Water Research 201 (2021) 117286

Contents lists available at ScienceDirect

Water Research

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

Forecasting water temperature in lakes and reservoirs using seasonal climate prediction

Daniel Mercado-Bettín[a,b,*], Francois Clayer[c], Muhammed Shikhani[d], Tadhg N. Moore[e], María Dolores Frías[f], Leah Jackson-Blake[c], James Sample[c], Maialen Iturbide[f], Sixto Herrera[f], Andrew S. French[g], Magnus Dahler Norling[c], Karsten Rinke[d], Rafael Marcé[a,b]

[a] Catalan Institute for Water Research (ICRA), Girona, Spain
[b] Universitat de Girona, Girona, Spain
[c] Norwegian Institute for Water Research (NIVA), Oslo, Norway
[d] Department of Lake Research, Helmholtz Centre for Environmental Research, Magdeburg, Germany
[e] Dundalk Institute of Technology, Dundalk, Co. Louth, Ireland
[f] Grupo de Meteorología. Dpto. de Matemática Aplicada y Ciencias de la Computación, Universidad de Cantabria, Santander, Spain
[g] Foras na Mara - Marine Institute, Furnace, Newport, Co. Mayo, Ireland

ARTICLE INFO

Article history:
Received 28 November 2020
Revised 13 May 2021
Accepted 19 May 2021
Available online 24 May 2021

Keywords:
Seasonal forecasting
Water management
Hydrologic modeling
Lake modeling

ABSTRACT

Seasonal climate forecasts produce probabilistic predictions of meteorological variables for subsequent months. This provides a potential resource to predict the influence of seasonal climate anomalies on surface water balance in catchments and hydro-thermodynamics in related water bodies (e.g., lakes or reservoirs). Obtaining seasonal forecasts for impact variables (e.g., discharge and water temperature) requires a link between seasonal climate forecasts and impact models simulating hydrology and lake hydrodynamics and thermal regimes. However, this link remains challenging for stakeholders and the water scientific community, mainly due to the probabilistic nature of these predictions. In this paper, we introduce a feasible, robust, and open-source workflow integrating seasonal climate forecasts with hydrologic and lake models to generate seasonal forecasts of discharge and water temperature profiles. The workflow has been designed to be applicable to any catchment and associated lake or reservoir, and is optimized in this study for four catchment-lake systems to help in their proactive management. We assessed the performance of the resulting seasonal forecasts of discharge and water temperature by comparing them with hydrologic and lake (pseudo)observations (reanalysis). Precisely, we analysed the historical performance using a data sample of past forecasts and reanalysis to obtain information about the skill (performance or quality) of the seasonal forecast system to predict particular events. We used the current seasonal climate forecast system (SEAS5) and reanalysis (ERA5) of the European Centre for Medium Range Weather Forecasts (ECMWF). We found that due to the limited predictability at seasonal time-scales over the locations of the four case studies (Europe and South of Australia), seasonal forecasts exhibited none to low performance (skill) for the atmospheric variables considered. Nevertheless, seasonal forecasts for discharge present some skill in all but one case study. Moreover, seasonal forecasts for water temperature had higher performance in natural lakes than in reservoirs, which means human water control is a relevant factor affecting predictability, and the performance increases with water depth in all four case studies. Further investigation into the skillful water temperature predictions should aim to identify the extent to which performance is a consequence of thermal inertia (i.e., lead-in conditions).

1. Introduction

Water resources are closely dependent on the services supplied by ecosystems that maintain both water quantity and qual-

* Corresponding author at: Catalan Institute for Water Research (ICRA), Girona, Spain.
E-mail address: dmercado@icra.cat (D. Mercado-Bettín).

https://doi.org/10.1016/j.watres.2021.117286

ity (Carpenter et al., 2009), and lakes and reservoirs constitute key ecosystems for the provision of such services. However, these services are continuously threatened by climate extreme events (hours to days), seasonal climate variations (1–3 months), and long-term climate change (many years), which are affecting water management decisions around the world.

Hence, climate predictions encompass a time frame that can potentially be useful for early decision-making in the water resources sector, allowing implementation of preventive and mitigation measures to reduce the vulnerability to foreseen climate extreme anomalies (e.g., floods and droughts (Pozzi et al., 2013)). This decision-making is affected depending on the time scale, from hours to many years, of the climate anomalies.

We focus on seasonal forecast (1–3 months) of key variables for the water sector for two reasons: (i) there are some studies presenting predictions in a short-term scale in water bodies (e.g. Frassl et al., 2018; Thomas et al., 2020) and many relate projections of long-term climate change to consequences in the same systems (e.g. Komatsu et al., 2007; Woolway et al., 2021), but studies relating seasonal prediction to lakes or reservoir are less common; (ii) for water managers, a short-term prediction helps in taking reactive decisions and a long-term projection supports general decisions beyond the real-case timing of water management, but a seasonal prediction for water quality variables introduces an opportunity for controlling key variables in a feasible time-scale for water management treatment.

In addition, most seasonal climate prediction exercises in water resources have focused on hydrologic applications (Bazile et al., 2017; Emerton et al., 2018; Greuell et al., 2019; Luo et al., 2007; Rosenberg et al., 2011; Yuan et al., 2011), but in this study, we go one step further and also connected seasonal climate predictions to water bodies, such as lakes and reservoirs.

Besides a few basic applications (e.g., climate.copernicus.eu/lake-surface-water-temperature; no longer operational), studies applying seasonal climate prediction for forecasting water temperature (the most basic water quality variable) in lakes and reservoirs are absent in the literature, despite the manifold consequences of temperature changes on lake thermal regimes, lake ecosystem processes, and the provision of lake ecosystem services (Yang et al., 2020). This is partly attributable to the challenges in applying seasonal climate forecasts to catchment hydrologic simulations and water temperature predictions in lakes (Sene et al., 2018; Turner et al., 2017; Yuan et al., 2015).

These challenges are overcome in this study, such as: the complexity of accessing the climate data by non-climate experts (multiple databases, formats, and variables) (Wood et al., 2002); the spatial-scale mismatch between the global circulation modeling data and a local catchment (Blöschl and Sivapalan, 1995); finding a proper physical representation of the problem (impact model) applicable in different forecasting scenarios (Gupta et al., 1998); the probabilistic nature of the predictions; and the mounting uncertainty propagated to the final prediction through the connection of climate, catchment, and lake models.

The aim of this work is to establish a feasible and reproducible workflow that facilitates the application of seasonal climate forecasts to the water sector through a catchment-lake impact model chain. The workflow connects seasonal climate data to hydrologic and lake modeling to obtain seasonal predictions of water temperature profiles.

The workflow evaluates the performance of the predictions in relation to three areas: (i) bias-corrected (calibration process to adjust climate model outputs using as reference local observations) seasonal climate forecasts for hydrologic and lake model forcing variables. Note that this step is necessary before using model data in impact studies; (ii) lake inflow discharge derived from hydrologic models forced by bias-corrected seasonal climate forecasts; and (iii) lake temperature profiles derived from lake models forced by model-derived discharge and bias-corrected seasonal climate forecast.

The implementation of the workflow is exemplified in four case studies (catchment-lake (or reservoir) systems) for which water temperature is a relevant water quality variable that is routinely monitored by managers and stakeholders. To facilitate reproducibility, code and data are publicly available at https://nivanorge.github.io/seasonal_forecasting_watexr/ and https://github.com/NIVANorge/seasonal_forecasting_watexr/tree/main/paper1_Mercado_etal

The following sections introduce the workflow and its applicability. Section 2 presents the four catchment-lake/reservoir systems where the workflow was applied, describes the different climate data used (seasonal forecast and reanalysis) and the preprocessing needed to use them on a local scale, and introduces the hydrologic and lake/reservoir temperature models (hereafter termed “lake models”). Section 3 introduces the workflow. Section 4 shows the results of performance evaluations for seasonal climate forecasts (i.e., seasonal predictions of discharge and lake model meteorological forcing variables) and impact variable forecasts (i.e., seasonal predictions of discharge and lake/reservoir temperature). Section 5 discusses the implications of our results in terms of future applications and limitations. Finally, Section 6 highlights the main conclusions of the manuscript.

