high is strong, the Atlantic storm track is shifted northwards, resulting in drier than normal conditions in the Mediterranean and wetter than normal conditions in northern Europe (Athanasiadis et al., 2010; Wettstein and Wallace, 2010). During the negative NAO phase the opposite happens. Storms are directed to the southern Europe, affecting the Mediterranean.

To predict the precipitation using NAO as a predictor, we first perform linear regression of the observed aggregated precipitation anomalies in each basin onto the observed NAO index, using the least squares method. We perform the regression on the decadal components of the two timeseries, derived from the 10-year running average from 1961 to 2019. In order to predict the decadal mean precipitation anomalies in each basin ($\overline{pr_B'}$), the regression coefficients ($a, b$) of the observed linear fit are combined with the NAO index predicted by the DPSs ($\overline{NAO_{DPS}}$) according to:

[3] available on the C3S website ( https://climate.copernicus.eu/decadal-predictions-energy)

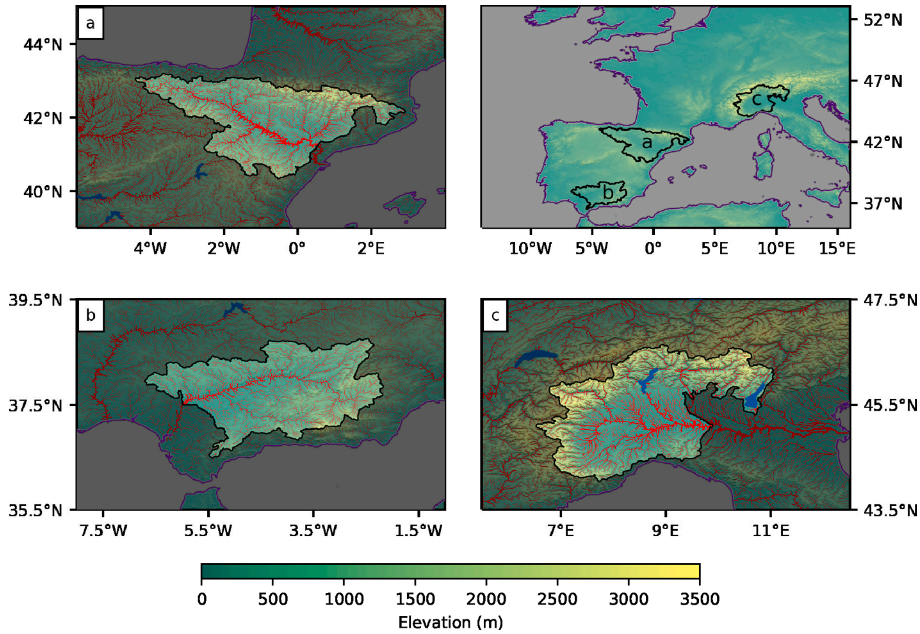


**Fig. 1.** Topography and river network of the three drainage basins: Ebro (a), Guadalquivir (b) and Po (c).

**Table 1**
Specifications of the Decadal Prediction Systems.

| Prediction System | | CMCC-CM2-SR5 | EC-Earth3 | HadGEM3-GC3.1-MM | MPI-ESM-1-2-HR |
|---|---|---|---|---|---|
| **Atmospheric Model** | **Name** | CAM5 | IFS36R4 | UM | ECHAM6 |
| | **Resolution** | ~100 km | ~80 km | ~60 km | ~100 km |
| | **Vert. Levels** | 30 | 91 | 85 | 95 |
| **Ocean Model** | **Name** | NEMOv3.6 | NEMOv3.6 | NEMOv3.6 | MPIOM |
| | **Resolution** | 1° | 1° | 0.25° | 0.4° |
| | **Vert. Levels** | 50 | 50 | 75 | 40 |
| **Ensemble Size** | | 14 | 10 | 10 | 10 |

$$\overline{pr'_B[t]} = a \times \overline{NAO_{DPS}[t]} + b$$

where $t = 1, 2 \ldots n$ indicates the decadal mean, $B \in \{Ebro, Po, Guadalquivir\}$ refers to the basin, the prime (′) signifies the anomalies with respect to 1981–2010 and the overbar () signifies decadal averaging.

### 2.3.5. Validation Metrics

The predictive skill of both the dynamical (DPS) and the hybrid approach is firstly assessed by the anomaly correlation coefficient (ACC), which measures the strength of the linear relationship between the model and observations and the ability to predict the co-variability of the two timeseries. The ACC lies between −1 and + 1. Positive values indicate that the model co-varies with the observations, and the closer to + 1 the better the synchronization between modeled and observed anomalies on average (Wilks et al., 2011). For the verification, in order to use the same initialization years for all forecast periods (1961–2009), the verification period varies for different forecast year ranges given the availability of the observations. For example, for the first 5 forecast years (lead years 1–5) the verification period is 1961–2014, while for the first 10 forecast years (lead years 1–10)forecast range 1–10 years the verification period is 1961–2019. We test the statistical significance of the ACC, at the 95% significance level against the null hypothesis of non-positive correlation using a one-sided Student's t-test. We compute the effective degrees of freedom following Bretherton et al. (1999) in order to account for the impact of the temporal auto-correlation.

