BAMS Article

Advances in the Application and Utility of Subseasonal-to-Seasonal Predictions

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ABSTRACT: The subseasonal-to-seasonal (S2S) predictive time scale, encompassing lead times ranging from 2 weeks to a season, is at the frontier of forecasting science. Forecasts on this time scale provide opportunities for enhanced application-focused capabilities to complement existing weather and climate services and products. There is, however, a "knowledge–value" gap, where a lack of evidence and awareness of the potential socioeconomic benefits of S2S forecasts limits their wider uptake. To address this gap, here we present the first global community effort at summarizing relevant applications of S2S forecasts to guide further decision-making and support the continued development of S2S forecasts and related services. Focusing on 12 sectoral case studies spanning public health, agriculture, water resource management, renewable energy and utilities, and emergency management and response, we draw on recent advancements to explore their application and utility. These case studies mark a significant step forward in moving from *potential* to *actual* S2S forecasting applications. We show that by placing user needs at the forefront of S2S forecast development—demonstrating both skill and utility across sectors—this dialogue can be used to help promote and accelerate the awareness, value, and cogeneration of S2S forecasts. We also highlight that while S2S forecasts are increasingly gaining interest among users, incorporating probabilistic S2S forecasts into existing decision-making operations is not trivial. Nevertheless, S2S forecasting represents a significant opportunity to generate useful, usable, and actionable forecast applications for and with users that will increasingly unlock the potential of this forecasting time scale.

KEYWORDS: Ensembles; Forecast verification/skill; Climate services; Decision support; Emergency preparedness; Societal impacts

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This paper presents a global community exploration of the application and utility of S2S predictions, comprising 12 case studies from across public health, agriculture, water resource management, energy and utilities, and emergency management.

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The subseasonal-to-seasonal (S2S) predictive time scale, encompassing forecast ranges from 2 weeks to a season, is a rapidly maturing discipline. The S2S time scale is a frontier of forecasting science, with emerging recognition for both the need and the potential utility of forecasts on this time scale (White et al. 2017; Merryfield et al. 2020; Mariotti et al. 2020). It is now over a decade since Brunet et al. (2010) recommended that the weather and climate communities, under the auspices of World Weather Research Programme (WWRP) and World

Climate Research Programme (WCRP), collaborate to jointly tackle the challenge of providing skillful and useable S2S forecasts. Significant advancements have been made in this time, including the joint WWRP–WCRP Subseasonal to Seasonal Prediction Project[1] (Robertson et al. 2018), which is advancing the science in identifying and simulating key sources of S2S predictability and identifying "windows of opportunity" (Vitart 2014; Mariotti et al. 2020), quantifying and reducing inherent uncertainties, and working toward their future operationalization (Robertson et al. 2014; Vitart et al. 2017; Lang et al. 2020). As S2S prediction science continues to mature, the availability of extended-range forecasts provides opportunities for enhanced application-focused capabilities to complement existing services and develop new ones. Applications of S2S forecasts are increasingly being explored and assessed across a range of sectors (White et al. 2017), with efforts also underway to test their application in real time through the S2S Real-Time Pilot Initiative[2] (Robbins 2020).

[1] WWRP–WCRP "Subseasonal to Seasonal Prediction Project" (http://s2sprediction.net/).

[2] S2S Real-Time Pilot Initiative (http://s2sprediction.net/xwiki/bin/view/dtbs/RealtimePilot).

There remains, however, a "knowledge–value" gap, where evidence of the potential socioeconomic benefits of S2S forecasts supported by demonstrations of their utility across a number of sectors, has been limited to date. The 2018 international conference on S2S prediction in Boulder, reported in Merryfield et al. (2020), brought together research, operational prediction, and application expertise to help identify such gaps and provide pathways to address them. Several recommendations were identified for action, including the creation of a summary of application-focused S2S case studies that highlight past and ongoing projects to encourage and promote better engagement with end users and stakeholders. As user needs vary greatly between different sectors and regions, the wider community is increasingly working together on the cogeneration of S2S predictions, yet such application-focused studies are typically either reported as a "side story" to S2S predictability studies, or are simply not publishable in their own right. However, to guide further user-driven decision-making products and support the continued development and utility of S2S forecasts and related services, these efforts need to be catalogued and widely disseminated.

This study is the first coordinated global community effort at summarizing the experiences of application-relevant forecasts on the S2S time scale across sectors and regions. Focusing on 12 sectoral S2S application case studies spanning the public health, agriculture, water resource management, energy and utilities, and emergency management and response domains (Table 1), we draw on recent advancements to explore the use and utility of S2S predictions and demonstrate how they can be employed to benefit society. We explore common challenges and learnings, and why it is appropriate to integrate S2S forecasts with other predictive, verification, and risk-based systems for various decision-making purposes to seamlessly extend the forecast horizon. Through this collective exploration of existing applications, we aim to unlock the potential of S2S predictions.

