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Long-range hydrological drought forecasting using multi-year cycles in the North Atlantic Oscillation

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ABSTRACT

With global temperatures, populations and ecological stressors expected to rise, hydrological droughts are projected to have progressively severe economic and environmental impacts. As a result, hydrological drought forecasting systems have become increasingly important water resource management tools for mitigating these impacts. However, high frequency behaviours in meteorological or atmospheric conditions often limit the lead times of hydrological drought forecasts to seasonal timescales, either through poorer performance of multi-year meteorological forecasts or the lack of multi-year lags in atmosphere-hydrology systems. By contrast, low frequency behaviours in regionally important teleconnection systems (such as the North Atlantic Oscillation, NAO) offer a novel way to forecast hydrological drought at longer lead times. This paper shows that, by using a data-driven modelling approach, long-term behaviours within the NAO can be skilful predictors of hydrological drought conditions at a four-year forecasting horizon. Multi-year semi-periodic patterns in the NAO were used to forecast regional groundwater drought coverage in the UK (proportion of groundwater boreholes in drought), with the greatest forecast performance achieved for longer duration droughts, and for hydrogeological regions with longer response times. Model errors vary from 14 % (proportion of boreholes, (MAE)) in flashy hydrological regions or short droughts (<3 months), to 2 % for longer duration droughts (>8 months). Model fits of r^2 up to 0.8 were produced between simulated and recorded regional drought coverage. As such our results show that teleconnection indices can be a skilful predictor of hydrological drought dynamics at multi-year timescales, opening new opportunities for long-lead groundwater drought forecasts to be integrated within existing drought management strategies in Europe and beyond.

1. Introduction

Drought hazards that can affect all regions of the world can cause considerable damage to economies and ecosystems. Hydrological drought (where river or groundwater systems display prolonged periods of below-average water levels) can exhibit a large spatial domain and/or extend across multiple seasons, resulting in chronic impacts to water supply, aquatic ecosystems and food supply chains (Hasan et al., 2019; van Loon, 2015). Climate change has already intensified hydrological droughts in some regions (Cammalleri et al., 2020; Barker et al., 2019) and is expected to further exacerbate the severity and spatial footprint (coverage) of drought under future climate change scenarios (Peña-Angulo et al., 2022). Combined with increased water demand through population growth, this means that proactive water management is an utmost priority in many countries (Barker et al, 2019; Wilhite et al., 2000).

Forecasting systems for drought are a critical part of proactive water resource management (Nandgude et al., 2023; Ascott et al., 2021). For instance, they can estimate a range of dynamic drought characteristics (e.g., intensity, onset, spatial extent) before they are likely to occur, making them valuable tools in operational drought response (Fung et al., 2020). Dynamic drought forecasting can be broadly split into process-based and statistical approaches, often depending on the scale at which they are used. Process-based methods seek to replicate locally important hydrological processes; using forecasted meteorological variables and a hydrological model to estimate catchment-scale drought response (Sutanto et al., 2020). For decision making at a strategic or regional scale, more generalised drought information is required, such

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as aggregated or classified drought metrics (e.g., SPEI or SGI) that indicate whether or not a region will be in a drought condition (Tijdeman et al., 2022). In these cases, statistical forecasts are commonly used (Alawsi et al., 2022). These rely on a statistical relationship between indicator variables (i.e., predictors) and drought metrics, and require either forecasted indicators or lagged indicator-metric relationships to forecast regionalised drought characteristics. Indicators can be measured values (such as sea level pressure) or calculated teleconnection indices (such as the Nort Atlantic Oscillation Index (NAOI) or Southern Oscillation Index (SOI), which represent large portions of oceanic or atmospheric variability (Hurrell et al., 2003; Bridgman and Oliver, 2014). However, the stochastic nature of atmospheric and weather behaviour typically limits the performance of meteorological forecasts beyond a seasonal timescale (Toth and Buizza, 2019; Svensson and Hannaford, 2019; Sutanto et al., 2020), as well as the presence of indicator-drought relationships at lags beyond a seasonal timescale. As such, both process-based and statistical drought forecasts are often limited to seasonal (or sub-seasonal) lead times, in contrast to existing drought management strategies which typically operate on multi-year cycles of strategy development. Therefore, the current lack of multi-year hydrological drought forecasting capability inhibits many proactive drought management strategies, such as abstraction restrictions or catchment transfers (Wendt et al., 2021; Steinemann, 2006).

Recent hydroclimate research has highlighted that multi-year behaviours in teleconnection index time series may be stronger indicators for recorded hydrological drought, in some regions, when compared to monthly or winter-averaged indices (Rust et al., 2022). These latent relationships are typically strongest in hydrological systems that are most sensitive to long-term changes in meteorological variables, such as groundwater or groundwater-driven streamflow (Liesch and Wunsch, 2019; Neves et al., 2019; Baulon et al 2022a; Massei et al, 2010). In NW Europe, strong relationships have been found between multi-year semi-periodic behaviours in the NAO and groundwater drought coverage, at multi-year lags (Rust et al., 2022). This is in contrast to seasonal lags which are typically identified when assessing NAO-hydrology systems using monthly or winter-averaged data (e.g., Wedgbrow et al., 2002; Demirel et al., 2013). Multi-year lags in atmosphere-hydrology systems offer a novel way to forecast hydrological drought at multi-year timescales. However, the relationship between semi-periodic behaviours in the NAO and hydrological variables in NW Europe is highly non-stationary, posing a challenge to the application of these relationships for drought forecasting (Rust et al, 2022). Furthermore, the lack of a modelled relationship has precluded, in part, the investigation of control linkages between semi-periodic patterns in the NAO and drought behaviours across different hydrogeological systems. For instance, the influence of constructive or deconstructive interference between periodic behaviours in the NAO and other atmospheric systems (Holman et al., 2011, Jin and Kirtman, 2010). In this paper, we term these behaviours as semi-periodic as they are, at least in part, emergent properties from red-noise processes within the atmosphere and, as such, are not true periodicities (Hurrell et al., 2003).

Increasing availability of hydrometeorological data has driven recent developments in hydrological modelling towards statistical approaches that are less concerned with representing a systematic relationship and, instead, leverage a range of available data to explain hydrological behaviour (Papacharalampous et al., 2019). These are often called data-driven approaches. Examples of these approaches for drought forecasting include multiple regression (e.g., Svensson et al, 2015; Ionita and Nagavciuc, 2020), ARIMA or ARIMAX (e.g., Kim et al., 2019; Myronidis et al., 2018, Prodhan et al., 2022) or, more recently, Machine Learning tools such as Artificial Neural Networks (ANN) or Support Vector Regression (SVR) (e.g., Granata and Di Nunno, 2023; Dikshit et al., 2021). These methods take advantage of multiple explanatory variables (either endogenous of exogenous), making them adaptable to systems that exhibits strong seasonal or periodic components, or where non-stationarities are dominant (Yaseen et al., 2015). Here, we propose a novel approach, taking advantage of data-driven methods, to use multi-year lags between semi-periodic behaviours in the NAO and groundwater response to forecast groundwater drought characteristics at new multi-year timescales.

The aim of this study is to evaluate the potential of semi-periodic behaviours in the NAO for forecasting groundwater drought coverage at multi-year timescales, using data-driven approaches. We define drought coverage as the proportion of boreholes, within a region, experiencing a drought response. Drought response criteria are described in the methods section. The aim will be achieved by meeting the following research objectives:

1. Identify and quantify semi-periodic behaviours in groundwater drought coverage series that covary with the NAOI, across a range of hydrogeological regions.
2. Develop and apply a data-driven modelling approach to use semi-periodic behaviours in the NAOI to forecast drought coverage at multi-year timescales.
3. Evaluate the performance of drought forecasts against existing forecasting systems.

2. Data and methods

2.1. Groundwater data

Monthly groundwater level data has been taken from the National Groundwater Level Archine (NGLA) for 136 observation boreholes (OBHs), with record lengths of more than 20 years and data gaps no longer than 24 months. While monthly level data were used to calculate drought events, the main analysis was undertaken on annually summarized data, meaning a data gap of no more than two points. The boreholes cover all the major aquifers in the UK (Allen et al., 1997) and a range of unconfined and confined aquifers and have been categorised into groups based on generalised hydrogeological properties and behaviour. These are Chalk (74 sites), Limestone (12 sites), Oolite (12 sites), Sandstone (31 sites). Given the spatially heterogenous response of the Chalk aquifer to droughts (Marchant and Bloomfield, 2018), Chalk sites were subdivided into four groups based on aquifer region: East Anglian basin (17 sites), Lincolnshire basin (8 sites), Southern basin (21 sites) and Thames and Chiltern basin (28 sites) (Allen et al., 1997; Marchant and Bloomfield, 2018). Fig. 1a shows the distribution of OBHs used in this study, with all regions' record lengths centred around 50 years. Fig. 1b shows the number of active OBHs over time, with most boreholes, across the hydrogeological regions, active from the 1980s. Fig. 1c shows the location of all OBHs used in this study.

2.2. North Atlantic Oscillation Index

We used the calculated winter-time (DJFM) North Atlantic Oscillation Index (NAOI) (station based) calculated by the National Centre for Atmospheric Research (NCAR) (Hurrell, 1995). Station-based NAOI has been shown to appropriately capture the control of the NAO on meteorological variables during winter months (West et al., 2019).

3. Methods

3.1. Data Pre-Processing

In this study we use the continuous and cross-wavelet transforms to quantify semi-periodic behaviours within groundwater drought series and within the NAOI.

Only records with a data length of 20 years or greater have been taken forward in this study, to ensure that all sites have sufficient data to quantify (as a minimum) the strength of the dominant ~7- to ~8-year cycle which has been detected in water resources in previous research (e.g., Rust et al., 2022, Liesch and Wunsch, 2019).

