https://doi.org/10.5194/hess-2021-443
Preprint. Discussion started: 10 September 2021

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Opportunities for seasonal forecasting to support water management outside the tropics

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Abstract. Advance warning of seasonal conditions has potential to assist water management in planning and risk mitigation, with large potential social, economic and ecological benefits. In this study, we explore the value of seasonal forecasting for decision making at five case study sites located in extratropical regions. The forecasting tools used integrate seasonal climate model forecasts with freshwater impact models of catchment hydrology, lake conditions (temperature, level, chemistry and ecology) and fish migration timing, and were co-developed together with stakeholders. To explore the decision making value of forecasts, we carried out a qualitative assessment of: (1) how useful forecasts would have been for a problematic past season, and (2) the relevance of any "windows of opportunity" (seasons and variables where forecasts are thought to perform well) for management. Overall, stakeholders were optimistic about the potential for improved decision making and identified actions that could be taken based on forecasts. However, there was often a mismatch between those variables that could best be predicted and those which would be most useful for management. Reductions in forecast uncertainty and a need to develop practical hands-on experience were identified as key requirements before forecasts would be used in operational decision making. Seasonal climate forecasts provided little added value to freshwater forecasts in the study sites, and we discuss the conditions under which seasonal climate forecasts with only limited skill are most likely to be worth incorporating into freshwater forecasting workflows.

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1. Introduction

We rely on freshwaters to deliver a range of vital services, and managing catchments and lakes to ensure these services are delivered can be highly challenging. Unexpected seasonal climate conditions can exacerbate the problem, as heatwaves, droughts or prolonged wet periods can stress already vulnerable systems. Advance warning of flow, water quality or biological conditions, a season in advance, could pave the way for protective measures to be put in place, with potentially great ecological, economic and societal benefits (Bruno Soares et al., 2018; Bruno Soares & Dessai, 2016). Seasonal forecasts have obvious potential to assist management of flow-regulated catchments, where water level can be adjusted in anticipation of wet or dry seasons, and much attention has been given to this in recent years (e.g. Maurer & Lettenmaier, 2004; Peñuela et al., 2020; Turner et al., 2017; Turner et al., 2020). But there are many other situations where forecasts could assist water managers to deliver key services, protect vulnerable aquatic habitats/species and meet environmental objectives.

Within the water sector, predicting conditions a season in advance can make use of two sources of seasonal predictability: (1) antecedent and initial conditions, for example how much water is stored in the catchment/lake at the start of the period; and (2) how weather is likely to evolve over the coming season. The relative importance of these varies greatly by location and depends on the catchment/lake characteristics, season, forecast horizon and variable of interest (e.g. Arnal et al., 2018; Shukla & Lettenmaier, 2011). To incorporate both sources of predictability into forecasts, seasonal climate model output can be used to drive statistical or process-based surface water models. Seasonal climate models provide probabilities of wetter or drier, cooler or hotter conditions several months in advance. One of the main sources of seasonal climate predictability is the coupled ocean–atmosphere El Niño/ La Niña pattern (Troccoli, 2010), so seasonal climate models tend to perform better in the tropics, which are more affected by these phenomena (e.g. Beverley et al., 2019; Johnson et al., 2019; Manzanas et al., 2014). Away from the tropics, seasonal climate forecasting is challenging, and forecast quality varies geographically and strongly depends on the variable and season of interest. The added value of using seasonal climate forecasts in freshwater forecasting outside the tropics is therefore often less clear (e.g. Arnal et al., 2018; Peñuela et al., 2020).

Many seasonal hydrologic and drought prediction systems have been developed over the last decade using a variety of forecasting methods. Seasonal streamflow forecasting is the most advanced, with many examples of systems that produce regional or even global operational forecasts (e.g. Arnal et al., 2018; Bennett et al., 2017; Emerton et al., 2018; Prudhomme et al., 2017; Wood & Lettenmaier, 2006). For lake water level, probably the longest-established operational seasonal forecasting system is for the Great Lakes in the USA/Canada, where empirical and process-based catchment/lake models are used with historical meteorological forcing data and long-term climate projections (Gronewold et al., 2017; Gronewold et al., 2011). Seasonal forecasts of water quality and ecology are however rare, despite their potential relevance for management. The few examples we could find included river nutrient loads in a Korean catchment (Cho et al., 2016) and turbidity exceedance in a drinking water source in the Pacific Northwest (Towler et al., 2010), both of which showed promising results. For standing waters, the use of short-term weather forecasts, i.e. timescales of up to a few weeks, has been advanced

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in a number of lake water quality studies (e.g. Carey et al., 2021; Thomas et al., 2020), but seasonal time-scales have not been addressed to our knowledge. The focus of the WATExR project, a European Union (EU) project funded by ERA4CS, was therefore to help address this gap. Pilot seasonal forecasting tools were co-developed with water managers at five catchment-lake case study sites, four in Europe and one in South Australia. The focus was on extratropical areas, where seasonal climate predictability is lower. Tools link seasonal climate forecasts with models which predict freshwater variables of interest to decision makers, including river discharge, lake water level and water temperature (described in detail in Mercado-Bettín et al., 2021), water quality, algal bloom risk and fish migration.