Sectoral case studies

Public health. Public health is a key sector for the development and application of S2S forecasts, where decisions over extended-range forecasting time scales are directly contributing to positive health outcomes (e.g., expected disease outbreaks, morbidity and mortality predictions, poverty, and nutrition indicators). The benefits are perhaps greatest in regions where climate-sensitive diseases pose a continuous threat to the lives and livelihoods of millions of people (White et al. 2017). In this section, we explore three diverse applications of S2S predictions in the public health domain, including mortality predictions during extreme weather events in the United Kingdom, malaria occurrence in Nigeria, and an early-action system for acute undernutrition in Guatemala.

Table 1. Description of sectoral case studies with notable prior or related studies where applicable. Note that not all case studies are based on previously published work; for some, this is the first time they have been documented (shown as long dashes). In other cases, such as study 2 and study 4, the studies listed describe key motivations, partially related components of the case study, or prediction of events different to that of the main study theme and should not be taken as a more complete account of the case study.

Description	Sector	S2S application/product	Prior or related studies
1) Mortality predictions during extreme cold weather events in the United Kingdom	Public health	Cold-wave mortality	Charlton-Perez et al. (2019), Huang et al. (2020)
2) Malaria occurrence prediction in Nigeria	Public health	Malaria prediction using a vector-borne disease model	Tompkins and Ermert (2013), Asare et al. (2016) (both related to the VECTRI model)
3) An early-action system for acute undernutrition in Guatemala	Public health	Early-action system for food security	—
4) Season onset timing in Kenya	Agriculture	Season onset timing for crop yield and food security	Kilavi et al. (2018), MacLeod et al. (2021a) (both primarily related to heavy rain events in the study region)
5) Agricultural management in Bihar	Agriculture	Monsoon signal for small-holder farmers	Robertson et al. (2019), Acharya (2018) (verification of district-level hindcasts and real-time forecasts in 2018)
6) Water management in Ceará State	Water resource management	Reservoir inflows for water management	—
7) Water management in the western United States	Water resource management	Atmospheric rivers, ridging events, and precipitation	DeFlorio et al. (2019a,b), Gibson et al. (2020a,b)
8) A decision-support tool for the renewable energy sector	Renewable energy and utilities	Renewable energy decision-support tool	Soret et al. (2019)
9) Hydropower inflow predictions in Scotland	Renewable energy and utilities	Reservoir inflows for hydropower	Graham et al. (2021)
10) Scenario planning for hydropower operations in Tasmania, Australia	Renewable energy and utilities	Low-rainfall scenarios for hydropower	—
11) Weather risk management for U.K. fixed-line telecommunications	Renewable energy and utilities	Telecommunication fault-rate maintenance scheduling	Brayshaw et al. (2020)
12) European flood forecasting	Emergency management and response	Hydrological flood forecasting	Wetterhall and Di Giuseppe (2018)

Mortality predictions during extreme cold weather events in the United Kingdom (authors: Andrew J. Charlton-Perez, Christian M. Grams, Dominik Büeler, Robert W. Lee, W. T. Katty Huang, and Ting Sun). Extreme weather, such as cold and heat waves, often increases human mortality in temperate countries (e.g., Anderson and Bell 2009; Ryti et al. 2016). Anomalous mortality can be particularly high during events that last several weeks, meaning mortality predictions on S2S time scales are of specific interest. Here we examine the application of S2S forecasts for predicting mortality in the United Kingdom during a recent cold wave event in 2018, colloquially "The Beast from the East," by combining a statistical mortality model (Vicedo-Cabrera et al. 2019) with 2 m temperature (T2m) and weather regime (Michelangeli et al. 1995; Grams et al. 2020) predictions from S2S forecasts. The event was characterized by two intense cold waves peaking on 28 February and 18 March 2018 in the United Kingdom (Fig. 1a), which were both associated with a cold Greenland blocking weather regime (cf. Grams et al. 2017) (Fig. 1c). The statistical model, estimating temperature-related mortality from observed T2m, indicates more than 300 mortalities per day attributable to the event's cold temperatures (Fig. 1b), totaling an estimated burden of 9,568 deaths during March that largely exceeded the 20-yr average. During the peak of the cold wave in the first week of March, the excess daily mortality compared to the 20-yr average (cf. differences of blue lines in Fig. 1b) matches the mortality attributable to cold weather (black line in Fig. 1b).