2. Methods

2.1. Catchment-lake systems

The workflow presented here describes the application of seasonal climate forecasts to four geographically separate catchment-lake/reservoir case studies (Table 1) included in the EU-funded WATExR project (https://watexr.eu and https://nivanorge.github.io/seasonal_forecasting_watexr/) ; three of them located in Europe and one located in South Australia (Fig. 1). The Australian case study was selected to provide an example application of the workflow in a region of the world where seasonal climate forecasts are typically more skillful (better performance) than in Europe (Zhang et al., 2019); however, as we further demonstrate, this was not the case on this occasion.

To implement the performance assessment of the seasonal forecast, the availability of long-term term water quality data is not needed but is recommended (especially in this case, where we are introducing the workflow), and these four case studies have the information needed to validate the results. However, the use of pseudo-observations or reanalysis (see next section), as used in this study, provides the opportunity to apply the workflow to any water body, even under very different climate conditions and limited observations (see discussion section).

The details relating the actual management challenges and other characteristics of the four catchment-lake systems can be found in supplementary material (Supplementary.pdf) at https://git.io/J3tDN (GitHub).

2.2. Climate data

We used two different climate datasets in this study, a climate reanalysis and a seasonal climate forecasting product. These two products are necessary to implement a performance assessment, or in other words, to assess whether the forecast system has skill or not. The word “skill“ is common in climate science but less common in water science. “Skill” is a metric used for seasonal forecast performance evaluation, a general definition is: “a set of forecasts is “skilful” if it is better than another set, known as the reference forecasts. Skill is therefore a comparative quantity rather than an

Table 1
Main characteristics of lakes and reservoirs studied.

Case study	Country	Altitude (m)	Surface area (ha)	Volume (hm^3)	Water retention time (years)	Max. depth (m)	Mixing regime
Sau	Spain	425	575	165	0.20	60	monomictic
Mt. Bold	Australia	244	254	46.4	0.2–0.6 years	44.5	monomictic
Vansj	Norway	26	3600	252	1.1 years	19	dimictic
Wupper	Germany	250	211	26	0.20 years	31	dimictic

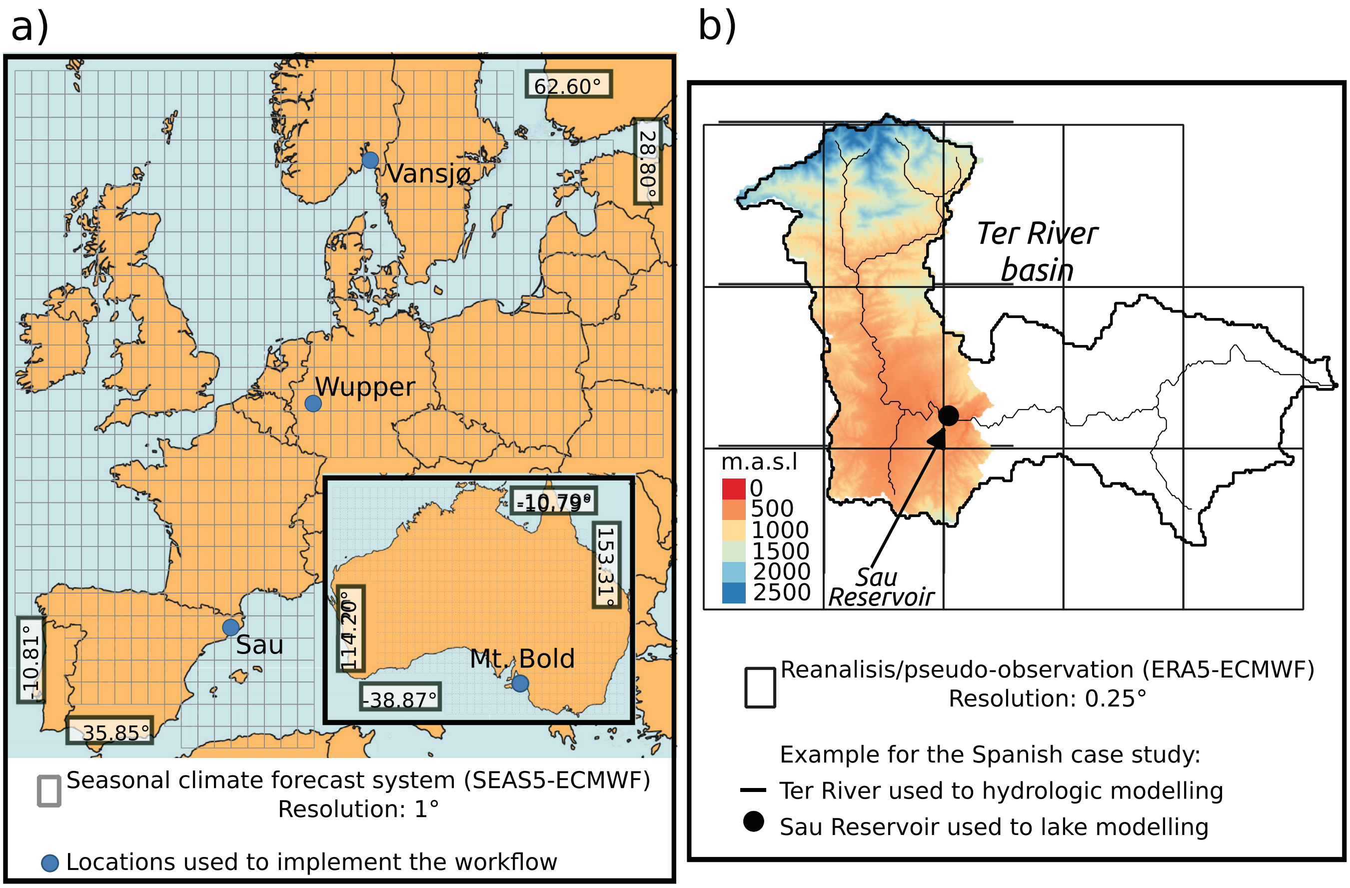

Fig. 1. a) Location of the four catchment-lake/reservoir systems used to develop our workflow for seasonal probabilistic lake/reservoir water temperature and discharge forecasts. Three are located in Europe and one in South Australia. It also shows the spatial resolution of the seasonal climate forecast system (SEAS5, 1° used in the four systems). b) Shows the reanalysis or (climate) pseudo-observation (ERA5, 0.25°) used in the four systems. This is an example for the Spanish case study (Sau Reservoir), but the same resolution and datasets apply for all case studies. The figure illustrates the Ter River watershed boundary in relation to the digital elevation model (colors) and the studied lake (Sau Reservoir, black point) for this case study.

absolute quantity" (Mason, 2013), i.e., the skill reflects the performance or quality of the forecast system.

A reanalysis is a pseudo-observation obtained from modeling exercises and data assimilation applied to local measured observations (that might be more precise but limited in time and space) to obtain historical data with a homogeneous spatial and temporal coverage. Taking advantage of its potential, here we used it for: (i) workflow verification (performance assessment) in past conditions (known as hindcast period) to build confidence in subsequent predictions about the future, (ii) for bias-correction of climate predictions and (iii) to derive historical (pseudo-)observations for catchment hydrology (i.e., discharge) and lake/reservoir thermal metrics (i.e., water column temperatures at multiple depths) for the same hindcast period. We use the latest reanalysis (Hersbach et al., 2020) produced by the European Centre for Medium-Range Weather Forecasts (ECMWF): ERA5. Specific details about ERA5 are presented in Table 2.

A seasonal forecasting system provides an ensemble of coupled ocean-atmosphere model runs (known as members), whereby each member represents a different prediction of the medium-term (weeks to months) evolution of the climate system (i.e., a co-varying multi-variable system) with global coverage. This ensemble of members must be used together with a reanalysis with historical observations (ERA5 in this study), it is imposed by the complexity, uncertainties, and non-linear interactions in the Earth climate system. We used the latest seasonal forecasting system provided by the ECMWF: SEAS5 (Johnson et al., 2019). Specific details about SEASS5 are presented in Table 2.

