ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Seasonal forecasts have sufficient skill to inform some agricultural decisions

To cite this article: Ashish Kondal *et al* 2024 *Environ. Res. Lett.* **19** 124049

View the article online for updates and enhancements.

IOP Publishing Environ. Res. Lett. 19 (2024) 124049 https://doi.org/10.1088/1748-9326/ad8bde

ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
31 May 2024

REVISED
8 October 2024

ACCEPTED FOR PUBLICATION
28 October 2024

PUBLISHED
15 November 2024

LETTER

Seasonal forecasts have sufficient skill to inform some agricultural decisions

Ashish Kondal[1,*], Katherine Hegewisch[2], Mingliang Liu[1], John T Abatzoglou[2], Jennifer C Adam[1], Bart Nijssen[3] and Kirti Rajagopalan[4,*]

[1] Washington State University, Civil and Environmental Engineering, Pullman, WA 99163-2618, United States of America
[2] University of California Merced, Management of Complex Systems, Merced, CA 95343-5001, United States of America
[3] University of Washington, Civil and Environmental Engineering, Seattle, WA 98195-2700, United States of America
[4] Washington State University, Biological Systems Engineering, Pullman, WA 99163-2618, United States of America
[*] Authors to whom any correspondence should be addressed.

E-mail: ashish.kondal@wsu.edu and kirtir@wsu.edu

Keywords: seasonal forecasts, NMME, forecast skill, seasonal climate forecast, agricultural decision-making, drought forecasting, fertilizer application decision

Abstract

Seasonal forecasts, which look several months into the future, are currently underutilized in active decision-making, particularly for agricultural and natural resource management. This underutilization can be attributed to the absence of forecasts for decision-relevant variables at the required spatiotemporal resolution and at the time when the decisions are made and a perception of poor skill by decision-makers. Addressing these constraints, we quantified the skill of seasonal forecasts in informing two agricultural decisions with differing decision timeframes and influencer variables: (a) whether to apply fertilizer in fall or wait until spring based on expected winter temperatures, and (b) drought response, such as whether to lease water based on expectations of drought. We also looked into how early the forecast can be provided without significant degradation in skill. Currently, drought response decisions are typically formulated in April, utilizing drought forecasts issued in the same month, while fall fertilization decisions are generally made between August and September. There is growing interest among stakeholders in the availability of earlier forecasts to inform these critical choices. We utilized the North American multi-model ensemble (NMME) hindcasts for the time period 1982–2020 over the Pacific Northwest US (PNW) to obtain meteorological variables. Runoff was estimated via simulations of the coupled crop-hydrology VIC-CropSyst model. The skill assessment with the Heidke Skill Score (HSS) yielded promising outcomes in both decisions for the entire PNW region. Notably, NMME's positive skill (median HSS of 30%) in predicting warmer winters identifies years when fertilizer application should be avoided to prevent fertilizer loss through mineralization (and associated costs). Similarly, there is skill in forecasting drought conditions in most irrigated watersheds for up to two months in advance of April, the current decision time. In conclusion, our findings affirm that contrary to the perception of low skill and resulting underutilization, current seasonal forecasts hold the potential to inform at least some key agricultural decisions.

1. Introduction

Agricultural and natural resources management decisions are directly and indirectly influenced by uncertainties of future weather and seasonal climatic conditions. These uncertainties pose management challenges to agricultural decision-makers (Meza *et al* 2008, Lipper *et al* 2014) and result in economic, environmental, and social risks for farmers, agribusinesses, agencies, and governments (Hammer *et al* 2001). Seasonal forecasts, looking out several months into the future, have the potential to mitigate these risks by assisting decision-makers in making improved climate-sensitive agricultural decisions (An-Vo *et al* 2021). The advent of multi-model and multi-ensemble forecasting systems (e.g. North American multi-model ensemble (NMME) (Kirtman *et al* 2014, Becker *et al* 2020), European Center for Medium-Range Weather Forecast (ECMWF)—SEAS5 (Johnson *et al* 2019) has resulted in potential utility of such forecasts to inform actions in diverse domains on various time scales (seasonal, subseasonal and decadal) (Becker *et al* 2022). Moreover, these forecasts are available at global spatial scales, and there is potential to apply them in most agricultural areas of the world.

However, seasonal forecast skill assessments have primarily focused on meteorological variables themselves (e.g. Barnston *et al* 2019, Andrian *et al* 2023, Kowal *et al* 2023, Zhang *et al* 2023) or crop yield/phenology assessments (e.g. Ceglar and Toreti 2021, Bento *et al* 2022, Boas *et al* 2023, Chinyoka and Steeneveld 2023), and to a limited extent on streamflow or drought prediction (Candogan Yossef *et al* 2017, Arnal *et al* 2018, Greuell *et al* 2019, Greuell and Hutjes 2023). There is a need for this skill assessment to expand to decision-relevant contexts, given that seasonal forecasts and climate information currently remain underutilized in actual decision contexts (Hu *et al* 2006, Bruno Soares and Dessai 2016, Smith *et al* 2021), especially in agriculture. Reasons for this underutilization in agricultural decisions include a user perception of poor forecast quality and the absence of decision-relevant forecasts (Hu *et al* 2006, Ash *et al* 2007, Kusunose and Mahmood 2016, Klemm and McPherson 2017, Smith *et al* 2021). Considering the aforementioned impediments, a clear demonstration of forecast skill for agricultural decisions (utilizing forecast of decision-relevant variables with appropriate spatiotemporal aggregations and decision timeframes) can bring us closer to bridging the perception and underutilization gaps. This is also an important first step in transitioning from forecast skill assessments to forecast value assessments for specific decisions, as the appropriate decision-relevant skill assessment is a key input to quantify the value of a forecast for decision-making.

Agricultural decisions encompass a wide array of activities, including but not limited to seed purchase, crop and cultivar selection, sowing and harvesting, tillage and conservation practices, application of fertilizers, and strategies to mitigate the impacts of drought conditions. These decisions are conceived, planned, and implemented throughout the year, tailored to specific crops, varieties, and geographical locations. For instance, Takle *et al* (2014) consolidate specific decisions pertinent to corn cultivation that necessitate access to climate information and underscore the crucial aspects that climate forecasters must comprehend to facilitate informed decision-making processes. Analogous to agricultural decisions, skill in a seasonal forecast of influencer variables, which directly or indirectly shape agricultural decisions, varies across different regions, seasons, and lead times. Thus, it is imperative to evaluate forecast skill in decision-relevant variables to establish the usefulness of forecasts in the decision-making process for different decisions and regions. Through this study, we aimed to demonstrate the utility of seasonal forecasts in informing agricultural decisions. We took two specific decisions: fall fertilizer application and drought response (e.g. water leasing decisions), and asked the following research questions.

(a) What is the skill for the variables that can inform drought response and fall fertilization decisions?
(b) How early can the information be provided without a significant degradation in skill?

Table 1. Summary of characteristics of the two decisions considered. The decision timing relates to when the decision is being made. The decision variable corresponds to the variable that directly governs the decision.

Decision attributes	Fall fertilization	Drought response
Decision timing	Between August and September	April
Variable and time frame of information	Expected temperature between November and February.	Drought forecast based on expected water supply between April and September.

These example decisions were intentionally selected to be contrasting (table 1) in terms of when the decision is made, what time frame of information the decision uses, and the decision variable itself.

Fall fertilization for dryland spring crops offers logistical and management advantages to farmers (personal communications with university extension professionals) as it cuts down a time-intensive farm operation in the spring and allows nutrients to be better positioned within the soil matrix to be efficiently taken up by spring crops. However, high soil temperatures during late fall and early winter can lead to enhanced nitrogen mineralization (Kladivko and Keeney 1987), volatilization (He *et al* 1999), and denitrification (Stanford *et al* 1975), causing a loss of available nitrogen for the following growing season. Prior knowledge of an unusually warm winter will allow postponing fertilization till spring and avoid multiple applications, especially since fertilizer prices have increased rapidly in recent years (e.g. 125% surge in global fertilizer price between January 2021 and 2022 (Hebebrand and Laborde Debucquet 2023)). Soil temperature is well correlated with air temperature (Zheng *et al* 1993, Xing *et al* 2018), and therefore we analyze seasonal air temperature forecasts during the late fall and early winter. Farmers can utilize this forecast information to decide whether to apply fertilizer in the fall or wait till the spring season.

