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Inertia and seasonal climate prediction as sources of skill in lake temperature, discharge and ice-off forecasting tools

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Abstract. Despite high potential benefits, the development of seasonal forecasting tools in the water sector has been slower than in other sectors. Here we assess the skill of seasonal forecasting tools for lake and reservoir set up at four sites in Australia and Europe. These tools, as previously presented, consist of coupled hydrological catchment and lake models forced with seasonal climate forecast ensembles to provide probabilistic predictions of seasonal anomalies in water discharge, temperature and ice-off. Successful implementation requires a rigorous assessment of the tools' predictive skill and an apportionment of the predictability between legacy effects and input data. To this end, models were forced with two meteorological datasets from the European Centre for Medium Range Weather Forecasts (ECMWF), the seasonal forecasts SEAS5 and the ERA5 reanalysis. Historical skill was assessed by comparing both model outputs, i.e., seasonal lake hindcasts (forced with SEAS5) and pseudo-observations (forced with ERA5). The skill of the seasonal lake hindcasts was generally low, but higher than SEAS5 climate hindcasts. Nevertheless, lake and SEAS5 windows of opportunity were identified, although they were not always synchronous, raising questions on the source of the predictability. A set of sensitivity analyses showed that most of the forecasting skill originates from legacy effects, although during winter and spring in Norway some skill was coming from SEAS5 over the target season. When SEAS5 hindcasts were skillful, additional predictability originates from the interaction between legacy and SEAS5 skill. We conclude that a climatology driven forecast is currently likely to yield higher quality forecasts.

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1. Introduction

Freshwater provides essential services for food and energy production, manufacturing, cultural heritage, and natural habitats. However, it is threatened by more frequent extreme events (Jeppesen et al., 2021), climate change (Labrousse et al., 2020), anthropogenic water depletion (Yi et al., 2016) and agricultural pressures (Wuijts et al., 2021). Implementation of mitigation measures can help preserve freshwater resources, although they come with trade-offs between production from economic sectors with related social benefits, and availability of good quality freshwater. Hence, successful implementation of measures requires capacity at the local-regional level for cross-sectoral decision-making (Wuijts et al., 2021). Seasonal forecasting tools for water quality can help facilitate the decision-making process by refining optimal actions over the next season, e.g., magnitude and timing of reservoir drawdowns. Indeed, they can supply knowledge on the impacts of future climatic conditions on freshwater over a realistic time frame enabling implementation with reduced negative effects on economic activities. Nevertheless, the use and access to forecasting tools is still very limited for water managers (Lopez & Haines, 2017; Soares et al., 2018). The probabilistic nature of seasonal forecasts can be a key barrier coupled with the lack of reliability and credibility of these predictions in most regions out of tropics. Hence, a better access to seasonal forecasting tools as well as increased comprehension and description of these tools are required prior to their successful implementation in the decision-making process within the water sector.

Seasonal climate predictions provide a probabilistic description of the weather over the next few months, e.g., an 80% chance of the weather being wetter than normal. Seasonal climate predictability mainly originates from ocean–atmosphere interactions (Troccoli, 2010). In fact, the ocean inertia, given its volume and the heat capacity of liquid water, exerts an influence on the atmosphere on the scale of months which allows us to estimate its future effect on weather. Given that ocean–atmosphere interactions are relatively strong in the equatorial region (Troccoli, 2010), seasonal climate predictions typically show stronger predictive skill around the tropics (Johnson et al., 2019; Manzanas et al., 2014). Under higher latitudes, skills from seasonal climate predictions are patchy and less consistent among variables and seasons. Hence, seasonal climate forecasts are usually not the main source of predictability outside the tropics, at least for stream flow (Greuell et al., 2019; Harrigan et al., 2018; Wood et al., 2016). Nevertheless, climate models producing seasonal climate forecasts are constantly improving and it is reasonable to expect that forecast opportunities will expand in the future (Mariotti et al., 2020). Developing seasonal forecasting workflows, quantifying the skill and investigating the source of predictability represent a necessary and essential step towards reliable water quality seasonal forecasting.

While some of the first forecasting tools were originally developed for flood warnings (e.g., Pagano et al., 2014; Werner et al., 2009), applications to other sectors are becoming more frequent. In the agricultural sector, for example, a recent study shows that flowering time can be reliably predicted from seasonal climate forecasts in central and eastern Europe, enabling early variety selection and planning of farm management (Ceglar & Toreti, 2021). Seasonal climate forecasts were also shown to provide useful information for the wind energy sector (Lledó et al., 2019), and to avoid significant economic losses from hydropower generation during droughts (Portele et al., 2021). Nevertheless, the use of seasonal climate forecasts for water quality in lakes and reservoirs has been limited so far, where the focus has been on water quantity (Arnal et al., 2018; Giuliani et al., 2020; Greuell et al., 2019; Pechlivanidis et al., 2020). Studies forecasting water temperature, a fundamental water quality variable, are rare in the literature (Mercado-Bettin et al., 2021; Zhu et al., 2020), despite the diverse influence of this variable on lake ecosystem structure and functioning (Dokulil et al., 2021). Nevertheless, a simple lumped model (*air2water*; Piccolroaz et al., 2013), previously developed to estimate surface lake water temperature as a function of air temperature, has been applied to predict water temperature in thousands of lakes (Zhu et al., 2021). While this hybrid approach yielded skillful surface lake water temperature predictions and forecasts (Piccolroaz et al., 2018; Toffolon et al., 2014), it doesn't take seasonal climate forecast ensembles as inputs, i.e., climate data products specifically designed for seasonal forecasting, and it doesn't allow forecasting any other lake variable, such as bottom temperature or ice-off.

Research on seasonal forecasting in hydrology has started more than a decade ago (Troin et al., 2021) and now represents a source of knowledge for other research fields. When forecasting river flow, for example, predictability can originate from two main sources: (i) catchment water stores of initial soil moisture, groundwater, and snowpack, which are directly linked to the water residence time; and (ii) seasonal climate prediction (Greuell et al., 2019). Throughout the many studies of river flow seasonal forecasting in Europe, it appears that initial conditions form the dominant source of skill in run-off (Greuell et al., 2019; Harrigan et al., 2018; Wood et al., 2016) and predictability can be extended up to a year ahead in case of very low flow (Staudinger & Seibert, 2014). When dealing with standing water bodies, antecedent conditions are also likely to provide significant predictability, given that the water storage in lakes and reservoirs is large compared to river channels, providing higher inertia. Water residence time is thus expected to exert a strong influence on water flow predictability. Water temperature, on the other hand, is influenced by multiple meteorological variables, e.g., wind, and radiation, in addition to water stores which can affect the source of its predictability.

Here, we further investigate the performance and in particular the source of skill of water quality seasonal forecasting tools first described by Mercado-Bettin et al. (2021) and Jackson-Blake et al. (2022). These tools integrate seasonal climate predictions and water impact models at four case study sites in Europe and Australia. The objective of this study is to assess whether seasonal climate forecast ensembles used as inputs to catchment and lake process-based models provide some predictive skill to seasonal lake forecasts. To this end, the forecasting skill of the tools was assessed for combinations of season and freshwater variables, i.e., discharge, water temperature or ice-off. In parallel, we quantified the forecasting skill of each meteorological variable of the seasonal climate prediction at each site. A set of sensitivity analyses was performed to identify input-output relationships and to partition the source of the predictability for each window of opportunity among warm-up, (transition) lead-month and seasonal climate predictions. The comparison in hindcasts with the aim of isolating the contributions of different sources to skill has been applied before on streamflow hindcasts (e.g., Arnal et al., 2018; Greuell et al., 2019), but this is, to our knowledge, the first study investigating the origin of seasonal hindcast ensemble skills on water discharge, temperature and ice-off in lakes and reservoirs. The implications for water quality forecasting tools are discussed.