In order to assess the skill of the hybrid approach to predict the magnitude of the observed variability we also use the Mean Squared Skill Score (MSSS) (Murphy et al., 1988) relative to the climatology. The MSSS is based on the Mean Squared Errors (MSE) of the model predictions and climatology with respect to the observations. Since here we use the MSE of the anomalies and not of the full values, the MSSS does not include the error of the unconditional bias (mean bias), but combines only the correlation and the conditional bias (Murphy et al., 1988; Goddard et al., 2013). Negative values of MSSS indicate that the climatological forecast performs better, while positive MSSS indicates that the model holds an added value compared to climatology. MSSS equal to zero indicates no improvement over the climatology. Statistical significance is tested against the null hypothesis that there is no difference between the mean squared errors of the modeled and climatological forecasts, using a two-sample t-test.

In addition, we use contingency tables along with the hit rates and false alarm rates, in order to demonstrate the forecast reliability in predicting a categorical (yes/no) outcome. The contingency table indicates the counts of four types of classification between the predicted and observed events. These are: (i) the number of events predicted to occur that have occurred (hits), (ii) the number of events predicted to occur but have not occurred (false alarms), (iii) the number of events predicted to not occur but have occurred (misses) and (iv) the number of events predicted to not occur that have not occurred (correct rejections). The hit rate is the ratio of the successfully predicted events to the times this event has occurred [hits/(hits + misses)] while the false alarm rate is the ratio of the erroneously predicted non-occurrence to the times that the event has not occurred [false alarms/(false alarms + correct rejections)] (Wilks et al., 2011). Here, we define the dichotomous event as the above/below average aggregated precipitation in each basin, based on the time period 1961–2019.

Probabilistic skill metrics were considered in the discussions with the end user and were also included (Brier Skill Score) in the respective fact sheets. For reference, we point the reader to the respective web page: https://climate.copernicus.eu/decadal-predictions-energy.

## 3. Results

### 3.1. Dynamical Predicted Precipitation

The dynamically simulated and observed annual cycle of precipitation in each basin is presented in Fig. 2. All the basins exhibit a pronounced annual cycle. Guadalquivir has a typical Mediterranean climate with more precipitation during the cold season, between October and April, and a large deficit during the summer season. It is the driest of the three basins, receiving an annual average precipitation of 438 *mm*. On the other hand, Ebro and Po, with annual mean precipitation of 592 *mm* and 1035 *mm* respectively, show two maxima, in spring (MAM) and late autumn (SON). However, while the Ebro basin shows higher precipitation in the winter (DJF) than in the summer (JJA), with minimum in July, summer in the Po basin is considerably wetter than winter. This is mainly due to the rather complex climatology of the Po basin, characterized by an Alpine climate in the north with low precipitation during winter and maximum precipitation during summer (Supplemental Fig. S1). In the other two basins the annual cycle is more homogeneous in space in terms of seasonality, but the magnitude of precipitation is spatially highly variable (Supplemental Fig. S1).

The grey lines in Fig. 2 represent the annual cycles over different decades as an indication of the decadal variability of precipitation. In all basins there are significant decadal fluctuations in all seasons, except for the warm season in Guadalquivir, from April to October, when the decadal variability is weak. The multi-model ensemble mean is generally successful in capturing the annual cycle in the three basins. However, it underestimates the amplitude of precipitation in Guadalquivir during the wet season, especially in autumn, while it shows greater than the observed precipitation in Ebro during the spring peak and the adjacent months. In the Po basin, the summer low is shifted by one month (August) and is considerably lower than the observed minimum. Drier conditions are also simulated during autumn while there is an overestimation of the precipitation during the spring peak.

Fig. 3 shows the multi-model deterministic skill (ACC) of the annual and seasonal precipitation in south-western Europe, for the first 10 forecast years (lead years 1–10). Correlations of annual precipitation anomalies are relatively high in most of the Iberian Peninsula, although there are large areas where the correlation is not statistically significant, particularly in the eastern part of the peninsula, including a large portion of the Ebro basin. In winter, positive skill is found only in the western part of Andalusia, where the Guadalquivir basin is located, while in the rest of the domain the skill is poor. During the transition seasons (MAM, SON) the ACC is mostly negative, or not significant, over the whole domain, excluding the north western part of the Iberian Peninsula during spring. Summer precipitation shows significant skill over some parts of the Mediterranean region. Over the Iberian peninsula the multi-model ensemble shows high skill exceeding 0.7 in some areas, including Guadalquivir. However, we should note that these regions during summer are generally dry with little interannual to decadal variability (see Fig. 2, Guadalquivir).