In the case of drought response, decision-makers such as water managers have to take actions (e.g. lease water for the upcoming growing season) based on drought or regional water supply forecasts. Water markets facilitate the trading and/or leasing of water rights and involve reallocating water from lower-value activities to higher-value activities (Chong and Sunding 2006, Brewer *et al* 2007). In the western US, a majority of water market transactions originate from agriculture (Brewer *et al* 2007, Schwabe *et al* 2020). Reallocation of water across locations and water-use sectors (e.g. agriculture to instream flow) can lead to third-party effects such as an intermediary water right holder's access being unintentionally compromised (Doherty and Smith 2012, Schwabe *et al* 2020). Legal and regulatory requirements are imposed by regional institutions/governments to reduce these third-party effects, which can delay the water transfer process and raise the transaction cost in terms of connecting the right buyers and sellers (Colby 1990, Doherty and Smith 2012). The transaction costs and delays in the water transfer process (i.e. the long time needed to receive approval) have been identified as a key deterrent to the practical application and success of water markets (Doherty and Smith 2012), and providing a forecast with ample time to navigate the transactions (i.e. giving sufficient time to take care of legal requirements and compensate for underlying delays in the process) can be beneficial. In snow-dominant agricultural regions like the Western US, most of the irrigation water demand in the growing season (April through September) is met with snowmelt-originated streamflow (Mote *et al* 2018). Water supply and drought forecasts are needed to help facilitate drought response decisions before and during the growing season. Given that the peak snowpack accumulation—an important driver of water supply—is around April 1 in the Western US, forecasts of the seasonal supply are expected to be reliable at or after this timeframe (Pagano *et al* 2004). However, this timing is too close to the start of the growing season, impairing a timely and optimized drought response and thus, there is interest in earlier availability of forecasts that do not rely on the information of observed snowpack around April 1st.

We take the Pacific Northwest US (PNW) as a case study. This region encompasses the states of Washington, Oregon, Idaho, and western Montana (figure 1). It houses the Columbia River basin, whose longitudinal extent falls between the Cascade Ranges in the west and the Rocky Mountain Range in the east (Zarekarizi *et al* 2018). PNW is an economically significant region from an agricultural perspective and one of the major exporters of agricultural produce, including hay, winter wheat, apples, potatoes, and barley (Mu *et al* 2019, Seamon *et al* 2023); it has been continuously ranked among the top five in the US for crop production and provides more than 600 thousand jobs in the region (Seamon *et al* 2023). Given the substantial significance of agriculture and its diversity across the PNW region, it is a suitable candidate for our investigation into the utility of seasonal climate forecasts in the agriculture and water management sector.

2. Data and methods

The data and methodology used in the paper are briefly summarized in figure 2 and each component is discussed in detail later in this section.

2.1. Seasonal forecasts of meteorological variables

Monthly retrospective hindcasts (1982–2010) and forecasts (2011–2020) of temperature and precipitation are acquired for the PNW region of the United States from five models (CFSv2, NASA GEOS5v2, CanCM4i, GEM-NEMO, and NCAR-CCSM) participating in the NMME project (Kirtman *et al* 2014). These models, detailed in table 2 with more recent information available in (Becker *et al* 2022), are initialized monthly to provide a forecast of 0–9 months at a $1.0^\circ \times 1.0^\circ$ spatial resolution. The multi-model ensemble mean (ENSMEAN) is then generated for each initialization by simply averaging all considered models and their ensemble members. Monthly ENSMEAN forecast (and hindcast; for simplicity, we employ the term 'forecast' which includes both hindcast and forecast NMME data throughout this paper) is bias-corrected and spatially downscaled to 1/24th degree using the methodology described in Wood *et al* (2002) and Barbero *et al* (2017) using historical meteorological data (gridMET; Abatzoglou 2013) as the baseline. Then, the downscaled ENSMEAN data are temporally disaggregated to daily timescales using an analog approach. The closest analog month for the ENSMEAN forecast is found from the gridMET dataset by minimizing the root mean square error of monthly gridMET and forecast precipitation (excluding gridMET data for the target month). Other daily meteorological variables (such as maximum and minimum temperature, maximum and minimum relative humidity, wind speed, and specific humidity) are extracted from the same analog month to use as input for the coupled crop-hydrology model. As a last step to the analog approach, the process corrects the bias between the forecast and analog month to ensure that monthly mean temperature and accumulated precipitation match those of the original forecast. This processed data is available at Hegewisch and Abatzoglou (2024). In this paper, lead month or lead time stands for how long before the forecasted month (the month for which the forecast is made) the forecast is made available. For instance, if the forecasted month is March and the forecast is made available in January, then the lead time would be two months.

2.2. Observational dataset of meteorological variables

The gridMET dataset is chosen as the observational dataset, which is a daily high-resolution dataset