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2. Methods

2.1 Description of the forecasting tools

The forecasting tools consist of a coupled catchment runoff model to a one-dimensional water column lake model, forced by seasonal climate predictions, to simulate three impact variables at daily resolution: inflow discharge, and lake surface and bottom temperature. For Lake Vansjø in Norway, the timing of ice melt (ice-off) was also included in the impact variables in spring.

2.1.1 Case study sites

Water quality forecasting tools were developed for four regulated water lakes/reservoirs in Europe and Australia which have been described earlier (Mercado-Bettin et al., 2021;Table 1). Briefly, Sau (Spain) and Mount Bold (Australia) reservoirs large water supplies for the cities of Barcelona and Adelaide, respectively. Lake Vansjø (Norway), is a drinking water source for three municipalities and the Wupper reservoir (Germany) is used for flood control, environmental flows, and recreation.

Table 1: Characteristics of the study sites. Mixing timing refers to boreal seasons only.

Case study (Country)	Catchment area (km^2)	Surface area (ha)	Volume (hm3)	Water retention time (yrs)	Max. Depth (m)	Mixing regime	Mixing timing
Sau (Spain)	1680	575	165	0.2	60	monomictic	Winter
Mt Bold (Australia)	357	254	46.4	0.2-0.6	44.5	monomictic	Summer
Vansjø (Norway)	690	3600	252	1.1	19	dimictic	Spring Fall
Wupper (Germany)	215	211	26	0.2	31	dimictic	Spring Fall

2.1.2 Climate data

We used two different climate datasets to force the impact models (catchment and lake models) in our tools: a climate reanalysis (ERA5) and a seasonal climate forecasting product (SEAS5) which both offer a relatively homogeneous spatial and temporal coverage. ERA5 is the latest reanalysis at 0.25° spatial resolution (Hersbach et al., 2020) produced by the European Centre for Medium Range Weather Forecasts (ECMWF; https://www.ecmwf.int) within the Copernicus Climate Change Service (C3S, https://climate.copernicus.eu/). ERA5 data (1988-2016) were used (i) to correct for bias in the SEAS5 data as described by Mercado-Bettin et al. (2021); (ii) to provide climate pseudo-observations for retrospective skill evaluation of SEAS5 hindcasts, (iii) to force impact models to produce pseudo-observations of the impact variables, (iv) to force our impact models to produce antecedent/warm-up period data preceding seasonal forecast periods (i.e., combined one lead-month and three-month target season) . SEAS5 is the latest seasonal forecasting system from the ECMWF at 1° spatial resolution and provides operational seasonal forecasts and retrospective seasonal forecasts for past years (hindcasts). We used hindcasts

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(1994-2016) in this study. A hindcast with 25 members was considered for the period 1993-2016 for the three-month boreal seasons (spring: March through May; summer: June through August; autumn: September through November; winter: December through February), with one month as lead time. Climate data were downloaded, down-scaled and bias-corrected with a dedicated R package (climate4R; Iturbide et al., 2019). SEAS5 members were pre-processed using the quantile mapping technique (Gutiérrez et al., 2019) to correct for systematic bias relative to climate (pseudo-)observations (ERA5 reanalysis). We used the empirical approach (EQM) due to its ability to deal with multivariate problems (Wilcke et al., 2013). More details about bias-correction are given in Mercado-Bettin et al. (2021).

Climate datasets include daily air temperature (tas), wind speed (u and v components; uas and vas), air pressure (psl), relative humidity (tdps), cloud cover (tcc), solar radiation (rsds), and precipitation(tp).

2.1.3 Observations

Daily inflow discharge and daily to monthly lake water temperature observations (Table S1) were used for catchment and lake model calibration and validation, as well as quantification of forecasting skills.

2.1.4 Catchment-lake process-based model setup and calibration

A catchment-lake process-based model chain was setup at each site to predict daily inflow discharge into the lake/reservoir and daily lake water temperature. Given the specificity of each catchment regarding flow dynamics and water management, different models were used at each site (Fig. 1). While this disparity prevents us from an in-depth comparison among case-studies, the common methods and code established to manipulate input and output data enable us to quantify forecast performance and the source of the predictability at each site in a consistent and comparable way.

Inflow water temperature and discharge for Sau and Vansjø was modelled with the mesoscale Hydrologic Model (mHM v5.9: http://www.ufz.de/mhm) and SimplyQ (hydrological module of SimplyP; Jackson-Blake et al. (2017), respectively. Inflow water temperature and discharge for Wupper and Mt Bold was modelled with the *Génie Rural* (GR) suite of models implemented within the R package airGR (Coron et al., 2017), GR6J and GR4J, respectively. mHM and SimplyQ hydrologic models were forced with ERA5 tp and tas, and the GR models were forced with tp and petH (Hargreaves-Samani potential evapotranspiration, derived from tmin and tmax and implemented in drought4R; Iturbide et al., 2019). All hydrological models were calibrated and validated against observations using the Nash–Sutcliffe efficiency coefficient (NSE) as the objective function.

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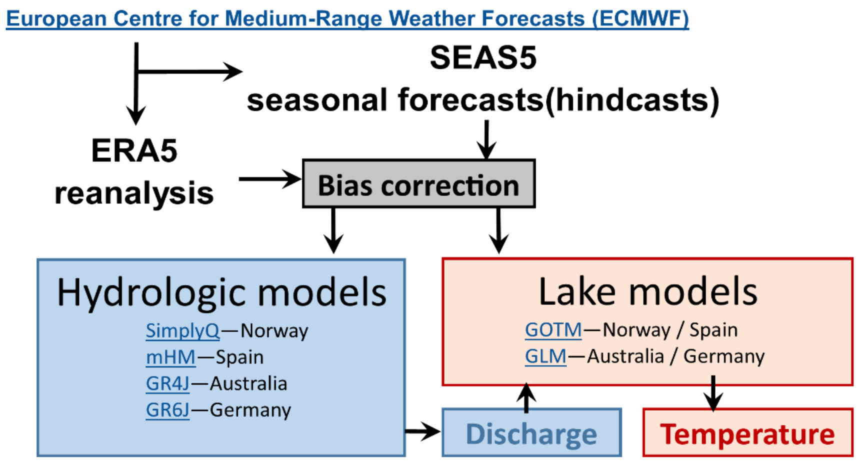

Figure 1: Description of the forecasting workflow—Calibrated hydrologic and lake models are used to produce seasonal forecasts of water quality with 25 climate seasonal members

The General Ocean Turbulence Model (GOTM, http://gotm.net) was used to simulate the water temperature profile of Sau Reservoir and Lake Vansjø. The General Lake Model (GLM, Hipsey et al., 2019) was used to simulate water temperature in the Mt. Bold and Wupper reservoirs. Lake models were forced with ERA5 tas, uas, vas, psl, tdps tcc, rsds and tp, and calibrated and validated against observations using the Root-Mean-Square Error (RMSE) and NSE as objective functions.

For Lake Vansjø, the water level was set to constant given that observed fluctuations are < 1 m which are not critical for the lake heat and water budgets. The three reservoirs, on the other hand, experience much larger water level fluctuations because of complex water pumping patterns and/or water scarcity. It was thus critical to allow for water level fluctuations and parametrize the outflows to avoid dry outs. We opted for a simple linear regression between observed inflow and outflow to predict the outflow in the absence of observations.

Most common statistical goodness-of-fit parameters, e.g., Kling-Gupta efficiency (KGE), NSE and RMSE, for hydrological and lake modeling were calculated.