The annual and seasonal correlations of the aggregated precipitation anomalies in the three drainage basins are summarized in Table 2. As it was already depicted by the correlation maps in Fig. 3, the direct predictive skill for the DPSs precipitation in the three basins is quite poor except for the annual, winter and summer precipitation anomalies in the Guadalquivir basin where the skill is statistically significant with values of 0.42, 0.34 and 0.67 respectively. In the Po basin the ACC is negative in all seasons, while in Ebro positive skill is found for annual and summer

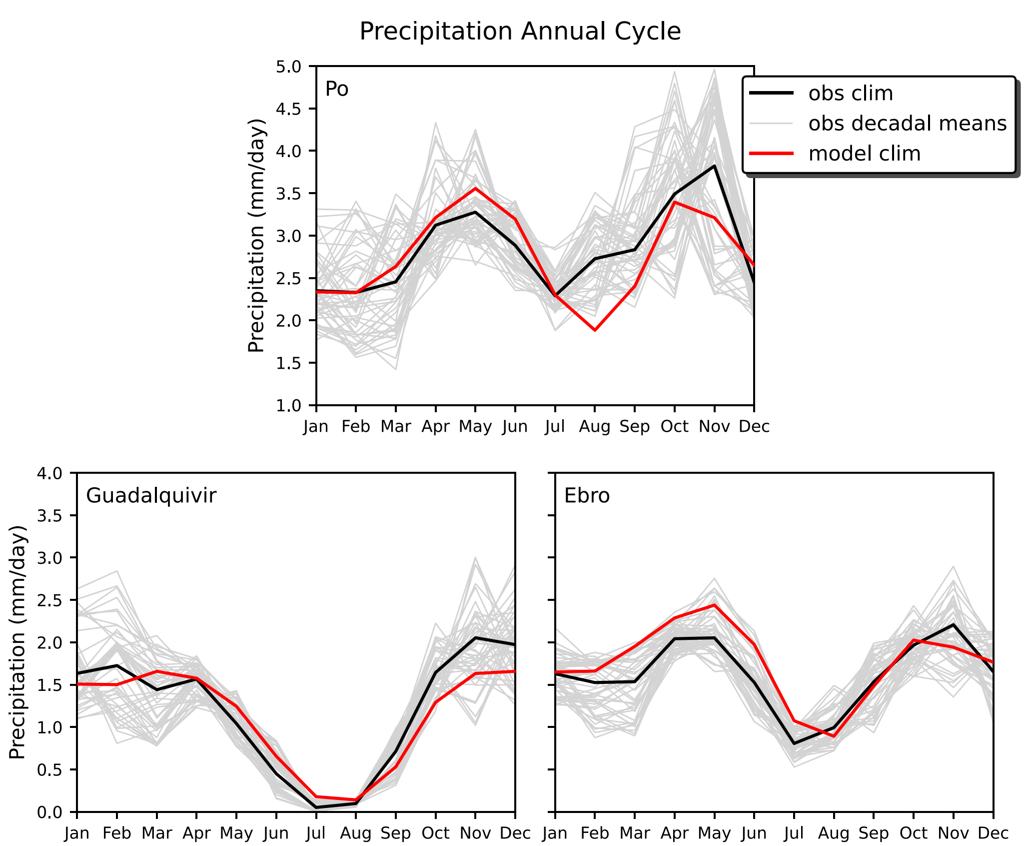


**Fig. 2.** Mean annual cycle of aggregated precipitation in the three basins for 1960–2019. The black line represents the E-OBS dataset, while the red line the multi-model output. The grey lines depict observed decadal means.