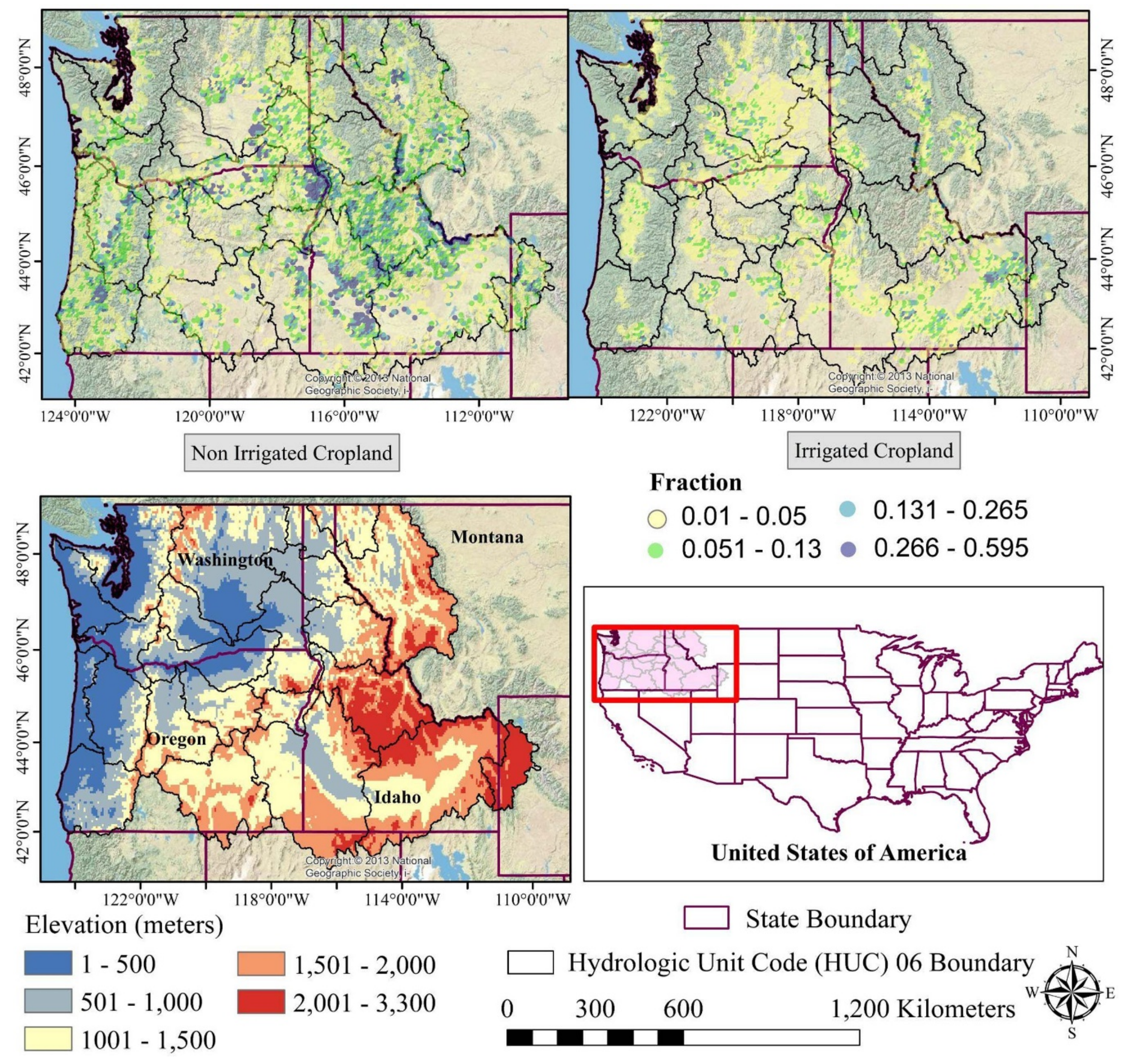

Figure 1. The depicted study region encompasses the Pacific Northwest (PNW) of the United States (US), which covers the US portion of the Columbia River basin and west of the cascades. The upper-left and right subplots show the region's distribution of non-irrigated and irrigated crops. Color variations in these two subplots represent the fraction of the grid under irrigated or non-irrigated crops. The bottom-left subplot depicts the region's elevation variations through the color band, and the inset map (lower-right) provides a geographical reference by illustrating the position of the PNW region in relation to the broader expanse of the United States.

(∼4 km, 1/24th degree) that provides surface meteorological variables over the contiguous United States from 1979 to the present (Abatzoglou 2013). It is developed by combining spatial attributes of gridded climate data (PRISM, Daly *et al* 2008) and temporal attributes of regional reanalysis (NLDAS-2, Mitchell *et al* 2004) blended along with daily gauge-based precipitation observations and being used in numerous studies over the years (Kuo and Fu 2021, Patricola *et al* 2022, Ali *et al* 2023, Schantz *et al* 2023).

2.3. Model for water supply

A coupled crop-hydrology model (VIC-CropSyst, Malek *et al* 2017) is used to derive hydrological variables such as surface runoff and baseflow (hereafter, we use cumulative runoff to represent the total of surface runoff and baseflow). VIC-CropSyst consists of a macroscale variable infiltration capacity (VIC) hydrologic model (Liang *et al* 1994) and the CropSyst agricultural model (Stöckle *et al* 2003) along with a mechanistic irrigation module to estimate water availability, crop water requirements for irrigation and agricultural productivity. In this integrated model, VIC simulates the hydrologic process to balance the energy and water budgets, whereas CropSyst simulates the agricultural processes such as transpiration, biomass accumulation, etc based on the information provided by VIC (Malek *et al* 2018). VIC-CropSyst has been extensively used in the field of agricultural and water resource management (Adam *et al* 2015, Rajagopalan *et al* 2018, Malek *et al* 2020, Yourek *et al* 2023).

2.4. Simulation setup

We simulated runoff and baseflow with the VIC-CropSyst model by using gridMET and NMME's ENSMEAN as inputs. Since the ENSMEAN data are only for nine months for a given initialization, these

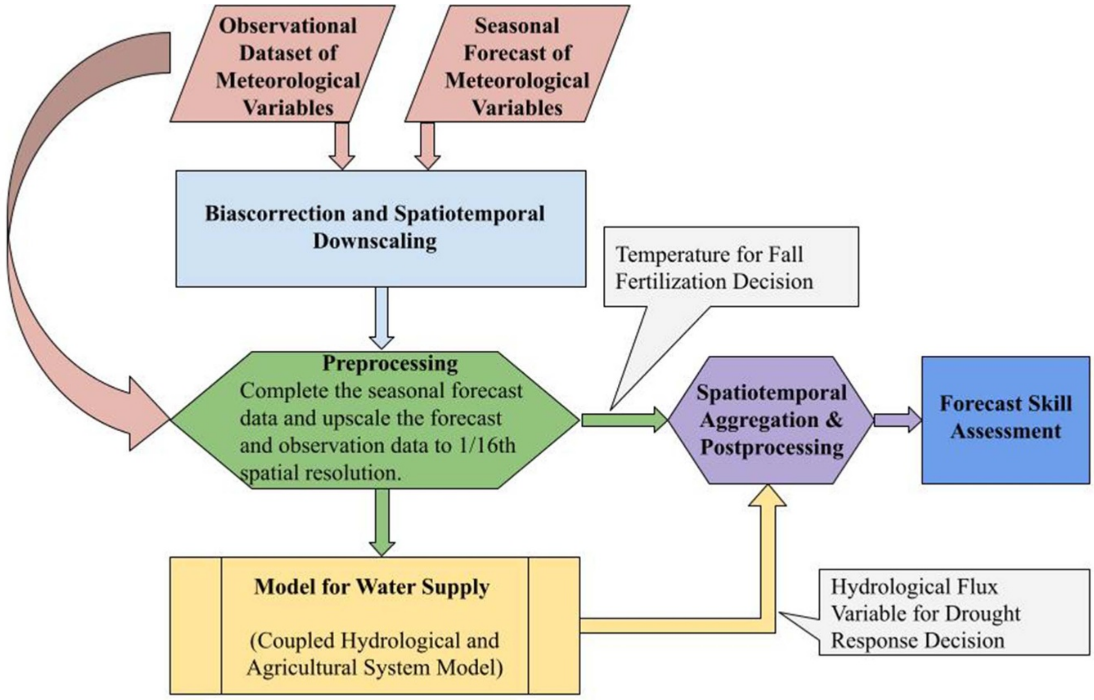

Figure 2. Overview of applied workflow and methodology.

Table 2. List of NMME models used in this study.

Model	Model expansion	Ensemble size	References
NCEP-CFSv2	Climate Forecast System, version 2	24	(Saha *et al* 2014)
NASA GEOS5v2	Goddard Earth Observing System, version 5	4	(Molod *et al* 2020)
CanCM4i	Fourth Generation Canadian Coupled Global Climate Model	10	(Merryfield *et al* 2013)
GEM—NEMO	Global Environmental Multiscale Model—Nucleus for European Modeling of the Ocean	10	(Lin *et al* 2020)
NCAR—CCSM	Community Climate System Model	10	(Kirtman and Min 2009)

data are annually completed by adding the remaining months' data from gridMET along with appending three years of gridMET data as a spinup before using it to run the VIC-CropSyst. As the forecast data are artificially annually completed, the VIC-CropSyst model is run on a per-forecast year basis in the case of ENSMEAN and during post-processing, the spin-up data and the extra three months of gridMET data are removed from the model output to get time-series output for actual nine forecasted months of each year from a given initialization. On the other hand, the VIC-CropSyst model is run for the whole period (1982–2020) together in the case of gridMET with an additional three years of data used as spinup. The VIC-CropSyst requires eight meteorological inputs, namely maximum and minimum temperature, precipitation, wind speed, shortwave solar radiation, maximum and minimum relative humidity, and specific humidity at the 1/16th spatial resolution on a daily time step. Given this requirement, the NMME and gridMET were aggregated to 1/16th degree to match the model's spatial resolution, and thus, subsequent skill assessment on all variables was also conducted at this spatial resolution for consistency.

2.5. Spatiotemporal aggregations

We conducted the analysis on both the grid and the watershed levels. For grid-wise calculations, we averaged the daily mean temperature between November and February to get the seasonal value for the fall fertilization decision, and in the case of drought response, the daily cumulative runoff between April through September months was summed up to get an

Figure 3. Hydrologic Unit Code (HUC) 06 aggregation of the Pacific Northwest (PNW) of the United States.

accumulated seasonal value at each grid. Hydrologic Unit Code 06 (HUC 06) aggregation was chosen as an aggregation extent for watershed level calculations (figure 3), and all the grids falling in a particular HUC are aggregated (average for temperature and sum of cumulative runoff) to generate a seasonal value. Subsequently, HSS is computed based on the seasonal value for a grid and watershed.