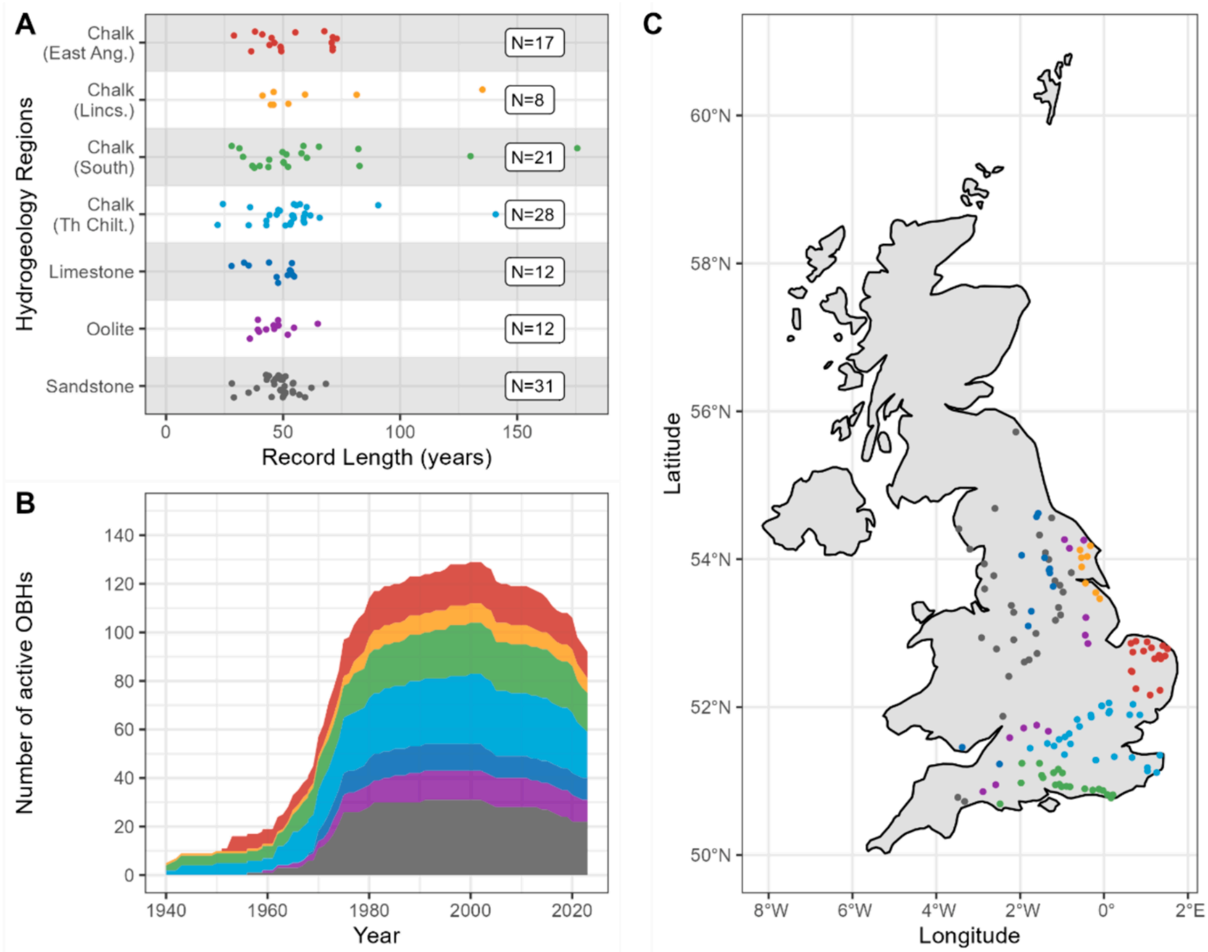

Fig. 1. Metadata for the groundwater level boreholes used in this study, showing a. the record lengths for each OBH, b. the number of OBHs in operation over time and c. the location of the OBHs, all classified by hydrogeological region.

For all groundwater level records, gaps of 2 years or less were infilled to a monthly time step using a cubic spline. For time series with a gap greater than 2 years, the longest period of continuous record either side of the gap, that still met the minimum record length of 20 years, was used as the final record. Finally, all records were detrended using a 3rd order polynomial to remove any long-term trends and maximise the detection of periodic behaviours. This follows the approaches of other applications of the wavelet transform for geophysical datasets (e.g., Kuss and Gurdak, 2014, Hanson et al., 2004).

Data was only assessed after 1960 given the few numbers of OBHs active before this time, and up to 2023.

3.2. *Calculation of drought and drought coverage*

Many different drought definitions and metrics have been proposed in existing literature, including threshold-based measures (e.g., Peters 2003; Sutanto and Van Lanen 2021), and standardized measures (e.g., Standardized Groundwater Index (Bloomfield and Marchant, 2013)). For strategic planning purposes, existing measures are often summarized to regional levels (Tijdeman et al., 2022) which can introduce errors or biases (such as sensitivity to outliers). As such, this paper targets a regional-scale relationship by utilizing the coverage drought metric (i.e., proportion of boreholes within a region that exceed a groundwater threshold or meet some other condition), proposed by Rust et al., (2022).

A range of drought conditions were selected to measure both drought intensity (from mild water stress to more severe drought) and duration at each OBH. For interpretability, a percentile threshold approach was used to define these drought conditions. For drought intensity; these conditions are where a local minima in monthly GWL fall; 1) between 20th and 10th percentile of GWL at that OBH; 2) between 10th and 5th percentile and 3) below the 5th percentile. For drought duration, coverage has been calculated where GWL is below the 20th percentile for 1) less than 3 consecutive months, 2) between 3 and 8 consecutive months, and 3) more than 8 consecutive months. Duration conditions have been based on the least severe intensity (20th percentile) to maximise the number of conditions met. A final drought measure, which captures any droughts, has been calculated as the proportion of boreholes that experience a GWL below their 20th percentile in each year. For each region and for each drought condition, the drought coverage series is then calculated as the proportion of boreholes within that region that exhibited the drought condition, in any month of the year. A minimum of 5 boreholes per region were used in the analysis to ensure a stable calculation of the proportion of boreholes within a region in a drought condition.

3.3. *Quantification of periodic behaviours*

We identify key semi-periodic behaviours (or components) in the drought coverage time series using the continuous wavelet transform (CWT) and their covariance with similar behaviours in the NAOI using the cross-wavelet transform (XWT). By assessing both of these, we identify NAO-driven periodic components in drought coverage series that have the greatest impact on overall drought coverage behaviour.

The wavelet transform is a method for frequency decomposition that is commonly used for assessing periodic behaviours within geophysical datasets (e.g., Kuss and Gurdak, 2011; Velasco et al., 2015), has been previously used to detect periodic behaviours shared between atmospheric processes and hydrological records in Europe (e.g., Lorenzo-Lacruz et al, 2022; Rust et al, 2022), and in particular has been used successfully as a pre-processing step for hydrological modelling (e.g., Massei et al 2017; Wu et al 2021; Hadi and Tombul, 2018). The Morlet wavelet was favoured over other candidates due to its good definition across the time and frequency domains, with a wavenumber of 6 (Tremblay et al. 2011; Holman et al. 2011; Rosch & Schmidbauer, 2018)). A period range of between 2 and 24 years was selected to capture major semi-periodic behaviours previously identified in European hydrometeorological variables, e.g., rainfall (Massei et al., 2007; Rust et al, 2019); streamflow (Massei et al 2010), and groundwater level (Liesch and Wunsch, 2019; Neves et al., 2019; Rust et al., 2022; Baulon et al, 2022a).

Significance testing has been conducted using 1000 monte-carlo generated series of the same length and with the same AR1 coefficient, using an ARIMA model. AR1 was calculated using the partial autocorrelation function. Significant powers are therefore representative of periodicities that cannot be explained by entirely a red noise process. The 95 % CI is used.

In this study we have employed the CWT over other wavelet transforms (such the Discrete Wavelet Transform, or maximum-overlap discrete wavelet transform) since the CWT allows for identification and reconstruction of behaviours along a continuous frequency range, whereas discrete versions are limited to lumped, dyadic frequency bands which may limit the precision of identifiable frequency behaviours within the NAOI and drought series. However, a potential limitation of the CWT is the presence of edge-effect which introduce uncertainties in the frequency estimation at the start and end of the analysed signal. Here, the impact of edge-effects was minimized by transforming the entire historical record as a pre-processing step before subsetting data to emulate a real-time forecast (See Modelling Framework in section 3.4).

3.4. Rolling lag correlation

To develop the modelling framework, it was necessary to understand the range of lags between the NAOI and the drought coverage series, for key semi-periodic components identified at the previous step. This was achieved by undertaking a moving-window lag (Pearson's) correlation. Within a rolling 16-year window, cross-correlation coefficients were calculated for lags between 0 and 9 years, for the preceding 16 years record. This identifies the dominant lag between semi-periodic components of the NAOI and drought coverage series at each year on record. Only positive lags (groundwater components responding after NAO components) were identified.

3.5. Modelling framework

3.5.1. Modelling summary

We develop a modelling framework here to use key reconstructed semi-periodic components of the NAOI to forecast drought coverage series. These components, identified in the NAOI and drought series using the continuous wavelet transform (see **Quantification of periodic behaviours** section), were approximately 8-year and approximately 16-years in period length (see Results Section). The modelling framework is based on the assumption that these two key semi-periodic components within the drought coverage series, when composited, capture the majority of variance in the original drought coverage series (Rust et al, 2019).

The modelling framework comprises two parts, summarised here and expanded upon below.

1- Exogenous model which forecasts semi-periodic components of drought coverage series using reconstructed components of the NAOI as exogenous variables. A separate instance of this model is used for the 8-year and 16-year components. Forecasted values of the drought series 8-year and 16-year components are combined to produce a forecasted composite semi-periodic component series of drought coverage.

2- Endogenous model which uses a historical regression between the composited 8- and 16-year components of the drought coverage series, and original feature space drought series to rescale the forecasted composite semi-periodic series back into the original drought coverage units (proportion of boreholes in drought).

3.5.2. Exogenous model

3.5.2.1. Moving window regression. As mentioned previously, the time-lag between semi-periodic behaviours in the NAOI and in groundwater level has been shown to be non-stationary (Rust et al., 2022). To account for this, we build an adaptive approach using a moving-window regression between reconstructed components (8- and 16-years) from the NAOI and drought coverage series. For each year on record, a regression is built using the previous 16 years' values from the reconstructed semi-periodic components, therefore representing an updated lagged relationship. A window length of 16 years was selected, as this captures two cycles of the dominant 8-year, and one of the secondary 16-year cycle. Additionally, given the time-varying lag, a lagged regression would produce an intermittent or non-constant forecast horizon which would limit the utility of the forecasting system. Therefore, we use a combination of distributed lag models (DLaMs) and the autoregressive properties of NAOI semi-periodic components to produce forecasted values of drought coverage at a fixed lead time.