The substantial advances in the development of operational streamflow forecasting systems have enabled improved water management in some areas of the world. In a recent study, for example, Turner et al. (2020) found that a large proportion of dams and reservoirs in the US use seasonal stream inflow forecasting to inform water release. However, snowpack-information was inferred to be the main source of information for deriving streamflow forecasts, although there was also some evidence of seasonal climate information being used. Certainly in Europe, recent studies have found that seasonal climate products are still rarely used to inform water management (e.g. Bruno Soares et al., 2018). Barriers to use include low climate forecast skill at extratropical latitudes and the probabilistic nature of the forecasts, as well as factors such as a lack of awareness of what is available, accessibility, and level of expertise or training required (Bolson et al., 2013; Bruno Soares & Dessai, 2016). A variety of studies have emphasized that a key way of increasing the use of climate products in decision making is co-development, whereby scientists and decision-makers together frame and develop the scientific information and tools that are useful and usable for decision-making (Brasseur & Gallardo, 2016; Bruno Soares & Dessai, 2016). Another key aim of the WATExR project was therefore to facilitate and explore the value of using seasonal climate information to help support freshwater management. A case study-based approach, and involving stakeholders through every stage of development, ensured that the forecasting tools developed were user-friendly and tailored to individual stakeholder needs.

In this paper, our main aim is to test how useful the forecasting tools developed as part of the WATExR project are for supporting decision making in real life management situations. To do this, we first used the forecasting tools to simulate historic seasons at the case study sites, and then assessed, together with end users, the potential for improved management and key challenges. This assessment process involved two exercises. In the first (Sect. 3.1), we generated forecasts for a single historic season, selected by stakeholders, when seasonal climate resulted in problematic conditions in each study site. Stakeholders then assessed how useful forecasts would have been, whether they would have helped mitigate the impacts of the seasonal event, and identified barriers to operational use. In the second exercise (Sect. 3.2), we carried out a more comprehensive assessment of the seasonal forecasting windows of opportunity at each site, i.e. those seasons/variables/event types which could be reliably forecasted, their perceived usefulness, and which windows of opportunity would be of most use for management. We then discuss results in terms of the wider literature, and review the opportunities and barriers for seasonal forecasting to support water management (Sect. 4). This includes a discussion of conditions under which seasonal

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forecasting is most likely to be useful for decision-making, where the use of seasonal climate forecasts is most likely to provide added value, and future priorities.

2. Methods

2.1. Case study sites

Forecasting tools were developed at five case study sites, four in Europe and one in South Australia (Fig. 1, Table 1). All are catchment-lake systems, and at all but the Irish site the lake water level is regulated. Sau reservoir in Spain, Mount Bold in Australia and lake Vansjø in Norway are all important drinking water sources, and lake Vansjø is also used for hydropower generation. Sau, Vansjø and Wupper reservoir in Germany are also managed for flood control and are important recreational areas. All but Lake Vansjø are part of a larger chain of reservoirs, and water managers therefore face challenges in developing optimum release/pumping strategies throughout the chain. All the lake/reservoir sites face water quality challenges, in particular relating to high/low water levels associated with flooding/droughts, as well as elevated nutrient inputs and associated algal blooms, which may be exacerbated by warmer water temperatures. In lake Vansjø, for example, toxic cyanobacteria blooms led to bathing bans in much of the period 2000-2007. The primary management opportunity at these sites is therefore adjusting water storage/pumping strategies to minimise operational costs, whilst ensuring drinking water provision, flood protection, recreation, maintaining minimum environmental flows and meeting environmental water quality targets. Additional background information on these four lake/reservoir sites is provided in Mercado-Bettín et al. (2021). In the Burrishoole catchment in northwest Ireland, the focus was on the timing of fish migration. This site is an extremely important Atlantic salmon and eel research catchment, with historic data on diadromous fish migration since the 1950s together with a comprehensive catchment monitoring programme. The primary stakeholder interest at this site was therefore monitoring and sustainable management of diadromous fish stocks.

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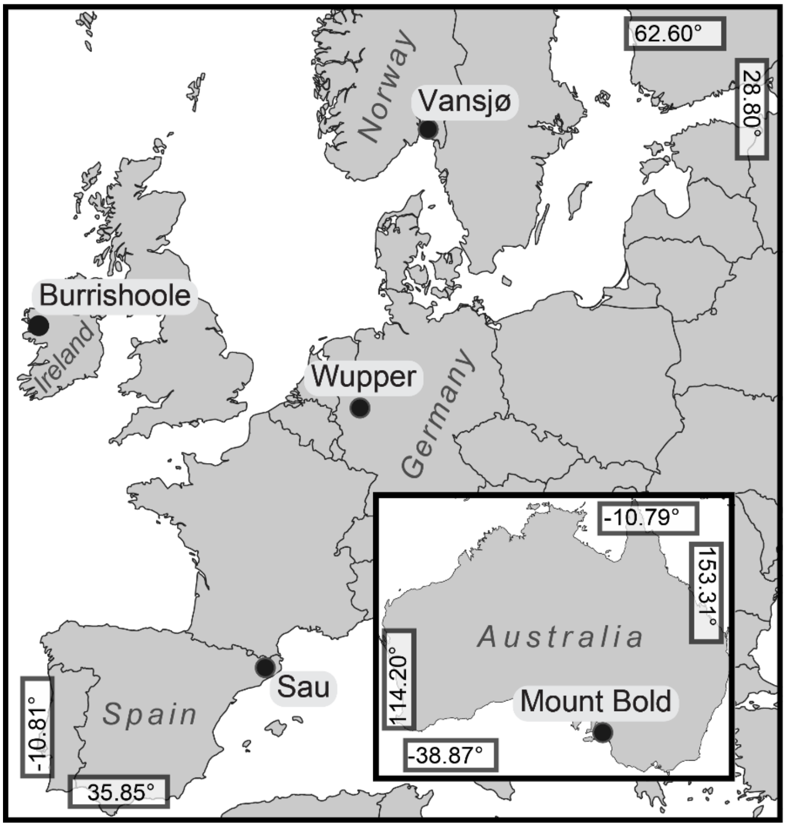

Figure 1. Location of the five study sites in Europe and Australia.