Drought response decisions are made based on the drought forecast, and to generate the drought forecast, we follow Washington State's definition of drought years, which are years when the streamflow/water supply is less than 75% of the median flow of the recent climatic period (i.e. 1991–2020) (Parker 2024). Based on this definition, we classified the forecast of seasonally accumulated cumulative-runoff (April through September) as drought or non-drought. On the other hand, we generated terciles of November through February mean temperature for fall fertilizer application decision where the lower extreme category encompasses temperatures below the 33rd percentile, signifying favorable conditions for fall fertilization, whereas the upper extreme category covers temperatures above the 67th percentile, representing unfavorable conditions. Since we focused on quantifying the contrast in skill among extreme conditions, we did not display the forecast performance in the 'normal' category for the fall fertilization decision.

2.6. Skill metrics

Seasonal forecast skill assessment of decision-relevant variables is the primary objective of this study, so we used the Heidke Skill Score (HSS) as the forecast verification measure, which is widely used to assess categorical forecasts, especially the high and low extreme categories (Kowal *et al* 2023). For HSS computation (equation (1)), the proportion of correct forecasts is estimated after accounting for the number of correct forecasts that are expected due to random chance (Heidke 1926, Hyvärinen 2014). It is an easy-to-understand metric that describes how the forecast compares to a reference value (which can be climatology or the proportion of forecasts correct by chance) and has been used in previous studies for seasonal forecast verifications (Higgins *et al* 2004, Peng *et al* 2012, Barbero *et al* 2017, Walker *et al* 2019). A positive HSS indicates a skilled forecast, meaning the forecast performs better than the reference value. Conversely, a negative HSS indicates a poor forecast, signifying that the forecast is worse than the reference value, and an HSS of zero indicates no skill, referring to a forecast as good as the reference value. We use the proportion of forecasts correct by chance as the reference value for which the HSS equation for a binary forecast translates to equation (1),

$$\mathrm{HSS} = \frac{2\,(ad - bc)}{(a+b)\,(b+d) + (a+c)\,(c+d)} \times 100\%. \tag{1}$$

In this equation, a, b, c, and d stand for true positive, false positive, false negative, and true negative, respectively.

We computed the HSS of the binary forecast for both decisions. In the case of fall fertilization decision, the HSS is calculated for each individual extreme category (i.e. forecast either falls into a particular category or not). Whereas in the case of drought response, computed HSS indicates skill in predicting drought or non-drought conditions. With this

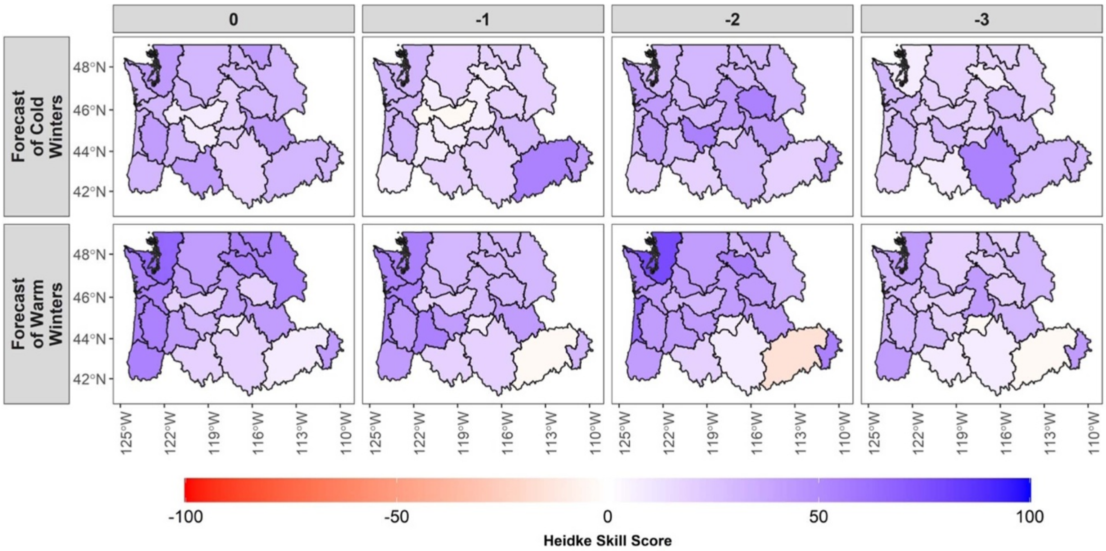

Figure 4. Heidke Skill Score (HSS) of average temperature for the November–December–January–February (NDJF) season at HUC06 levels in the Pacific Northwest region of the United States. The subplots from the left to the right correspond to the forecast lead month from the beginning of a season, i.e. when the forecast is made available for a particular season. The forecast is initialized in the same month as it is made available. The top row exhibits the HSS for lower extreme (below 33rd percentile, i.e. forecast of cold winter versus non-cold winters), whereas the bottom row shows the HSS for upper extreme (above 67th percentile, i.e. forecast of warm winter versus non-warm winters). HSS values range between −100% (Red) and 100% (Blue). HSS values above zero indicate skill in the forecast.

verification measure, we can identify the time span (lead months) and spatial hotspots where forecast skill is high and can add value to the decision-making process.

3. Results and discussion

3.1. Forecast skill in fall fertilization application decision

We observe a positive skill (median HSS of ∼30%) in forecasting winter temperatures relevant to the fall fertilization decision for almost the entire study area at all lead times (figure 4). This is consistent with a reported high forecast skill for temperature compared to other variables like precipitation in the PNW (Barbero *et al* 2017) and other parts of the US (Becker *et al* 2014, 2020. Furthermore, we observe higher skill in forecasting the upper extreme category (i.e. forecast of warm winters), which constitutes unfavorable conditions for fall fertilization application that could lead to loss of fertilizer and subsequent economic losses, compared to the lower extreme category (i.e. forecast of cold winters). This result aligns with Krakauer (2019)'s conclusion that NMME models have higher skill in predicting extreme hot and cold categories compared to normal category and are particularly good at forecasting hot extremes globally. Especially in non-irrigated lands where the fall fertilization decision has far greater economic importance, HSS in forecasting warm winters is higher (between 20% to 30%) than in irrigated lands (figure 5(b)). In general, the HSS for the forecast of warm winters exhibited a distinct spatial pattern, with the Northwestern and Northern regions displaying higher forecasting skill than the Southeastern regions (which can be potentially attributed to persistent cold pools and temperature inversions occurring in low-lying regions (Whiteman *et al* 2001)) and a reasonable positive skill is available up to three months in advance (i.e. in August) for the fall fertilizer decision, depending on geographical location of the HUC's. Overall, the median change in HSS between Lead 0 and other considered lead times ranges between 0 and −11.54% (figure A1) which is indicative of the utility of seasonal forecast for fall fertilization decision at longer lead time. The observed seasonal skill in predicting favorable and unfavorable years for fall fertilization provides valuable insights, with a particularly robust ability to forecast unfavorable years. This knowledge is instrumental in assisting farmers in making informed decisions for optimizing agricultural practices in fertilization scheduling.