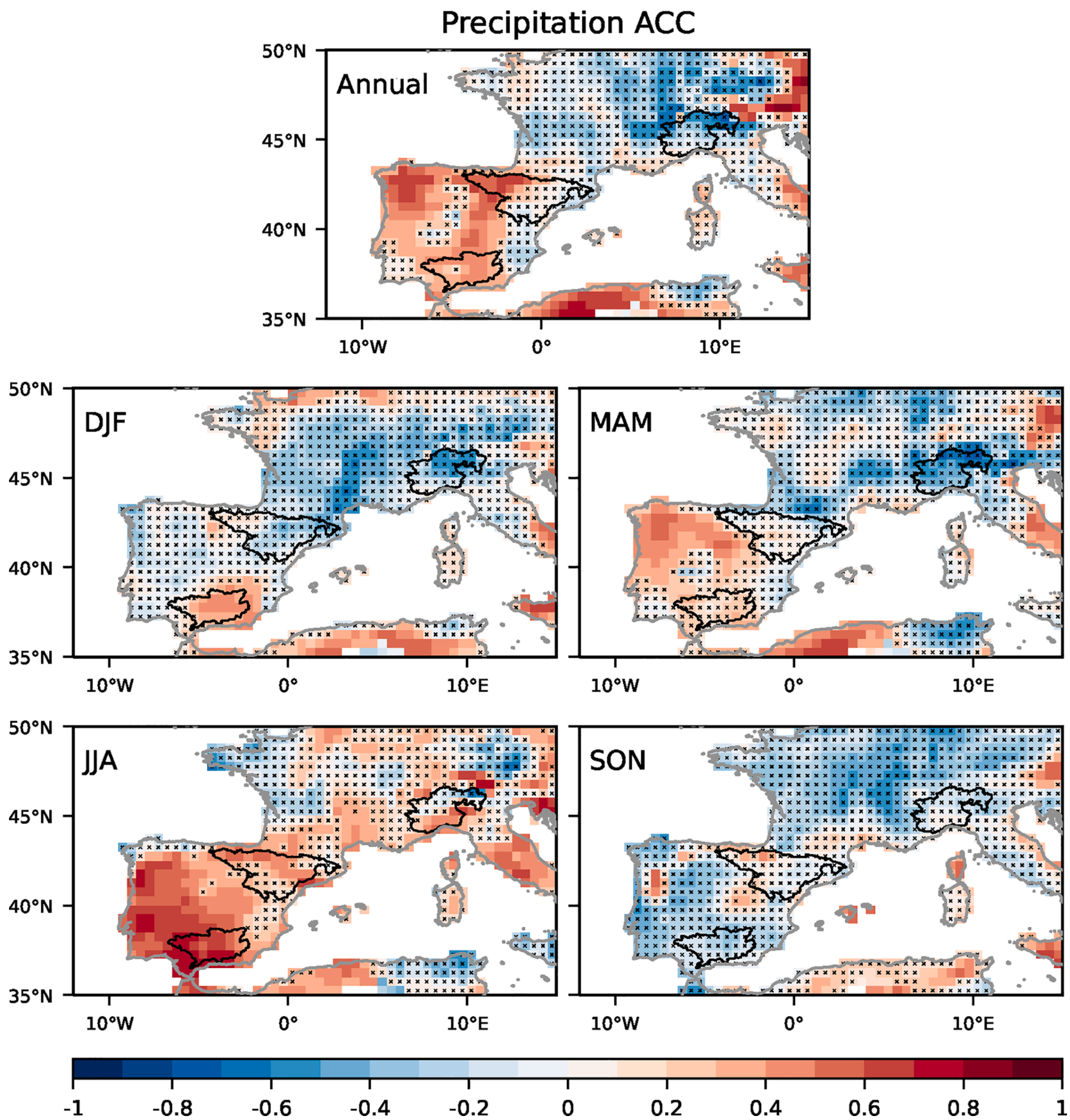


**Fig. 3.** Anomaly correlation coefficient (ACC) maps for annual and seasonal precipitation (DJF: winter, MAM: spring, JJA: summer, SON: autumn) at the first 10 forecast years (lead years 1–10), between the multi-model ensemble mean and the observations. The black lines represent the borders of each basin. Stippling indicates statistically insignificant values at 95% significance level, against the null hypothesis of non-positive correlation, using a one-sided t-test, accounting for autocorrelation.

**Table 2**
Anomaly Correlation Coefficient (ACC) between the observed and the multi-model ensemble mean aggregated precipitation in the three drainage basins for different seasons. ACC is computed for the first 10 forecast years (lead years 1–10). Statistical significance is tested against the null hypothesis of non-positive correlation, using a one-sided Student's t-test, accounting for autocorrelation.

| Basins | Annual | DJF | MAM | JJA | SON |
|---|---|---|---|---|---|
| **Guadalquivir** | 0.42 | 0.34 | 0.14* | 0.67 | −0.19* |
| **Ebro** | 0.17* | −0.28* | −0.08* | 0.29* | 0.05* |
| **Po** | −0.38* | −0.25* | −0.6* | −0.06* | −0.19* |

*Statistically insignificant values at 95% level.

anomalies, although ACC values are low and not significant.

### 3.2. Building a Hybrid Approach to Predict Precipitation

Given the overall poor predictive skill for precipitation, particularly in Ebro and Po, we explore the potential of using NAO as a predictor in the framework of a hybrid approach based on the observed statistical relationship between the NAO and precipitation in the three basins and the dynamical predictions of the NAO index. Such a hybrid approach, in order to be skillful, requires a physical connection between the NAO and precipitation and a skillful dynamical predictions of the predictor.

To assess the ability of the multi-model ensemble in predicting the NAO, we compute the ACC for the extended winter NAO (November–March, NDJFM) for all possible forecast-year ranges (Fig. 4, left). The skill is statistically significant for various forecast-year ranges, and is generally increasing for longer averaging periods, with a maximum of 0.56 for forecast years 1–10 (indicated by the ”X” marker). In Fig. 4 (on the right) we also present the observed and simulated NAO timeseries for the first 10 forecast years (lead years 1–10), along with the 75% and 95% of the ensemble spread (the darker and lighter shading, respectively). The observed timeseries is the 10-year running average of the NDJFM NAO index, while the predicted NAO timeseries are calibrated in order to adjust the variance, since otherwise the model signal is too low due to the small signal-to-noise ratio (Eade et al., 2014; Scaife et al., 2018). The multi-model ensemble is able to capture most of the decadal variability of the NAO depicting the prominent positive trend from the