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Table 1. Main characteristics of the catchment-lake study sites, forecasted variables at each site, and models used to simulate freshwater variables of interest.

Site	End user	Catchment area (km^2)	Lake surface area (km^2)	Forecasted variables	Impact models
Mount Bold reservoir, Australia	South Australian Water	357	2.5	Streamflow, water temperature	GR4J, GLM
Wupper reservoir, Germany	Wupperverband	215	2.1	Streamflow, water temperature	GR6J, GLM
Burrishoole catchment, Ireland	Marine Institute	85	3.9	Fish migration timing	GR4J, statistical models
Lake Vansjø, Norway	Morsa river basin management authority	690	36	Streamflow, water temperature, cyanobacteria bloom risk	SimplyQ, GOTM, BN
Sau reservoir, Spain	ATL Water Supply Company	1522	5.7	Streamflow, water temperature	mHM, GOTM

2.2. Co-development and assessment

Water managers were involved in the design of the forecasting tools from the start as active project members, to ensure the tools matched their interests and needs. This also meant that they were able to interpret the probabilistic forecasts and the reliability information included with forecasts, and so carry out an informed assessment of the value of forecasts for decision making. Formal co-development and assessment exercises included:

- An initial workshop to introduce seasonal forecasting and define the main management challenges and priorities at each site and ways in which forecasts could contribute to decision making;
- A forecasting tool co-development workshop to agree on desired features, functionality and information layout at each site;
- A workshop on communicating and visualising seasonal forecast uncertainty and reliability information;
- Two interactions to assess stakeholder perceptions on the qualitative value of forecasts, i.e. the practical potential for improved management (the focus of this paper):
    1. *Assessment of the usefulness of forecasts for a selected historic event* (Sect. 3.1): this involved stakeholders first selecting a historic season of interest. Researchers then generated forecasts for this season, and shared them with stakeholders, who were asked a set of questions via an on-line questionnaire to determine their interpretation of the forecasts and their potential usefulness (questions are given in SI1 in the data repository; see Sect. 6). Results were

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then discussed individually between researchers and stakeholders at each case study site via a facilitated virtual call, and then case studies shared experiences and main findings at an all-hands workshop.

2. *Assessment of the usefulness of windows of opportunity* (Sect. 3.2): researchers at each case study site generated a list of the variables/seasons/event types that could be reliably forecasted (the windows of opportunity). The potential value of these for management was then explored via an on-line survey, where stakeholders were also asked to select those windows they would most want reliable forecasts for (see SI2 for survey design; Sect. 6).

2.3. Forecasting workflows

The surface water variables of relevance for management varied by site (Table 1). All lake/reservoir site managers were interested in streamflow. Water temperature was also of broad interest, as the most basic water quality parameter which affects a host of other biogeochemical and ecological processes. In Vansjø, water temperature alone would not be enough to inform decision making, and the end user was also eager for forecasts of water quality parameters, in particular the risk of toxic cyanobacteria blooms. The Irish site focused on the timing of diadromous fish migration to inform fisheries management.

A range of different models were used to produce forecasts for the freshwater variables of interest (hereafter termed "impact models"). These impact models integrate seasonal climate forecasts, knowledge of antecedent conditions and the characteristics of the system to predict the future state. The following models were used to simulate the different variables of interest:

- **Streamflow, lake level and lake water temperature**: Details of the modelling workflow used in the lake/reservoir sites are given in Mercado-Bettín et al. (2021). In brief, at all but the Irish site a process-based catchment hydrology model was used to simulate streamflow, and in turn drive a process-based lake model which simulated lake water level and temperature. Differences in site characteristics led to different models being used at different sites (Table 1). Catchment hydrology models used included the spatially distributed mesoscale Hydrologic Model (mHM, www.ufz.de/mhm), the semi-distributed *Genie Rural* (GR) models GR4J or GR6J implemented within the *airGR* R package (Coron et al., 2017), or the semi-distributed SimplyQ model (Jackson-Blake et al., 2017). The process-based lake models GOTM (http://gotm.net) or GLM (Hipsey et al., 2019) were used for simulating lake thermodynamics and water level.
- **Timing of fish migration:** At the Irish site, a statistical model was developed to predict the timing of seawards migration of Atlantic salmon (*Salmo salar*), brown trout (*Salmo trutta*) and European eel (*Anguilla anguilla*). Daily fish counts were estimated for each species using correlative models, with predictor variables stream discharge, water temperature, a proxy for fish preparedness for migration, moonlight exposure and, for eels, rate of change in water temperature over the previous 20 days. Daily stream discharge was estimated using GR4J. Daily water temperature was estimated using a four parameter air temperature to water temperature statistical model, where daily water temperature was linearly correlated with lagged air temperature. Fish preparedness for migration was estimated by first estimating the photoperiod-weighted

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degree days after the winter solstice (taking as input photoperiod and water temperature data), and then fitting fish count data to non-linear unimodal functions of photoperiod-weighted degree days.

- **Algal bloom risk:** At the Norwegian site, algal bloom risk was estimated using a continuous Gaussian Bayesian Network (BN). Water quality observations from the previous year were used to produce probabilistic estimates for growing season (May-October) mean concentrations of total phosphorus (TP), chlorophyll-a (chl-a) and lake colour, and growing season maximum cyanobacteria biovolume (cyano), incorporating interrelationships between these variables. Meteorological nodes were not included in the network, after cross-validation showed that they did not increase (and sometimes decreased) predictive performance.