3.2. Forecast skill in predicting drought based on the regional water supply

Forecast skill was positive in predicting seasonal watershed-scale drought with a median HSS score of 48% for forecasts made with a lead of 0 in the month of April. The skill varied spatially from −18% to 77%, with relatively higher skill in the central and eastern HUCs (east of the cascades) where the

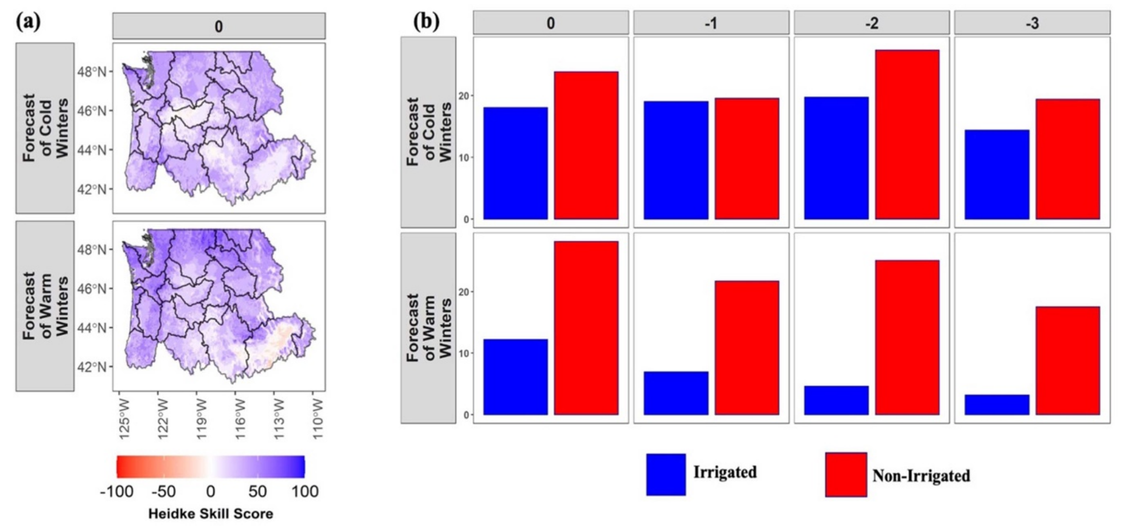

Figure 5. Heidke Skill Score (HSS) of average temperature for November–December–January–February (NDJF) season in the Pacific Northwest region of the United States (a) HSS at each grid for Lead 0, i.e. for the forecast available in November. (b) Mean HSS aggregated grouped by irrigation condition. The arrangement of the subplots is the same as in figure 4.

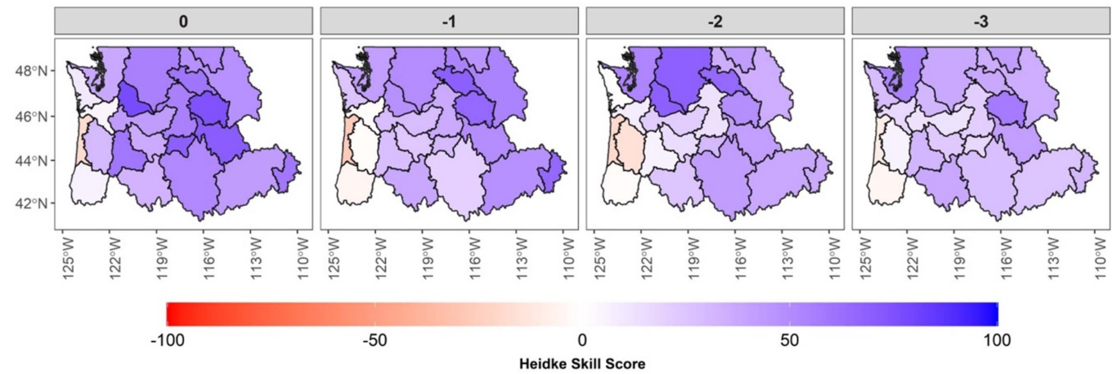

Figure 6. Heidke Skill Score (HSS) of drought forecast based on the regional water supply for the growing season at HUC06 levels in the Pacific Northwest region of the United States. The subplots from the left to the right correspond to the forecast lead month from the beginning of a season, i.e. when the forecast is made available for a particular season. HSS values range between −100% (Red) and 100% (Blue). HSS values above zero indicate skill in the forecast.

irrigated croplands are concentrated. Forecast skill was lower in the west of the Cascades mountains (figure 6). We also observe that, particularly for the eastern irrigated watersheds, the overall positive skill does not substantially degrade for forecasts made up to two months in advance in February (median HSS of 32% as compared to 48% in April) (figure 6). Overall, the median change in HSS between Lead 0 and other considered lead time ranges between −8.78 to −17.66% (figure A2). This has important implications for drought management in this region, where currently decisions are typically made using drought forecasts made in April resulting in a tight decision timeline and compromising the ability to facilitate effective drought response (such as water leasing) as agricultural producers are already starting to commence irrigation by this point (personal communications with the WA Department of Ecology). The ability to have similar skill in drought prediction up to two months in advance of the start of the irrigation season will allow better facilitation of emergency drought declarations and programs, and strategies, such as water leases, to mitigate the impacts of drought.

In the watersheds with relatively high drought forecast skill (e.g. Yakima, Middle Snake-Powder, Clearwater, and Salmon river basins) at Lead 0 (dark blue in figure 6), higher skill is either due to higher skill in most of the grids within these watersheds (as in the case of Salmon, Clearwater, and Middle Snake-Powder where median HSS is around ∼65%) or at high-elevations i.e. snow-covered grids, that contribute the most (for example, ∼70% in case of Yakima River Basins) to the watershed-scale runoff. Specifically, in the Yakima River Basin, a larger across-grid variability in skill (median HSS of 42% and range of −1.53% to 98%) was observed as shown in figure 7(b).

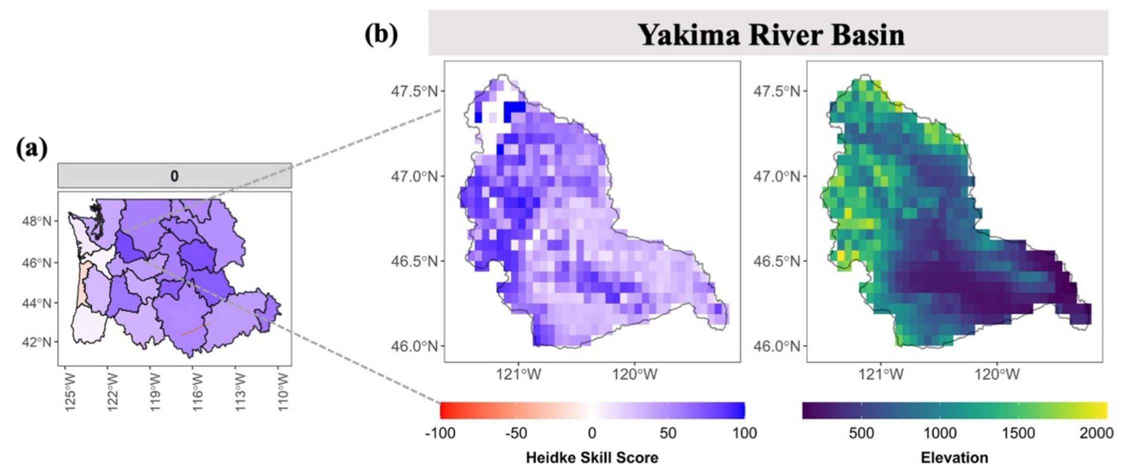

Figure 7. Heidke Skill Score (HSS) of drought forecast based on the regional water supply for the growing season (AMJJAS) at lead month 0 on (a) HUC 6 level and shows the relative position of the Yakima River Basin in PNW (see figure 6 for enlarged view) (b) HSS and the elevation characteristics of the Yakima River Basin.

While other studies have not evaluated seasonal forecast skill for the drought definition and associated temporal aggregation used by agencies (e.g. Washington Department of Ecology), we can place our results in the context of other studies that have evaluated the seasonal forecast skill of streamflow or cumulative runoff, which is the driver of drought forecasts. Our positive skill in drought forecasts is consistent with positive skill noted for cumulative runoff (Wood and Lettenmaier 2006, Shukla and Lettenmaier 2011) or runoff (Mo and Lettenmaier 2014) for multiple seasons in parts of the Western United States.