SEAS5 provides both real-time seasonal forecasts and retrospective seasonal forecasts for past years (hindcasts), but in this study, only retrospective seasonal forecasts (hindcasts) were used to validate the workflows. Due to the intrinsic probabilistic nature of seasonal forecasts, it is essential to provide measures of the quality (accuracy, reliability, etc.) and how much better are the forecasts compared to a reference prediction system (e.g, climatology). In this study, a hindcast is used for this forecast verification.

The graphical comparison of the spatial resolution between SEAS5 and ERA5 is shown in Fig. 1a and b, respectively. The period from 1994 to 2016 is considered in this study for the same variables selected for the ERA5 data. The analysis is focused on the boreal seasons (Table 1), with one month as lead time (i.e. forecasts are initialised one month in advance of the target season). To access, download, bias-correct and visualize the climatic data, we used an R based framework (climate4R bundle, Iturbide et al., 2019)

Prior to hydrologic and lake model forcing and retrospective forecast performance (skill) evaluation, seasonal climate forecast members must be pre-processed to minimise systematic bias implicit in the raw gridded outputs of global climate models (relative to climate (pseudo-)observations; ERA5 reanalysis in this case).

The quantile mapping technique was selected to correct the global climate model data used (Gutiérrez et al., 2018). We used the empirical approach (EQM) due to its ability to deal with multivariate problems (Wilcke et al., 2013). Specific details about this technique are presented in supplementary material (Supplementary.pdf) at https://git.io/J3tDN (GitHub).

The resulting bias-corrected data were used for hydrologic and lake model meteorological forcing. The time-series obtained for appended ERA5-SEAS5 meteorological hydrologic and lake model forcing variables revealed smooth transitions from climate (pseudo-)observations during the spin-up period (ERA5) to the seasonal climate forecast ensemble predictions (SEAS5); we found no evidence of discontinuities or “jumps”.

2.3. Hydrologic and lake temperature modeling

Owing to different flow regimes and water management challenges in the various catchment-lake/reservoir systems, we used a variety of hydrologic and lake models. However, the common workflow transcends model choices by providing common methods and code to manipulate input and output data for the various models. The role of the models in the workflow is producing seasonal forecasts for impact variables (discharge and water temperature profiles), but are not the main focus of the article, nor is comparing the catchment-lake systems (in which case, it would be mandatory to use the same model setups).

Four hydrologic models were used to simulate lake/reservoir inflow discharge; one for each case study. The mesoscale Hydrologic Model (mHM v5.9: http://www.ufz.de/mhm) was used to simulate hydrology in the Ter River catchment, which is the main inflow for Sau Reservoir. The *Génie Rural* (GR) suite of models implemented within the R package *airGR* (Coron et al., 2017) were used to model the inflows for the Wupper Reservoir and the Mt. Bold Reservoir (Onkaparinga and Echunga Creek), namely GR6J and GR4J, respectively. The hydrologic module of the SimplyP catchment model for phosphorus, SimplyQ, was used to model the inflows to Lake Vansj (Norway), and is described in detail by Jackson-Blake et al. (2017).

Two 1D lake models were used to simulate lake/reservoir water column temperature. The General Ocean Turbulence Model (GOTM, http://gotm.net) was used for simulating the thermal dynamics of Sau Reservoir (Spain) and Lake Vansj (Norway). The General Lake Model (GLM, Hipsey et al., 2019) was used for simulating the thermal dynamics of the Mt. Bold and Wupper reservoirs.

Calibration of models against observations using reanalysis data (pseud-observations) was implemented for all case studies. Tables 1 and 2 in the supplementary material (Supplementary.pdf) at https://git.io/J3tDN (GitHub) provide details about calibration, periods and fitting statistics; plots showing the resulting calibration are show at the same link following the corresponding folder for each case study, e.g, Spain/River/calibration_plots or Spain/Lake/calibration_plots, for the Spanish case study (since calibration plot contains observations, for Australia they are not shown to avoid issues that could compromise the data provider commercially or reputationally).

Table 2
Climate Data: details of the reanalysis and seasonal forecast system used in this study. All datasets have been retrieved using the Copernicus Climate Data Store (cds.climate.copernicus.eu) or University of Cantabria climate User Data Gateway (UDG, meteo.unican.es/trac/wiki/udg, Cofiño et al., 2018).

Type	Name	Time coverage	Resolution	Members (runs)	Lead time	Variables for hydrologic modeling	Variables for lake modeling	Seasons studied
Reanalysis	ERA5	1988–2016	0.25	NA	NA	pr, t tmin and, tmax	pr, t, u-v, rh, cc, and sr	spring:Mar-May summer:Jun-Aug autumn:Sep-Nov winter:Dec-Feb
Seasonal forecast	SEAS5	1993–2016	1	25	1	pr, t tmin and, tmax	pr, t, u-v, rh, cc, and sr	spring:Mar-May summer:Jun-Aug autumn:Sep-Nov winter:Dec-Feb

pr: precipitation; t, tmin and tmax: mean minimum and maximum temperature; u-v: wind speed; rh: relative humidity; cc: cloud cover; sr: solar radiation.

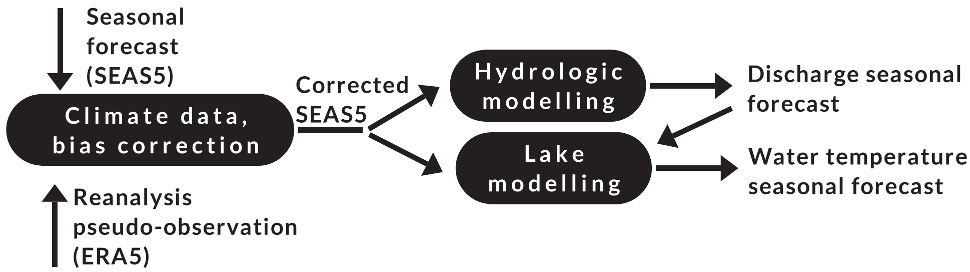

Fig. 2. Schematic illustration of climate, hydrologic and lake data collation required for workflow implementation in each catchment-lake/reservoir systems to produce a single seasonal climate forecast during the hindcast period. The scheme shows left to right: (i) atmospheric data pre-processing including bias correction applied to the seasonal climate forecasts (SEAS5) using the reanalysis data (ERA5) as a previous step before running the impact models; (ii) the hydrologic part implemented in the catchment which includes the hydrologic model used to produce the discharge forced by the seasonal climate forecast; and (iii) the lake part implemented in lakes/reservoirs consisting in the lake temperature model considered to predict water temperature.

Finally, after calibration, lake models (water temperature calibrated) and hydrologic models (discharge calibrated) were forced with ERA5 data for the full reanalysis period (1988–2016), obtaining pseudo-observations of discharge and water temperature profile for the same period.

3. The workflow: seasonal prediction

The workflow to apply seasonal forecasting to the four catchment-lake/reservoir systems followed a two-step process. Seasonal climate forecasts were downscaled (see Section 3.1.1.) before forcing hydrologic and lake temperature models in a sequential chain; thus incorporating the influence of both inflow discharge and meteorological forcing on lake water temperature (Fig. 2). The downscaling procedure corrects the bias associated with the seasonal climate forecast data (SEAS5) before using it to force the hydrologic and lake temperature models.

This correction is implemented after calibrating and validating the models for water temperature and discharge using ERA5 as meteorological pseudo-observational forcing data (Tables 1 and 2 of supplementary material (Supplementary.pdf) in https://git.io/J3tDN (GitHub) and calibration plots in the same link).

Seasonal forecast ensemble predictions were derived for each boreal season and case study model chain (i.e., watershed and lake temperature models) considering three periods: model spin-up (forced by ERA5), forecast initialisation month (SEAS5), and target season (SEAS5) (See Fig. 3 as an example of Spring 2003).