To produce seasonal surface water forecasts, impact models were first 'warmed up' where necessary using historic meteorological forcing data, and then run for the future target season of interest using seasonal climate model output as forcing data. For historic meteorological data, we used the ERA5 reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ECMWF; Hersbach et al., 2020). For seasonal climate predictions, we used the ECMWF's long-range forecasting system SEAS5 (Johnson et al., 2019), bias corrected using ERA5 data using quantile mapping (see Mercado-Bettín et al., 2021 for details). All climate data were downloaded and post-processed using the climate4R bundle of packages (Iturbide et al., 2019).

Forecasts of catchment discharge and lake temperature were produced four times a year for the boreal seasons spring (March-May), summer (June-Aug), autumn (Sep-Nov) and winter (Dec-Feb). The fish model and BN produce one forecast per year, for the months when seaward fish migration occurs in Ireland and the 6-month 'growing season' used in Water Framework Directive (WFD) classification in Norway.

2.4. What does a seasonal forecast look like?

Seasonal climate forecasts are predictions of how the weather will evolve over the next season (typically three to six months ahead). Day-to-day forecasts are unreliable over such long horizons, so forecasts are instead used to say whether the next season will, on average, show broad differences to normal. Forecasts are therefore usually given as the probability of falling into one of three terciles: below normal, normal or above normal. The statistical fish model uses terciles to summarise whether migration timing is likely to be early, normal or late relative to normal. Instead of terciles, a binary classification was used to summarise BN predictions in Norway, with the probability of being in two WFD-relevant classes (e.g. above or below 'Good' ecological status).

Quantification and effective communication of forecast quality is a crucial element of seasonal forecasting. Following literature recommendations (Gill, 2008; Taylor et al., 2015), two kinds of forecast quality information were provided alongside forecasts:

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1. **Predictability of the future state of the environment.** SEAS5 has 50 ensemble members, or 25 in hindcast mode. Each member is *a priori* equally likely and was used to produce 25 impact model forecasts. The divergence of members provides information about future predictability, with better agreement between members meaning higher predictability. In practice, this information is given as the probability of the tercile, i.e. the percentage of ensemble members which fall into each tercile.
2. **Historic skill.** This describes how well the forecast performed historically when compared to observations. Forecasts should not be used to inform management if the system has no skill, regardless of the agreement between ensemble members. Skill was quantified for each season and tercile using the probabilistic Relative Operating Characteristic Skill Score (ROCSS). This is a simple and easy-to-interpret measure of skill, which is well-suited to communication with decision-makers. It ranges from 1 (a perfect forecast) to -1 (a perfectly bad forecast). A value of zero indicates no skill compared to a climatological prediction. A significance test was carried out to indicate whether forecasts were significantly better than climatology ($\alpha = 0.05$). In Norway, only two classes were forecast by the BN and so Matthew's correlation coefficient (MCC) was used instead of ROCSS, as it is well suited to summarizing the overall skill of binary classifiers. MCC ranges between 0 and 1.

To help managers correctly interpret these two sources of quality information, tercile probabilities and historic skill scores were categorised and descriptive text summaries were also provided in the seasonal forecast. Managers were involved in deciding on appropriate categories and wording. Tercile probabilities (i.e. agreement between ensemble embers) were split into four categories: 'Very low' (<35%), 'Low' (35-49%), 'Medium' (50-64%) and 'High' (65-100%). For historic skill, the ROCSS text summary was 'Skilled' or 'None', according to whether ROCSS was significantly positive or not. Historic skill given by MCC in Norway was summarized qualitatively as 'None' (< 0.2), 'Low' (0.2-0.39), 'Medium' (0.4-0.59) or 'High' (> 0.6). A combined confidence score was also provided, integrating the two types of forecast skill information. This is important, to ensure for example that managers are mistrustful of forecasts with no historic skill, regardless of whether tercile probability is 'High'. We opted to derive the combined confidence by setting it to be the same as the tercile probability unless the historic skill was 'None', in which case it was also 'None'. For BN forecasts in Norway, if class probability was 'High' then overall confidence was the same as the historic skill; if class probability was 'Medium', overall confidence was historic skill reduced by one class.

2.5. Identifying windows of opportunity

'*Windows of opportunity*' for seasonal forecasting were required for the second assessment exercise (Sect. 3.2). These were identified at each site using historic skill scores (Sect. 2.5). SEAS5 hindcasts were compared to ERA5 data, and impact model forecasts were compared to observations. Skill was calculated for every season in the 24 year period 1993-2016, or longer where possible (1981-2019 for the BN in Norway and 1993-2019 for fish migration timing in Ireland). At the Irish and Norwegian sites, real observations were used to assess skill. Elsewhere, forecasts were compared to 'pseudo-observations', model output derived by running models with ERA5 data. Skill calculated using pseudo-observations ignores impact model error and is therefore a best case estimate, although as seasonal climate skill is likely the largest source of uncertainty, this is still a useful first assessment of forecast performance. Statistical significance (95% confidence) of ROCSS was then used to identify windows of opportunity, i.e. season/variable/tercile combinations for which forecast performance was significantly better than expected from climatology. Results reported in this paper summarise those already reported in Mercado-Bettín et al. (2021) for the Spanish and Australian sites and for stream and lake water temperature forecasting in the Norwegian site, as well as including updated results for Germany using an improved model calibration, and results for the Irish site and for lake water quality/ecology forecasting in Norway. Results present a useful first indication of where seasonal forecasts are most likely to be reliable enough to support decision making, but should be interpreted with some caution due to the small sample size (a short hindcast period is split into 3 terciles, i.e. 8 data points per tercile), the use of pseudo-observations for some variables, and the fact that 5% significance does not necessarily reflect the practical decision-making value of forecasts.