3.5.2.2. Autoregressive properties of NAOI reconstructed LF components. The reconstructed 8- and 16-year semi-periodic components from the NAOI have strong autocorrelations at half-period time lags (4-years and 8-years respectively) (see SM Fig. 1). As an autoregressive property, these are $r^2 = 0.9$ at the 4-year lag in the 8-year cycle, and $r^2 = 0.7$ for the 8-year lag in the 16-year cycle (r^2 values were calculated by the square of Pearson's r for the total length of NAOI record used in this study; 1960 – 2023). As such, we use the n-4 and n-8 values of the NAOI's reconstructed 8- and 16-year components (respectively) to extend the systematic lag between NAOI and drought coverage components. This provides a minimum forecast horizon of 4-years for in the 8-year cycle, and 8-year in the 16-year cycle. Since both 8 and 16-year components are used to produce a composite semi-periodic series, we take the maximum overlap of a 4-year forecast.

3.5.2.3. Distributed lag models. The minimum 4-year lag provided by the autoregressive properties of the NAOI's semi-periodic behaviours are in addition to the systematic lags between the NAOI and drought coverage. These lags are captured using a distributed lag model (DLaM). DLaMs represent a relationship between a dependent variable and various lagged values of an independent variable. As such, they are particularly useful in representing lagged relationships with persisting temporal patterns (such as periodic or semi-periodic behaviours) (Rushworth et al., 2013; Lu et al., 2022). Here, we use DLaMs to capture the influence of NAOI semi-periodic behaviours on drought coverage, at between zero and 5-year lags. While there were few instances of calculated lags greater than 5 years ($<5\%$, see SM Fig. 1), a maximum of 5-year was selected to ensure there were sufficient data within each 16-year window. Within each windowed instance of the DLaM, unnecessary coefficients (for instance, those with a non-significant impact on the regression) were not removed as it was not necessary to produce a generalized model – each windowed instance of the DLaM was only be used for one forecast.

The general DLaM formula is given by:

$$Y_t = a + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \beta_n X_{t-n} + \epsilon t \quad (1)$$

Y_t is the dependent variable at time t. $X_t, X_{t-1}, X_{t-2}, \ldots, X_{t-n}$ are the independent variable values at time t and its lags (previous time periods). α is the intercept term. $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are the coefficients for the independent variable and its lags. ∊t is the error term at time t. n is the number of lag periods included in the model.

3.5.3. Endogenous model

The Endogenous model converts the forecasted composite semi-periodic components into an estimate of the drought coverage (original feature space), utilizing the historical relationship between these two endogenous variables. Since no time-varying lag was expected between composite semi-periodic components and drought coverage values (due to their internal relationship), an expanding window regression has been used (starting at 16 years, to align with the first instance of the rolling-window regression from the Exogenous model). A DLaM was used again in this component to capture any constant lagged response to semi-periodic behaviours within the drought coverage series. In addition, two lags from the drought coverage series are included within the DLaM to capture antecedent conditions in the drought series. This can be considered representing the forcing of semi-periodic components on the in-year mean and trend of the drought coverage series.

3.6. Model performance testing

In existing drought forecasting literature, two types of model performance metrics are typically used. Statistical measures (such as r^2, root mean square error, or mean absolute error (MAE)) are often used to evaluate the performance of statistical forecasts, since predicted variables from these systems can be either real-world or constructed variables (such as SGI; Marchant and Bloomfield, 2018), and are often non-continuous (e.g., Svensson et al., 2015; Prudhomme et al., 2017). Conversely, dynamic or continuous forecasts of real-world variables (such as groundwater level in MacKay et al., 2019) are assessed on their likelihood to capture the occurrence of a ‘drought’ or ‘non-drought’, based on a chosen drought classification; comparing historical and recorded drought occurrences using probabilistic measures such as ROCC or Brier Score. The modelling approach presented here is based on forecasting a constructed drought measure (proportion of in-region boreholes in drought) and as such probabilistic performance measures are not appropriate. R^2 and MAE have been used.

For each year on record, the modelling framework produces a four-year ahead forecast of drought coverage. In order to test model performance, each of the 1-year, 2-year, 3-year and 4-year forecasts were concatenated together into four new and separate time series. Model performance was tested using performance metrics (Mean Absolute Error (MAE) and coefficient of determination (r^2)) which were calculated comparing each of these n-year forecast series with the observed drought coverage series.

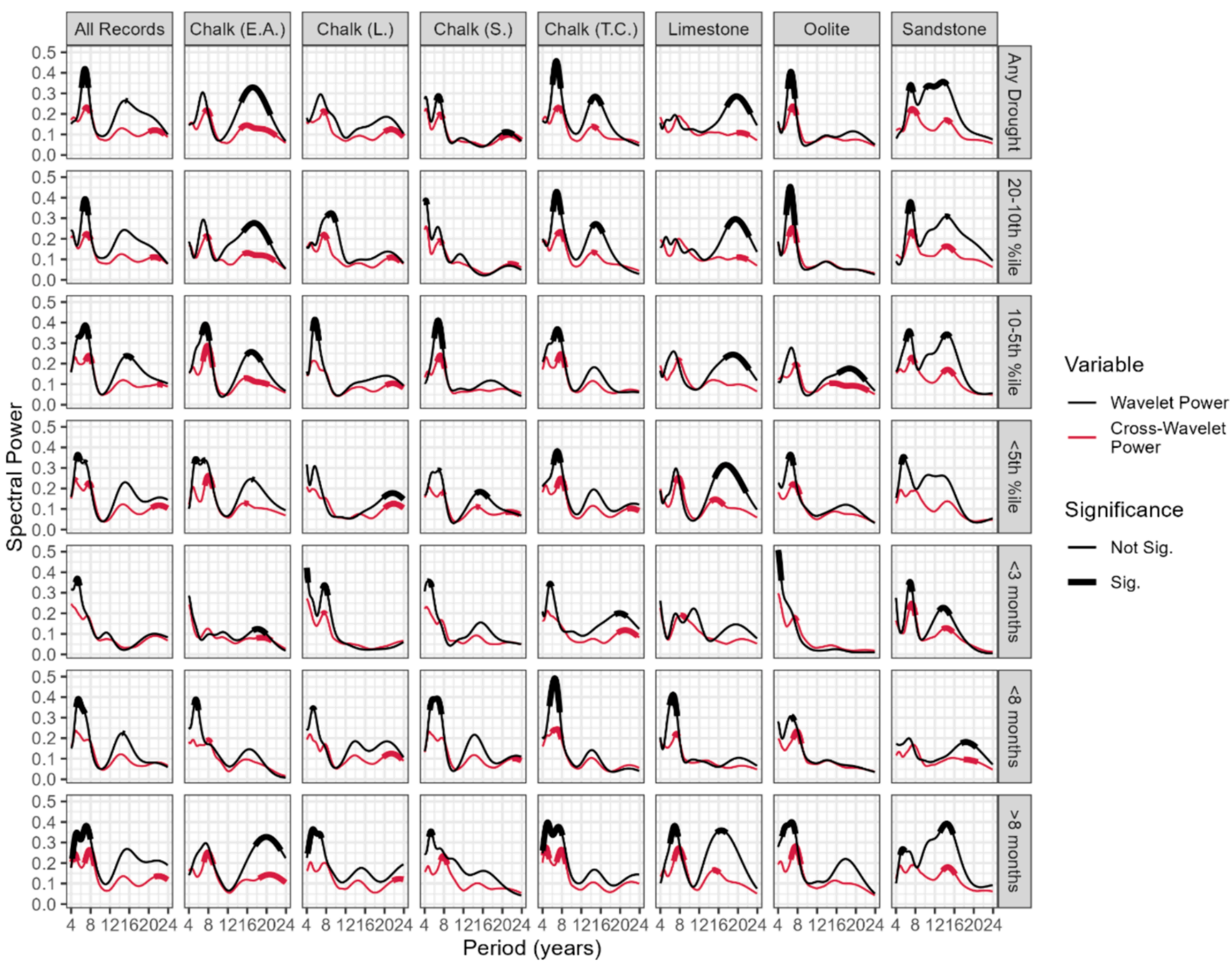

Fig. 2. Global Wavelet and cross-wavelet powers showing the strength of semi-periodic components across each Hydrogeology region and for each drought type series.

Mean absolute error is given by:

$$MAE = \frac{1}{n}\sum\nolimits_{i=1}^{n} |x_i - y_i| \tag{2}$$

where x represented the recorded values and y represents the predicted values.

R^2 was calculated as the square of the Pearson's r between the recorded and predicted drought coverage values.

4. Results

4.1. Cross wavelet transform

Fig. 2 shows the global wavelet powers (black) and cross-wavelet power with the NAOI (red) across all drought coverage series and across each region (including all records). Wavelet powers are a representation of the strength of different (semi-)periodic components within the drought coverage series. Cross-wavelet power is analogous to covariance in the frequency domain between NAOI and drought coverage. Significant wavelet and cross-wavelet powers (>95th CI) are in bold.

Drought coverage can be characterized by key semi-periodic components at the 6- to 10-year range (approximately centred on the 8 years), and at the 14 to 20-year range (approximately centred on 16 years). This is the case across different drought conditions and each hydrogeological region. In most instances, where wavelet powers are significant in the drought series, there is also a significant covariance with the NAOI, suggesting that the NAO is driving these increases in wavelet power at these frequency bands.

Across the All Records group, all drought conditions show a significant 8-year and a strong 16-year component, except for the shortest duration (<3 months) which shows no clear 8-year or 16-year components, and instead exhibits a shorter approximate 6-year component. Only the Any Drought, 10th-5th %ile and < 8 months duration conditions show a significant 16-year component. All conditions except for the <3 months and <8 months series show a significant covariance with the NAOI at the 8-year period length. No conditions show a significant covariance at a 16-year component, however all drought conditions show increased cross-wavelet power at a 16-year component suggesting a wide-spread influence.

Drought coverage series in the East Anglian Chalk, Thames / Chiltern Chalk and Sandstone regions are characterised by strong 8-year cycles and 16-year components. With the exception of the <3-month droughts in the East Anglian Chalk, and the <8 month series in the Sandstone, all 8-year components are significant. Significance of the 16-year component is variable across the drought regions, except for Sandstone which shows significant 16-year components in all drought series except the <5th %ile series. Significant covariance with the NAOI is also found at the 8-year component for these regions, with significant 16-year covariance more often found in the Thames / Chiltern Chalk and Sandstone regions.