The impact models need a spin-up period before the forecast initialisation period to avoid the impact of physically inconsistent initial hydrologic and lake conditions across state variables on model results. Trial and error showed that the hydrologic models were no longer affected by initial conditions (mainly related to subsurface water storage) after 5 years, whereas lake temperature models were insensitive to initial conditions after 1 year of simulation. Spin-up periods were simulated using ERA5. Thus, for every modelled season during the hindcast period (time range 11/1993–11/2016, that is, 92 runs from 23 years x 4 seasons), the following procedure was implemented to obtain seasonal river discharge (hydrologic) and surface and bottom water temperature (lake) ensemble predictions:

1. the impact models (hydrologic and lake) were warmed up (spin-up) using ERA5,
2. then a 4-month long simulation was run driven by the 25 ensemble members from the bias-corrected SEAS5 hindcast set for each initialisation considered (e.g., February for spring). Hydrologic and lake model outputs for the final 3 months (March to May) corresponding to the target season are selected (for calculation of probabilistic expectations), while the initialisation month is removed from the analysis since it is considered as a transitory period.

This procedure was applied for each case study and is exemplified for Sau Reservoir in Fig. 3. To simulate the spring of 2003, the hydrologic and lake models were first run for 5 and 1 year respectively using ERA5 as spin-up forcing data. Then, the first four months of each of the 25 ensemble members of the bias-corrected SEAS5 hindcast initialised in February 2003 were used for model forcing. Finally, the seasonal forecasts resulting from the target season, March to May for spring of 2003, were selected for subsequent derivation of probabilistic analysis. It is important to mention that our workflow implies that most of the uncertainty propagated to final forecasts comes from the 25 ensemble members of the seasonal climate prediction. Although it may be reasonable to consider the climate prediction as the main source of uncertainty in the modeling chain (this has been recently demonstrated by Thomas et al., 2020 in a similar workflow-like study), other sources of uncertainty would also be present (e.g., uncertainties arising from the parameterisation of hydrologic and lake temperature models or structural uncertainty in those models).

In this paper our focus is on exploring how errors introduced by the seasonal climate forecasts propagate through the process-based model chains. We examine whether seasonal climate forecasts introduce any added value in seasonal lake predictions compared to predictions produced by running models driven by historic observed meteorological data alone. Other sources of uncertainty (e.g., uncertainties in climate reanalysis and lake models themselves) are not considered, nor is model performance compared to actual lake observations; we used lake (pseudo-)observations (although calibration details are included in the supplementary materials). These additional sources of error, and their significance in terms of water management, will be more fully explored in subsequent work.

3.1. Analysing the forecast performance

To analyse the forecast performance (skill) for climate variables, discharge, and water temperature in the lake, the visualizeR package (Frías et al., 2018) was used to obtain tercile plots (Fig. 4) for bias-corrected climate variables, discharge, and water temperature hindcasts. To build a tercile plot for a given variable and season, observations and multi-member ensemble derived predictions of the forecast system are categorised into three (anomaly) categories, according to the statistical distribution of the variable being assessed during the selected season throughout the entire hindcast period ("Above normal" (upper tercile) for data points falling in the percentile range 66–100%, "Normal" for the range 33–66%, and "Below normal" (lower tercile) for the range 0–33%).

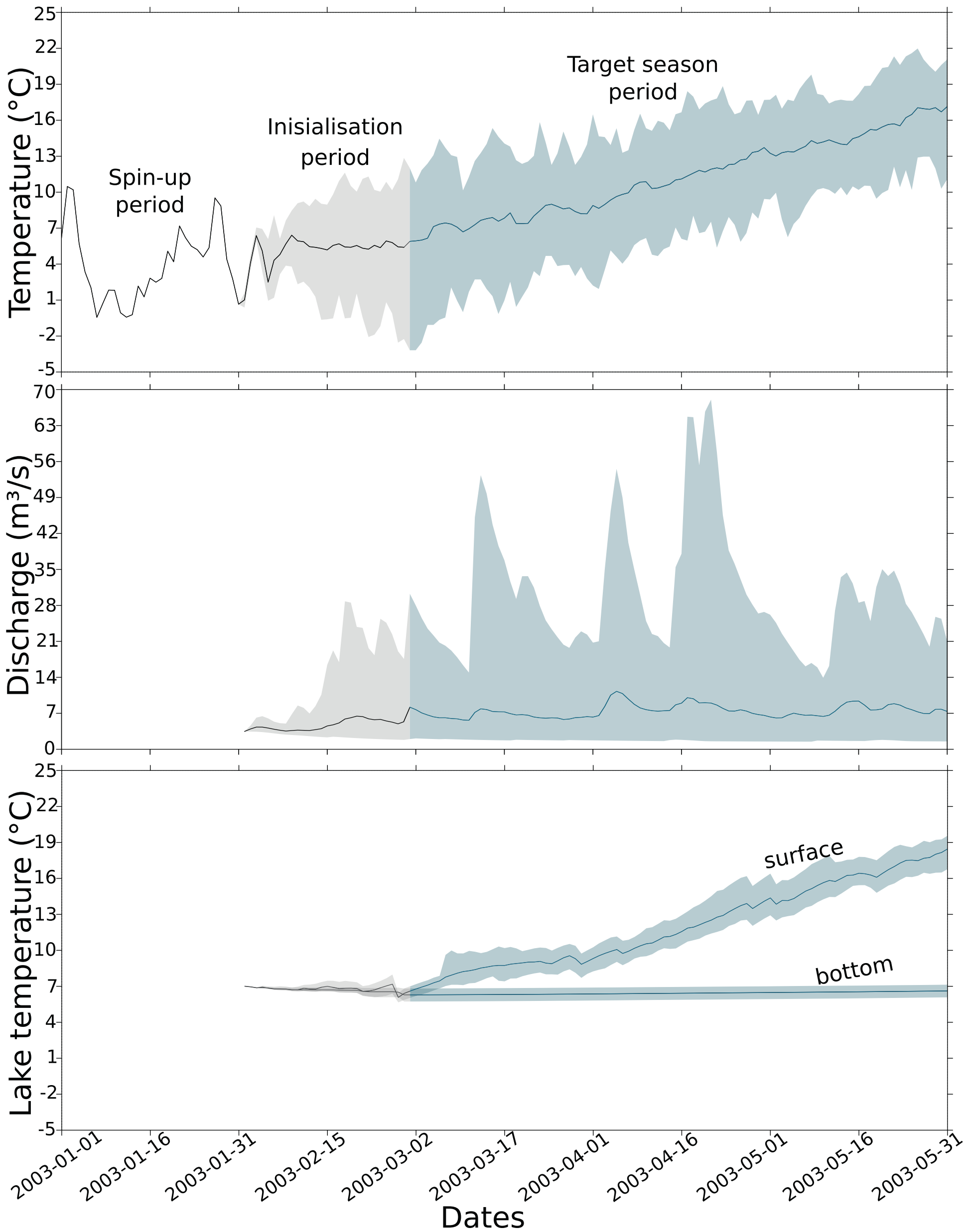

Fig. 3. Time series of the atmospheric mean temperature (top) from ERA5 data set (black line) followed by bias-corrected SEAS5 seasonal forecast for the initialisation of February 2003, and seasonal forecasts of discharge (middle) and lake temperature (bottom and surface) for Spring 2003. Only one month (January 2003) is shown on the top panel for the spin-up period for better readability of the rest of the periods. Gray shading shows the spread of the ensemble (25 members) for the initialisation-month (February 2003) and blue shading for the target season (spring 2003). The ensemble mean is represented by a solid line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

A tercile plot illustrates the distribution of hindcast member seasonal summary statistics among these three anomaly categories for all years in the hindcast period, together with an indication of the categories into which each year's seasonal summary statistic calculated from observations falls. Forecast member seasonal summary statistic distributions among categories are quantified in terms of proportions per category (i.e., 0 for no members in a category, 1 for all members in a category) and are indicated by a color ramp. Each year's corresponding "observed anomaly" is indicated by a symbol in the appropriate category. The tercile plot therefore facilitates a visual comparison between the relative strengths of probabilistic expectations among anomalies derived from the seasonal forecast system and observed anomalies for the entire hindcast period.