3. Results

3.1. Usefulness of seasonal forecasts during a historic season

In the first exercise for assessing forecast potential to support management, stakeholders were asked to choose a historic season when seasonal climate resulted in problems in their study site. The events chosen are summarised in Table 2, along with associated surface water impacts and opportunities identified for mitigating the impacts, given a reliable-enough forecast. Dry and hot seasons were chosen in Australia and Germany, with associated problems with low reservoir water levels, problems meeting demand and poor water quality. A dry season was also selected in Ireland, which was accompanied by a later than normal salmon run. Prolonged wet periods and associated lake flooding and poor water quality were selected in Spain and Norway.

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Table 2. Seasonal events selected by water managers, associated surface water impacts and management opportunities.

Site	Climate event	Surface water impacts	Management opportunities
Mt Bold (Au)	Boreal autumn 2006 (Australian spring; Sep-Nov). A dry and hot autumn during the 'Millennium Drought' (1996 to mid-2010)	High water demand. Low reservoir level at the beginning of the pumping season. Poor water quality.	Strategic planning of water pumping and associated lower water pumping costs.
Wupper (Ge)	Summer 2003 heatwave	Reservoir level had to be lowered substantially to supply drinking water. Associated eutrophication. Downstream water quality was also impacted.	Store extra water in a series of upstream reservoirs in advance.
Burrishoole (Ir)	Low rainfall in spring 2010, following a very cold winter	Around 80% of salmon migrated during 19th-22nd May, later than average.	Being prepared for data collection during key migration periods is very important to reduce fish mortality.
Vansjø (No)	Very high rainfall in autumn 2000	High water level, flooding of farm land and sewage stations, high nutrient inputs. Toxic algal blooms in summer 2001 (and proceeding summers until 2007).	Lower lake level in advance. Extra monitoring to screen for toxic blooms at bathing sites.
Sau (Sp)	High precipitation in autumn 2019	Large water, sediment and organic matter fluxes from upstream, lake flooding, poor reservoir water quality. Increased treatment costs.	Lower the lake level in advance. Store good quality water in an upstream reservoir.

3.1.1 Forecasts for the selected events

Forecasts produced for the seasons of interest and presented to stakeholders are summarised in Table 3 (see Sect. 2.4 for an explanation of the confidence information that accompanied the forecasts). For climate forecasts, overall confidence in predictions was uniformly low. Even when there was good agreement between forecast ensemble members and therefore high tercile probability, low historic skill and non-significant ROCSS meant that no confidence could be placed in forecasts. However, some positive ROCSS were present (e.g. in Australia) and, although not significant, may be providing added value to freshwater impact model forecasts.

Impact model forecasts, meanwhile, had medium or high skill in one or more of the variables of interest at most sites, suggesting a lack of sensitivity to seasonal climate (discussed further in Sect. 4).

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Table 3. Summary of forecasts for the historic events selected by stakeholders. Abbreviations: cyano: cyanobacteria, D: day of migration, BT: bottom water temperature, P: precipitation, Q: inflow discharge, ST: surface water temperature, T: air temperature, var: variable.

Site	Target season	Model	Var	Observed tercile	Forecasted tercile		Confidence	
						Probability[a]	Skill[b]	Overall confidence[c]
Mt Bold (Au)	2006, southern spring (Sep-Nov)	SEAS5	P	below	below	Medium (60%)	None (0.27)	None
			T	above	above	Low (40%)	None (0.33)	None
		Impact	Q	below	below	High (72%)	Skilful (0.48)	Medium
			ST	normal	above	Low (44%)	None (−0.04)	None
			BT	above	below/normal	Low (36%)	None (0.38/0.4)	None
Wupper (Ge)	2003, summer (Jun-Aug)	SEAS5	P	below	above	Medium (55%)	None (−0.14)	None
			T	above	above/below	Low (35/35%)	None (−0.61)	None
		Impact	Q	below	above	Medium (52%)	None (−0.59)	None
			ST	above	below	Low (44%)	None (−0.15)	None
			BT	above	above	High (92%)	Skilful (0.71)	High
Booris-hoole (Ir)	2010, spring (Mar-Jun)	SEAS5	P	below	below	Low (48%)	None (−0.23)	None
			T	normal	below	Low (44%)	None (0.23)	None
		Impact	Salmon mean D	later	later	High (88%)	None (0.25)	None
Vansjø (No)	2000, autumn (Sep-Nov)	SEAS5	P	above	normal	Low (36%)	None (0.25)	None
			T	above	below	Medium (56%)	None (−0.26)	None
		Impact	Q	above	below	Low (36%)	None (−0.01)	None
	2001, summer (May-Oct)	Impact	Chl-a	≤ Poor	≤ Poor	N/A	High (0.71)	Medium
			Cyano	≥ Good[d]	≤ Moderate	Medium (64%)	High (0.78)	Medium
Sau (Sp)	2019, Autumn (Sep-Nov)	SEAS5	P	above	above	Low (48%)	None (0.1)	None
			T	normal	above	Medium (52%)	None (0.17)	None
		Impact	Q	above	above	Low (43%)	Skilful (0.47)	Medium
			ST	above	normal	High (76%)	None (0.05)	None
			BT	normal	above	High (100%)	Skilful (0.54)	High

[a] Probability of the most likely tercile, discretized into categories Low (33-49%), Medium (50-64%) or High (65-100%).
[b] Historic skill score is ROCSS (summarised qualitatively as ‘None’ for non-significant results, otherwise ‘Skilful’) or MCC in Norway (discretized into None (< 0.2), Low (0.2-0.39), Medium (0.4-0.59) or High (> 0.6).
[c] Probability and skill were combined into a single score with four classes, None, Low, Medium or High (see Sect. 2.4).
[d] Cyanobacterial blooms did occur near the bathing beaches, but not at the lake monitoring point.