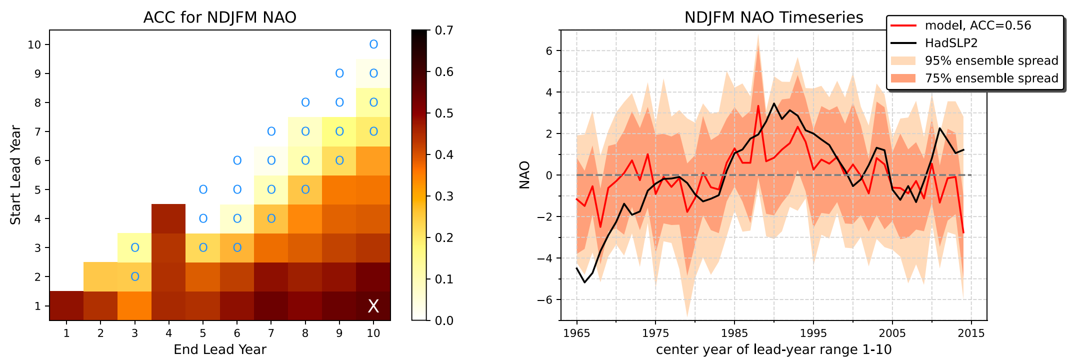


**Fig. 4. Left**: Anomaly correlation coefficient (ACC) for extended winter (NDJFM) NAO between the multi-model ensemble mean and the observations, for different forecast-year ranges. The cyan 'O' markers indicate statistically insignificant correlations, at 95% significance level. The white 'X' marker indicates the forecast-year range with the highest ACC (=0.56). Statistical significance is tested against the null hypothesis of non-positive correlation, using a one-sided Student's t-test, accounting for autocorrelation. **Right**: Predicted (red line) and observed (black line) timeseries of NDJFM NAO for the first 10 forecast years (lead years 1–10). The ensemble spread (centered 75% and 95% percentiles) are shown in shading (darker and lighter shading, respectively).

mid 60's until the 90's and a negative trend afterwards. However, after 2012 the predicted winter NAO shows predominantly negative anomalies, while observations tend to positive anomalies. Despite these discrepancies, the multi-model ensemble is in good agreement with the observations and shows statistically significant ACC.

Fig. 5 shows the Pearson's correlation coefficient between the observed 10-year running averages of the NAO and precipitation anomalies for each grid point over Europe, during NDJFM for the period 1961–2019. The results depict the characteristic north–south dipole over Europe (Thompson and Wallace, 2001; Woollings et al., 2015). The NAO is negatively correlated with the precipitation anomalies in southern Europe while positive correlations are observed in northern Europe. The two bands of strong correlations are separated by a zone of not statistically significant correlations in central Europe. Focusing on the three drainage basins, we find significant linear relationships between the aggregated precipitation anomalies and the NAO. Precipitation in the Spanish basins exhibits high anti-correlation with the NAO, exceeding -0.8, while moderate anti-correlation is observed for the Po basin (-0.62).

The fact that the multi-model ensemble can skillfully predict the phase of decadal fluctuations of NDJFM NAO, along with the strong link of NAO with the precipitation over the target basins, indicates that NAO is a suitable predictor for rainfall this season. Therefore, we developed a hybrid approach where the predicted NDJFM NAO is combined with the observed linear relationship of the NAO and precipitation in each basin. We focus on NDJFM since for the other calendar seasons, either the predictive skill of the NAO is low, or the relationship between the NAO and precipitation in the basins is not robust (Supplemental Fig. S2,S3, Table S1).

In Fig. 6, we present the observed and the predicted through the hybrid approach precipitation anomalies, as percent deviations from the 1981–2010 climatology. Even though the hybrid approach does not capture all the observed precipitation fluctuations, we find statistically significant ACCs at 95% level in all basins. The hybrid approach exhibits ACC = 0.59, 0.46, 0.54 for Po, Guadalquivir and Ebro respectively, outperforming the direct multi-model ensemble output which shows statistically significant ACC only for the Guadalquivir basin (0.34), while for Ebro and Po its ACC is close to zero (-0.01 and 0.16 respectively). The MSSS is lower in all basins, due to the small signal-to-noise ratio and/or the fact that precipitation is not controlled solely by the NAO. Other modes of atmospheric variability, such as the Eastern Atlantic Pattern (EAP) (Wallace and Gutzler, 1981) and the