Two common measures to evaluate the skill of the probabilistic forecast (Jolliffe and Stephenson, 2003; Mason, 2013) for each variable were used: the Ranked Probability Skill Score (RPSS) and the Relative Operating Characteristic Skill Score (ROCSS). The Ranked probability Score (RPS) compares the probabilities given by the forecast to the distribution of observations over a given number of discrete probability categories (3 considered here: above normal, normal and below normal), and it is calculated as a squared-error between the probability distribution of forecasts and observations across categories. The RPSS compares RPS for the forecast with RPS from a reference (usually average climate), which in this study, is the climatology derived from (pseudo)observation. Then, RPSS is a measure of the relative improvement of the probabilistic ensemble-based forecast over climatology in predicting the category into which the observations fall. As a result, an RPSS > 0

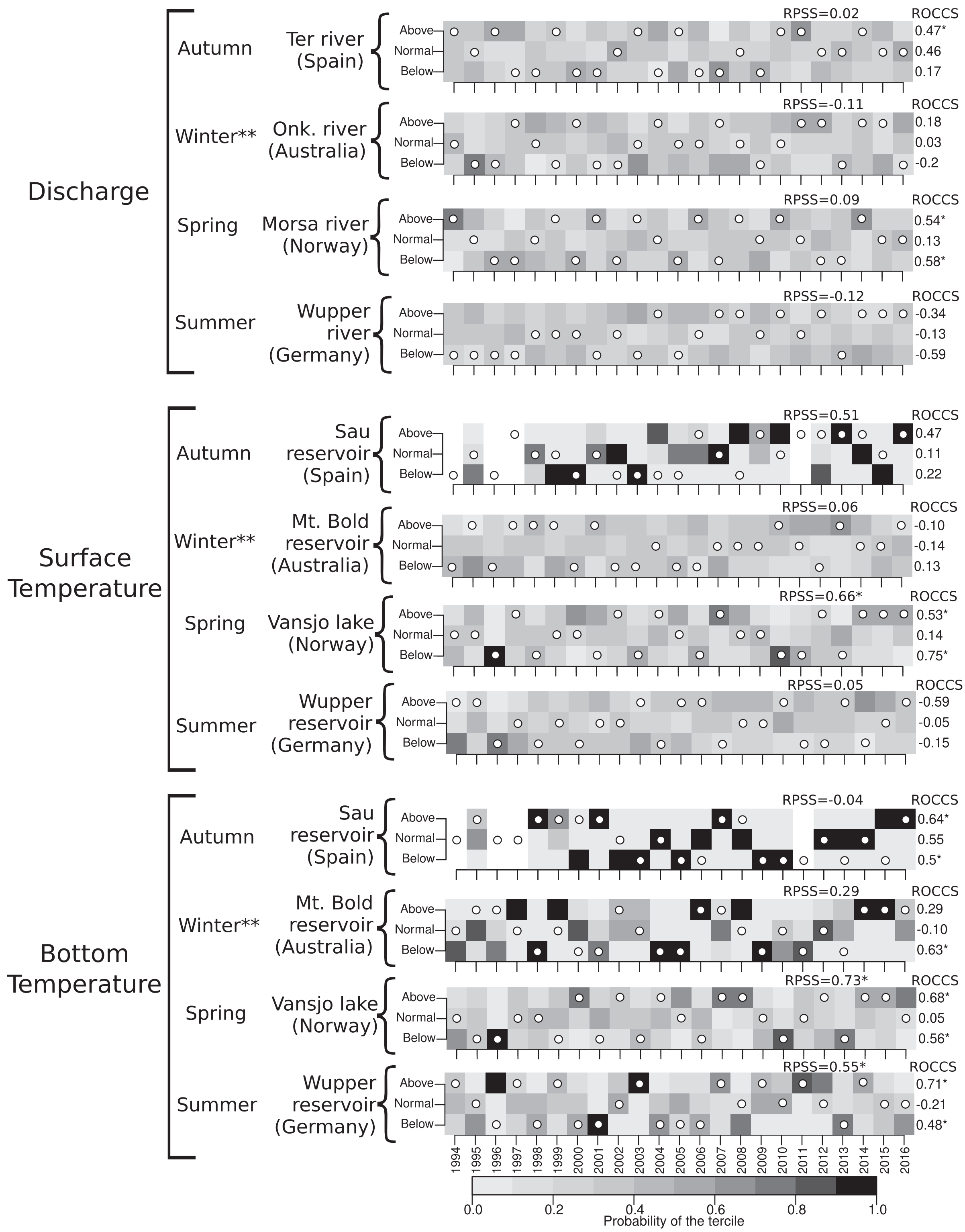

Fig. 4. Tercile plots for seasonal discharge, surface and bottom water temperature forecasts during selected seasons across the four case studies. Forecast probabilities are shown in a white (0, no member forecasts that category) to black (1, all the members agree in the same category) scale. This scale applies for the probability for the next season of being above, within and below normal conditions (categories). The bullets represent the observed category according to the ERA5 dataset, so individual hits and misses can be analysed along the period. RPSS values are shown at the top of each panel and the ROCSS values on the right of the three categories. * indicate significant values (at 95% confidence). ** Austral summer.

means that forecasts is better than the reference (1 indicates perfect multi-category probabilistic forecasts), while a zero value or less indicates the forecast performed not better than the reference (climatology in this study).

On the other hand, the Relative Operating Characteristic (ROC) quantifies the ability of the forecast to discriminate between events and non-events (i.e., translating the probabilistic forecast into a deterministic forecast by picking the most probable tercile). ROC is based on the ratio between the hit rate and the false alarm rate and is evaluated for each category (above normal, normal or below normal) separately. ROCSS evaluates the relative improvement to ROC provided by the forecast expectations relative to reference forecast, and ranges from 1 (perfect discrimination) to 1 (perfectly bad discrimination), a zero value indicating no skill (low quality or performance) compared to a long-term climatology.

4. Results and discussion

4.1. Seasonal climate forecast

According to RPSS values, there was no significant (95% confidence) improvement of the prediction respect to climatology for the climate variables in any of the case studies, except for potential evaporation during spring in Mt. Bold Reservoir (Australia), and during summer in Wupper Reservoir (Germany). This suggests substantial biases in the forecast for climate variables.

However, ROCSS scores showed more significant results for all case studies in some terciles and variables, which suggested some discrimination power: autumn potential evaporation and summer dew point for Sau Reservoir; solar radiation, horizontal wind, potential evaporation, pressure, cloud cover, and temperature in autumn, pressure and dew point in winter, long-wave radiation in spring, and cloud cover in summer for Mt. Bold Reservoir; solar radiation, long-wave radiation, cloud cover, and vertical wind in winter, pressure, cloud cover, long-wave radiation, dew point, temperature, and both wind components in spring, and long-wave radiation in summer for Vansjo (Norway); and temperature in autumn, long-wave radiation and vertical wind in winter, dew point in spring and horizontal wind in summer for Wupper Reservoir. Note that some of these significant results could also be due to chance given the 95% significance level used in the test.

The complete set of plots and results for all climate variables and seasons for each case study can be found at https://git.io/J3tDN (GitHub), from here following the folder for each case study, e.g., "Spain/Atmosphere/plots" for the Spanish case study).

4.2. Seasonal forecast for discharge and water temperature

In this section we analyze predictions for discharge and water temperature for one relevant season for each case study (Fig. 4). Subsequently, we evaluate all seasons for each case study (Table 3).

A key-season for the Spanish case study (Sau Reservoir) is autumn, because most of the annual rainfall is produced during these 3 months, influencing the water quantity and quality of the river and, consequently, of the reservoir. Management of the reservoir during this season requires a number of decisions by the stakeholder to keep water quality at the inlet of the water treatment plant within safe operational standards (e.g., temperature, turbidity, reduced metals, organic matter). Among management actions, outflow rate and withdrawal depth selection are the most relevant. However, predictions for discharge from the Ter River showed low values of the RPSS suggesting that they are not reliable (biased), even if there was significant discrimination (ROCSS value) for the upper tercile. Overall, the analysis suggests that the predicted skill for discharge is very limited, i.e., there is a low performance of seasonal forecast discharge (Fig. 4), and that while we found some capacity for discrimination, predictions seemed to be biased (very low RPSS).