4. Conclusion

For a seasonal forecast to have any value in the decision-making process, it must be foremost a forecast of decision-relevant variables, have a skill better than climatology, and be made available at the right time. Herein, we demonstrated the potential utility of seasonal climate forecasts in agricultural decision-making over the PNW region of the United States and ascertained that the seasonal forecasts are likely skilled enough to be actively included in agricultural and water-management decision-making. We conducted a skill assessment on the decision-relevant variables for fall fertilization and drought response decisions to investigate the utility of forecast in informing these two characteristically different decisions and yielded the following general conclusion:

1. A positive HSS is observed for both decision variables at multiple lead times and at the locations where the skill actually matters the most. The seasonal forecast skill varies geographically and with lead time regardless of the decision variable.
2. In the context of fall fertilization, a relatively higher skill exists in identifying the warmer years (upper-temperature extreme years) as compared to colder years (lower temperature extreme years), especially the skill was higher in non-irrigated (dryland) regions where this decision has a larger negative economic impact as a wrong forecast would lead to loss of fertilizer.
3. Positive skill in drought forecasting was observed as early as February, which provides an advance window of two months compared to the current operational forecast release month (i.e. April) to water managers, farmers, and other entities associated with drought response (water leasing) decisions to act accordingly.

Through our study, we highlighted that the current seasonal forecasts can still inform decision-making even with limited predictability (An-Vo *et al* 2021), and this analysis can be extended for other climate-dependent decisions (such as seed selection, irrigation planning, etc) through skill analysis on respective decision-relevant variables (such as crop yield, irrigation net demand, etc). For instance, Takle *et al* (2014) provide a decision calendar for corn where a climate forecast can inform decision-making at varied time scales, and applying this analysis for the seasonal climate-sensitive decisions highlighted in the aforementioned study can yield meaningful insights for corn growers. The knowledge and techniques used in this study are not confined to PNW and can be transferable to other regions to identify the high-skill spatiotemporal hotspots (regions with high skill during different times of the year at multiple lead times) and for different management decisions.

Additionally, there is an opportunity to improve this study by providing probabilistic uncertainty information associated with seasonal forecasts to end-users. We limit our skill analysis to deterministically assessing the forecast of decision-relevant variables based on an ENSMEAN forecast, as they perform better than the participating individual models on average (Kirtman *et al* 2014, Becker *et al* 2020, 2022). However, this study can be expanded to do a comprehensive skill assessment involving all participating models of NMME and their ensembles instead of using ENSMEAN. Furthermore, an ex-ante and ex-post economic analysis can be done to substantiate the findings and associate a monetary value to the forecast skill as several factors other than skill play into value quantification; this way, decision-makers can be encouraged to integrate seasonal forecasts into the decision-making process intuitively.

There are a series of onerous data processing steps involved in translating raw meteorological forecasts to information that is readily usable by the end user. Therefore, investments in the development of infrastructure that supports this will be key to the successful use of seasonal forecasts for decision-making. Moreover, this investment will likely pay off more in the long run as forecast skill has improved over time and is expected to improve. For example, the skill for the NMME product used in this study improved by 9% between 2011 and 2020 (Becker *et al* 2020). New approaches, including AI and hybrid AI and biophysical approaches, are evolving (Slater *et al* 2023) and the trend in accuracy improvements can be expected to continue. Against this background, this study showcases the utility of seasonal forecasts available at the time and lays the foundation for its implementation to wider uses and varied decisions.

Data availability statement

The downscaled seasonal forecast data (Hegewisch and Abatzoglou 2024) that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.14043453.

Acknowledgment

This work was supported by USDA NIFA Award Number 1016467 under the *Water For Agriculture* program.

Code availability

The sample data and code to generate the findings of this paper are available at https://github.com/Ashish-Kondal/SF_Skill-Decision_Variables.

Conflict of interest

The authors declare that they have no conflicting interests.

Appendix

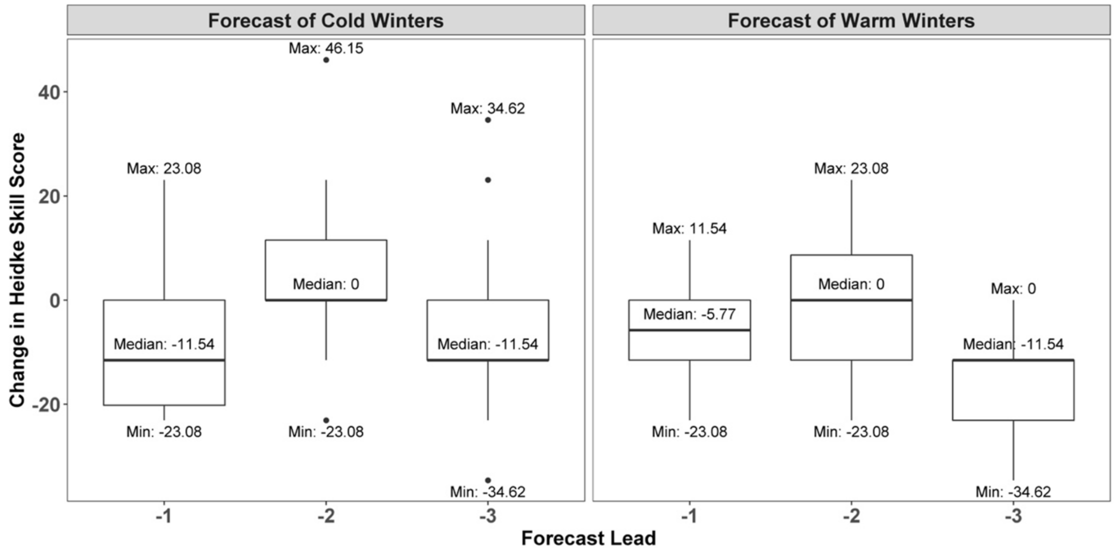

Figure A1. Box plot depicting changes in HSS for fall fertilization decision between lead 0 and other lead time. Negative values correspond to a decrease in skill relative to lead 0 skill.

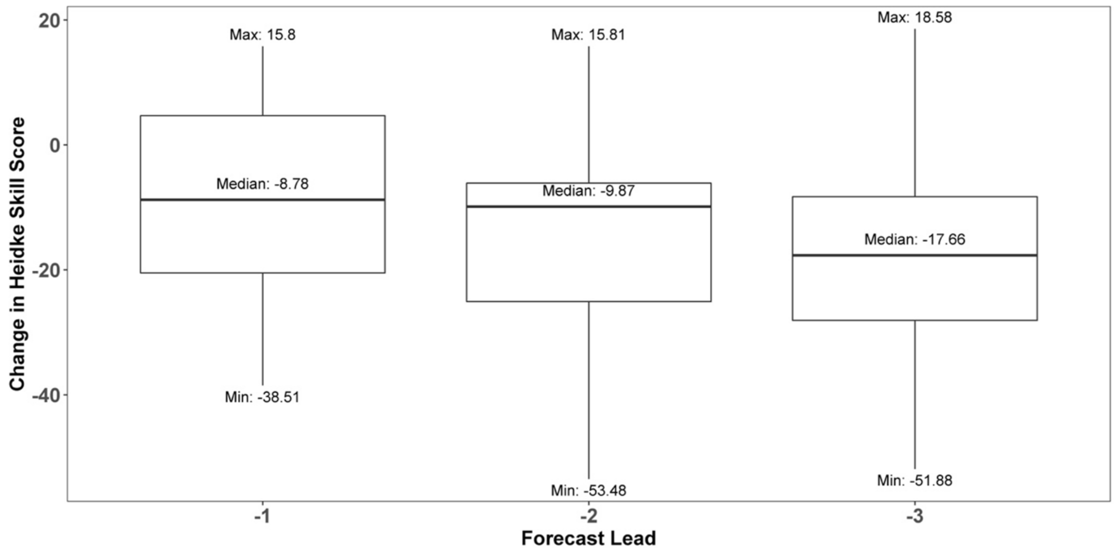

Figure A2. Box plot depicting changes in HSS for drought response decision between lead 0 and other lead time. Negative values correspond to a decrease in skill relative to lead 0 skill.