2.1.5 Pseudo-observations (Lake_PO)

Following calibration, lake and hydrologic models were forced with ERA5 over 1993-2016 to produce daily pseudo-observations of river discharge, daily surface and bottom temperature, as well as presence or absence of ice (for Lake Vansjø only). The output of this simulation is hereafter referred to as lake pseudo-observations (Lake_PO). Theoretical prediction skill of seasonal forecasts is commonly evaluated against pseudo-observations (Greuell et al., 2019; Harrigan et al., 2018; Wood et al., 2016). In contrast to real observations, Lake_PO have the advantages of being complete and allow to disregard changes in skill related to model errors or biases (Harrigan et al., 2018), and to focus on skill originating from initial and boundary conditions. The total prediction skill of seasonal forecasts was also evaluated against real observations, when those were available and covering a representative time period.

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2.1.6 Seasonal forecasts (Lake_F)

For each of the 92 three-month hindcast seasons (11/1993 to 11/2016), we simulated ensemble predictions of daily river discharge, daily surface and bottom water temperature as well as presence or absence of ice (for Lake Vansjø only; Fig. 2). Impact models were forced with ERA5 data over the 1-year warm-up period followed by a set of 25 members of SEAS5 data covering an initialization month and the 3-month long target season. Over the initialization month, the 25 members of SEAS5 progressively diverge from ERA5 to their respective SEAS5 member. Model outputs for the final 3 months, i.e., the target season, were selected and used to calculate the probabilistic forecasts of seasonal summary statistics (i.e., mean surface and bottom water temperature and cumulative seasonal inflow discharge). The output of this simulation is hereafter referred to as lake forecasts (Lake_F).

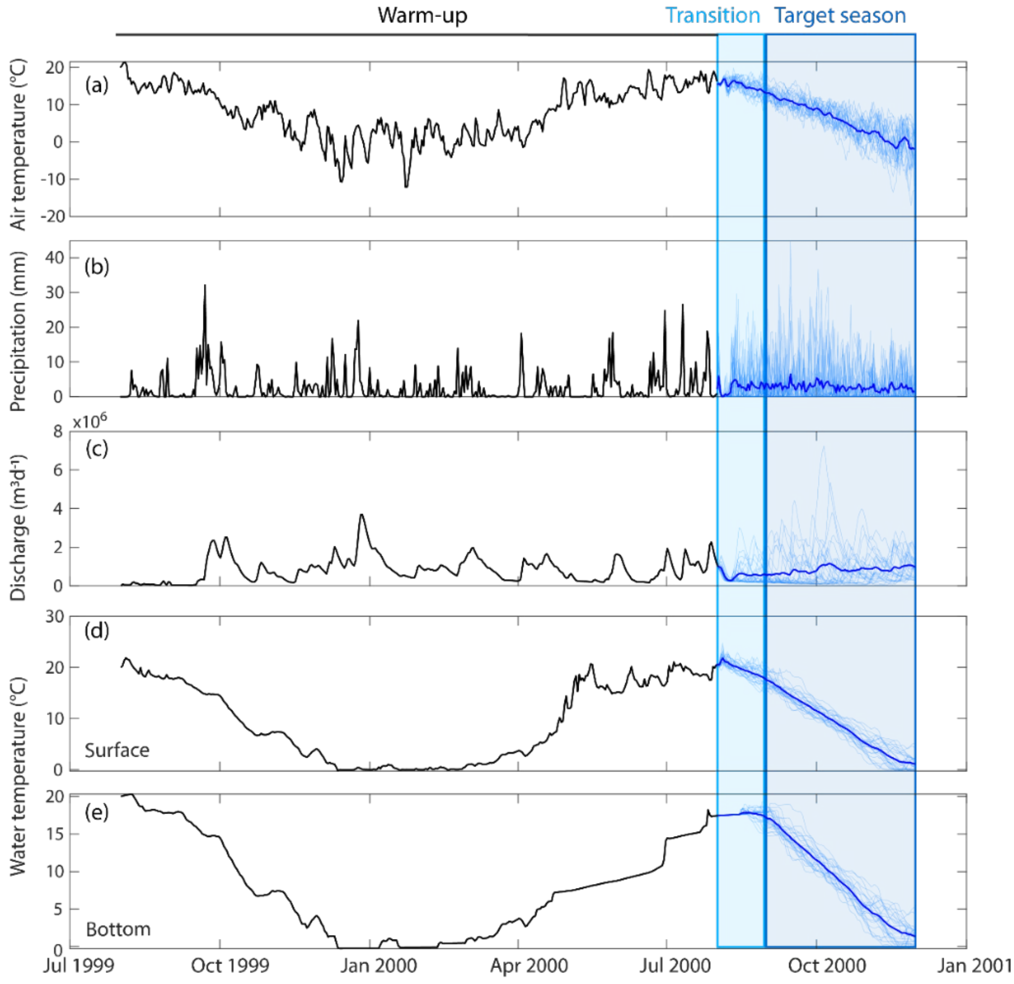

Figure2: Time series of the air temperature (a), precipitation (b), discharge (c), surface (d) and bottom (e) water temperature over the warm-up, transition month and target season for Autumn 2000. The black lines indicate ERA5 (a and b) and Lake_PO (c–e) data, the light and dark blue lines are, respectively, the 25 members and the mean of SEAS5 (a and b) and Lake_F (c–e).

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2.2 Assessment of modeling performance and source of forecasting skills

2.2.1 Assessment of model performance

Lake_PO and Lake_F were compared to one another and to observations, when available, to evaluate the performance of different components of the model chain (Table 2).

Forecast performance was quantified with the Ranked Probability Skill Score (RPSS) and the Relative Operating Characteristic Skill Score (ROCSS). RPSS and ROCSS are commonly used as evaluation measures of probabilistic forecasting skill (Jolliffe & Stephenson, 2012; Müller et al., 2005). The visualizeR package (Frías et al., 2018) was used to compute the RPSS and ROCSS for Lake_PO and Lake_F. Briefly, the RPSS provides a relative performance measure on how well the probabilistic ensemble is distributed over the lower, middle and upper terciles, while the ROCSS provides a relative measure of discriminative skill for each category. Both skill scores are expressed as relative to a reference forecast, i.e., climatology. A RPSS > 0 is associated with a better forecast than the reference (1 being a perfect score), while RPSS ≤ 0 indicates no improvement compared to the reference. The ROCSS value ranges from -1 (perfectly bad forecast) to 1 (perfect forecast) and a zero value indicates no skill compared to the reference. Threshold RPSS and ROCSS values above which RPSS and ROCSS are significant at 95% confidence are calculated by built-in VisualizeR functions and were used to identify windows of opportunity (i.e., combinations of seasons, variables and terciles for which forecast performance was significantly better than the reference). In our case, these thresholds typically range between 0.47 and 0.55. When possible, ROCSS values were calculated against climatology from real observations ($ROCSS_{Obs}$), in addition to pseudo-observations ($ROCSS_{original}$).

Table 2: Comparison carried out to evaluate model performance

Expt	Outputs used	Evaluation data	Purpose	Statistics
1	Lake_F	Lake_PO	Assess the transfer of climate model forecast skill through process-based models – Perfect model forecasting skill	$ROCSS_{original}$
2	Lake_PO	Observations	Assess lake model skill	KGE NSE RMSE
3	Lake_F	Observations	Assess total forecasting skill	$ROCSS_{Obs}$

2.2.2 Sensitivity analyses to explore inheritance of forecasting skill

A set of sensitivity analyses (SA; Table 3) were performed to identify the origin of the forecasting skill for a given window of opportunity. These SA allowed quantifying the sensitivity of hindcasts to forcing data over specific periods. It was thus possible to quantify the proportion of skills originating from the forcing data over the 3-month target season (SEAS5 data), the transition lead-month, or the warm-up period (ERA5 data).