The Lincolnshire Chalk, Southern Chalk and Oolite can be characterised by strong and significant 8-year components and variable 16-year component strength. For instance, the Lincolnshire Chalk and Oolite show weak 16-year components for all but a few drought series (e.g., <8 month and >8 month in the Chalk and 10th-5th %ile and >8-month drought series in the Oolite). Whereas the Southern Chalk shows more consistent, yet still weak, 16-year component. Significant covariance between drought series in the Southern Chalk and the NAOI are typically found where there are also significant components in the drought series.

Finally, the Limestone is characterised by variable 8-year and 16-year components, while either can be strong and significant across the different drought series. For instance, the Any Drought, and all the intensity drought series can be characterised by weak 8-year components, but strong and significant 16-year components. Conversely across the duration series there is considerable variance. For instance, the <3-month series show no clear semi-periodic components, the <8-month series shows a strong and significant 8-year but no 16-year components, while the >8-month drought series shows strong and significant 8-year and 16-year component.

Finally, while most of the drought series show varying characteristics (as described above), the shortest drought series (<3 months) typically shows least consistency in the wavelet spectra and often shows a greater power at higher frequencies. This drought coverage series (<3 months duration) also exhibits little significant covariance with the NAOI.

4.2. Forecasted drought coverage series

Forecasted drought coverage drought series at 1- through 4-year lead times have been displayed in Figs. 3–5 for selected drought coverage series. These are Any Drought, <5%ile droughts and >8-month duration droughts, to capture all droughts, the most severe droughts and the longest droughts, respectively. Forecasted time series are shown for all drought coverage series in the supplementary materials. Model error (MAE) and fit (r^2) are also displayed for each forecast horizon. Metrics have been calculated in forecasted data after 1990 to allow comparison with shorter records (such as the Limestone region).

Fig. 3 shows the forecasted values for the Any Drought coverage series, which represents droughts where groundwater level fell below the 20th %ile in any year. While this is a broad characterisation of drought, the drought coverage series show strong variance over time often between ~10 % to ~90 % of resources, suggesting that this captures an important mode of drought behaviour across the hydrogeological regions.

The forecasted 20th %ile drought coverage values fit well with low errors across all the regions, however the errors and fits across the Southern Chalk and East Anglian Chalk regions indicate reduced performance in these areas. As expected, the 1-year forecast typically shows the greatest performance. In order of error in the 1-year forecast, the best forecasts were achieved in the Sandstone region (MAE = 0.11, r^2 = 0.73); followed by All Records (MAE = 0.11, r^2 = 0.65), Thames / Chiltern Chalk (MAE = 0.13, r^2 = 0.72), Southern Chalk (MAE = 0.13, r^2 = 0.60), Lincolnshire Chalk (MAE = 0.14, r^2 = 0.69), Oolite (MAE = 0.15, r^2 = 0.53), Limestone (MAE = 0.15, r^2 = 0.41) and East Anglian Chalk (MAE = 0.19, r^2 = 0.51). Across all regions, the 10- to 15-years at the start of the forecasted records is typically noisy, particularly within the 2-, 3-, and 4-year forecasts. This is likely due to the lower number of active OBHs in these year ranges. There is also a notable period of decreased model performance between 1980 and 1990 across the records that cover that period, within the >1 year forecasts, likely due to the step-change in lag between NAO and groundwater semi-periodic behaviours identified at this time period by Rust et al, (2022). Beyond this, there is good alignment between all forecast horizons, which typically capture the general trends (e.g., peaks and troughs) in drought coverage well.

Fig. 4 shows the forecasted drought coverage series for severe droughts, where groundwater level fell below the 5th %ile level. Error and fit across this drought series is typically reasonable although model performance appears less than for the Any Drought series in Fig. 3. In order of error in the 1-year forecast, the best forecasts were achieved in the Sandstone (MAE = 0.07, r^2 = 0.58), followed by All Records (MAE = 0.09, r^2 = 0.59), Thames / Chiltern Chalk (MAE = 0.10, r^2 = 0.64), Southern Chalk (MAE = 0.13, r^2 = 0.58), Oolite (MAE = 0.13, r^2 = 0.55), Limestone (MAE = 0.14, r^2 = 0.40), Lincolnshire Chalk (MAE = 0.15, r^2 = 0.56) and finally East Anglian Chalk (MAE = 0.15, r^2 = 0.56). Beyond 1990, forecasted series typically fit recorded series well, with the exception of 2011 and 2022 which show spikes in drought coverage that is underpredicted in the EA Chalk, Lincs. Chalk, South Chalk, Limestone and Oolite regions. Also, the model over predicts drought coverage for the period 2003 to 2008. This is most pronounced in the

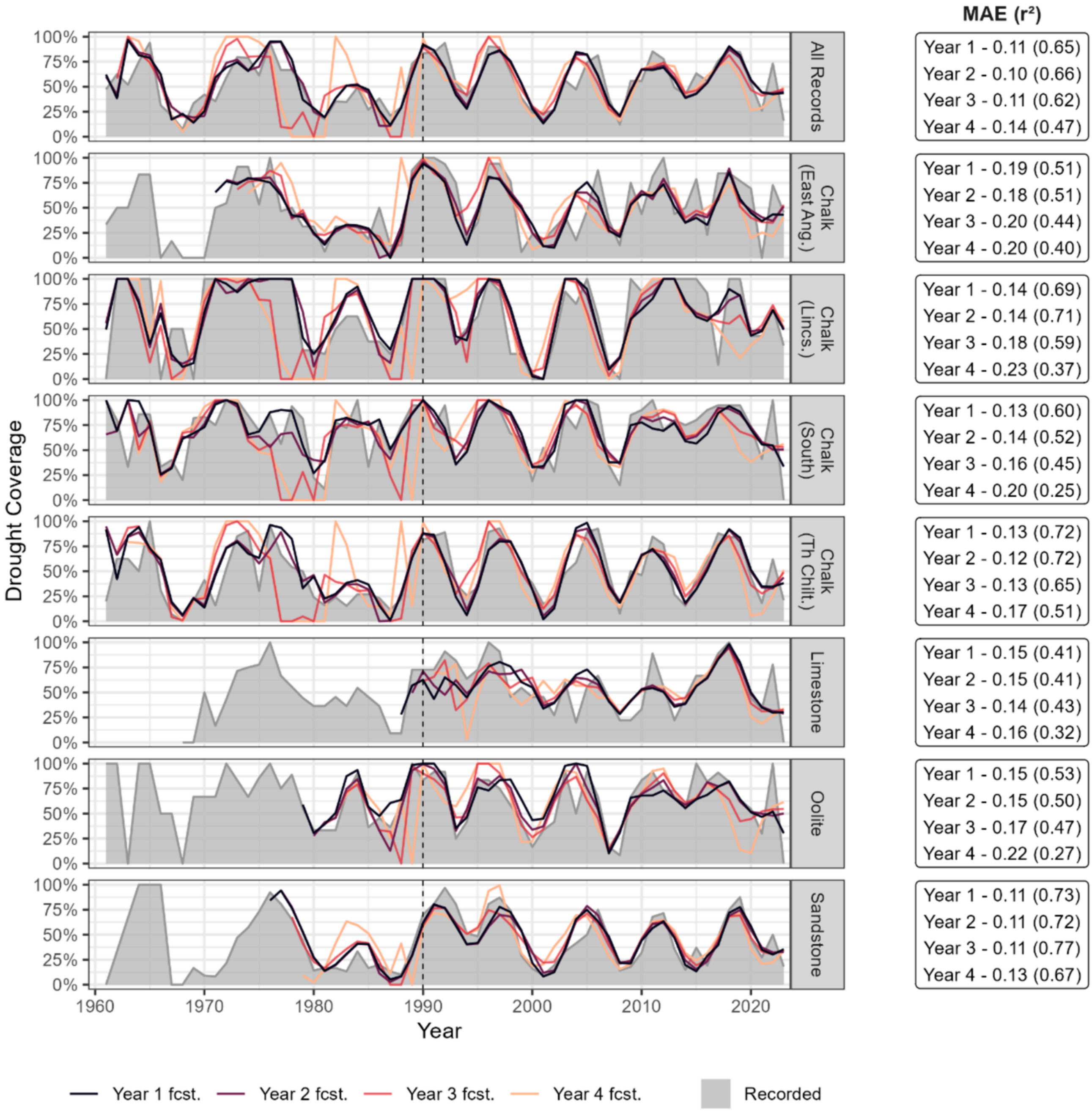

Fig. 3. Forecasted drought coverage for any recorded drought (GWL < 20th %ile). To ensure the error and fit measures (MAE and r^2) are comparable between records of different lengths, values are tabulated for forecasted values after 1990.

Lincolnshire Chalk region which shows no recorded drought response for this period.

Finally, Fig. 5 shows the forecasted drought coverage series for droughts that lasted for 8 consecutive months or more. The model performed best for this drought type across all regions. In order of error in the 1-year forecast, the best forecasts were achieved in the Southern Chalk (MAE = 0.02, r^2 = 0.69), followed by Oolite (MAE = 0.04, r^2 = 0.77), All Records (MAE = 0.06, r^2 = 0.79), Thames / Chiltern Chalk (MAE = 0.08, r^2 = 0.82), Sandstone (MAE = 0.08, r^2 = 0.74), Limestone (MAE = 0.08, r^2 = 0.64), Lincolnshire Chalk (MAE = 0.10, r^2 = 0.81), and East Anglian Chalk (MAE = 0.10, r^2 = 0.78). All forecasts (across forecast horizons) were below an error of 0.15 and exhibited an r2 greater than 0.5. The period 2003 – 2008 also showed overpredicted drought coverage, but this was less notable than for other drought metrics, with the exception of the Lincolnshire Chalk, which was forecast to exhibit a drought response, but this was not apparent in the recorded drought series.