We explore how far in advance the European Centre for Medium-Range Weather Forecasts (ECMWF) extended-range (Vitart 2004; Vitart et al. 2008, 2014) S2S ensemble forecasts,[3] available from the S2S global repository, indicated the first cold wave to occur at the end of February. The T2m forecast converges toward a cold scenario after the 13 February initialization, which is indicated by the substantial drop in the ensemble mean and the gradual reduction in ensemble spread (Fig. 1d). The consideration of weather regime forecasts provides additional insight into the predictability of the large-scale conditions determining the cold temperatures. Both Scandinavian blocking and Greenland blocking probabilities were relatively high in the S2S forecasts from 5 February (Fig. 1e); as these regimes typically coincide with colder-than-average temperatures in the United Kingdom, the forecast thus indicates a possible cold scenario up to 3 weeks in advance. Nevertheless, the regime prediction is rather uncertain until a sudden stratospheric warming (e.g., Lee et al. 2019) occurs on 12 February, indicated by the gradual increase in the probability for the two blocking regimes and the decrease in the probability for the typically mild cyclonic regimes.

These results reveal the potential for predicting mortality on an operational basis when combining a statistical mortality model with S2S forecasts. Our analysis shows that a sophisticated combination of both temperature and weather regime information from S2S forecasts as predictors might generate useful operational mortality forecasts, such as national or regional mortality exceedance probabilities, that could support National Health Service (NHS) decision-making (e.g., NHS Improvement 2018). This builds on previous investigations that systematically linked weather regimes with the likelihood of high mortality (Charlton-Perez

[3] ECMWF extended-range forecasts (www.ecmwf.int/en/forecasts/documentation-and-support/extended-range-forecasts).