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3.1.2 Value of forecasts for decision making

Stakeholders were then asked to assess whether forecasts would have been useful had they been available in advance and, if so, how. Questions and full responses are given in SI1 in the data repository (see Sect. 6) and are summarised in Table 4, where common themes which emerged across study sites have been highlighted. Managers at all sites could see the potential value of forecasts. However, even given skilful forecasts for at least some of the variables of interest, forecasts would only have been used qualitatively as a pointer to the best strategies, rather than directly feeding into operational management. Main barriers were forecast skill and more general issues of trust. Even where skill was high, stakeholders said that they would need to observe the forecasts performing well themselves to build confidence that they were providing trustworthy additional information, showing the importance of personal experience. Managers at all but the Norwegian and Irish sites also stated that their trust in the freshwater impact model forecasts was low in part because of the low skill of the seasonal climate forecasts.

Table 4. Aggregation of stakeholder feedback on the usefulness of forecasts for the chosen historic seasons.

Question	Response	Australia	Germany	Ireland	Norway	Spain
Would the forecasts have been useful?	Yes					
	Somewhat	✓	✓	✓	✓	✓
	No					
If so, how would they have been used?	Indication of appropriate reservoir management strategies	✓	✓			✓
	Inform staffing levels/monitoring			✓	✓	
Key barriers?	Uncertainty and low historic skill	✓	✓	✓	✓	✓
	Need to develop personal experience of 'added value'		✓		✓	✓

3.2. Windows of opportunity and assessment of their usefulness

In the second exercise for exploring the potential for forecasts to support management, we carried out a more comprehensive assessment of whether the seasons, variables and terciles which could be forecasted with reasonable confidence (the windows of opportunity) were considered useful for water management, as well as which windows stakeholders most wished to obtain skilful forecasts for.

There were few windows of opportunity in seasonal climate (see SI3 in the data repository for full results; Sect. 6). There were no windows in Ireland, 3 in Germany, 5 in Spain, 9 in Australia and 10 in Norway. The 5% significance level used

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means that some of these may be false positives (tests were carried out on up to 108 data slices per site; 4 seasons × 3 terciles × up to 9 variables, so we would expect on average 5 false positives per site).

A substantially larger number of impact model variables showed significant skill (Table 5). This suggests that antecedent conditions/inertia are responsible for much of the skill, further supported by the fact that bottom water temperature was better predicted than surface water temperature (15 versus 5 windows, respectively; Table 5), likely because of its lower sensitivity to seasonal climate (discussed in Sect. 4.2).

Opinions on the usefulness of the windows of opportunity are summarised in Table 5 (full responses are given in SI4 in the data repository; see Sect. 6), together with the windows which stakeholders were most interested in. All the windows of opportunity for discharge were thought to be of medium or high relevance, and almost all combinations of season/tercile were highlighted as being desirable for management. For surface water temperature, spring to autumn ‘above normal’ forecasts were seen to be the most useful, due to often strong links at the sites between warm summer water and problematic algal growth. Many of the other windows of opportunity in surface water temperature were thought to be of medium or low relevance. As mentioned above, bottom water temperature was the variable that was most successfully forecasted, with 15 windows of opportunity across the case study sites. However, it was also the variable that was thought to be least useful for management, with four of the windows being ranked as having low or no relevance. Overall, we found a mismatch between the variables that were thought to be most useful for management, and those which could best be forecast. This can be seen, for example, in the difference between the number of current versus desired skilful windows for the different variables (Table 5; discussed further in Sections 4.1 and 4.2).

In addition, a number of stakeholders commented that they would require information on more than just the most probable tercile, but rather the likelihood of extremes, which are particularly challenging for management.

Responses from the Irish site are not shown in Table 5 as a large range of population statistics were explored. Three windows of opportunity were found: early median day of migration for trout, later than normal day when 5% of salmon have migrated, and later than normal day when 25% of eel have migrated. These were all thought to be extremely relevant for management. The most desired windows of opportunity were the day when 25% of the population has migrated, the mean day of migration and, for eel, the day when 75% of the population has migrated, although skill in the timing of all percentiles was of interest to check forecast consistency. Although all terciles were thought to be relevant, "earlier than normal" was considered the most useful, as acting on a wrong “early” forecast would have relatively minor consequences, whilst delaying action because of a “later than normal” forecast could result in fish mortality if the forecast were wrong.

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Table 5. Windows of opportunity in surface water variables and stakeholder assessment of their usefulness for management ('L': low/none, 'M': medium, 'H': high). Ticks show the windows which stakeholders particularly wanted skilful forecasts for. Where letters and ticks coincide, the window was both skilfully forecasted, and particularly desirable for water managers. Irish case study responses are given in the text.

Variable	Boreal season	Tercile	Windows of opportunity & their relevance for management				Total windows	Desired windows
			Spain	Germany	Norway	Australia		
Discharge	winter	above		✓	✓	✓	6	39
		normal	M	✓	✓	✓		
		below		✓	✓	✓		
	spring	above		✓	M ✓	✓		
		normal		✓	✓	✓		
		below	✓	✓	M ✓	H ✓		
	summer	above		✓	✓	✓		
		normal		✓	✓	✓		
		below	M	✓	✓	✓		
	autumn	above	H ✓	✓	✓	✓		
		normal		✓	✓	✓		
		below	✓	✓	✓	✓		
Surface water temperature	winter	above					5	15
		normal						
		below			L			
	spring	above	✓	✓	M ✓			
		normal			✓			
		below			M ✓			
	summer	above	H ✓	✓	✓			
		normal			✓			
		below	L		✓			
	autumn	above	✓	✓	✓			
		normal			✓			
		below			✓			
Bottom water temperature	winter	above			L	✓	15	8
		normal						
		below			L	M		
	spring	above	L	M ✓	M			
		normal						
		below		M ✓	M			
	summer	above	M	M ✓	✓			
		normal			✓			
		below	L	M ✓	✓	M		
	autumn	above	L					
		normal						
		below	L					
chl-a	Growing season (May-Oct)	upper or lower	N/A	N/A	H ✓	N/A	3	4
cyanobacteria					H ✓			
colour					M			
total P					✓			

https://doi.org/10.5194/hess-2021-443
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4. Discussion: opportunities and barriers for seasonal forecasting to inform water management