The SA consisted of replacing the forcing data of interest by data from an equivalent season/period but from a randomly selected year. For the target season SA (S-SA), the SEAS5 forcing data covering the 3-month target season was replaced by

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SEAS5 data from a randomly selected equivalent season. The SA for the warm-up period (W-SA) consisted in replacing the ERA5 data covering the warm-up period by ERA5 data from a randomly selected equivalent time-period. The last SA covered warm-up and transition month (W+T-SA) and consisted in replacing ERA5 data over the warm-up, as in W-SA, but also SEAS5 data over the transition month. To ensure that the randomly sampled forcing data are representative of the whole SEAS5 or ERA5 datasets, we introduce two levels of repetitions for all experiments. First, we randomly selected a year for each of the 25 members of SEAS5, meaning that the data selected to replace the original SEAS5 forcing data is extremely likely to be from a different year for each SEAS5 member. Second, we repeated the analysis 25 times, for each season. Sensitivity analyses were only carried out for Spain and Norway because of the low number of windows of opportunity at the two other sites and considering the resources needed to execute these hindcast experiments.

The outputs of S-SA, W-SA, and W+T-SA were used to produce tercile plots and calculate ROCSS. The comparison of the ROCSS values ($ROCSS_i$) obtained for the various SAs were compared to the original Lake_F ROCSS values ($ROCSS_{original}$) to investigate the sources of predictability. An estimation of the proportion of predictability originating from the SEAS5 data over the target season (P_{season}) was expressed as follows:

$$P_{season} = ROCSS_{original} - ROCSS_S \tag{1}$$

Similarly, the proportions of predictability originating from the ERA5 data over the warm-up ($P_{warm-up}$) and from the SEAS5 data over the transition month ($P_{transition}$) can be respectively estimated as:

$$P_{warm-up} = ROCSS_{original} - ROCSS_W \tag{2}$$

$$P_{transition} = ROCSS_W - ROCSS_{W+T} \tag{3}$$

In Eq. 1–3, predictability was assumed to linearly scale with ROCSS values and predictability from any interaction effect was neglected. While we admit that Eq. 1–3 are not necessarily statistically correct, they are useful to quantify the relative importance of the sources of skill. Hence, the values of P_{season}, $P_{warm-up}$ and $P_{transition}$ should be interpreted with care.

2.1.1 Sensitivity analyses to trace forecasting skill from input to impact

To further investigate through which process forecasting skill is transferred from input to impact variables, a one-at-a-time sensitivity analysis (OAT-SA) was performed for Lake_PO and the Pearson partial correlation coefficients (PPCC) between each Lake_PO variables and a set of relevant input variables were determined (Table 3). The OAT-SA consisted in replacing the data for a specific input climate variable by data from an equivalent target season but from a randomly selected year. The seasonal means of OAT-SA outputs were compared to default outputs (Lake_PO) with R^2. Higher $(1 - R^2)$ values indicate more influence of input variables on Lake_PO.

PPCC allowed quantifying the sensitivity of model outputs to a given input variable while removing the effect of the remaining input variables. To ensure that PPCC were statistically appropriate, i.e., only when a linear relationship exists between the input factors and the output (Pianosi et al., 2016), the linearity assumption was checked through visual inspection of scatter plots between each input and output variables. Partial correlation coefficients are a good alternative to 'All-At-a-Time' (or

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global) SA when the latter is not possible because of the lack of computing resources (Pianosi et al., 2016). To avoid misleading conclusions, correlation between input variables should be minimized (Marino et al., 2008). Hence, only the most relevant input variables were included. Precipitation and air temperature were retained for discharge, while air temperature, precipitation, wind speed (net wind speed calculated from uas and vas) and solar radiation were retained for surface and bottom temperature. In fact, solar radiation was retained over relative humidity, cloud cover and air pressure because it was responsible for over 50% of all air-water heat fluxes. Wind was retained because of its impact on thermal stability (Blottiere, 2015).

Table 3: List of sensitivity analyses (SA) performed

SA	Forcing data to be replaced: Period	Forcing data to be replaced: Variable	Model output	Purpose	Sensitivity index
S-SA	Target season (SEAS5)	All	Lake_F	Quantifying the proportion of forecasting skill originating from SEAS5 data over the target season	$ROCSS_S$
W-SA	Warm-up period (ERA5)	All	Lake_F	Quantifying the proportion of forecasting skill originating from ERA5 data over the warm-up season – initial conditions	$ROCSS_W$
W+T-SA	Warm-up period (ERA5) and transition month (SEAS5)	All	Lake_F	Quantifying the proportion of forecasting skill originating from SEAS5 data over the transition month	$ROCSS_{W+T}$
OAT-SA	Target season (ERA5)	One	Lake_PO	Quantifying the sensitivity of Lake_PO to a specific forcing variable	$1 – R^2$
PPCC	None	None	Lake_PO	Quantifying the sensitivity of Lake_PO to a specific forcing variable while removing the effect of the remaining variables	PPCC

3 Results

3.1 Performance of the calibrated impact models (Lake_PO)

Catchment and lake models calibrated against local observations performed reasonably well. For river discharge, NSE and KGE both ranged between 0.51 and 0.85 over the calibration and validation periods. For surface water temperature, RMSE ranged from 1.10 to 1.63 and NSE from 0.78 to 0.94 over the calibration and validation periods. Over each season, however, Lake_PO showed more heterogeneous performance (Table S2). Discharge simulations were usually worse in summer, except in Australia where performance was poor for most seasons. Surface water temperature modeling typically showed better performance during spring and fall than during summer or winter. There is no clear pattern for bottom water temperature, but overall, it seems more difficult to be accurately simulated compared to surface temperature.

3.2 Skill of the seasonal climate (SEAS5) and water quality (Lake_F) hindcasts

For SEAS5 seasonal climate hindcasts, only 3 to 10 windows of opportunity were observed for each case study out of the 96 possibilities, i.e., 3 terciles of 8 variables over 4 seasons (Table 4). Regarding Lake_F, larger proportions of the 36–39 possible variable-tercile-season combinations were associated with significant ROCSS values. Winter and Spring in Norway, as well as Summer and Autumn in Spain were the seasons associated with the most skillful Lake_F hindcasts. Lake Vansjø in Norway was the only case study where windows of opportunity for SEAS5 and Lake_F were consistently concentrated within the same seasons, i.e., mostly in Spring and to a lesser extent in Winter. For the other case studies, there were fewer windows of opportunity for SEAS5 and those were more randomly distributed over the year. Significant fair RPSS values were typically reported for surface water temperature in spring and autumn, except for autumn in Spain. Norway and Germany also showed significant fair RPSS for bottom water temperature in spring and autumn, and summer and autumn, respectively. Note that neither river discharge nor any of the SEAS5 variables had significant fair RPSS values in any case study. Windows of opportunity for bottom temperature represented more than half of the total for all case-studies and variables while those for surface temperature and discharge were more sporadic.

The comparison of SEAS5 and Lake_F skillful hindcasts in Table 4 is already useful for identifying possible transfer of forecasting skill from the SEAS5 seasonal climate hindcasts to the impact models. Only 0 to 10% of the SEAS5 climate hindcasts are skillful, on average. However, for Norway, there is a higher number of skillful climate and water-quality hindcasts in spring than in the other seasons. For the other case-studies, such a clear connection between SEAS5 climate hindcasts and impact model outputs is not as apparent. We can thus hypothesize that the skill of impact model hindcasts in Norway is more inherited from the SEAS5 data than at other case studies. In contrast, skill of the impact model hindcasts at the other case-studies is hypothesized to originate from the legacy of the warm-up period or from the parametrization of the inflow-outflow water balance.