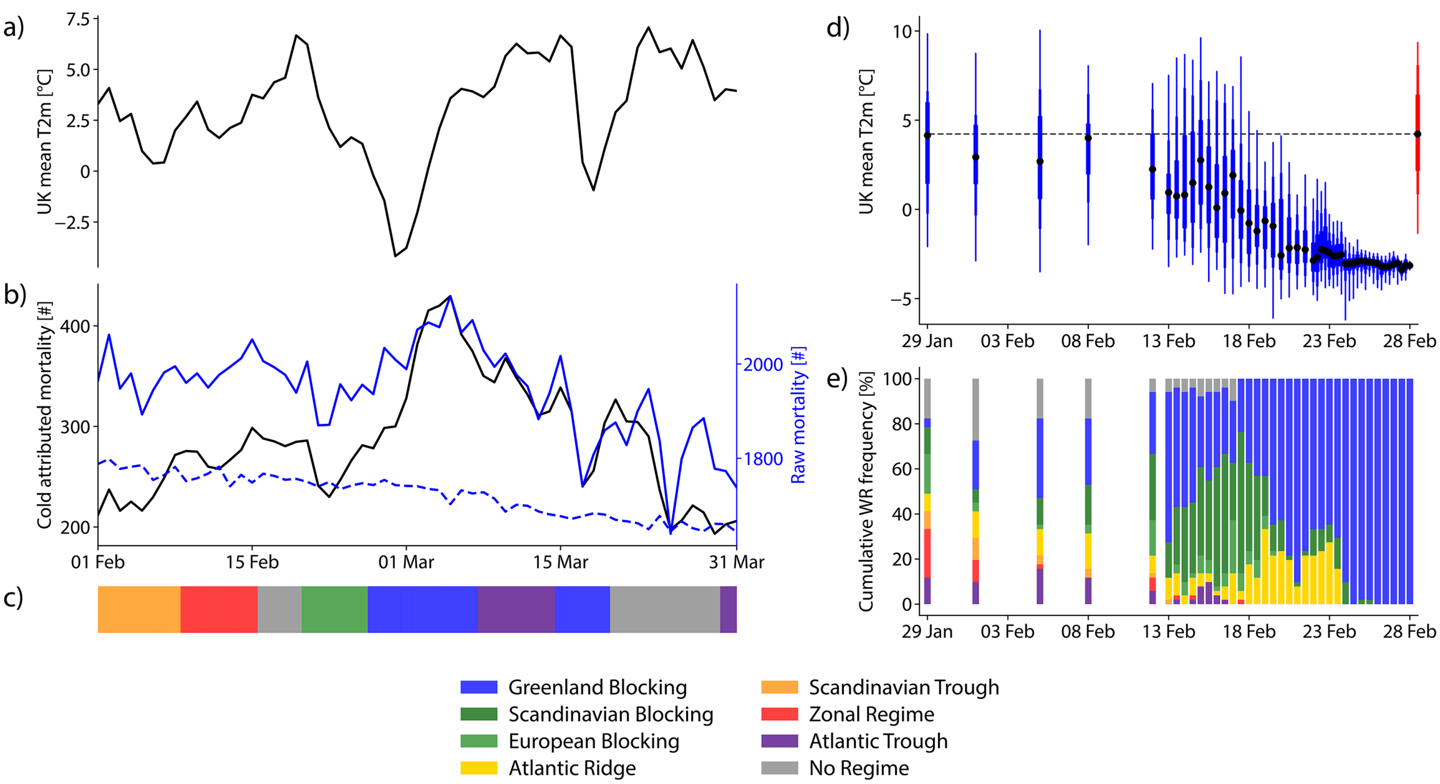

Fig. 1. Mortality during extreme cold weather events in the United Kingdom, showing (a) HadUK-Grid mean 2-m temperature (T2m) observations for the two cold waves in February and March 2018; (b) estimated U.K. mortality attributable to the cold weather (black line), observed raw total mortality (blue line), and 1998–2017 average (dashed line); (c) observed weather regime evolution (based on ECMWF analysis) during the same period for a life cycle definition of seven weather regimes (cf. Grams et al. 2017); (d) ECMWF extended- and medium-range U.K. mean T2m ensemble forecasts valid for 0000 UTC 28 Feb 2018 (*y* axis) as a function of forecast initial time (*x* axis), with the blue box-and-whiskers showing the 99th, 75th, 50th, 25th, and 1st percentiles, the black dots the control forecast, and the red box-and-whiskers the model climatology for 0000 UTC 28 Feb 2018 (plotting tool provided by Linus Magnusson, ECMWF); (e) as in (d), but for the predicted probabilities of the active weather regime (regime projection > 1 sigma) in the ensemble indicated by the corresponding color (gray indicates the "no regime" category representing an atmospheric state not resembling any of the seven regimes).

et al. 2019; Huang et al. 2020). Engagements with national health boards and public health agencies in the United Kingdom through webinars and one-on-one interviews indicate interest by stakeholders (particularly once the capability of S2S forecasts is clearly communicated).[4] However, the lack of operational planning focused on S2S time scales and health services' limited capacity to react to moderate probability events are challenges that need to be overcome.

[4] "Addressing the resilience needs of the U.K. health sector: climate service pilots" project, part of the U.K. Climate Resilience Programme (www.ukclimateresilience.org/projects/addressing-the-resilience-needs-of-the-uk-health-sector-climate-service-pilots/).

Malaria occurrence prediction in Nigeria (authors: Eniola Olaniyan, Elijah A. Adefisan, Ahmed A. Balogun, John A. Oyedepo, and Kamoru A. Lawal). Malaria is one of the largest contributors to disease in Nigeria. Humans contract the malaria parasite through mosquitos (Githeko and Ndegwa 2001; Jones and Morse 2010), the distribution and survival of which is largely influenced by environmental and atmospheric factors such as temperature and rainfall (Abiodun et al. 2016; Asare and Amekudzi 2017). The vector-borne disease community model of International Centre for Theoretical Physics (ICTP), Trieste (VECTRI) (Tompkins and Ermert 2013), a distributed open-source dynamical malaria model that resolves the growth stages of the egg–larvae–pupa in addition to the gonotrophic and the sporogonic cycles, has demonstrated predictive skill over different regions in Africa using both modeled and observed climatic drivers (Tompkins and Ermert 2013; Asare et al. 2016; Asare and Amekudzi 2017). The Nigerian Meteorological Agency (NiMet) and the National Weather and Hydrological Centers (NWHC) are collaborating with researchers globally[5] to develop a sustainable African weather forecasting and application system. Under these auspices, NiMet has developed a real-time monitoring system based on temperature and rainfall conditions for malaria transmission and has been issuing early warning forecasts for the potential occurrence of malaria on the S2S time scale (2–6 weeks) using VECTRI. Despite the potential benefits of forecasting malaria distribution in West Africa on the S2S time scale (Olaniyan et al. 2018), the utility of S2S forecasts in the operational early warning system has yet to be explored in this region.

Here we explore the potential benefits of S2S forecasts for the hyperendemic malaria zones in Nigeria using the VECTRI model. Observed daily temperature and rainfall datasets were obtained from the Nigerian Meteorological Agency, together with ensemble hindcasts from ECMWF (VarEPS, based on IFS version 41r1), China Meteorological Administration (CMA) (BCC-CPS-S2Sv1 version 1) and the Met Office (UKMO) (GloSea4) from the S2S global repository. Clinically reported malaria cases were obtained from of the "Roll Back Malaria" program.[6] Two evaluations were undertaken between 2013 and 2017: first, reported (observed) malaria cases were used to evaluate the skill of the VECTRI model using an estimated entomological inoculation rate (EIR) as a measure of exposure to infectious mosquitoes; second, the skill of the S2S predictions in driving the VECTRI model. The EIR from the observed-driven VECTRI model was then compared with the EIR from the S2S-driven VECTRI model. Preliminary results show that the estimated EIR from the S2S-driven VECTRI model (and as also seen in the observed-driven VECTRI model) increases from the Gulf of Guinea to the Sahel as a function of the population profiles, with the ensemble means of both the CMA and ECMWF S2S ensembles showing correlations with the observed-driven EIR ranging from 0.7 to 0.85. A correlation of approximately 0.9 was found over all regions from the UKMO model.