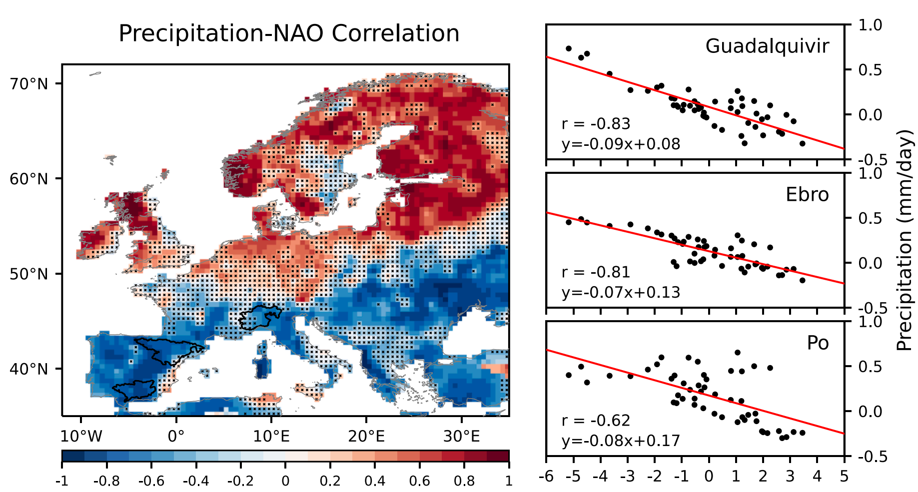


**Fig. 5. Left**: Correlation map between the decadal components (10-year running average) of the observed NAO and the precipitation anomalies during the extended winter (NDJFM) for the period 1961–2019. Stippling indicates statistically insignificant values at 95% significance level. **Right**: Scatter plots of the observed decadal precipitation anomaly in each basin against the observed NAO index during the NDJFM for the period 1961–2019 (from top to bottom: Guadalquivir, Ebro, Po). The red solid line shows the respective linear regression line. The Pearson's correlation coefficient (r) along with the equation of the linear fit are indicated at the left bottom corner of each plot. All the correlations are statistical significant at 95% significance level. Statistical significance is tested against the null hypothesis of zero correlation, using a two-sided Student's t-test, accounting for autocorrelation.

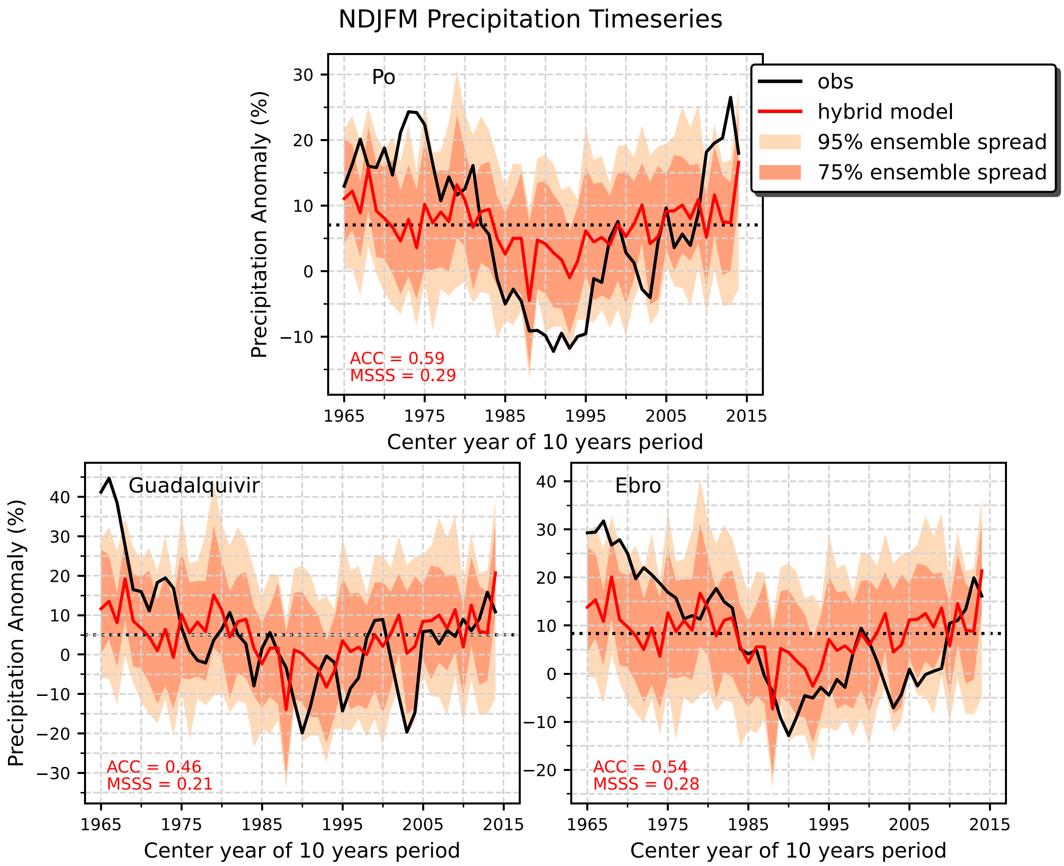


**Fig. 6.** Predicted and observed timeseries of extended winter (NDJFM) precipitation anomalies the first 10 forecast years (lead years 1–10). The black line represents the observations while the red line the output of the hybrid approach. The precipitation anomalies are presented as percent deviations from the 1981–2010 climatology. The ensemble spread (centered 75% and 95% percentiles) are shown in shading (darker and lighter shading, respectively).The horizontal dotted line indicates the observed 1960–2019 climatological average.

Scandinavian Pattern (SCAN) (Moore et al., 2013), also affect on precipitation over Europe (Moore et al., 2013; Comas-Bru and McDermott, 2014). Despite the low values, MSSS is positive ($p_{value}$= 0.246, 0.063, 0.053 for Guadalquivir, Ebro and Po respectively) in all basins indicating that this model is an improvement over the climatological forecast. Table 3 presents the contingency tables for forecasting above or below average precipitation, and the corresponding hit and false alarm rates for each basin. In general the hybrid approach can discriminate above/below average precipitation events with hit rates ranging between 72% and 81%, and false alarm rates lower than 36%.