4.1. Water manager views on forecast value and key barriers

Water managers were generally enthusiastic about the forecasting tools developed and their potential to assist them in preparing for the coming season. They identified actions that could be taken, given a reliable-enough forecast, to help reduce the negative impacts of otherwise unforeseen events. They were well aware of the limited skill of many of the forecasted variables, and were generally comfortable with the idea of working with probabilistic forecasts. For most sites, the act of setting up the impact models was in itself a valuable process, and managers were often enthusiastic about the new system knowledge gained in doing so and for the workflows to be more generally useful (e.g. for use in shorter-term forecasting using weather forecasts).

Despite general enthusiasm, no-one felt that forecasts could be incorporated directly into operational management straight away. In all cases, forecasts would only be used qualitatively in the first instance, to provide a general indication of how conditions might evolve, rather than to e.g. drive operational models (Sect. 3.1.2), matching the findings of Bruno Soares et al. (2018). Trust and lack of personal experience was one key issue raised by most managers. The other key limitation, raised at all sites, was low forecast reliability, including often high uncertainty in model outputs and poor historic performance. The similarity in stakeholder responses across the contrasting study sites suggests these results are likely to be more widely applicable. A reduction in uncertainty and higher historic skill are therefore still likely to be general requirements for increased uptake of seasonal forecasts in operational water management. Ways of achieving this are discussed further in Sect. 4.4.

There was general enthusiasm for many of the 'windows of opportunity', the variables, seasons and terciles for which the forecasting systems showed most potential. However, there was often a mismatch between what could best be predicted and what was considered most useful (Table 5). Seasonal discharge forecasts were of particular interest, for example, and yet there were few discharge windows of opportunity. Bottom water temperature, meanwhile, could be forecasted reasonably well at many sites, and yet had limited management relevance.

4.2. Sources of seasonal predictability and management implications

As mentioned in the introduction, seasonal predictability in freshwater impact model predictions derives from knowledge of initial conditions and of climate over the target season. At the majority of study sites there were a number of windows of opportunity where freshwater variables could be forecasted with reasonable skill (Sect. 3.2). Seasonal climate forecasts themselves had very limited skill at these extratropical latitudes, so it seems likely that the impact model windows of opportunity were primarily due to models capturing how initial conditions and system inertia influence the target season.

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This could explain the better performance of bottom water temperature forecasts compared to surface water temperature and discharge forecasts, as the latter two are likely more sensitive to seasonal climate. Although further work is needed to confirm the sensitivity of the different variables to seasonal climate and initial conditions (and will be the topic of an upcoming paper), the initial indication is that those variables that are most sensitive to climate over the target season are the hardest to generate reliable seasonal forecasts for (due to low seasonal climate model skill in our study areas), and yet are also the variables which are most useful for management. Windows of opportunity may therefore be rarer, and yet particularly valuable.

The low skill of the seasonal climate forecasts is typical of skill over much of Europe, parts of North America, Russia, northern China and other mid-latitude areas (Johnson et al., 2019; MacLachlan et al., 2015). Seasonal forecasting to support water management in these areas with low climate model skill will therefore be largely reliant on initial conditions as the main source of seasonal predictability. High quality forecasts, which can be used to inform management, are then most likely in catchments/lakes where initial conditions exert a larger influence. This is the case in larger systems and for variables or ecological species which are less sensitive to seasonal climate. For streamflow forecasts, for example, initial conditions provide much of the forecasting skill and predictability is highest in slower-responding catchments with larger water storage and groundwater contributions (Donegan et al., 2020; Girons Lopez et al., 2021; Harrigan et al., 2018; Pechlivanidis et al., 2020). Many successful streamflow forecasting systems do not include seasonal climate model forecasts, showing that a great deal can be achieved using only historic information, in some cases/seasons outperforming predictions which use seasonal climate model forecasts (e.g. Arnal et al., 2018; Peñuela et al., 2020). In lakes and reservoirs, the storage buffering effect has also been shown to reduce the importance of streamflow forecast skill, particularly when the reservoir capacity is large compared to variability in inflow (Maurer & Lettenmaier, 2004; Turner et al., 2017). Studies looking at sources of predictability for seasonal water quality and ecology appear to be currently lacking, but similar concepts will likely hold.

4.3. Do seasonal climate forecasts provide added value at extratropical latitudes?

Where seasonal climate forecasts are skilful, they undoubtedly have potential to provide added value to surface water impact model forecasts. All water managers in this study were very enthusiastic about the potential benefit of skilful climate forecasts for improving their operations and were particularly interested in variables which are more likely to be sensitive to seasonal climate (e.g. discharge and surface water temperature). Several studies have shown that skilful seasonal climate forecasts can lead to sometimes large improvements in streamflow forecasting ability (e.g. Shukla & Lettenmaier, 2011), which may, for example, have economic value for reservoir operations (Maurer & Lettenmaier, 2004; Turner et al., 2017).