Goodness of fit statistics for Lake_PO seasonal means compared to observations (Table 5) show that the impact models performed well at the Norwegian and Spanish sites in capturing interannual variability. In Germany and Australia, performance was lower. Note that when observation coverage was below 50%, no statistics were calculated given the low number of seasons represented and the risk of bias when computing seasonal averages. The difference between $ROCSS_{original}$ (comparing Lake_F and Lake_PO) and $ROCSS_{Obs}$ (comparing Lake_F and lake observations) did not necessarily scale inversely with the goodness of fit statistics (Table 5). In fact, the $ROCSS_{Obs}$ reported for the German site were slightly lower or even larger than their respective $ROCSS_{original}$ with differences lower than 0.23. Whereas, for the Spanish site, three $ROCSS_{Obs}$ values out of 4 were significantly lower than the $ROCSS_{original}$ with a difference larger than 0.33. These results highlight the point that the goodness of fit statistics apply to the full data distribution while ROCSS are specific to a tercile. Hence, even if the model captures the interannual variability over the whole data distribution relatively well, predictions within a given tercile may be poor, and vice versa. Nevertheless, several impact variables, e.g., bottom temperature in Germany and ice-off in Norway, are associated with significant $ROCSS_{original}$ and $ROCSS_{Obs}$ which provides further confidence in model calibration and low

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model error. In contrast, even if the goodness of fit statistics for discharge were not worse than for the other variables, $ROCSS_{Obs}$ values are all below the significance threshold pointing towards some limitations in predicting hydrology.

Table 4: SEAS5 climate and Lake_F water quality hindcasts associated with significant FRPSS or ROCSS at each case-study. ST, BT and Q stand for surface-, bottom-temperature and discharge, respectively. -, + and = stands for lower, upper and middle terciles, respectively.

Site	Indexes	Numbers of skillful hindcasts variable (tercile)									
		Winter		Spring		Summer		Autumn		TOTAL	
		SEAS5	Lake_F	SEAS5	Lake_F	SEAS5	Lake_F	SEAS5	Lake_F	SEAS5	Lake_F
Norway	FRPSS				ST; BT				ST; BT	**0/32**	**4/12**
	ROCSS	3 tcc (−) rsds (+) rlds (=)	3 ST (−) BT (−,+)	7 psl(=,+) tas (+) tcc (=) tdps (−) uas (+) vas (−)	8 Q (−,+) ST (−,+) BT (−,+) Ice-off (−,+)	0	0	0	0	**10/96**	**11/39**
Australia	FRPSS				ST				ST	**0/32**	**2/12**
	ROCSS	2 psl (+) tdps (+)	1 BT (−)	1 rlds (+)		1 tcc (=)	1 BT (−)	4 psl (+) tcc (+) tas (=) rsds (+)	1 Q (−)	**8/96**	**3/36**
Spain	FRPSS				ST					**0/32**	**1/12**
	ROCSS	0	1 Q (=)	2 tcc (+) psl (+)	1 BT (+)	2 tcc (+) tdps (+)	5 Q (−) ST (+) BT (−,+)	1 tcc (+)	3 Q (+) BT (−,+)	**5/96**	**9/36**
Germany	FRPSS				ST		BT		ST; BT	**0/32**	**4/12**
	ROCSS	2 rlds (=) vas (−)	0	1 tdps (+)	2 BT (−,+)	0	2 BT (−,+)	0	0	**3/96**	**4/36**

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Table 5: Goodness of fit statistics (NSE, R^2, RMSE, RMSE/sd, bias) for Lake_PO seasonal means, as well as comparison of the $ROCSS_{original}$.(comparing Lake_F and Lake_PO) and $ROCSS_{Obs}$ (comparing Lake_F and lake observations). Only impact variables associated with significant $ROCSS_{original}$ are included. Significant ROCSS are highlighted with an asterisk. "Obs coverage" is the percentage of seasons (S), months (M) and days (D) covered by observations.

Site	Variable	Season	Obs coverage S	Obs coverage M	Obs coverage D	NSE	R^2	RMSE	RMSE/sd	bias	$ROCSS_{original}$ lower	$ROCSS_{original}$ middle	$ROCSS_{original}$ upper	$ROCSS_{Obs}$ lower	$ROCSS_{Obs}$ middle	$ROCSS_{Obs}$ upper
Norway	Discharge	SP	100	96	93	0.72	0.80	2.0	0.52	-1.0	0.58*		0.54*	0.36		0.34
	Surface	WI	0	0	0						0.48*			n.a		
	Temperature	SP	48	58	5						0.75*		0.53*	n.a		n.a
	Bottom	WI	0	0	0						0.48*		0.53*	n.a		n.a
	Temperature	SP	43	52	4						0.56*		0.68*	n.a		n.a
	Ice-on		100	-	-	0.97	0.99	2.2	0.16	1.8			[a]			
	Ice-off		100	-	-	0.36	0.76	19.3	1.09	-14.7	0.69*		0.75*	0.55*		0.68*
Spain	Discharge	WI	100	100	99	0.88	0.89	3.9	0.34	-0.6		0.52*			0.18	
		SU	100	100	98	0.51	0.62	3.5	0.69	-1.6	0.73*			0.40		
		AU	100	100	98	0.73	0.74	4.0	0.51	-0.8			0.47*			0.40
	Surf. Temp.	SU	78	78	3	0.12	0.40	1.1	0.87	-0.6			0.57*			-0.08
	Bottom Temperature	SP	48	70	3								0.86*			n.a
		SU	48	67	2						0.53*		0.72*	n.a		n.a
		AU	35	58	3						0.50*		0.64*	n.a		n.a
Ger.	Bottom	SP	100	96	6	-5.01	0.49	1.2	2.40	1.0	0.59*		0.60*	0.41		0.46*
	Temperature	SU	100	100	7	-8.63	0.26	3.8	3.04	3.6	0.48*		0.71*	0.51*		0.49*
Australia	Discharge	AU	43	100	100	-0.67	0.41	1.61	1.23	-1.27	0.48*			n.a		
	Bottom	WI	23	100	82	-0.70	0.32	1.98	1.17	1.51	0.63*			n.a		
	Temperature	SU	17	75	46						0.60*			n.a		

[a]Ice-on typically occurs between November and December which is the autumn and winter boundary. Therefore, ROCSS values could not be calculated for ice-on.

3.3 Sensitivity analyses

The ROCSS values obtained for each run of S-SA, W-SA and W+T-SA are summarized in boxplots in Figure 3 together with the original ROCSS value for each window of opportunity at the Norwegian and Spanish sites. In general, impact variable sensitivity to SEAS5 data over the target season (S-SA) is small relative to sensitivity to ERA5 data over the warm-up season and/or SEAS5 data over the transition month. In fact, at Sau, replacing SEAS5 data over the target season with random data (S-SA) does not yield any significant change in the ROCSS values, except for the surface temperature upper tercile (Fig. 3l). However, significant changes in ROCSS values are seen for W-SA compared to $ROCSS_{original}$ indicating high sensitivity to warm-up. The similar ranges in $ROCSS_W$ and $ROCSS_{W+T}$ values suggest limited or no impact of the SEAS5 data over the transition month on impact variable forecasts.