Despite the absence of skill found in the seasonal climate and discharge forecasts in Sau Reservoir in autumm, the water temperature forecasts in this system revealed discrimination skill (it is able to discriminate the occurrence or not of events) for the lower and upper terciles for bottom temperature (Fig. 4). However, the forecast does not improved respect to climatology (non significant RPSS) in deep layers, probably due to the effect on RPSS of forecasts which are sometimes very concentrated in the wrong tercile. That discrimination skill is apparently disconnected from prediction skill in climate and discharge suggests that the source of predictability for water temperature in deep water was the inertia of the system. In surface waters, the skill was non-significant (the performance of the forecast was low for surface temperature) probably because this layer is more affected by inflow and climate conditions which we cannot predict with much confidence. Similar results were found for the rest of the seasons (Table 3), with the presence of more discrimination skill for bottom temperature (5 terciles in total) than for surface layers (2 terciles in total). Only spring forecasts for surface waters presented improvement respect to climatology (significant RPSS), but no discrimination skill (non significant ROCSS) was detected. In general, there could be some windows of opportunity for using seasonal prediction for this case study, particularly when discriminating between below and above normal categories during summer and autumn. The low RPSS scores suggested biased forecasts that could be improved by additional improvements to impact models calibration.

The Australian case study (Mt Bold reservoir) showed very little skill (low performance) across all meteorological variables for each season. The winter season (which is the austral summer) is characterised by the absence of precipitation, leading to multiple management decisions related to transferring water from other sources, algal bloom events and in general, water quality issues associated with low flows. From the discharge and water temperature results (Fig. 4), only bottom temperature shows the below normal category as significant. In spite of this, having knowledge of bottom temperature conditions in this season is important for assessing the potential risks of phosphorus re-suspension and potential transfer further downstream. Overall, for the impact models, there were few variables that exhibited significant skill, also supported by the rest of the seasons (Table 3). In summer, the lower category was significant for bottom temperature, no variables were significant in autumn and one of the inflows, Echunga Creek, had significance for the lower category in spring. This highlights that for this reservoir there is low confidence in climate and impact model predictions.

For the Norwegian case study (Lake Vansj), the most skillful forecasts for both, the river and lake, were obtained during spring with the highest ROCSS obtained for lower and higher categories (see Fig. 4). ROCSS show significant discrimination skill (the system is prone to discriminate between occurrence and non-occurrence of events) for the outputs of the coupled hydrologic and lake model: discharge and surface and bottom lake temperature; while RPSS attributed significant improvement respect to climatology to the surface and bottom temperature forecasts. For the other seasons (Table 3), some discriminating skill (ROCSS) was found in winter for surface (below normal category) and bottom (below and above normal categories) temperature. Autumn was also another interesting season, since the seasonal forecast improved with respect to climatology (significant RPSS) for surface and bottom temperature. Lake Vansj presented the best prediction skill (the best performance) among all case studies because (i) it has the highest (or less bad) predictability in the atmospheric variables, especially in spring and winter, (ii) it shows some skill in discharge, particularly in spring, and (iii) there is less human management

Table 3
Summary of all significant skill scores, both ROCSS and RPSS for each case study in all seasons. Since the ROCSS discriminate among terciles, 3 categories (above normal, normal and below normal) are shown, while the RPSS reflect the improvement or not of the seasonal forecast with respect to climatology. Significant values are represented by an “x”.

	Discharge									
			Signif.	*ROCSS*				*Signif.*	*RPSS*	
	Tercile	Winter	Spring	Summer	Autumn	Total skillful	Winter	Spring	Summer	Autumn
	above				x					
Sau (Spain)	normal	x				3				
	below			x						
	above									
Mt. Bold (Australia)	normal					1				
	below				x					
	above		x							
Vansjo (Norway)	normal					2				
	below		x							
	above									
Wupper (Germany)	normal					0				
	below									
	Surface Temperature									
			Signif.	*ROCSS*				*Signif.*	*RPSS*	
	Tercile	Winter	Spring	Summer	Autumn	Total skillful	Winter	Spring	Summer	Autumn
	above			x						
Sau (Spain)	normal					2		x		
	below			x						
	above									
Mt. Bold (Australia)	normal					0	x			x
	below									
	above		x							
Vansjo (Norway)	normal					3		x		x
	below	x	x							
	above									
Wupper (Germany)	normal					0		x		x
	below									
	Bottom temperature									
			Signif.	*ROCSS*				*Signif.*	*RPSS*	
	Tercile	Winter	Spring	Summer	Autumn	Total skillful	Winter	Spring	Summer	Autumn
	above		x	x	x					
Sau (Spain)	normal					5				
	below			x	x					
	above									
Mt. Bold (Australia)	normal					2				
	below	x		x						
	above	x	x							
Vansjo (Norway)	normal					4		x		x
	below	x	x							
	above		x	x						
Wupper (Germany)	normal					4			x	x
	below		x	x						

controlling the water balance, which reduces the need for precise inflow and outflow forecasts (which were required for the other three case studies) and therefore avoids (“unpredictable”) anthropogenic consequences affecting the thermal dynamics of the water body.

For the German case study (Wupper Reservoir), summer represents the most critical season in terms of water quality owing to the association between high temperature and algal growth. In terms of seasonal climate forecasts, there was no skill (low performance) in any of the meteorological variables in summer (Fig. 4). For this target season, seasonal forecasts for discharge and surface temperature revealed no significant discrimination or improvement respect to climatology, whereas bottom temperature exhibited significant RPSS and discrimination (ROCSS) skill for the below and above normal categories. For the Wupper Reservoir, which has a bottom outlet, discrimination skill for bottom temperature is relevant as the reservoir’s discharge directly impacts the downstream water quality. For all other seasons (Table 3), there appears to be no windows of opportunity when discriminating among terciles, however, the RPSS values reflect that SEAS5 can improve the prediction with respect to climatology in predicting the spring and autumn seasons for surface temperature, and the autumn season for bottom temperature.

5. Applications and limitations

Overall, the predictability for climate variables in our case studies was limited to some combinations of seasons and variables. Predictability concentrates in Mt. Bold Reservoir and Vansj in autumn and spring, respectively. This is not at odds with the well-known observation that the skill (performance of the forecast system) of seasonal climate forecasts at extratropical latitudes is limited (Manzanas et al., 2014), and related to windows of opportunity connected to relevant drivers of predictability, such as El Niño/La Niña events (Frías et al., 2010).

The limited predictability of climate variables at the seasonal scale in our case studies poses a fundamental obstacle for the usability of hydrologic (discharge) and water quality (water temperature) predictions. However, the general trend is that predictability increases as we move from climate to discharge to lake temperature predictions. This is an intriguing result and, although it is out of the scope of this study, it may be explained by either the temporal or across variables integration of the climate signal by watershed hydrologic processes and lake temperature dynamics, or by strong inertia of these two variables.

If the inertia highly influenced the scores found here, all predictability found in this study would be independent of climate predictions, and should be attributed to the initial conditions. Indeed, a close inspection of the tercile plots across seasons showed that both mechanisms may apply, since correct tercile predictions coincided with seasons in which the tercile did not change between initial conditions and prediction, but we also identified many cases in which a correct prediction implied a change in the tercile, suggesting there are windows of opportunity when seasonal climate prediction can be useful. Exploring this in depth will be the subject of future work and must be considered in relation to statistical power. Benchmarking against climatology and testing the seasonal forecast with multiple scenarios should be an appropriate next step to follow.

In any case, the accumulation of skill, i.e., the increase in performance of the forecast system, in the downstream part of our modeling chain is a stimulating result suggesting that the mounting uncertainty as we progress through the modeling chain is not an insurmountable obstacle to produce useful seasonal predictions for water quality variables.