However, in our study catchments, seasonal climate models did not produce skilful forecasts for the selected historic events (Sect. 3.1), and there were few windows of opportunity for seasonal climate (Sect. 3.2). In areas where seasonal climate model skill is low, the extra resources required to work with seasonal climate data may not be worth potentially marginal performance gains, particularly as poor seasonal climate forecasting skill may reduce trust in any skilful impact model forecasts that use seasonal climate as input (Sect. 3.1.2). Particularly in larger catchments and lakes, which are less sensitive to seasonal climate, it is likely that attention would be better spent on developing simpler benchmark systems. Methods inspired by Ensemble Streamflow Prediction (ESP; Day, 1985) are likely candidates, potentially made more nuanced by, for example, using North Atlantic Oscillation (NAO) index or other climate signals to condition the forecast (e.g. Donegan et al., 2020; Najafi et al., 2012; Sabzipour et al., 2020), or longer-term climate projections (Gronewold et al., 2017).

In systems that are particularly sensitive to meteorological forcing at seasonal timescales (e.g. small catchments and lakes/reservoirs with short residence times), and where the benefits of any windows of opportunity are large (e.g. a large potential cost saving or particularly sensitive drinking water source/habitat), then the potential benefits of incorporating seasonal climate data are greater. In this case, it may be worth incorporating seasonal climate data into the forecasting workflow, as long as there are some windows of opportunity at lead times of interest for management.

4.4. Future priorities for more skilful seasonal predictions

A key barrier to the use of seasonal forecasts in operational management is forecast performance (Sect. 4.1). To help improve performance, we see the need for progress to be made on two fronts:

(1) *Improvements in seasonal climate model skill*. Seasonal climate models are under active development, and recent advances in the prediction of climate teleconnections, such as the NAO in Europe (Wang et al., 2017; Scaife et al., 2014; Svensson et al., 2015), may lead to improvements in coming years.

(2) *Improvements in impact model performance*. Probably the greatest potential here is through improved/increased data collection. Although not considered in detail here, the importance of this cannot be understated. For example, observed data is fundamental to developing and calibrating trustworthy impact models, correctly initialising impact models and evaluating the historic skill of forecasting systems, which is a key element for building trust in predictions.

5. Conclusions

In this study, we have explored whether pilot seasonal forecasting tools developed at five case study sites could usefully support practical water management. Tools integrated seasonal climate model forecasts and freshwater impact models to produce forecasts of streamflow, lake water level, lake water temperature and, at some sites, lake water quality/ecology and fish migration timing. Co-development was a key part of the process, i.e. researchers and end users worked closely to design tools that were relevant and tailored to the individual needs at each of the study sites. This meant that the user-community was able to make well-informed assessments of forecast skill and qualitative value for decision-making. Key outcomes include:

- At the majority of case study sites there were windows of opportunity where surface water forecasts could be produced with enough skill to be potentially useful for management.

- End users were enthusiastic about the potential for improved decision making and identified actions that could be taken based on forecasts. However, even skilful forecasts would only be used qualitatively in the first instance, until trust had been built up through practical hands-on experience.
- Reduced uncertainty and higher historic skill were identified as key requirements for the operational use of forecasts, as was an ability to forecast more extreme seasonal events rather than just terciles (below normal, normal or above normal).
- There was often a mismatch between those variables that could best be predicted and those which would be most useful for management, likely related to sensitivity to seasonal climate.
- Where seasonal climate forecasts are skilful, they undoubtedly have potential to provide added value to freshwater model forecasts and assist management, in particular in smaller systems which are more responsive to climate.
- Outside the tropics, seasonal climate forecast skill is limited. Despite this, forecasting within the water sector can still be usefully carried out, but relies on seasonal predictability derived from antecedent/initial conditions and system inertia. The best chance of developing useful seasonal forecasting tools is then in slower-responding systems (e.g. larger catchments and lakes), which are less sensitive to climate over the target season. In this case, time is probably best spent on developing tools which use re-sampled historical meteorological data rather than seasonal climate model output to force impact models.
- Seasonal climate model forecasts with only patchy skill are most likely to be worth incorporating into freshwater seasonal forecasting workflows when: (1) the system is particularly sensitive to seasonal climate (e.g. small catchments and lakes), and (2) the potential benefits of any windows of opportunity are large.

6. Supplementary information, supporting data, tools and code

Seasonal forecasting tools and/or underlying code are available for several of the study sites in the WATExR GitHub repository (website: https://nivanorge.github.io/seasonal_forecasting_watexr/; repository: https://github.com/NIVANorge/seasonal_forecasting_watexr; last accessed May 2021). Supplementary information is in the folder 'paper3_JacksonBlake_etal'. **An archived (citable) version of the repository will be available through Zenodo after paper review, and citations added to the paper**.

Author contribution

AF, DMB, FC, MDF, MS, LJB, RM and TM developed and applied the modelling workflows, with input from all co-authors; LP facilitated the first stakeholder assessment exercise; LJB prepared the manuscript with contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

Thanks to all our co-developers, some of whom are co-authors, but also: Carina Isdahl (Norway), Juan Carlos Garcia Pradell (Spain) and Marc Scheibel, Eleni Teneketzi and Paula Lorza (Germany). Thanks to Sixto Herrera, Justin Brookes and Sigrid Haande for valuable contributions and/or comments on the manuscript. Data was provided by ATL, SA Water, Wupperverband, NIVA, NVE and the Marine Institute. SEAS5 and ERA5 meteorological data were based on data and products of the European Centre for Medium-Range Weather Forecasts (ECMWF). Funding: This work was carried out as part of the WATExR project, part of ERA4CS, an ERA-NET initiated by JPI Climate and funded by MINECO-AEI (ES, projects PCIN-2017-062 and PCIN-2017-092), FORMAS (SE), BMBF (DE), EPA (IE), RCN (NO), and IFD (DK), with co-funding by the European Union (Grant 690462).

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