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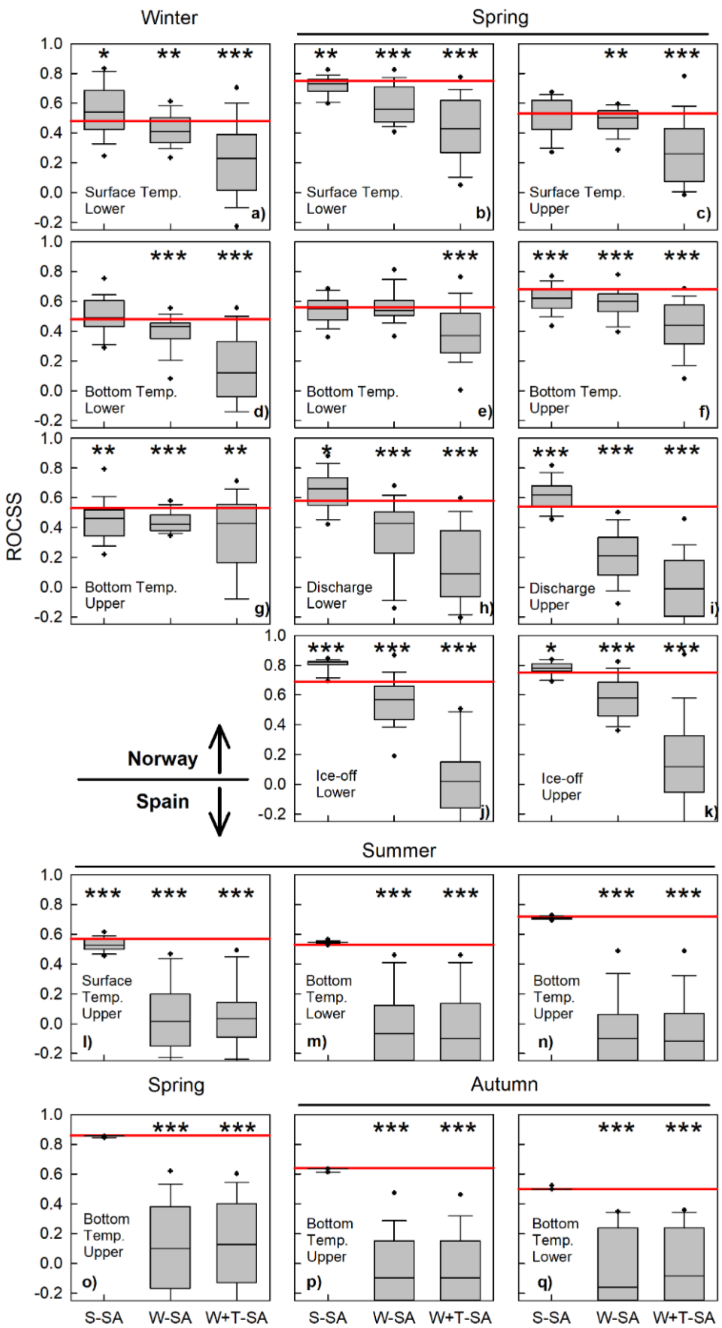

310 **Figure 3: Box plots (n = 25) of $ROCSS_S$, $ROCSS_W$ and $ROCSS_{W+T}$ from sensitivity analysis runs S-SA (replacing target season SEAS5 data with random data), W-SA (replacing warm-up ERA5 data with random data) and W+T-SA (replacing warm-up period – ERA5 and transition month – SEAS5 data with random data) for each window of opportunity at the Norwegian (a–k) and Spanish (l–q) sites. $ROCSS_{original}$ is given by the red line, so $ROCSS_i$ below the red line indicate a loss of skill and values above the line indicate higher skill than the original. ***, ** and * indicate significant difference between a given group of $ROCSS_i$ values and**
315 **$ROCSS_{original}$ following Mann−Whitney Rank Sum test at a significance level of 0.001, 0.01 and 0.05, respectively.**

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At Vansjø in Norway, on the other hand, 8 out of 11 windows of opportunity show significant changes in $ROCSS_S$ values, indicating higher sensitivity to SEAS5 data over the target season than at Sau. Furthermore, 3 windows of opportunity are associated with $ROCSS_S$ that are lower than $ROCSS_{original}$ (Fig. 3b, f and g), i.e., suggesting SEAS5 is providing some skill, while 5 have $ROCSS_S$ that are higher than $ROCSS_{original}$ (Fig. 3a, h–k), suggesting the use of SEAS5 is in fact reducing forecasting skill compared to a random forecast. Then, a progressive decrease in ROCSS values is typically observed for all windows of opportunity following W-SA and W+T-SA, indicating a progressive loss of forecasting skill related to ERA5 data over the warm-up and SEAS5 data over the transition month.

3.4 Tracing of forecasting skill

Seasonal means of Lake_PO at Vansjø also showed higher sensitivity to specific input variables than Lake_PO at Sau (Fig. 4). In fact, surface temperature is highly sensitive to tas over the year while some other input variables have more specific influence. Bottom temperature is also highly sensitive to tas but wind also plays a large role, especially in summer which is consistent with its expected impact on lake thermal stability (Blottiere, 2015). Finally, as expected, discharge at Vansjø is highly sensitive to tp, and to a lesser degree to tas, except in winter where tas has a larger influence on discharge.

The PPCC also show similar patterns regarding sensitivity (Fig. 5) where discharge is highly correlated with tp at the four sites and tas plays a secondary role for specific seasons. Once again, surface and bottom temperature at Sau stand out due to their limited sensitivity to input variables while at the three other sites, surface temperature, and to a lesser degree bottom temperature, are generally strongly positively correlated with tas. Others, like tp and rsds have more of an anecdotal influence on lake temperature, while wind shows a more consistent negative impact on surface temperature at Vansjø, Wupper and Mt Bold. Wind also shows some impact on bottom temperature, although less consistent. At Vansjø and Mt Bold following the coldest season, wind is positively correlated with bottom temperature, while at Wupper during the two coldest seasons, wind is negatively correlated with bottom temperature. Finally, ice-off date in Vansjø shows a strong negative correlation with tas (Fig. 5m) that can be linked back to the snow content and the intensity of snow melt in the catchment (Fig. 5n and o).

Next, we use SA outputs to better describe the origin of the predictability, considering inertia, time integration as well as variable interactions. Assuming that climate signals in the ERA5 and SEAS5 input data over the warm-up, transition and target periods are additive sources of predictability, we can use Eqs 1–3 to partition the predictability originating from those time periods, i.e., $P_{warm-up}$, $P_{transition}$ and P_{season}, respectively. For Sau reservoir, this calculation yields $P_{warm-up}$ of 0.94 to 1.0 leaving only an unsignificant fraction of predictability to the target season and transition month, as illustrated in Fig. 3. At this site, the impact variables show in parallel very low sensitivity to input variables (Fig. 4 and 5) which supports a strong role of inertia or long-term time integration in hindcast predictability. The fact that 5 out of the 6 windows of opportunity are for bottom water is also consistent with inertia as the main source of skill given the low circulation rate and inertia of hypolimnions. For Lake Vansjø, Eqs 1–3 yielded P_{season} of 0.003 (range: -0.19 to 0.18), $P_{transition}$ of 0.19 (0.04 to 0.37) and $P_{warm-up}$ of 0.29 (0.09 to 0.60). Hence, a significant fraction of predictability is originating from the SEAS5 dataset although the largest

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source remains ERA5 data over the warm-up. Interestingly, the SEAS5 data over the transition month is also a significant source of predictability. In fact, in decreasing order of importance, predictability originates from the warm-up, the transition month and the target season. This progressive decrease in predictability is only observed at Lake Vansjø and suggests that across-variable integration of climate signals persists through the transition month and, in some cases, the target season, but is progressively deteriorating as we move to the target season. Indeed, there is additional consistency between the SEAS5 input variables showing some forecasting skill and the impact variables. In fact, surface, and bottom temperature in spring at Vansjø are sensitive to tas and wind (Fig. 5 b and c), and tas, uas and vas are associated with some windows of opportunity in spring (Table 4). Similarly, ice-off is sensitive to tas, as are snow quantities and melt intensities in the catchment (Fig. 5m–o). Hence, in contrast to Sau reservoir where most of the predictability seems to originate from inertia, at Lake Vansjø, across-variable integration contributes to predictive skills.