ORCID iDs

Ashish Kondal https://orcid.org/0000-0002-9739-5760
Katherine Hegewisch https://orcid.org/0000-0002-9539-2929
Mingliang Liu https://orcid.org/0000-0002-1963-5933
John T Abatzoglou https://orcid.org/0000-0001-7599-9750
Jennifer C Adam https://orcid.org/0000-0003-4205-8860
Bart Nijssen https://orcid.org/0000-0002-4062-0322
Kirti Rajagopalan https://orcid.org/0000-0002-7086-9858

References

Abatzoglou J T 2013 Development of gridded surface meteorological data for ecological applications and modelling *Int. J. Climatol.* **33** 121–31

Adam J C *et al* 2015 BioEarth: envisioning and developing a new regional earth system model to inform natural and agricultural resource management *Clim. Change* **129** 555–71

Ali J, Wahl T, Enriquez A R, Rashid M M, Morim J, Gall M and Emrich C T 2023 The role of compound climate and weather extreme events in creating socio-economic impacts in South Florida *Weather Clim. Extremes* **42** 100625

An-Vo D-A, Radanielson A M, Mushtaq S, Reardon-Smith K and Hewitt C 2021 A framework for assessing the value of seasonal climate forecasting in key agricultural decisions *Clim. Serv.* **22** 100234

Andrian L G, Osman M and Vera C S 2023 Climate predictability on seasonal timescales over South America from the NMME models *Clim. Dyn.* **60** 3261–76

Arnal L, Cloke H L, Stephens E, Wetterhall F, Prudhomme C, Neumann J, Krzeminski B and Pappenberger F 2018 Skilful seasonal forecasts of streamflow over Europe? *Hydrol. Earth Syst. Sci.* **22** 2057–72

Ash A, McIntosh P, Cullen B, Carberry P and Smith M S 2007 Constraints and opportunities in applying seasonal climate forecasts in agriculture *Aust. J. Agric. Res.* **58** 952–65

Barbero R, Abatzoglou J T and Hegewisch K C 2017 Evaluation of statistical downscaling of North American multimodel ensemble forecasts over the Western United States *Weather Forecast.* **32** 327–41

Barnston A G, Tippett M K, Ranganathan M and L'Heureux M L 2019 Deterministic skill of ENSO predictions from the North American multimodel ensemble *Clim. Dyn.* **53** 7215–34

Becker E J, Kirtman B P, L'Heureux M, Muñoz Á G and Pegion K 2022 A decade of the North American multimodel ensemble (NMME): research, application, and future directions *Bull. Am. Meteorol. Soc.* **103** E973–E995

Becker E, Dool H V D and Zhang Q 2014 Predictability and forecast skill in NMME *J. Clim.* **27** 5891–906

Becker E, Kirtman B P and Pegion K 2020 Evolution of the North American multi-model ensemble *Geophys. Res. Lett.* **47** e2020GL087408

Bento V A, Russo A, Dutra E, Ribeiro A F S, Gouveia C M and Trigo R M 2022 Persistence versus dynamical seasonal forecasts of cereal crop yields *Sci. Rep.* **12** 7422

Boas T, Bogena H R, Ryu D, Vereecken H, Western A and Hendricks Franssen H-J 2023 Seasonal soil moisture and crop yield prediction with fifth-generation seasonal forecasting system (SEAS5) long-range meteorological forecasts in a land surface modelling approach *Hydrol. Earth Syst. Sci.* **27** 3143–67

Brewer J, Glennon R, Ker A and Libecap G D 2007 Water markets in the west: prices, trading, and contractual Forms 13002 (National Bureau of Economic Research) (https://doi.org/10.3386/w13002) (Accessed February 2024)

Bruno Soares M and Dessai S 2016 Barriers and enablers to the use of seasonal climate forecasts amongst organisations in Europe *Clim. Change* **137** 89–103

Candogan Yossef N, van Beek R, Weerts A, Winsemius H and Bierkens M F P 2017 Skill of a global forecasting system in seasonal ensemble streamflow prediction *Hydrol. Earth Syst. Sci.* **21** 4103–14

Ceglar A and Toreti A 2021 Seasonal climate forecast can inform the European agricultural sector well in advance of harvesting *npj Clim. Atmos. Sci.* **4** 42

Chinyoka S and Steeneveld G J 2023 Evaluation of downscaling seasonal climate forecasts for crop yield forecasting in Zimbabwe *Clim. Serv.* **30** 100380

Chong H and Sunding D 2006 Water markets and trading *Annu. Rev. Environ. Resour.* **31** 239–64

Colby B G 1990 Transactions costs and efficiency in western water allocation *Am. J. Agric. Environ.* **72** 1184–92

Daly C, Halbleib M, Smith J I, Gibson W P, Doggett M K, Taylor G H, Curtis J and Pasteris P P 2008 Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States *Int. J. Climatol.* **28** 2031–64

Doherty T and Smith R 2012 Water transfers in the west: projects, trends, and leading practices in voluntary water trading *Whitepaper* (The Western Governor's Association) (available at: https://search.issuelab.org/resource/water-transfers-in-the-west-projects-trends-and-leading-practices-in-voluntary-water-trading.html)

Greuell W, Franssen W H P and Hutjes R W A 2019 Seasonal streamflow forecasts for Europe—Part 2: sources of skill *Hydrol. Earth Syst. Sci.* **23** 371–91

Greuell W and Hutjes R W A 2023 Skill and sources of skill in seasonal streamflow hindcasts for South America made with ECMWF's SEAS5 and VIC *J. Hydrol.* **617** 128806

Hammer G, Hansen J, Phillips J, Mjelde J, Hill H, Love A and Potgieter A 2001 Advances in application of climate prediction in agriculture *Agric. Syst.* **70** 515–53

He Z L, Alva A K, Calvert D V and Banks D J 1999 Ammonia volatilization from different fertilizer sources and effects of temperature and soil pH1 *Soil Sci.* **164** 750–8

Hebebrand C and Laborde Debucquet D 2023 High fertilizer prices contribute to rising global food security concerns *IFPRI Book Chapters* (*The Russia-Ukraine conflict and global food security*) (International Food Policy Research Institute (IFPRI)) ch 7, pp 38–42 (available at: https://ideas.repec.org/h/fpr/ifpric/9780896294394_07.html)

Hegewisch K and Abatzoglou J T 2024 Downscaled North American multi-model ensemble forecast for the Pacific Northwest USA [Data set] *Zenodo* (https://doi.org/10.5281/zenodo.14043453)

Heidke P 1926 Berechnung Des Erfolges Und Der Güte Der Windstärkevorhersagen Im Sturmwarnungsdienst *Geogr. Ann.* **8** 301–49

Higgins R W, Kim H-K and Unger D 2004 Long-lead seasonal temperature and precipitation prediction using tropical Pacific SST consolidation forecasts *J. Clim.* **17** 3398–414

Hu Q, Zillig L M P, Lynne G D, Tomkins A J, Waltman W J, Hayes M J, Hubbard K G, Artikov I, Hoffman S J and Wilhite D A 2006 Understanding farmers' forecast use from their beliefs, values, social norms, and perceived obstacles *J. Appl. Meteorol. Climatol.* **45** 1190–201

Hyvärinen O 2014 A probabilistic derivation of heidke skill score *Weather Forecast.* **29** 177–81

Johnson S J *et al* 2019 SEAS5: the new ECMWF seasonal forecast system *Geosci. Model Dev.* **12** 1087–117

Kirtman B P *et al* 2014 The North American multimodel ensemble: phase-1 seasonal-to-interannual prediction;