5. Discussion

5.1. Multi-year NAOI patterns as predictors of drought coverage across different hydrogeologies

Numerous hydroclimate studies have speculated that (semi-)periodic behaviours in teleconnection systems (such as the NAO) may be used to predict hydrological behaviour or provide foresight of extremes such as drought (Rust et al., 2022, Baulon et al 2022b, Lorenzo-Lacruz et al., 2022, Neves et al., 2019; Liesch and Wunsch, 2019). The results presented in this study confirm, for the first time, that multi-year semi-periodic behaviours in the NAO can be used to forecast hydrological

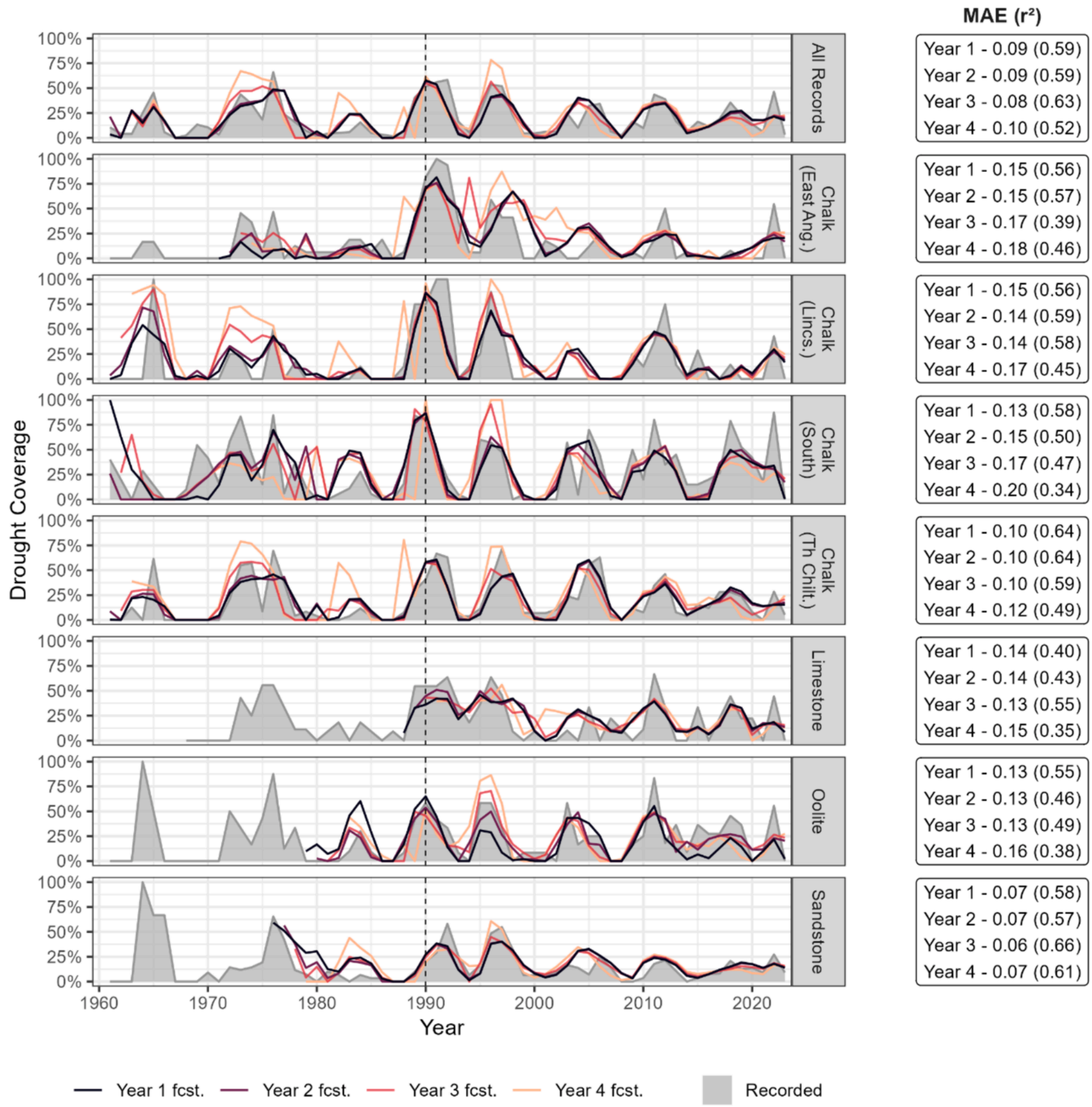

Fig. 4. Forecasted drought coverage for droughts where GWL falls below the 5th %ile. To ensure the error and fit measures (MAE and r^2) are comparable between records of different lengths, values are tabulated for forecasted values after 1990.

drought characteristics through data-driven techniques. Furthermore, forecasts are possible at multi-year timescales, providing a new way to plan and prepare for hydrological drought at strategic timescales.

The use of semi-periodic NAO behaviours to explain hydrological drought requires two assumptions. Firstly, that these NAO behaviours are the cause of similar patterns in hydrometeorological variables. These can be directly measured variables such as rainfall or groundwater levels or constructed variables such as SPI or drought coverage. Secondly, that these semi-periodic behaviours in hydrological behaviour are sufficiently dominant to have a leading effect on drought development. Many studies have focused on attributing multi-year (semi-)periodic behaviours detected in European hydrometeorological records (such as rainfall (Lukovič, et al., 2014; Rust et al., 2019), streamflow (Lorenzo-Lacruz et al., 2022; Massei et al, 2010) and groundwater (Neves et al., 2019; Rust et al., 2022) to NAO behaviours; often identifying covariances centred around the 8-year and 16-year period lengths (Baulon et al 2022a; Liesch and Wunsch, 2019; Rust et al., 2022; Luque-Espinar et al., 2008). However, semi-periodic behaviours in the NAO, and their relationship with hydrological variables, can be noisy and non-stationary (Rust et al., 2022), leading some studies to include other atmospheric systems in the North Atlantic region as additional covariates to explain the frequency structure of drought in Europe (e.g., the East Atlantic Pattern (Holman et al., 2011; Neves et al., 2019), or Scandinavian Pattern (Lorenzo-Lacruz et al., 2022). Results from the Exogenous Model (presented in Supplementary materials Figs. 6–19) show that the NAO can explain over 96 % of semi-periodic behaviour in regional drought coverage at 8- and 16-year period lengths ($r^2 >= 0.96$ across all regions, for the 1-year forecast). This suggests that the NAO (or more specifically, the atmospheric behaviours it represents) is the primary driver for these periodic components in hydrometeorological

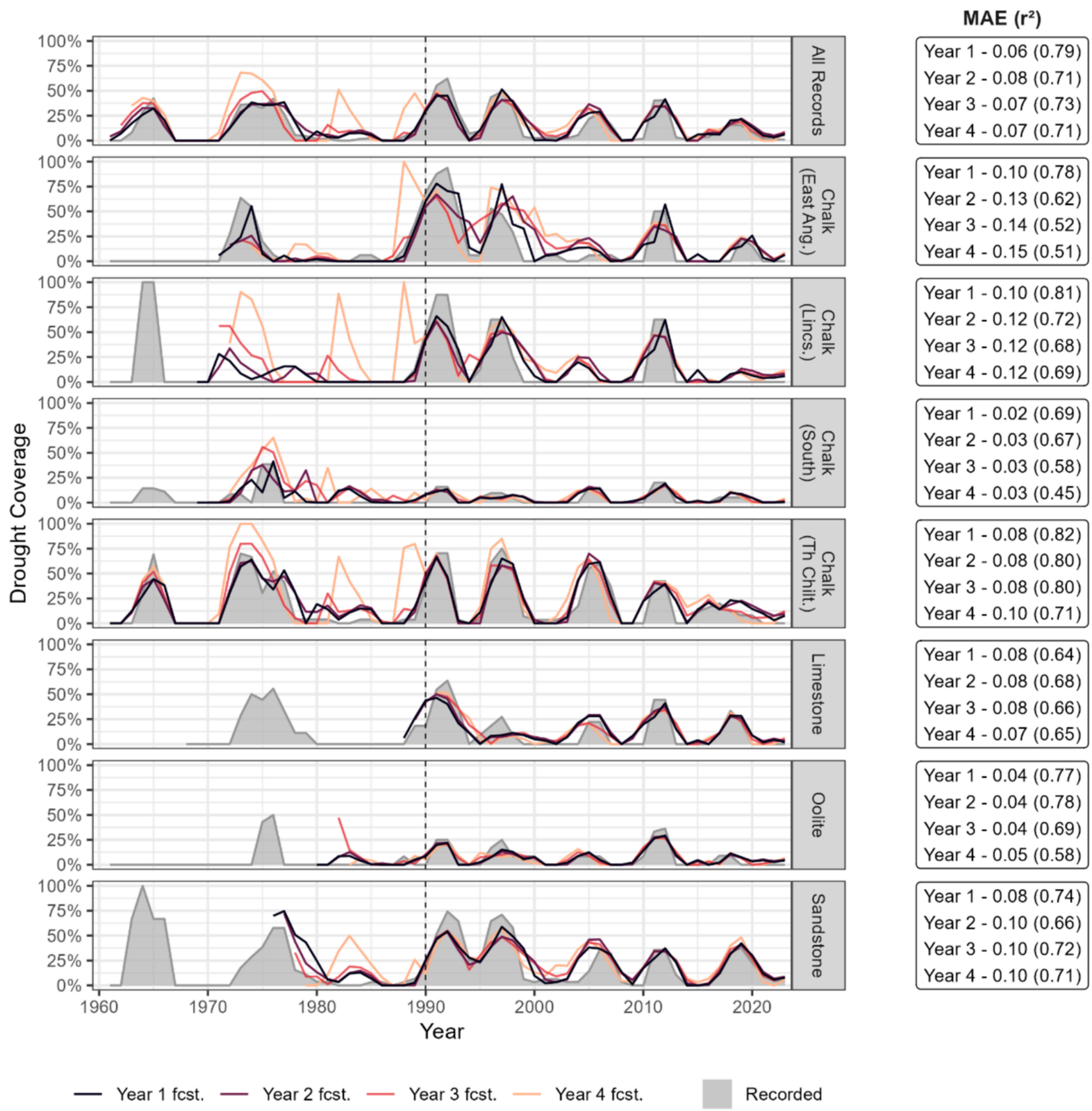

Fig. 5. Forecasted drought coverage for long droughts where below the 20 %ile for 8 months or longer. To ensure the error and fit measures (MAE and r^2) are comparable between records of different lengths, values are tabulated for forecasted values after 1990.

variables. Secondly, it suggests that any deviation of model performance is due to strength of these patterns within hydrometeorological variables, rather than the suitability of semi-periodic NAO behaviours as explanatory variables. Hydrogeological characteristics have been shown to influence the sensitivity of water resources to long-term behaviours in recharge signals (Bloomfield and Marchant, 2013). For instance, aquifers with lower transmissivity (such as Sandstone and some Chalks (Allen et al., 1997; Marchant and Bloomfield, 2018) may show stronger multi-year behaviours in groundwater level as they are unable to convey higher-frequency signals (Townley, 1995). Furthermore, Rust et al., (2021) shows that the strength of semi-periodic behaviours found in rainfall vary spatially, suggesting some regions may be exposed to stronger NAO signals in rainfall-recharge than others. These dynamics can explain the variance in our model performance results (Figs. 3–5) over the different hydrogeological regions. For instance, greatest model performance is typically found in the Sandstone and Thames Chiltern Chalk, both of which have been shown to be particularly sensitivity to multi-year NAO behaviours (Rust et al., 2019; 2022) than more responsive hydrogeologies (e.g., Limestone or Southern Chalk).