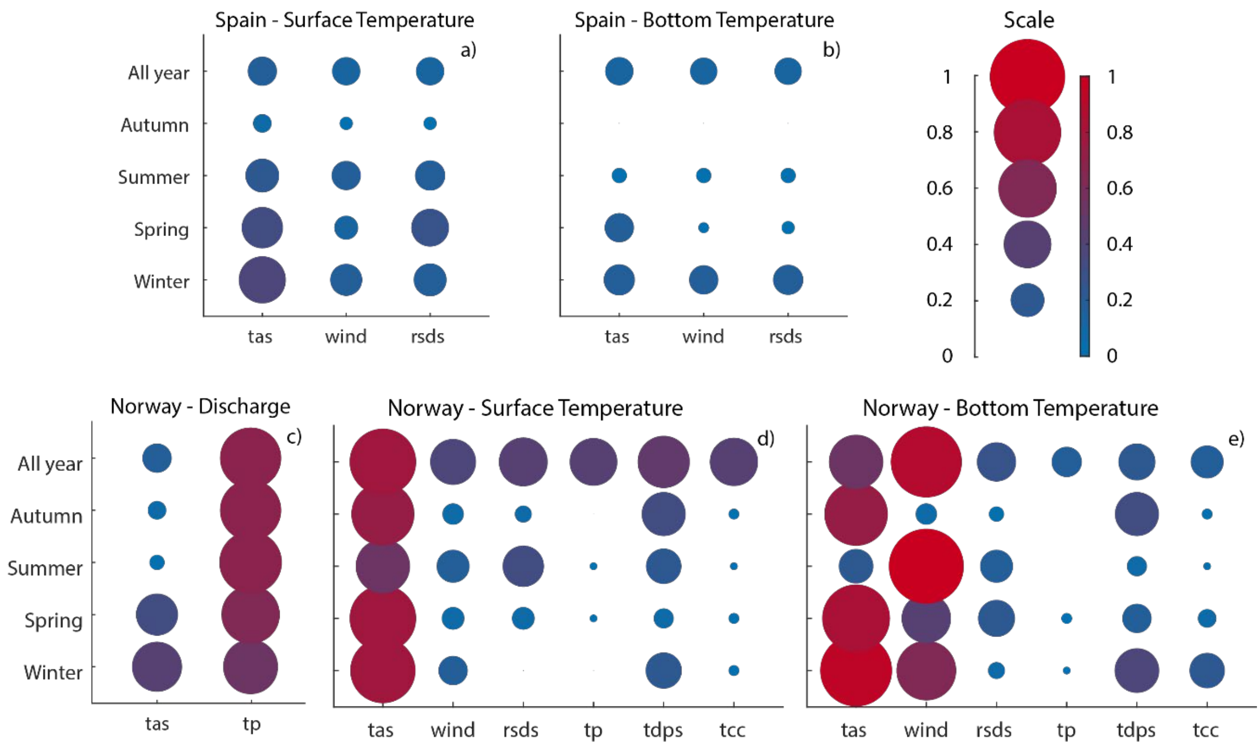

Figure 4: Relative sensitivity (see methods for details) of Lake_PO seasonal means to specific input variables estimated following the OAT-SA. Circle color and size both represent relative sensitivity on a scale from 0 to 1.

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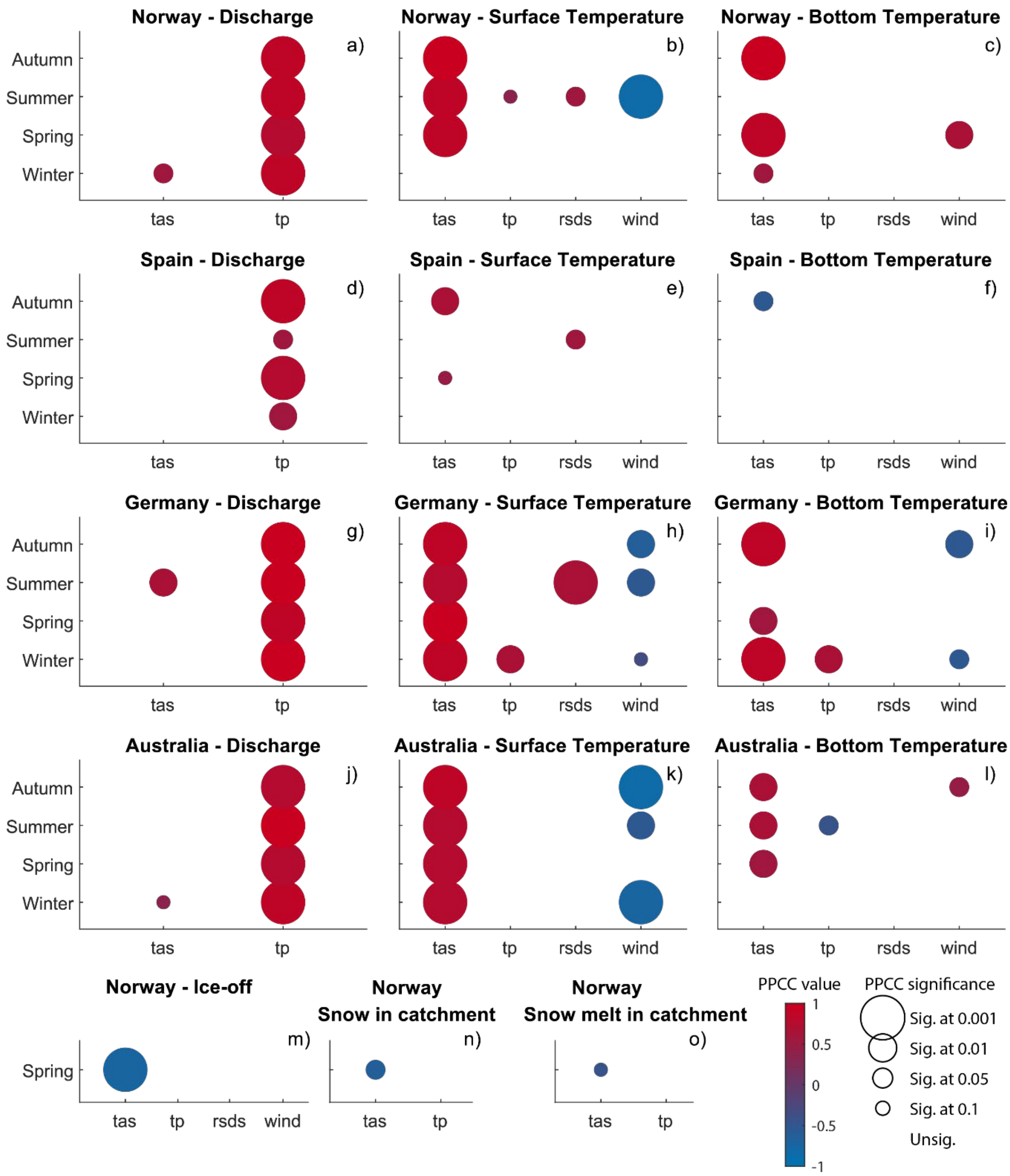

Figure 5: Pearson partial correlation coefficients (PPCC) between Lake_PO seasonal means and seasonal means of selected input variables. Circle color and size represent PPCC value (from -1 to 1) and significance, respectively.

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4 Discussion

4.1 Sources of skill

Our investigation into relationships between input and output variables and the sensitivity of predictive skill to meteorological data inputs over different time periods have yielded important insights into the sources of seasonal water quality skill in our case study sites.

A key finding is that predictive skill is mostly sensitive to meteorological inputs over the warm-up and transition months (Fig. 3, Section 3.4), although some specific windows of opportunity are also somewhat sensitive to the meteorological data over the target season. Hence, integration of the climate signal over time or across variables by catchment hydrologic and physical processes, e.g., snow accumulation (Harrigan et al., 2018) or heat accumulation in lakes, is likely a key source of predictive skill. In fact, Mercado-Bettin et al. (2021) already noted an increase in predictability when moving from climate to discharge to lake temperature, i.e., in an increasing order of time and across variable integration of climate signals. Strong inertia is also a potential source of predictability.