Nonetheless, discharge and water temperature predictions showed skill intermittently, which indicates that prediction would be useful only for certain windows of opportunity (i.e., for certain variables, terciles, and seasons). Also, the improvement of the prediction respect to climatology (RPSS) and discrimination (ROCSS) skill were usually not coincident, suggesting that the workflow can be improved by additional calibration of the model chain to move towards more useful forecasting. There are several approaches in the literature for forecasting hydrologic and water quality variables using statistical approaches such as neural networks (Palani et al., 2008), machine learning (Barzegar et al., 2018) and data assimilation (Loos et al., 2020), which may be easier to calibrate that the process-based models used in this study. However, these approaches also have limitations, such as the necessity of a large historical database, which could lead to inaccurate forecasts during extreme events for which extrapolation beyond historical observed ranges might be required. The use of process-based models makes the application of the workflow in data-limited regions/case studies easier, and would probably be more reliable (than a statistical approach) during climate extreme events.

The value of process-based models was made evident by the skillful forecasts for impact variables (discharge and water temperature) in a background of limited skill (performance) for climate variables. For instance, in Lake Vansj (Norway), the fact that the forecasts were most skillful for spring is likely related to the impact of the preceding winter on the lake, e.g., a cold, dry winter would involve lower lake temperature in spring. Similar outcomes were also present in Sau Reservoir, where changes in the atmospheric component had a low impact on water temperature in deep waters during some periods, which suggests inertia of the lake was the fundamental source of predictability. This kind of behaviour would be very difficult to mimic with a pure statistical modeling chain.

One limitation worth mentioning in the use of reanalysis (pseudo-observations), because it introduces an additional level of uncertainty to the workflow. Using real observations would be the ideal option when implementing seasonal forecasting, but then reduces the transferability of the workflow. The comparison of seasonal forecasts with real observations will be subject of future work. Here, we use a "perfect model assumption so that we can specifically explore how well seasonal climate forecast skill propagates through seasonal forecasting in lakes. The use of reanalysis together with seasonal forecast systems is a common approach when implementing seasonal forecasting of impact variables (e.g Pechlivanidis et al., 2020; Wood et al., 2016).

Another important issue emerges when predicting inflows and outflows in reservoirs, because our analysis suggested it affects predictability. This was made evident by the conspicuous reduced discrimination skill (decrease in the performance) for surface and bottom water temperature in Mt. Bold and Wupper Reservoirs (2 and 1 significant terciles, respectively) compared to Sau Reservoir (7 significant terciles). This was caused by a slight difference in the way water inflows and outflows were modelled to avoid water dry-outs in the reservoir during forecasting (Georgakakos and Graham, 2008; Li et al., 2014). In Mt. Bold and Wupper, inflows and outflows were dynamically corrected during runs to avoid water dry-outs (these may result due to inconsistencies between the forecasted discharge and the assumed outflows during the forecasted season), while in Sau Reservoir we did not correct for this effect, which resulted in some dummy predictions due to dry-outs (empty boxes in Fig. 7). However, discrimination skill in Sau was higher, suggesting the water level correction algorithm used in Mt. Bold and Wupper should be reconsidered.

6. Conclusions

Managing water quantity and quality is a challenging task for the catchment-lake systems presented here, since managers must regulate the water supply and ecological and recreational services under constant, and even unprecedented, changes in climate. This requires making decisions according to the changes in water quantity and quality over time, depending on the influencing meteorological and hydrologic conditions. Currently, the management of these lakes/reservoirs is mainly based on previous experience and expert decision. To support this decision-making, we have presented a feasible and robust workflow to connect climate forecast data with hydrologic and lake modeling, to obtain seasonal forecasts of discharge and lake temperature profiles.

Even considering the limited skill (performance) found in our seasonal predictions vs. climatology, the few windows of opportunity that seasonal prediction might offer may help managers to anticipate general trends of water quantity and quality changes. The advanced warning provided by seasonal forecasts could return huge benefits in terms of treatment costs, reputation of industry and water authorities, and safe provision of ecosystem services.

In any case, the probabilistic nature of seasonal predictions and the limited skill (performance) found in the studied regions requires careful approach when informing managers about these predictions and the confidence they may place in them. Failing to transparently convey these two properties would compromise the use of seasonal predictions in water resource management in a future with more reliable seasonal climate predictions outside the tropical regions. However, our study points to some windows of opportunity that are worth exploring to make the most of the current state-of-the-art of climate and water quality prediction.

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.

Acknowledgments

This is a contribution of the WATExR project (watexr.eu/), which is part of ERA4CS, an ERA-NET initiated by JPI Climate, and funded by MINECO-AEI (ES), FORMAS (SE), BMBF (DE), EPA (IE), RCN (NO), and IFD (DK), with co-funding by the European Union (Grant

690462). MINECO-AEI funded this research through projects PCIN-2017-062 and PCIN-2017-092. We thank all water quality and quantity data providers: Ens d'Abastament d'Aigua Ter-Llobregat (ATL, https://www.atl.cat/es), SA Water (https://www.sawater.com.au/), Ruhrverband (www.ruhrverband.de), NIVA (www.niva.no) and NVE (https://www.nve.no/english/). We acknowledge the contribution of the Copernicus Climate Change Service (C3S) in the production of SEAS5. C3S provided the computer time for the generation of the re-forecasts for SEAS5 and for the production of the ocean reanalysis (ORAS5), used as initial conditions for the SEAS5 re-forecasts.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.watres.2021.117286