Phase-2 toward developing intraseasonal prediction *Bull. Am. Meteorol. Soc.* **95** 585–601
Kirtman B P and Min D 2009 Multimodel ensemble ENSO prediction with CCSM and CFS *Mon Weather Rev.* **137** 2908–30
Kladivko E J and Keeney D R 1987 Soil nitrogen mineralization as affected by water and temperature interactions *Biol. Fertil. Soils* **5** 248–52
Klemm T and McPherson R A 2017 The development of seasonal climate forecasting for agricultural producers *Agric. For. Meteorol.* **232** 384–99
Kowal K M, Slater L J, García López A and Van Loon A F 2023 A comparison of seasonal rainfall forecasts over central America using dynamic and hybrid approaches from copernicus climate change service seasonal forecasting system and the North American multimodel ensemble *Int. J. Climatol.* **43** 2175–99
Krakauer N Y 2019 Temperature trends and prediction skill in NMME seasonal forecasts *Clim. Dyn.* **53** 7201–13
Kuo C-P and Fu J S 2021 Evaluating the impact of mobility on COVID-19 pandemic with machine learning hybrid predictions *Sci. Total Environ.* **758** 144151
Kusunose Y and Mahmood R 2016 Imperfect forecasts and decision making in agriculture *Agric. Syst.* **146** 103–10
Liang X, Lettenmaier D P, Wood E F and Burges S J 1994 A simple hydrologically based model of land surface water and energy fluxes for general circulation models *J. Geophys. Res.* **99** 14415–28
Lin H *et al* 2020 The Canadian seasonal to interannual prediction system version 2 (CanSIPSv2) *Weather Forecast.* **35** 1317–43
Lipper L *et al* 2014 Climate-smart agriculture for food security *Nat. Clim. Change* **4** 1068–72
Malek K, Adam J, Stockle C, Brady M and Rajagopalan K 2018 When should irrigators invest in more water-efficient technologies as an adaptation to climate change? *Water Resour. Res.* **54** 8999–9032
Malek K, Reed P, Adam J, Karimi T and Brady M 2020 Water rights shape crop yield and revenue volatility tradeoffs for adaptation in snow dependent systems *Nat. Commun.* **11** 3473
Malek K, Stöckle C, Chinnayakanahalli K, Nelson R, Liu M, Rajagopalan K, Barik M and Adam J C 2017 VIC–CropSyst-v2: a regional-scale modeling platform to simulate the nexus of climate, hydrology, cropping systems, and human decisions *Geosci. Model Dev.* **10** 3059–84
Merryfield W J, Lee W-S, Boer G J, Kharin V V, Scinocca J F, Flato G M, Ajayamohan R S, Fyfe J C, Tang Y and Polavarapu S 2013 The Canadian seasonal to interannual prediction system. Part I: models and initialization *Mon. Weather Rev.* **141** 2910–45
Meza F J, Hansen J W and Osgood D 2008 Economic value of seasonal climate forecasts for agriculture: review of ex-ante assessments and recommendations for future research *J. Appl. Meteorol. Climatol.* **47** 1269–86
Mitchell K E *et al* 2004 The multi-institution North American land data assimilation system (NLDAS): utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system *J. Geophys. Res.* **109** D07S90
Mo K C and Lettenmaier D P 2014 Hydrologic prediction over the conterminous united states using the national multi-model ensemble *J. Hydrometeorol.* **15** 1457–72
Molod A *et al* 2020 GEOS-S2S version 2: the GMAO high-resolution coupled model and assimilation system for seasonal prediction *J. Geophys. Res.* **125** e2019JD031767
Mote P W, Li S, Lettenmaier D P, Xiao M and Engel R 2018 Dramatic declines in snowpack in the western US *npj Clim. Atmos. Sci.* **1** 1–6
Mu J E, Antle J M and Abatzoglou J T 2019 Representative agricultural pathways, climate change, and agricultural land uses: an application to the Pacific Northwest of the USA *Mitig. Adapt. Strateg. Glob. Change* **24** 819–37
Pagano T, Garen D and Sorooshian S 2004 Evaluation of official Western U.S. Seasonal water supply outlooks, 1922–2002 *J. Hydrometeorol.* **5** 896–909
Parker B 2024 Drought in washington *Government Website* (Drought.Gov) (available at: www.drought.gov/states/washington)
Patricola C M, Wehner M F, Bercos-Hickey E, Maciel F V, May C, Mak M, Yip O, Roche A M and Leal S 2022 Future changes in extreme precipitation over the San Francisco Bay area: dependence on atmospheric river and extratropical cyclone events *Weather Clim. Extremes* **36** 100440
Peng P, Kumar A, Halpert M S and Barnston A G 2012 An analysis of CPC's operational 0.5-month lead seasonal outlooks *Weather Forecast.* **27** 898–917
Rajagopalan K *et al* 2018 Impacts of near-term climate change on irrigation demands and crop yields in the Columbia River Basin *Water Resour. Res.* **54** 2152–82
Saha S *et al* 2014 The NCEP climate forecast system version 2 *J. Clim.* **27** 2185–208
Schantz M C, Hardegree S P, James J J, Becchetti T, Abatzoglou J T, Hegewisch K C and Sheley R L 2023 Evaluating multimodel ensemble seasonal climate forecasts on rangeland plant production in the california annual grassland *Rangeland Ecol. Manage.* **88** 135–42
Schwabe K, Nemati M, Landry C and Zimmerman G 2020 Water markets in the Western United States: trends and opportunities *Water* **12** 233
Seamon E, Gessler P E, Abatzoglou J T, Mote P W and Lee S S 2023 Climatic damage cause variations of agricultural insurance loss for the Pacific Northwest Region of the United States *Agriculture* **13** 2214
Shukla S and Lettenmaier D P 2011 Seasonal hydrologic prediction in the United States: understanding the role of initial hydrologic conditions and seasonal climate forecast skill *Hydrol. Earth Syst. Sci.* **15** 3529–38
Slater L J *et al* 2023 Hybrid forecasting: blending climate predictions with AI models *Hydrol. Earth Syst. Sci.* **27** 1865–89
Smith A P, Yung L, Snitker A J, Bocinsky R K, Metcalf E C and Jencso K 2021 Scalar mismatches and underlying factors for underutilization of climate information: perspectives from farmers and ranchers *Front. Clim.* **3** 663071
Stanford G, Dzienia S and Vander Pol R A 1975 Effect of temperature on denitrification rate in soils *Soil Sci. Soc. Am. J.* **39** 867–70
Stöckle C O, Donatelli M and Nelson R 2003 CropSyst, a cropping systems simulation model *Eur. J. Agron.* **18** 289–307
Takle E S *et al* 2014 Climate forecasts for corn producer decision making *Earth Interact.* **18** 1–8
Walker D P, Birch C E, Marsham J H, Scaife A A, Graham R J and Segele Z T 2019 Skill of dynamical and GHACOF consensus seasonal forecasts of East African rainfall *Clim. Dyn.* **53** 4911–35
Whiteman C D, Zhong S, Shaw W J, Hubbe J M, Bian X and Mittelstadt J 2001 Cold pools in the Columbia Basin *Weather Forecast.* **16** 432–47
Wood A W and Lettenmaier D P 2006 A test bed for new seasonal hydrologic forecasting approaches in the western United States *Bull. Am. Meteorol. Soc.* **87** 1699–712
Wood A W, Maurer E P, Kumar A and Lettenmaier D P 2002 Long-range experimental hydrologic forecasting for the eastern United States *J. Geophys. Res.* **107** ACL6-1–15
Xing L, Li L, Gong J, Ren C, Liu J and Chen H 2018 Daily soil temperatures predictions for various climates in United States using data-driven model *Energy* **160** 430–40

Yourek M, Liu M, Scarpare F V, Rajagopalan K, Malek K, Boll J, Huang M, Chen M and Adam J C 2023 Downscaling global land-use/cover change scenarios for regional analysis of food, energy, and water subsystems *Front. Environ. Sci.* **11** 1055771

Zarekarizi M, Rana A and Moradkhani H 2018 Precipitation extremes and their relation to climatic indices in the Pacific Northwest USA *Clim. Dyn.* **50** 4519–37

Zhang J, Guan K, Fu R, Peng B, Zhao S and Zhuang Y 2023 Evaluating seasonal climate forecasts from dynamical models over South America *J. Hydrometeorol.* **24** 801–14

Zheng D, Hunt E R and Running S W 1993 A daily soil temperature model based on air temperature and precipitation for continental applications *Clim. Res.* **2** 183–91