[5] "GCRF African SWIFT" project (https://africanswift.org/).

[6] "Roll Back Malaria" program (https://endmalaria.org/).

Despite regional model biases, the findings show the use of S2S forecasts in a malaria early warning system to be realistic, supporting early identification of malaria hyperendemic areas, as well as prompt mobilization and intervention by the responsible health department, at least a month before the outbreak of the disease. However, the integration of S2S predictions into operational early warnings has its challenges, with real-time warnings only shared with "Roll Back Malaria" and Nigeria's Ministry of Health, reducing the potential for coproduction due to lack of feedback from users.

An early-action system for acute undernutrition in Guatemala (authors: Carmen González Romero, Ángel G. Muñoz, Ana María García-Solórzano, Xandre Chourio, and Diego Pons). The World Food Programme indicates the prevalence of stunting in children younger than 5 years old in Guatemala reaches 46.5% nationally, with peaks of 90% in the hardest-hit municipalities [World Food Programme (WFP); WFP 2020]. Food insecurity in Guatemala is driven by both climate and nonclimate factors, and its pathways are often complex (Beveridge et al. 2019). Additionally, 70% of the impoverished population in Guatemala lives in rural areas, where agricultural production is mainly rain fed (Lopez-Ridaura et al. 2019). Climate factors contribute to acute undernutrition in children under 5, especially in the dry corridor, a region already highly vulnerable to climate-related impacts.

Since September 2018, the National Secretariat for Food Security and Nutrition (SESAN) has been using a monitoring system called "Sala Situacional," to allow for an early-action system for food security. Some limitations, though, have been identified: the expert-based criteria and the survey-based method are labor intensive, and its outputs are more aligned with a monitoring system than an early warning system. These challenges limit the use of the system as a forecasting tool, since it does not provide enough forecast lead time for decision-makers to maneuver and distribute the resources available to better deal with food insecurity. To address these issues, an objective, automated forecast system that incorporates S2S forecasts that supports SESAN's current monitoring system is presented and discussed. Using the "Sala Situacional" approach as the base, the International Research Institute for Climate and Society (IRI) worked with SESAN to codevelop a system to forecast the number of cases of acute undernutrition for children under 5 per department.

The forecast system follows the NextGen methodology (Muñoz et al. 2019, 2020; WMO 2020) and promotes ecosystems of climate services (a climate services landscape that increases resilience to crises via optimal orchestration of available resources; see Goddard et al. 2020), considering the role of both climate and nonclimate factors in statistical models of increasing complexity. Observed total rainfall (or lack thereof) can be used as a predictor of acute undernutrition in children under 5, with lags (or lead times) ranging from 3 to 6 months depending on the geographical location. A combination of observed rainfall and calibrated rainfall forecasts produced by the S2S prediction project (Vitart and Robertson 2018) were found to provide monthly predictions of acute undernutrition for up to 5 months in advance—a lead time identified by SESAN as useful since it would allow the national government to deploy resources effectively. Calibration was found to be required in order to guarantee that the S2S forecasts could reproduce the observed (statistical) characteristics of acute undernutrition. The best predictive models were found to exhibit good forecast discrimination (as measured by the two-alternative forced-choice metric; Mason and Weigel 2009) for almost all departments in Guatemala, with the system forecast skill being highest over the eastern dry corridor (Fig. 2).

Although the interannual and seasonal characteristics (e.g., timing) of acute undernutrition are well captured by models using rainfall as the only predictor, the inclusion of nonclimate predictors, such as the price of maize, beans, and coffee, and user-defined probability of exceedance of thresholds, were found to increase forecast skill and usability. In other words, the inclusion of nonclimate predictors, which are consistent with the conceptual model of drivers for food security in Guatemala developed by SESAN, helps to reproduce the main features beyond the annual cycle and interannual variability of the undernutrition time series by better capturing peaks at monthly time scales.