As an attempt to provide some additional information to the end-user we also produced forecasts of the number of wet days in each basin during the NDJFM season (Supplemental Fig. S4). The number of wet days is a good indicator of the precipitation frequency and a rough estimator of its intensity, especially when it is combined with information regarding the mean precipitation. For example, an increased mean precipitation but a lower number of wet days during a season, could mean that the mean intensity of the rainy events increased. Following the same approach as for the precipitation forecasts, we find statistically significant ACC between observed and predicted number of wet days in all basins. However, given that both the precipitation anomaly and the number of wet days vary in the exact same way, as predicted through the NAO, no conclusions can be drawn for the mean precipitation intensity.

## 4. Discussion

Previous studies have provided evidence that coupling a statistical model to dynamical predictions of large-scale information, can improve the seasonal (Strazzo et al., 2019; Thornton et al., 2019; Cionni et al., 2022) and decadal (Simpson et al., 2019; Wu et al., 2019; Redolat et al., 2020; Borchert et al., 2021; Lockwood et al., 2023) forecasts of the local climate and/or other weather-related variables. However, in the case of decadal predictions, studies focusing on climate services for specific end-users are limited. Here, we developed a prototype climate service

**Table 3**
Contingency tables of above average precipitation.

| Above Average Precipitation | | Observed | | | | | |
|---|---|---|---|---|---|---|---|
| | | Guadalquivir | | Ebro | | Po | |
| | | Yes | No | Yes | No | Yes | No |
| **Predicted** | **Yes** | 18<br>Hits | 9<br>False alarms | 20<br>Hits | 7<br>False alarms | 21<br>Hits | 6<br>False alarms |
| | **No** | 7<br>Misses | 16<br>Correct rejections | 5<br>Misses | 18<br>Correct rejections | 5<br>Misses | 18<br>Correct rejections |
| **Hit Rate:** | | 72% | | 80% | | 81% | |
| **False Alarm Rate:** | | 36% | | 28% | | 25% | |

for the hydropower sector, by exploiting the predictive skill of NAO and its remote impact on precipitation in Southern Europe. This was a co-developed process, where we worked with the end-user (ENEL-GP, an operator of the renewable energy sector) to explore the current capability of a set of DPSs to meet their needs. Our results indicate that despite the low predictive skill for the precipitation in the direct multi-model ensemble output, predicting large-scale circulation anomalies that control precipitation can be key to improve substantially our predictive skill. Nevertheless, we recognise that further development and effort is needed in order to use this information in an operational context.

In the present study, precipitation forecast is one of the main needs of the end-user since it is a key driver of hydropower systems. However, the safety of the dams is also of great interest to the company. Extreme precipitation events can cause severe damages to their infrastructures and put the power plant operation in danger. Observations and climate projections indicate significant changes in the frequency and intensity of precipitation extremes in many regions over Europe (Coppola et al., 2021; Huo et al., 2021; Zittis et al., 2021). However, beyond any variability associated with long-term trends, decadal predictions generally exhibit low skill in predicting decadal variations of precipitation extremes. (Eade et al., 2012). In addition, while precipitation determines the water input in the reservoir, temperature and wind regulate the water losses through evapotranspiration. Moreover, changes in temperature, especially in mountainous regions, can alter the partitioning of precipitation to rain and snow, as well as the timing and intensity of spring snowmelt. As regards energy production, the end user would be ultimately interested in knowing the energy potential (level of water in the dam) for every month, yet in order to do so one would need a hydrological model, etc. After discussing this with the end user it was decided to stick to predicting precipitation.

Forecasts of 10-year averages provided here could be beneficial to a company operating in the hydropower sector for general planning, including new investments and contracts. However, different temporal horizons (e.g. 6–24 months) would be more useful for plant management purposes at operational level. Thus, bridging the gap between the seasonal and decadal predictions, providing information at an intermediate, multi-annual timescale, is a challenge we should overcome in the future in order to better address user needs. Forecasts for the other calendar seasons are also important for assisting the operational planning of hydropower systems. The multi-model ensemble used in this study shows generally low skill in predicting precipitation in the basins of interest and the NAO in the transitional seasons and summer. We point out though that the multi-model ensemble used here is only a subset of a larger set, currently available through the CMIP6 DCPP archive. Utilizing more models and a larger ensemble has been shown to increase the predictive skill in decadal predictions (Smith et al., 2019; Smith et al., 2020; Athanasiadis et al., 2020; Meehl et al., 2021). In addition, not all models display the same skill in predicting different variables in different regions (Supplemental Fig. S5, S6; (Delgado-Torres et al., 2022)). Selecting the best model or multi-model ensemble (or sub-ensemble) for each specific region, season, variable and forecast period could significantly increase the skill (Dobrynin et al., 2018; Neddermann et al., 2019; Dalelane et al., 2020; Smith et al., 2020).