References

Barzegar, R., Moghaddam, A.A., Adamowski, J., Ozga-Zielinski, B., 2018. Multi-step water quality forecasting using a boosting ensemble multi-wavelet extreme learning machine model. Stoch. Environ. Res. Risk Assess. 32 (3), 799–813.
Bazile, R., Boucher, M.A., Perreault, L., Leconte, R., 2017. Verification of ECMWF system 4 for seasonal hydrological forecasting in a northern climate. Hydrol. Earth Syst. Sci 21, 5747–5762.
Blöschl, G., Sivapalan, M., 1995. Scale issues in hydrological modelling: a review. Hydrol. Process. 9 (3–4), 251–290.
Carpenter, S.R., Mooney, H.A., Agard, J., Capistrano, D., DeFries, R.S., Díaz, S., Dietz, T., Duraiappah, A.K., Oteng-Yeboah, A., Pereira, H.M., et al., 2009. Science for managing ecosystem services: beyond the millennium ecosystem assessment. Proc. Natl. Acad. Sci. 106 (5), 1305–1312.
Cofiño, A.S., Bedia, J., Iturbide, M., Vega, M., Herrera, S., Fernández, J., Frías, M.D., Manzanas, R., Gutiérrez, J.M., 2018. The ECOMS user data gateway: towards seasonal forecast data provision and research reproducibility in the era of climate services. Clim. Serv. 9, 33–43. https://doi.org/10.1016/j.cliser.2017.07.001.
Coron, L., Thirel, G., Delaigue, O., Perrin, C., Andréassian, V., 2017. The suite of lumped GR hydrological models in an R package. Environ. Model. Softw. 94, 166–171. doi:10.1016/j.envsoft.2017.05.002.
Emerton, R., Zsoter, E., Arnal, L., Cloke, H.L., Muraro, D., Prudhomme, C., Stephens, E.M., Salamon, P., Pappenberger, F., 2018. Developing a global operational seasonal hydro-meteorological forecasting system: GloFAS-Seasonal v1.0. Geosci. Model Dev. 11 (8), 3327–3346. doi:10.5194/gmd-11-3327-2018.
Frassl, M.A., Boehrer, B., Holtermann, P.L., Hu, W., Klingbeil, K., Peng, Z., Zhu, J., Rinke, K., 2018. Opportunities and limits of using meteorological reanalysis data for simulating seasonal to sub-daily water temperature dynamics in a large shallow lake. Water 10 (5), 594.
Frías, M.D., Herrera, S., Cofiño, A.S., Gutiérrez, J.M., 2010. Assessing the skill of precipitation and temperature seasonal forecasts in Spain: windows of opportunity related to ENSO events. J. Clim. 23 (2), 209–220.
Frías, M.D., Iturbide, M., Manzanas, R., Bedia, J., Fernández, J., Herrera, S., Cofiño, A.S., Gutiérrez, J.M., 2018. An R package to visualize and communicate uncertainty in seasonal climate prediction. Environ. Model. Softw. 99, 101–110.
Georgakakos, K.P., Graham, N.E., 2008. Potential benefits of seasonal inflow prediction uncertainty for reservoir release decisions. J. Appl. Meteorol. Climatol. 47 (5), 1297–1321.
Greuell, W., Franssen, W.H., Hutjes, R.W., 2019. Seasonal streamflow forecasts for Europe-part 2: sources of skill. Hydrol. Earth Syst. Sci. 23 (1), 371–391.
Gupta, H.V., Sorooshian, S., Yapo, P.O., 1998. Toward improved calibration of hydrologic models: multiple and noncommensurable measures of information. Water Resour. Res. 34 (4), 751–763.
Gutiérrez, J.M., Maraun, D., Widmann, M., Huth, R., Hertig, E., Benestad, R., Roessler, O., Wibig, J., Wilcke, R., Kotlarski, S., San Martín, D., Herrera, S., Bedia, J., Casanueva, A., Manzanas, R., Iturbide, M., Vrac, M., Dubrovsky, M., Ribalaygua, J., Pórtoles, J., Räty, O., Räisänen, J., Hingray, B., Raynaud, D., Casado, M.J., Ramos, P., Zerenner, T., Turco, M., Bosshard, T., tpnek, P., Bartholy, J., Pongracz, R., Keller, D.E., Fischer, A.M., Cardoso, R.M., Soares, P.M.M., Czernecki, B., Pagé, C., 2018. An intercomparison of a large ensemble of statistical downscaling methods over Europe: results from the VALUE perfect predictor cross-validation experiment. Int. J. Climatol. 1–36. doi:10.1002/joc.5462.
Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Hornyi, A., Muoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hlm, E., Janiskov, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., Thpaut, J.-N., 2020. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. doi:10.1002/qj.3803.
Hipsey, M.R., Bruce, L.C., Boon, C., Busch, B., Carey, C.C., Hamilton, D.P., Hanson, P.C., Read, J.S., Sousa, E.D., Weber, M., Winslow, L.A., 2019. A general lake model (GLM 3.0) for linking with high-frequency sensor data from the global lake ecological observatory network (GLEON). Geoscientific Model Development.
Iturbide, M., Bedia, J., Herrera, S., Baño-Medina, J., Fernández, J., Frías, M.D., Manzanas, R., San-Martín, D., Cimadevilla, E., Cofiño, A.S., Gutiérrez, J.M., 2019. The R-based climate4R open framework for reproducible climate data access and post-processing. Environ. Model. Softw. 111, 42–54.
Jackson-Blake, L.A., Sample, J.E., Wade, A.J., Helliwell, R.C., Skeffington, R.A., 2017. Are our dynamic water quality models too complex? Acomparison of a new parsimonious phosphorus model, Simply P, and INCA-P. Water Resour. Res. 53 (7), 5382–5399.
Johnson, S.J., Stockdale, T.N., Ferranti, L., Balmaseda, M.A., Molteni, F., Magnusson, L., Tietsche, S., Decremer, D., Weisheimer, A., Balsamo, G., et al., 2019. SEAS5: the new ECMWF seasonal forecast system. Geosci. Model Dev. 12 (3), 1087–1117.
Jolliffe, I.T., Stephenson, D.B., 2003. Forecast Verification: A Practitioner's Guide in Atmospheric Science. John Wiley & Sons.
Komatsu, E., Fukushima, T., Harasawa, H., 2007. A modeling approach to forecast the effect of long-term climate change on lake water quality. Ecol. Model. 209 (2–4), 351–366.
Li, W., Sankarasubramanian, A., Ranjithan, R.S., Brill, E.D., 2014. Improved regional water management utilizing climate forecasts: an interbasin transfer model with a risk management framework. Water Resour. Res. 50 (8), 6810–6827.
Loos, S., Shin, C.M., Sumihar, J., Kim, K., Cho, J., Weerts, A.H., 2020. Ensemble data assimilation methods for improving river water quality forecasting accuracy. Water Res. 171, 115343.
Luo, L., Wood, E.F., Pan, M., 2007. Bayesian merging of multiple climate model forecasts for seasonal hydrological predictions. J. Geophys. Res. 112 (D10).
Manzanas, R., Frías, M.D., Cofiño, A.S., Gutiérrez, J.M., 2014. Validation of 40 year multimodel seasonal precipitation forecasts: the role of ENSO on the global skill. J. Geophys. Res. 119 (4), 1708–1719. doi:10.1002/2013JD020680.
Mason, S.J., 2013. Guidance on verification of operational seasonal climate forecasts. Commission for Climatology XIV Technical Report. World Meteorological Organization.
Palani, S., Liong, S.-Y., Tkalich, P., 2008. An ann application for water quality forecasting. Mar. Pollut. Bull. 56 (9), 1586–1597.
Pechlivanidis, I., Crochemore, L., Rosberg, J., Bosshard, T., 2020. What are the key drivers controlling the quality of seasonal streamflow forecasts? Water Resour. Res. 56 (6).
Pozzi, W., Sheffield, J., Stefanski, R., Cripe, D., Pulwarty, R., Vogt, J.V., Heim Jr, R.R., Brewer, M.J., Svoboda, M., Westerhoff, R., et al., 2013. Toward global drought early warning capability: expanding international cooperation for the development of a framework for monitoring and forecasting. Bull. Am. Meteorol. Soc. 94 (6), 776–785.
Rosenberg, E.A., Wood, A.W., Steinemann, A.C., 2011. Statistical applications of physically based hydrologic models to seasonal streamflow forecasts. Water Resour. Res. 47 (3).
Sene, K., Tych, W., Beven, K., 2018. Exploratory studies into seasonal flow forecasting potential for large lakes. Hydrol. Earth Syst. Sci. 22 (1), 127–141.
Thomas, R.Q., Figueiredo, R.J., Daneshmand, V., Bookout, B.J., Puckett, L.K., Carey, C.C., 2020. A near-term iterative forecasting system successfully predicts reservoir hydrodynamics and partitions uncertainty in real time. Water Resour. Res. 56 (11).
Turner, S.W., Bennett, J.C., Robertson, D.E., Galelli, S., 2017. Complex relationship between seasonal streamflow forecast skill and value in reservoir operations. Hydrol. Earth Syst. Sci. 21 (9), 4841–4859.
Wilcke, R.A.I., Mendlik, T., Gobiet, A., 2013. Multi-variable error correction of regional climate models. Clim. Change 120 (4), 871–887.
Wood, A.W., Hopson, T., Newman, A., Brekke, L., Arnold, J., Clark, M., 2016. Quantifying streamflow forecast skill elasticity to initial condition and climate prediction skill. J. Hydrometeorol. 17 (2), 651–668.
Wood, A.W., Maurer, E.P., Kumar, A., Lettenmaier, D.P., 2002. Long-range experimental hydrologic forecasting for the eastern United States. J. Geophys. Res. 107 (D20), ACL–6.
Woolway, R.I., Sharma, S., Weyhenmeyer, G.A., Debolskiy, A., Golub, M., Mercado–Bettín, D., Perroud, M., Stepanenko, V., Tan, Z., Grant, L., et al., 2021. Phenological shifts in lake stratification under climate change. Nat. Commun. 12 (1), 1–11.
Yang, K., Yu, Z., Luo, Y., 2020. Analysis on driving factors of lake surface water temperature for major lakes in Yunnan–Guizhou Plateau. Water Res. 184, 116018.
Yuan, X., Roundy, J.K., Wood, E.F., Sheffield, J., 2015. Seasonal forecasting of global hydrologic extremes: system development and evaluation over GEWEX basins. Bull. Am. Meteorol. Soc. 96 (11), 1895–1912.
Yuan, X., Wood, E.F., Luo, L., Pan, M., 2011. A first look at climate forecast system version 2 (CFSv2) for hydrological seasonal prediction. Geophys. Res. Lett. 38 (13).
Zhang, W., Villarini, G., Vecchi, G.A., 2019. Impacts of the pacific meridional mode on rainfall over the maritime continent and australia: potential for seasonal predictions. Clim. Dyn. 53 (12), 7185–7199.