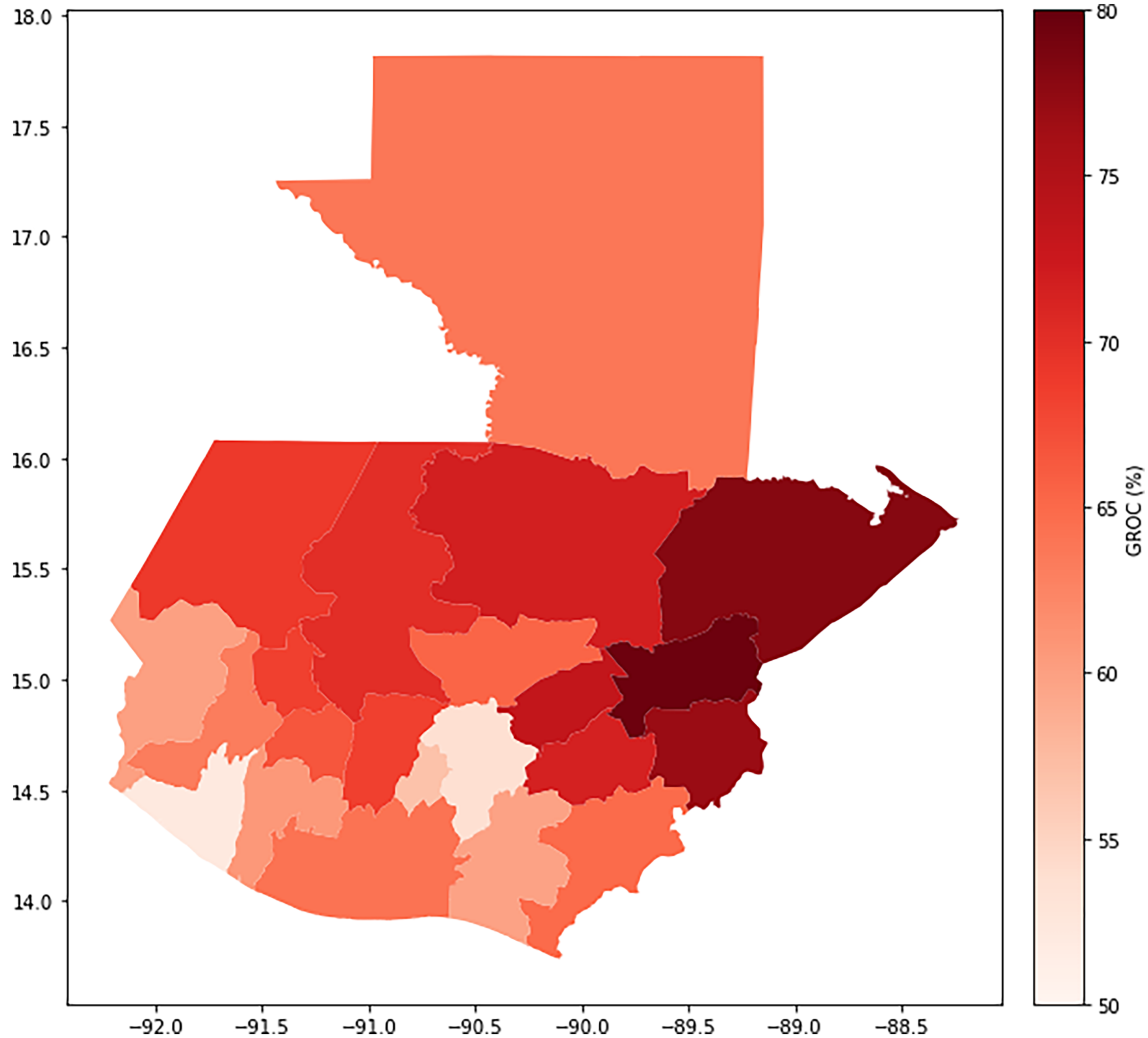

Fig. 2. **Skill assessment for the early-action system for acute undernutrition in Guatemala, showing the generalized relative operating characteristics (GROC) skill metric for cases of acute undernutrition for children under 5 years old in each department in Guatemala. GROC measures forecast discrimination, or how well the system discriminates between different categories (below-normal, normal, or above-normal values). This NextGen forecast system uses total monthly rainfall as a predictor of monthly cases of acute undernutrition for children under 5 years old. Values ~50% indicate discrimination as good as climatology, and values above (below) 50% indicate better (worse) discrimination than climatology. The skill shown corresponds to the average skill for the following target month (example, January, if the forecast is made in December), and considers the different lag/lead times between rainfall and acute undernutrition for each department.**

Agriculture. The agriculture sector is already one of the most advanced in terms of using weather forecasts and seasonal outlooks to support operational decisions (Clements et al. 2013). S2S forecasts are starting to provide additional decision-relevant information to support the timing of crop planting, irrigation scheduling, and harvesting, particularly in water-stressed regions. In this section, we explore agricultural applications of S2S forecasts of season onset timing in Kenya and agricultural management in India.

Rainy Season onset timing in Kenya (authors: Richard J. Graham, Mary Kilavi, David MacLeod, George Otieno, Martin C. Todd, and Stella Aura). Approximately 98% of Kenya's agricultural systems are rain fed (Ministry of Agriculture, Livestock and Fisheries 2017). Prediction of rainy season onset timing is therefore a key requirement for assisting farmers in timely land preparation and planting. The Kenya Meteorological Department (KMD) provides season onset predictions based on inferences from statistical and dynamical seasonal forecast systems.