A well-known issue of the statistical models, is their reliance on the assumption that the relationship between the predictor and the predictand (here the NAO and the precipitation) is stationary. However, previous studies (Walter and Graf, 2002; Pauling et al., 2006; Beranová et al., 2007; Rust et al., 2021) have demonstrated that the impact of NAO on the European climate changes in time, and this could cause loss of skill in future forecasts. This is related to the fact that NAO explains only a fraction of the overall precipitation variability over Europe, and other large-scale circulation patterns can actually enhance or cancel its effect on precipitation (Vicente-Serrano et al., 2008; Moore et al., 2013; Comas-Bru and McDermott, 2014). Implementing more complex statistical models such as multivariate regression, EOF-based analysis or elaborate machine learning techniques (Wu et al., 2019; Wang et al., 2021; Cionni et al., 2022) including more predictors could increase the accuracy and reliability of the predictions. However, careful selection of the predictors is required, since they have to be skillfully predicted by the DPSs.

Despite the limitations of this study, the current results are promising. Although the multi-model ensemble do not reproduce well the precipitation variability, the hybrid approach improves the predictive skill significantly. Coupling statistical models with the dynamical predictions can overcome the small signal-to-noise ratio of models and/or their deficiency to represent the main teleconnections, and thus present a high potential for supporting decision-making in the hydropower sector. Further effort and revision of this prototype climate service could lead to more mature products, which could help in the operational development of decadal climate services. Last but not least, this hybrid approach can be potentially extended and applied to other regions in Europe, while similar products can be developed to provide information for other renewable energy sources such as wind and solar power (Wohland et al., 2019; Correia et al., 2020).

## 5. Conclusions

This study, which was conducted in the framework of a C3S project, aims to reveal the potential of decadal predictions for the development of climate services for the energy industry. Through close interaction with a renewable energy company, we developed a prototype decadal climate service for the hydropower sector, predicting precipitation in three drainage basins in Southern Europe: Guadalquivir and Ebro in Spain and Po in northern Italy.

Using initialized predictions from four Decadal Prediction Systems (DPSs) (respective models: HadGEM3-GC3.1-MM, EC-Earth3, CMCC-CM2-SR5, MPI-ESM-HR), the predictive skill of precipitation was found to vary with the calendar season and the geographical area considered (basins). Even though statistically significant skill was found in a few cases, overall the direct skill of the multi-model ensemble was limited for the purposes of the climate service. For this reason, in order to better meet the needs of the end-user, we adopted a hybrid approach which combines a statistical model with the skillful dynamical predictions of the NAO. The statistical component is a simple linear regression model, using as a predictor the observed NAO which drives a large part of the precipitation variability in the three drainage basins. By implementing the hybrid approach significant skill arises in all basins for precipitation during the extended cold season (NDJFM) for the forecast range 1–10 years. The hybrid approach outperforms the direct output of the DPSs, especially for the cases of the Ebro and Po basins where the Anomaly Correlation Coefficient (ACC) reaches values greater than 0.5, compared to almost zero in the direct output. The Mean Squared Skill Score (MSSS) is low but positive, showing that the decadal predictions have an added value compared to the climatological forecasts, which are often used by end-users.

Our results indicate that deficiencies of the current generation DPSs can be overcome by combining high skill large-scale pressure patterns from the DPSs and their statistical relationships to regional precipitation. This enables useful information to be provided to the energy sector. However, future efforts are required to increase the skill and reliability of such predictions and extend their use to other temporal aggregations, seasons and user-relevant variables. Despite various challenges, our study provides encouraging results indicating that decadal predictions can be a useful tool for developing climate services and assisting decision-making for energy sector planning and operations.

## Data Availability

All data used in this study are publicly available online. The DPSs output is available on the Earth System Grid Federation (ESGF) under the references: CMCC-CM2-SR5 (Nicolì et al., 2020), MPI-ESM1–2-HR

(Pohlmann et al., 2019), EC-Earth3 (EC-Earth et al., 2019), HadGEM3-GC3.1-MM (Hermanson et al., 2020). The observational/reanalysis data are available at the NOAA Physical Sciences Laboratory ( https://www.esrl.noaa.gov/psd/data/gridded/data.hadslp2.html) for HadSLP2r and at the C3S ( http://surfobs.climate.copernicus.eu/dataaccess/access_eobs.php) for E-OBS.

## CRediT authorship contribution statement

**E.E. Tsartsali:** Conceptualization, Formal analysis, Software, Writing - original draft, Visualization. **P.J. Athanasiadis:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition, Software. **S. Materia:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition. **A. Bellucci:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition. **D. Nicolì:** Software, Writing - review & editing. **S. Gualdi:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition.

## Declaration of Competing Interest

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

## Acknowledgements

The authors acknowledge funding from the C3S_34c of the Copernicus Climate Change Service (C3S) (contract number: ECMWF/COPERNICUS/2019/C3S_34c_DWD) operated by ECMWF. We also like to thank ENEL-GP for their involvement in this project as a stakeholder in the hydropower sector and their contribution to the design and development of this case study. Last we acknowledge the developers of the other C3S_34c case studies for many useful discussions and valuable comments.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.cliser.2023.100422.

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