Long-term deficits in rainfall drive longer hydrological droughts (van Loon, 2015). This explains why multi-year semi-periodic NAO behaviours were better predictors of multi-seasonal or multi-year droughts (>8-months) than other drought conditions, since these NAO behaviours are long-term drivers on meteorological conditions (Rust et al., 2019). Whereas other drought categorisations (such as high severity, <5th %ile) may be driven by both long-term and short-term deficits (Brunner et al., 2022), for which multi-year NAO behaviours would have lower predictive capacity. For instance, the 2011 and 2018 hydrological droughts in Europe were characterised by long-term rainfall deficits compounded by short-term meteorological conditions (Blauhut et al., 2022), resulting in acute intense drought. Our results show that multi-year semi-periodic NAO behaviours can accurately predict the long-term component of these compound droughts but may underpredict the shorter-term dynamics. This can be seen for the <5th %ile series at years 2011 and 2018 in Fig. 4, particularly in flashier hydrogeologies such as the Southern Chalk, Limestone and Oolite which would be most responsive to short-term influence (Allen et al., 1997). By contrast, the wide-spread European drought between 1995 and 1998 was characterized by long-term rainfall deficits caused by persistent atmospheric blocking (Parry et al., 2012), and as such was more typical. Multi-year NAO behaviours captured this drought response well across both the long duration and high intensity drought coverage series, across most of the hydrogeological regions. This aligns well with Baulon et al (2022b) who suggest the NAO as a driver for a ~7-year semi-periodic component in GWL contributing to the 1995 groundwater drought in France. Within our results, flashier catchments such as Limestone or Oolite show reduced fits (but within 15 % error), since these catchments are less sensitive to long-term drivers such as multi-year behaviours captured by the NAO. This suggests that the NAO is a better predictor of drought response in instances where long-term deficits are the prevailing mechanism compared to shorter drought duration coverage series (shown in the Supplementary Materials).

5.2. *Predictive utility of NAO periodicities compared to other drought forecasting methods*

Existing hydrological drought forecasting approaches typically use relationships between explanatory variables and drought metrics / hydrological response within original feature space or in the data's native domain (e.g., Ionita and Nagavcuic, 2022; Svensson et al., 2015). By contrast, our results show that by decomposing NAO signals into periodic components (thereby reducing their stochasticity), it is possible to identify strong indicators for hydrological drought at longer lags, enabling longer forecasts. For instance, Ionita and Nagavciuc (2020) use a combination of predictors (including Sea level pressure, sea surface temperature and rainfall) with lags between 1 and 6 months to forecast river low flows at 1 month lead times, with high predictive performance ($r^2 = 0.8$). This is in agreement with our modelling framework, in that multiple lagged regressors can be skilful predictors of drought metrics, however comparison with our results highlights how the stochastic nature of instantaneous meteorological variables limits systematic lags to shorter timescales. Multiple studies have proposed methods to forecast European drought characteristics using lagged response from hydro-meteorological variables (including the NAO), with good forecasting performance (normalized performance measures (such as r^2) > 0.5), but with limited lead times (typically less than 6 months) (e.g., Santos et al., (2014), Sutanto et al., 2020a; Svensson et al., 2015; Scaife et al., 2014; Kingston et al., 2015; Svensson and Hannaford 2019). Sutanto et al., (2020b) highlights that longer drought forecast lead times can be achieved in systems with longer persistence times, demonstrated through a comparison between hydrological and meteorological drought forecasts. Our results align with this concept, showing that improved lead-times can also be found in atmosphere-drought linkages at multi-annual periodicities.

Our results show that multi-year NAO behaviours have less predictive performance in flashier catchments, or for short-term flash droughts, potentially limiting their application in certain regions or to certain hazards (such as agricultural drought). Fast-responding catchments typically exhibit a high degree of noise in their hydrological behaviour, as they respond to fine-scale variability in meteorological drivers (Carr and Simpson, 2018), making drought forecasting in these regions challenging. For instance, MacKay et al., (2015), found reduced model performance (Relative Operating Characteristics) of seasonal groundwater drought forecasts, using a process-based modelling approach, in quick-responding groundwater catchments when compared with forecasts from slower-responding hydrogeological catchments. Similarly, the UK Hydrological Outlook (a hybrid statistical and process-based hydrological framework used for hydrological extremes forecasting in the UK, Prudhomme et al., (2017) found reduced forecasting performance in flashier catchments (such as Limestone or Oolite) with hindcast correlations of between r = 0.23 and 0.5 in streamflow, at a seasonal forecasting horizon. These correlation ranges are equivalent to an r2 of between 0.05 and 0.25. As such, despite their reduced performance in fast-responding catchments, semi-periodic NAO behaviours as predictors for hydrological drought may outperform some existing forecasting systems, with the additional benefit of longer forecast horizons. Another potential limitation is the reliance on a locally stationary relationship between NAO and groundwater semi-periodic behaviours. While the model does not require a stationary relationship at timescales greater than 15-years (as defined by the window length), stationarity is assumed within this timescale. The impact of this can be seen in the forecasted time series between 1980 and 1990 where model performance is reduced across most regions (particularly at longer forecast horizons), likely due to a step-change in the NAO-groundwater lag that occurred during this time for these semi-periodic behaviours (Rust et al., 2022). The impact of these local non-stationarities may be reduced by combining multi-year NAO behaviours with other explanatory variables in future applications. For instance. previous research has shown that the performance of drought forecasting systems can be improved by including multiple explanatory variables or regressors from disparate systems (e.g. Wunsch et al., 2018; Svensson et al., 2015; Li et al, 2019). Finally, if the methods used here were applied in a real-time forecasting system, it is recommended that sensitivities of the wavelet transform are understood further, such as the impact of edge-effect or wavenumber on forecasting capability. For instance, Quilty and Adamowski, (2018) highlight the importance of accounting for edge-effects when using the wavelet transform in forecasting applications. While edge-effects were minimized in this study using full historical records (as previously discussed), corrections such as those proposed by Adamowski (2008) may be required if the wavelet transform is applied to a real-time system.

While there are limitations to the use of semi-periodic NAO behaviours as predictors for drought coverage, we show that the performance of these predictors may be better than existing dynamic seasonal drought forecasting systems while providing considerably longer forecast horizons. Most drought management plans in Europe require water authorities to define their drought management strategies every 5 or 6 years (Hervas-Gamez and Delgado-Ramos 2019; Rossi and Cancelliere, 2013; DEFRA, 2021). At present, dynamic hydrological forecasts are rarely used in these plans given their limited forecast horizons, instead favouring probabilistic approaches which do not given predictive information on water resource variability. Applying multi-annual periodicities in teleconnection systems to drought forecasting has the potential to transform current drought management practices by providing dynamic long-lead forecasts of drought-rich and drought-poor periods.

6. Conclusion

This paper evaluated the predictive capability of multi-year semi-periodic behaviours in the NAO for forecasting groundwater drought coverage at multi-year timescales. We apply a data-driven modelling approach to forecast an 8-year and 16-year semi-periodic component of groundwater drought coverage series (for a range of drought characteristics) using matching behaviours from the NAOI. Forecasted composite semi-periodic components were then converted back into original feature space via a regression model. Through this method, we show that NAO semi-periodic behaviours can be effective predictors of the regional and national extent of droughts of a range of severity and duration, and that multi-year lags in atmosphere-hydrology systems (at specific frequencies) provide a novel way to forecast drought at multi-year lead times. Performance of semi-periodic NAO behaviours as predictors for hydrological drought were greatest in hydrogeological regions dominated by lower transmissivity and longer response times. Conversely, model performance was lower in flashier catchments, or for short-term droughts where short-term meteorological variability has a greater influence on hydrological behaviour. Previous studies have highlighted that non-stationarities between multi-year semi-periodic behaviours in the NAO and hydrological variables may preclude the use of these relationships in forecasting applications, however we show here that there is sufficient permanence within the strength of these behaviours to generate skilful drought forecasts. At present, long-range dynamic drought forecasts are not utilized in drought management strategies due to limited lead times in existing drought forecasting approaches. Our results show that teleconnection indices can be a skilful predictor of hydrological drought dynamics at multi-year timescales, opening new opportunities for long-lead groundwater drought forecasts to be integrated within existing drought management strategies in Europe. Given the importance of other teleconnection systems (such as El-Nino Southern Oscillation, or Indian Ocean Dipole) for driving hydrometeorological variability across multiple global regions, the methods established in this study have the potential for worldwide application. This could markedly enhance the global resilience to hydrological drought in a changing climate.

CRediT authorship contribution statement

William Rust: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **John P Bloomfield:** Writing – review & editing, Resources, Methodology, Conceptualization. **Ian Holman:** Writing – review & editing, Methodology, Conceptualization.

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.

Data availability

The groundwater level data used in this study are from the WellMaster Database in the National Groundwater Level Archive of the British Geological Survey. The data are available under license from the British Geological Survey at https://www.bgs.ac.uk/products/hydrogeology/wellmaster.html (British Geological Survey, 2024).

The code that supports the findings of this study are available in Cranfield Online Research Data (CORD) at https://doi.org/10.17862/cranfield.rd.25225679.

This study was a re-analysis of existing data that are publicly available from NCAR at https://climatedataguide.ucar.edu/.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2024.131831.

References

Adamowski, J.F., 2008. River flow forecasting using wavelet and cross-wavelet transform models. Hydrol. Process. 22, 4877–4891. https://doi.org/10.1002/hyp.7107.

Alawsi, M.A., Zubaidi, S.L., Al-Bdairi, N.S.S., Al-Ansari, N., Hashim, K., 2022. Drought forecasting: a review and assessment of the hybrid techniques and data pre-processing. Hydrology 97, 115. https://doi.org/10.3390/hydrology9070115.

Allen, D.J., Brewerton, L.J., Coleby, L.M., Gibbs, B.R., Lewis, M.A., Macdonald, A.M., Wagstaff, S.J., Williams, A.T. 1997. The physical properties of major aquifers in England and Wales, Natural Environment Research Council.