A real-time trial of the utility of S2S forecasts was undertaken by KMD to assess their usefulness in strengthening these operational onset predictions, at lead times of up to 4 weeks, for improved agricultural decision-making, crop yield, and food security. The trial was part of the "Forecast-based Preparedness Action" (ForPAc) project,[7] conducted over five rainy seasons in the period 2018–20.

Met Office GloSea5 (MacLachlan et al. 2015) S2S forecasts[8] were provided to KMD in the form of weekly guidance bulletins with a supporting narrative. KMD used the guidance primarily for preoperational evaluation purposes; however, in some cases where confidence in the predictions was high (e.g., consistency over consecutive lead times), the information was used in operational forecasts to the Kenyan public, including farming communities. The bulletin was provided weekly throughout each rainy season, beginning 3–4 weeks ahead of the climatological start of the season. Products included maps of forecast probabilities for tercile categories of weekly averaged precipitation at weeks 1–4 ahead and forecasts of the Madden–Julian oscillation (MJO), a key driver of subseasonal rainfall in the region (Berhane and Zaitchik 2014), using phase and amplitude diagrams (Wheeler and Hendon 2004). The prediction skill and GloSea5's representation of the MJO phase teleconnections, which are generally well captured (MacLeod et al. 2021a), were also provided. Two March–May (MAM) rainy seasons and three October–December (OND) rainy seasons were sampled in the trial, each containing marked rainfall anomalies, including one with a widespread notable delay in rainfall onset (MAM 2019) and one with a marked early rainfall onset (OND 2019). In both of these highly impactful cases, predicted tercile category rainfall probabilities for the early weeks of the seasons were consistent with the observed onset anomaly, including at week 4 of early forecasts, with the forecast signal strengthening as the lead time shortened.

In the case of late onset (MAM 2019) the GloSea5 forecasts were used by KMD to update the previously issued seasonal forecast to delay the expected onset date by 3–4 weeks, thus providing the farming communities with improved information for scheduling of planting. The trial also documented examples of good predictability beyond week 2 for intraseasonal periods with rainfall above the upper tercile, generally when the MJO was predicted to be active in a rainfall-favoring phase. This supports the expectation that while, on average, skill drops sharply beyond 2 weeks lead time (MacLeod et al. 2021a), an active MJO can provide a "window of opportunity" for longer-lead warning (Kilavi et al. 2018). These results give clear indications that S2S predictions can assist KMD in strengthening its season onset predictions. Further, as part of a seamless approach such S2S predictions can add value to existing heavy rain hazard warnings (MacLeod et al. 2021b) by enabling early "horizon scanning" for upcoming heavy rain events and, potentially, by extending the warning lead time.

[7] "Toward Forecast-based Preparedness Action" (ForPAc) project (www.shear.org.uk/research/ForPAc.html).

[8] Met Office GloSea5 seasonal prediction system (www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/climate-models/glosea5).

Agricultural management in Bihar, India (authors: Nachiketa Acharya, Andrew W. Robertson, and Lisa Goddard). A probabilistic S2S forecast system was developed for the state of Bihar, one of the most climate-sensitive states in India. Precipitation forecasts were issued in real time during the June–September 2018 monsoon to explore the potential value of the S2S forecasts for small-holder farmers who operate farms of less than 5 acres.[9] Four districts were selected—two in the northern plains (flood prone) and two in the southern plains (drought prone). The project was a collaboration between IRI, The University of Arizona, Indian Meteorological Department (IMD), Regional Integrated Multi-Hazard Early Warning System for Africa and Asia (RIMES), and the government of Bihar.

[9] "International Research Applications Project" (IRAP) project (https://cpo.noaa.gov/Meet-the-Divisions/Climate-and-Societal-Interactions/IRAP).

Real-time National Centers for Environmental Prediction (NCEP) CFSv2 (Saha et al. 2014) S2S forecasts,[10] calibrated against observed gridded rainfall fields from the IMD using canonical correlation analysis, were generated each month during June–September 2018. The forecasts were limited to 2 weeks in advance as the calibrated probabilistic forecasts for weeks 3–4 were concentrated around climatological probabilities (0.33), which was a limitation of the forecast's potential utility. The 2018 monsoon recorded a large rainfall deficit over Bihar (~25% below its long-term average) with 11 of the 18 weeks registering deficits. The real-time S2S forecast captured the signal of the weaker monsoon in 2018 over Bihar, including the delayed monsoon onset and the observed break phase in August at the week 2 lead time. The quantitative verification of the district-level hindcasts and real-time forecasts over the monsoon season in 2018 is evaluated in Robertson et al. (2019) and Acharya (2018).