After accounting for forecasting skill from the forcing data over various periods (Section 3.4), a large proportion of the skill still remains unexplained, especially for some selected windows of opportunity at Lake Vansjø in Norway. Bottom water temperature at Lake Vansjø in spring shows the highest residual skill after removal of skill from warm-up and transition-month (Fig. 3e–f). Surface and bottom temperature show a different degree of coupling with air temperature. In fact, while surface temperature responds tightly to changes in air temperature (Butcher et al., 2015; Schmid et al., 2014), bottom temperature responds to a variety of complex interactions influenced by lake characteristics (e.g., fetch, surface area, depth, light penetration; Butcher et al., 2015). Indeed, bottom temperature in spring depends on preceding winter conditions but also on the intensity and length of the spring mixing event. To fully capture the intensity of this event, the model requires good initial water temperature inherited from previous winter but also skillful weather forcings, especially for tas and wind (Fig. 5c). In fact, for bottom temperature in spring to be higher than normal, it requires surface water to be heated up more than normal, mainly through heat exchange with air temperature, but also the lake to remain mixed for a longer time period than normal. The interaction between skill from legacy and from weather forcing might thus be another source of predictability. The fact that the proportion of forecasting skill progressively decreases from warm-up, through the transition-month and the target season at Vansjø suggests that the interactions between input variables, which are incorporated in the process representation within the models, provide some skill but progressively deteriorates as we move forward in time. At Sau reservoir in Spain, on the other hand, all skill is lost at the sharp boundary between the warm-up and the transition month. This difference might be related to the presence of skill from the SEAS5 data at Vansjø (Table 4) and not at Sau. In other words, in the absence of skill in SEAS5 data, no additional skill can originate from interaction effects.

Literature on streamflow hindcasts broadly shows that beyond the transition month, climatology-driven hindcasts are typically more skillful than hindcasts driven by seasonal climate predictions (Arnal et al., 2018; Bazile et al., 2017; Greuell et al., 2019). Hence, better water quality forecasting skills could likely be achieved by simply forcing our models with climatology. Our

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results partly fit with these findings, as the skill of S-SA hindcasts for selected windows of opportunity were higher than the original hindcasts (Fig. 3a, h–k). These S-SA hindcasts are similar to climatology-driven hindcasts, although they are associated with higher uncertainty since they are driven by random SEAS5 data and should therefore be regarded as a minimum forecasting potential. For some windows of opportunity, however, SEAS5 was a significant source of predictability (Fig. 3b, f, g and l). In those cases, only an improvement in SEAS5 forecasting skill is likely to improve water quality forecasts. Improvement for only selected variables in SEAS5 would likely be enough to yield a significant increase in water quality forecasting skill since most of the output variables presented here showed sensitivity to one or two input variables (Fig. 5).

4.2 Limitations and implications for seasonal water quality forecasts

One apparent limitation of our study is the use of reanalysis weather data and pseudo-observations as inputs and benchmark impact variables. Using pseudo-observations for skill assessment is a common methodology in streamflow forecasting studies (Alfieri et al., 2014; Wood et al., 2016) and it offers the opportunity to investigate the relationship between forecasting skills, initial and boundary conditions, while putting less emphasis on model errors and biases (Harrigan et al., 2018). Working with reanalysis weather data generates a less site-specific workflow and removes difficulties associated with dealing with temporal and spatial heterogeneity in observed data. Nevertheless, here we also evaluate the forecasting skill against catchment and lake observations when possible (Table 5) and show that most of the windows of opportunity reported for water temperature held while those for discharge are no longer significant compared to observations. This discrepancy between discharge and water temperature can be related to the fact that discharge tends to be more variable than water temperature, with short-lived high peaks which are difficult to model. The catchment models therefore performed less well than the lake models. This further suggests that evaluation against observations is likely more important for discharge than for water temperature.

Given that inertia and integration over time were the dominant sources of predictability at Sau reservoir and Lake Vansjø, useful hindcasts could already be issued without the use of SEAS5 data. In fact, our workflows show limited sensitivity to boundary conditions over the target season. Hence, future workflows should use selected climatology as forcing data over the target season, in addition to (or instead of) seasonal climate prediction. This benchmark forecasting workflow with climatology will likely yield similar or more skillful forecasts, as well as being less time-consuming to set up. Indeed, even with randomly years from the selected SEAS5 data, which can be seen as a highly uncertain climatology, some windows of opportunity are more skillful than with the correct SEAS5 data (Fig.3). Nevertheless, if seasonal climate prediction products become more skillful, they will likely be a real asset for water quality seasonal forecasting enabling additional skills through interactions over time.

State-of-the-art modeling practices typically involve calibrating hydrologic and lake models against daily observations. Nevertheless, daily observations of water quality are often not available or only cover a fraction of the time of interest. Table 5 illustrates the challenges related to data coverage and model evaluation where many calibration and validation statistics could not be estimated because of the lack of observations. In addition, calibrating to daily data prioritizes model parameterizations which are able to capture daily variability, but not necessarily seasonal or interannual variability, which are more relevant for

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seasonal forecasting. Calibrating the hydrologic and lake models using seasonal means or medians, in combination with daily data, could solve the observation coverage issue while improving seasonal predictive skill. Nevertheless, ones need to ensure that the seasonal averages are calculated from representative and well-distributed datasets. For Lake Vansjø, this would not have solved the lack of observations in Spring for example, because observations only cover April and May. For Sau and Wupper reservoirs, on the other hand, this would have been possible and potentially improve predictive skills. In any case, having access to more complete, long-term and systematic observations on water temperature, inflow and outflow discharge, including abstraction and over- flows for reservoirs, would facilitate robust model calibration and validation, and likely model predictive skills. The skill of water quality forecasting tools heavily depends on observation availability. Hence, continued efforts should be put on ensuring that observational programs are suited to providing the information needed by our models (Robson, 2014).

5 Conclusion

Water quality seasonal forecasts could provide valuable knowledge for water managers to preserve drinking water reserves, as well as ecological and recreational services under increasing pressures from water demand and climate change. Nevertheless, their use is still limited in the water sector. Here we unravel the source of predictability of water quality seasonal hindcasts at four case-studies across Europe and in Australia. Through sensitivity analyses, we contribute to the demystification of water quality forecasting tools with the long-term objective of facilitating their utilization in the water sector. In Spain, where the seasonal climate predictions have negligible skill, the source of predictability is mainly catchment and lake inertia. In Norway, where some seasonal climate predictions are skillful, the predictability is partitioned in decreasing order of importance between inertia, time- and across-variable integration of climate signals through catchment processes, and seasonal climate predictions over the target season (SEAS5). In Norway, skillful SEAS5 forecasts over some target seasons likely contribute to sustaining the predictability from interaction effects from antecedent conditions through to the target season.
Despite its central role in the probabilistic nature of the forecasting workflow, SEAS5 data contributes to a limited extent to the predictability, and often reduces the performance of the hindcasts. Hence, our findings suggest that using a climatology driven forecast is currently likely to yield higher quality forecasts, as demonstrated by hindcasts driven with randomly selected SEAS5 data. Nevertheless, upon skill improvement of the seasonal climate forecasts, a small step would be needed to provide more skillful water quality forecasts for better water management.

Computer code and models

Computer models used in this study are open-source and links to original resources are described here: https://nivanorge.github.io/seasonal_forecasting_watexr/. All codes for running the models, processing input and output data, as well as the input and output data files are available here: https://github.com/NIVANorge/seasonal_forecasting_watexr.

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