Ascott, M.J., Bloomfield, J.P., Karapanos, I., Jackson, C.R., Ward, R.S., McBride, A.B., Dobson, B., Kieboom, N., Holman, I.P., Van Loon, A.F., Crane, E.J., Brauns, B., Rodrigues-Yebra, A., Upton, K.A., 2021. Managing groundwater supplies subject to drought: perspectives on current status and future priorities from England UK. Hydrgeol. J. 29, 921–924. https://doi.org/10.1007/s10040-020-02249-0.

Barker, L.J., Hannaford, J., Parry, S., Smith, K.A., Tanguy, M., Prudhomme, C., 2019. Historic hydrological droughts 1891–2015: systematic characterisation for a diverse set of catchments across the UK. Hydrol. Earth Syst. Sci. 23, 4583–4602. https://doi.org/10.5194/hess-23-4583-2019.

Baulon, L., Massei, N., Allier, D., Fournier, M., Bessiere, H., 2022a. Influence of low-frequency variability on high and low groundwater levels: example of aquifers in the Paris Basin. Hydrol. Earth Syst. Sci. 26, 2829–2854. https://doi.org/10.5194/hess-26-2829-2022.

Baulon, L., Allier, D., Massei, N., Bessiere, H., Fournier, M., Bault, V., 2022b. influence of low-frequency variability on groundwater level trends. J. Hydrol. 606, 127436 https://doi.org/10.1016/j.jhydrol.2022.127436.

Blauhut, V., Stoelzle, M., Ahopelto, L., Brunner, M.I., Teutschbein, C., Wendt, D.E., Akstinas, V., Bakke, S.J., Barker, L.J., Bartošová, L., Briede, A., Cammalleri, C., Kalin, K.C., De Stefano, L., Fendeková, M., Finger, D.C., Huysmans, M., Ivanov, M., Jaagus, J., Jakubínský, J., Krakovska, S., Laaha, G., Lakatos, M., Manevski, K., Neumann Andersen, M., Nikolova, N., Osuch, M., van Oel, P., Radeva, K., Romanowicz, R.J., Toth, E., Trnka, M., Urošev, M., Urquijo Reguera, J., Sauquet, E., Stevkov, A., Tallaksen, L.M., Trofimova, I., Van Loon, A.F., van Vliet, M.T.H., Vidal, J.-P., Wanders, N., Werner, M., Willems, P., Živković, N., 2022. Lessons from the 2018–2019 European droughts: a collective need for unifying drought risk management. Nat. Hazards Earth Syst. Sci. 22, 2201–2217. https://doi.org/10.5194/nhess-22-2201-2022.

Bloomfield, J.P., Marchant, B.P., 2013. Analysis of groundwater drought building on the standardised precipitation index approach. Hydrol. Earth Syst. Sci. 17, 4769–4787. https://doi.org/10.5194/hess-17-4769-2013.

Bridgman, H.A., Oliver, J.E., 2014. The Global Climate System: Patterns, Processes, and Teleconnections. Cambridge University Press, p. 359.

Brunner, M.I., Van Loon, A.F., Stahl, K., 2022. Moderate and severe hydrological droughts in Europe differ in their hydrometeorological drivers. Water Resour. Res. 58 https://doi.org/10.1029/2022wr032871.

Cammalleri, C., Naumann, G., Mentaschi, L., Bisselink, B., Gelati, E., De Roo, A., Feyen, L., 2020. Diverging hydrological drought traits over Europe with global warming. Hydrol. Earth Syst. Sci. 24, 5919–5935. https://doi.org/10.5194/hess-24-5919-2020.

Carr, E.J., Simpson, M.J., 2018. Accurate and efficient calculation of response times for groundwater flow. J. Hydrol. 558, 470–481. https://doi.org/10.1016/j.jhydrol.2017.12.023.

DEFRA, 2021. Drought: how water companies plan for dry weather and drought. Policy Paper. https://www.gov.uk/government/publications/drought-managing-water-supply/drought-how-water-companies-plan-for-dry-weather-and-drought.

Dikshit, A., Pradhan, B., Alamri, A.M., 2021. Long lead time drought forecasting using lagged climate variables and a stacked long short-term memory model. Sci. Total Environ. 755, 142638 https://doi.org/10.1016/j.scitotenv.2020.142638.

Fung, K.F., Huang, Y.F., Koo, C.H., Soh, Y.W., 2020. Drought forecasting: a review of modelling approaches 2007–2017. J. Water Clim. Change 11, 771–799. https://doi.org/10.2166/wcc.2019.236.

Granata, F., Di Nunno, F., 2023. Neuroforecasting of daily streamflows in the UK for short- and medium-term horizons: a novel insight. J. Hydrol. 624, 129888 https://doi.org/10.1016/j.jhydrol.2023.129888.

Hanson, R.T., Newhouse, M.W., Dettinger, 2004. A methodology to asess relations between climatic variability and variations in hydrologic time series in the southwestern United States. J. Hydrol. 287, 252–269. https://doi.org/10.1016/j.jhydrol.2003.10.006.

Hasan, H.H., Mohd Razali, S.F., Muhammad, N.S., Ahmad, A., 2019. Research trends of hydrological drought: a systematic review. Water 11, 2252. https://doi.org/10.3390/w11112252.

Hervás-Gámez, C., Delgado-Ramos, F., 2019. Drought management planning policy: from Europe to Spain. Sustain. Sci. Pract. Policy 11, 1862. https://doi.org/10.3390/su11071862.

Holman, I., Rivas-Casado, M., Bloomfield, J.P., Gurdak, J.J., 2011. Identifying non-stationary groundwater level response to North Atlantic ocean-atmosphere teleconnection patterns using wavelet coherence. Hydrogeol. J. 19, 1269–1278. https://doi.org/10.1007/s10040-011-0755-9.

Hurrell, J.W., 1995. Decadal trends in the north atlantic oscillation: regional temperatures and precipitation. Science 269, 676–679. https://doi.org/10.1126/science.269.5224.676.

Hurrell, J.W., Kushnir, Y., Ottersen, G., Visbeck, M., 2003. An overview of the North Atlantic oscillation. In: The North Atlantic Oscillation: Climatic Significance and Environmental Impact. American Geophysical Union, pp. 1–35. https://doi.org/10.1029/GM134.

Ionita, M., Nagavciuc, V., 2020. Forecasting low flow conditions months in advance through teleconnection patterns, with a special focus on summer 2018. Sci. Rep. 10, 13258. https://doi.org/10.1038/s41598-020-70060-8.

Jin, D., Kirtman, B.P., 2010. The impact of ENSO periodicity on North Pacific SST variability. Clim. Dyn. 34, 1015–1039. https://doi.org/10.1007/s00382-009-0619-3.

Kim, T., Shin, J.-Y., Kim, H., Kim, S., Heo, J.-H., 2019. The use of large-scale climate indices in monthly reservoir inflow forecasting and its application on time series and artificial intelligence models. Water 11, 374. https://doi.org/10.3390/w11020374.

Kingston, D.G., Stagge, J.H., Tallaksen, L.M., Hannah, D.M., 2015. European-scale drought: understanding connections between atmospheric circulation and meteorological drought indices. J. Clim. 28, 505–516. https://doi.org/10.1175/JCLI-D-14-00001.1.

Kuss, A.M., Gurdak, J.J., 2014. Groundwater level response in U.S. principal aquifers to ENSO, NAO, PDO, and AMO. J. Hydrol. 519, 1939–1952. https://doi.org/10.1016/j.jhydrol.2014.09.069.

Li, M., Zhang, T., Li, J., Feng, P., 2019. Hydrological drought forecasting incorporating climatic and human-induced indices. Weather Forecast. 34, 1365–1376. https://doi.org/10.1175/WAF-D-19-0029.1.

Liesch, T., Wunsch, A., 2019. Aquifer responses to long-term climatic periodicities. J. Hydrol. 572, 226–242. https://doi.org/10.1016/j.jhydrol.2019.02.060.

Lorenzo-Lacruz, J., Morán-Tejeda, E., Vicente-Serrano, S.M., Hannaford, J., García, C., Peña-Angulo, D., Murphy, C., 2022. Streamflow frequency changes across western Europe and interactions with North Atlantic atmospheric circulation patterns. Global Planet. Change 212, 103797. https://doi.org/10.1016/j.gloplacha.2022.103797.

Lu, M., Zhao, Q., Ding, S., Lu, X., Jing, Y., Wang, S., Hong, Z., Wang, A., 2022. Lag response of groundwater to changes in water and sediment characteristics in the lower Yellow River, China. J. Hydrol. 612, 128048 https://doi.org/10.1016/j.jhydrol.2022.128048.

Luković, J., Bajat, B., Blagojević, D., Kilibarda, M., 2014. Spatial pattern of North Atlantic Oscillation impact on rainfall in Serbia. Spat. Stat. https://doi.org/10.1016/j.spasta.2015.04.007.

Luque-Espinar, J.A., Chica-Olmo, M., Pardo-Igúzquiza, E., García-Soldado, M.J., 2008. Influence of climatological cycles on hydraulic heads across a Spanish aquifer. J. Hydrol. 354, 33–52. https://doi.org/10.1016/j.jhydrol.2008.02.014.

Mackay, J.D., Jackson, C.R., Brookshaw, A., Scaife, A.A., Cook, J., Ward, R.S., 2015. Seasonal forecasting of groundwater levels in principal aquifers of the United Kingdom. J. Hydrol. 530, 815–828. https://doi.org/10.1016/j.jhydrol.2015.10.018.

Marchant, B.P., Bloomfield, J.P., 2018. Spatio-temporal modelling of the status of groundwater droughts. J. Hydrol. 564, 397–413. https://doi.org/10.1016/j.jhydrol.2018.07.009.

Massei, N., Durand, A., Deloffre, J., Dupont, J.P., Valdes, D., Laignel, B., 2007. Investigating possible links between the North Atlantic Oscillation and rainfall variability in northwestern France over the past 35 years. J. Geophys. Res. Atmos. 112, D9. https://doi.org/10.1002/joc.2022.

Massei, N., Laignel, B., Deloffre, J., Mesquita, J., Motelay, A., Lafite, R., Durand, A., 2010. Long-term hydrological changes of the Seine River flow (France) and their relation to the North Atlantic Oscillation over the period 1950–2008. Int. J. Climatol. 30, 2146–2154. https://doi.org/10.1002/joc.2022.

Massei, N., Dieppois, B., Hannah, D.M., Lavers, D.A., Fossa, M., Laignel, B., Debret, M., 2017. Multi-time-scale hydroclimate dynamics of a regional watershed and links to large-scale atmospheric circulation: application to the Seine river catchment, France. J. Hydrol. 546, 262–275. https://doi.org/10.1016/j.jhydrol.2017.01.008.

Myronidis, D., Ioannou, K., Fotakis, D., Dörflinger, G., 2018. Streamflow and hydrological drought trend analysis and forecasting in Cyprus. Water Resour. Manag. 32, 1759–1776. https://doi.org/10.1007/s11269-018-1902-z.

Nandgude, N., Singh, T.P., Nandgude, S., Tiwari, M., 2023. Drought prediction: a comprehensive review of different drought prediction models and adopted technologies. Sustain. Sci. Pract. Policy 15, 11684. https://doi.org/10.3390/su151511684.

Neves, M.C., Jerez, S., Trigo, R.M., 2019. The response of piezometric levels in Portugal to NAO EA, and SCAND Climate Patterns. J. Hydrol. 568, 1105–1117. https://doi.org/10.1016/j.jhydrol.2018.11.054.

Papacharalampous, G., Tyralis, H., Koutsoyiannis, D., 2019. Comparison of stochastic and machine learning methods for multi-step ahead forecasting of hydrological processes. Stoch. Env. Res. Risk A. 33, 481–514. https://doi.org/10.1007/s00477-018-1638-6.

Parry, S., Hannaford, J., Lloyd-Hughes, B., Prudhomme, C., 2012. Multi-year droughts in Europe: analysis of development and causes. Hydrol. Res. 43, 689–706. https://doi.org/10.2166/nh.2012.024.

Peña-Angulo, D., Vicente-Serrano, S.M., Domínguez-Castro, F., Lorenzo-Lacruz, J., Murphy, C., Hannaford, J., Allan, R.P., Tramblay, Y., Reig-Gracia, F., El Kenawy, A., 2022. The complex and spatially diverse patterns of hydrological droughts across Europe. Water Resour. Res. 58 https://doi.org/10.1029/2022wr031976.

Peters, E. 2003. Propagation of drought through groundwater systems – illustrated in the Pang UK and Upper-Guadiana ES catchments, PhD thesis, Wageningen University, Wageningen, https: //edepot.wur.nl/121490 last access: 15 February 2024.

Prodhan, F.A., Zhang, J., Hasan, S.S., Pangali Sharma, T.P., Mohana, H.P., 2022. A review of machine learning methods for drought hazard monitoring and forecasting: current research trends, challenges, and future research directions. Environ. Model. Softw. 149, 105327 https://doi.org/10.1016/j.envsoft.2022.105327.

Prudhomme, C., Hannaford, J., Harrigan, S., Boorman, D., Knight, J., Bell, V., Jackson, C., Svensson, C., Parry, S., Bachiller-Jareno, N., Davies, H., Davis, R., Mackay, J., McKenzie, A., Rudd, A., Smith, K., Bloomfield, J., Ward, R., Jenkins, A., 2017. Hydrological Outlook UK: an operational streamflow and groundwater level forecasting system at monthly to seasonal time scales. Hydrol. Sci. J. 62, 2753–2768. https://doi.org/10.1080/02626667.2017.1395032.

Quilty, J., Adamowski, J., 2018. Addressing the incorrect usage of wavelet-based hydrological and water resources forecasting models for real-world applications with best practices and a new forecasting framework. J. Hydrol. 563, 336–353. https://doi.org/10.1016/j.jhydrol.2018.05.003.

Rossi, G., Cancelliere, A., 2013. Managing drought risk in water supply systems in Europe: a review. Int. J. Water Resour. Dev. 29, 272–289. https://doi.org/10.1080/07900627.2012.713848.

Rushworth, A.M., Bowman, A.W., Brewer, M.J., Langan, S.J., 2013. Distributed lag models for hydrological data. Biometrics 69, 537–544. https://doi.org/10.1111/biom.12008.

Rust, W., Holman, I., Bloomfield, J., Cuthbert, M., Corstanje, R., 2019. Understanding the potential of climate teleconnections to project future groundwater drought. Hydrol. Earth Syst. Sci. 23, 3233–3245. https://doi.org/10.5194/hess-23-3233-2019.

Rust, W., Cuthbert, M., Bloomfield, J., Corstanje, R., Howden, N., Holman, I., 2021. Exploring the role of hydrological pathways in modulating multi-annual climate teleconnection periodicities from UK rainfall to streamflow. Hydrol. Earth Syst. Sci. 25, 2223–2237. https://doi.org/10.5194/hess-25-2223-2021.

Rust, W., Bloomfield, J.P., Cuthbert, M., Corstanje, R., Holman, I., 2022. The importance of non-stationary multiannual periodicities in the North Atlantic Oscillation index for forecasting water resource drought. Hydrol. Earth Syst. Sci. 26, 2449–2467. https://doi.org/10.5194/hess-26-2449-2022.

Santos, J.F., Portela, M.M., Pulido-Calvo, I., 2014. Spring drought prediction based on winter NAO and global SST in Portugal: SPRING DROUGHT PREDICTION. Hydrol. Process. 28, 1009–1024. https://doi.org/10.1002/hyp.9641.

Scaife, A.A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R.T., Dunstone, N., Eade, R., Fereday, D., Folland, C.K., Gordon, M., Hermanson, L., Knight, J.R., Lea, D.J., MacLachlan, C., Maidens, A., Martin, M., Peterson, A.K., Smith, D., Vellinga, M., Wallace, E., Waters, J., Williams, A., 2014. Skillful long-range prediction of European and North American winters. Geophys. Res. Lett. 41, 2514–2519. https://doi.org/10.1002/2014GL059637.

Steinemann, A.C., 2006. Using climate forecasts for drought management. J. Appl. Meterol. Climatiol. 45, 1353–1361. https://doi.org/10.1175/JAM2401.1.

Sutanto, S.J., van der Weert, M., Blauhut, V., Van Lanen, H.A.J., 2020a. Skill of large-scale seasonal drought impact forecasts. Nat. Hazards Earth Syst. Sci. 20, 1595–1608. https://doi.org/10.5194/nhess-20-1595-2020.

Sutanto, S.J., Van Lanen, H.A.J., 2021. Streamflow drought: implication of drought definitions and its application for drought forecasting. Hydrol. Earth Syst. Sci. 25, 3991–4023. https://doi.org/10.5194/hess-25-3991-2021.

Sutanto, S.J., Wetterhall, F., Van Lanen, H.A.J., 2020b. Hydrological drought forecasts outperform meteorological drought forecasts. Environ. Res. Lett. 15, 084010 https://doi.org/10.1088/1748-9326/ab8b13.

Svensson, C., Brookshaw, A., Scaife, A.A., Bell, V.A., Mackay, J.D., Jackson, C.R., Hannaford, J., Davies, H.N., Arribas, A., Stanley, S., 2015. Long-range forecasts of UK winter hydrology. Environ. Res. Lett. 10, 064006 https://doi.org/10.1088/1748-9326/10/6/064006.

Svensson, C., Hannaford, J., 2019. Oceanic conditions associated with Euro-Atlantic high pressure and UK drought. Environ. Res. Commun. 1, 101001 https://doi.org/10.1088/2515-7620/ab42f7.

Tijdeman, E., Blauhut, V., Stoelzle, M., Menzel, L., Stahl, K., 2022. Different drought types and the spatial variability in their hazard, impact, and propagation characteristics. Nat. Hazards Earth Syst. Sci. 22, 2099–2116. https://doi.org/10.5194/nhess-22-2099-2022.

Toth, Z., Buizza, R., 2019. Chapter 2 - Weather Forecasting: What Sets the Forecast Skill Horizon? In: Robertson, A.W., Vitart, F. (Eds.) Sub-Seasonal to Seasonal Prediction, Elsevier, pp. 17–45. doi: 10.1016/B978-0-12-811714-9.00002-4.

Townley, L.R., 1995. The response of aquifers to periodic forcing. Adv. Water Resour. 18, 125–146. https://doi.org/10.1016/0309-17089500008-7.

Tremblay, L., Larocque, M., Anctil, F., Rivard, C., 2011. Teleconnections and interannual variability in Canadian groundwater levels. J. Hydrol. 410, 178–188. https://doi.org/10.1016/j.jhydrol.2011.09.013.

Van Loon, A.F., 2015. Hydrological drought explained. WIREs Water 2, 359–392. https://doi.org/10.1002/wat2.1085.

Wedgbrow, R.L., Fox, H.R., O'Hare, G., Wilby, C.S., 2002. Prospects for seasonal forecasting of summer drought and low river flow anomalies in England and Wales. Int. J. Climatol. 22, 219–236. https://doi.org/10.1002/joc.735.

Wendt, D.E., Bloomfield, J.P., Van Loon, A.F., Garcia, M., Heudorfer, B., Larsen, J., Hannah, D.M., 2021. Evaluating integrated water management strategies to inform hydrological drought mitigation. Nat. Hazards Earth Syst. Sci. 21, 3113–3139. https://doi.org/10.5194/nhess-21-3113-2021.

West, H., Quinn, N., Horswell, M., 2019. Regional rainfall response to the North Atlantic Oscillation NAO across Great Britain. Hydrol. Res. 50, 1549–1563. https://doi.org/10.2166/nh.2019.015.

Wilhite, D.A., Hayes, M.J., Knutson, C., Smith, K.H., 2000. Planning for drought: moving from crisis to risk management 1. J. Am. Water Resour. Assoc. 36 (697–710), 2000. https://doi.org/10.1111/j.1752-1688.2000.tb04299.x.

Wu, C., Zhang, X., Wang, W., Lu, C., Zhang, Y., Qin, W., Tick, G.R., Liu, B., Shu, L., 2021. Groundwater level modeling framework by combining the wavelet transform with a long short-term memory data-driven model. Sci. Total Environ. 783, 146948 https://doi.org/10.1016/j.scitotenv.2021.146948.

Wunsch, A., Liesch, T., Broda, S., 2018. Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input NARX. J. Hydrol. 567, 743–758. https://doi.org/10.1016/j.jhydrol.2018.01.045.

Yaseen, Z.M., El-shafie, A., Jaafar, O., Afan, H.A., Sayl, K.N., 2015. Artificial intelligence based models for stream-flow forecasting: 2000–2015. J. Hydrol. 530, 829–844. https://doi.org/10.1016/j.jhydrol.2015.10.038.