To assess the usability and utility of the real-time S2S forecasts to the user community, "field schools" involving ~300 farmers were conducted prior to the monsoon in May 2018. The curriculum extended beyond the presentation of climate forecasts to include contextual information on climate systems and variability, the technology of forecasting, and the range of adaptations available under specific forecast conditions. During the monsoon season, real-time forecasts were displayed through a virtual "map room."[11] Text summaries based on the forecast maps were sent to two of Bihar's state agricultural universities (SAUs)—one for the flood districts and the other for the drought districts—who translated the forecast summary into the local language (Hindi). These were disseminated through a nongovernmental organization (NGO) directly to farmers via text message (Fig. 3). A user survey was conducted at the end of the 2018 monsoon season across the four districts to find out how farmers used the S2S forecasts for farm-level planning and decisions (October 2018). The survey found that almost half of the farmers that participated in the field school used the forecasts to change their farming practices and irrigation schedules compared to previous years. Farmers used the late arrival of the 2018 monsoon (~16 days), which was well captured across Bihar by the S2S forecast, to delay the sowing of rice and other crops until closer to the monsoon onset. They also changed to a less water-demanding variety of paddy rice in response to expectations of a weaker monsoon.

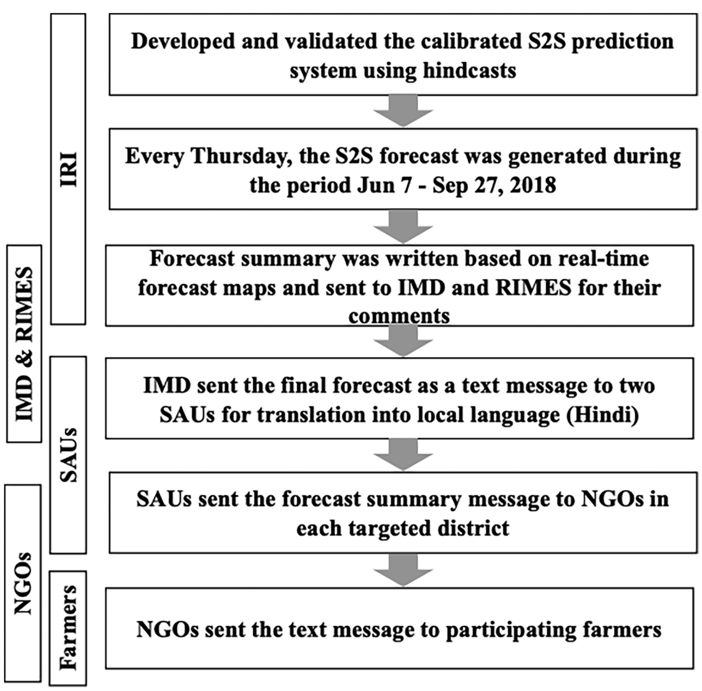

Fig. 3. Agricultural management in Bihar, showing a flowchart of the forecast generation and dissemination. Interactions between the institutions and actors involved are indicated. NGO: nongovernmental organization; IMD: India Meteorological Department; RIMES: Regional Integrated Multi-Hazard Early Warning System for Africa and Asia; SAU: state agricultural universities; IRI: International Research Institute for Climate and Society.

Water resource management. Forecast information on S2S time scales is crucial for managing water resources, especially in times of flood or drought.

[10] NCEP CFSv2 seasonal forecasts (www.cpc.ncep.noaa.gov/products/CFSv2/CFSv2_body.html).
[11] IRI Bihar Climate Maproom (http://iridl.ldeo.columbia.edu/maproom/Agriculture/bihar.html#tabs-2).

Combined S2S meteorological, climatological, and hydrological forecast systems provide valuable water resource information to reduce economic, social and environmental damages (White et al. 2015), particularly in climate-sensitive regions (Ralph et al. 2020). Here, we explore water resource management S2S forecasting applications in Brazil and the western United States.

Water management in Ceará State, Brazil (authors: Francisco C. Vasconcelos Jr., Dirceu S. Reis Jr., Caio A. S. Coelho, and Eduardo S. P. R. Martins). A combination of seasonal climate and hydrological models has been used for ~15 years by Ceará State Meteorology and Water Resources Foundation (FUNCEME) and Ceará State Water Resources Management Company to support reservoir operations by forecasting inflows for key regional basins in Brazil, for both water resources planning and drought risk response. Current efforts on improving the seasonal forecast system include the use of an interannual statistical model and both global and regional dynamical models, but forecast use on S2S time scales is still in its infancy (Fig. 4a). The Interagency Drought Contingency Group (IDCG) is responsible for monitoring and predicting the State drought status within a 30-day planning horizon for 184 municipalities, including triggering emergency warnings and responses for municipalities at risk. In the absence of operational S2S forecasts, these 30-day-ahead scenarios are based on seasonal forecasts updated monthly.

In this study, ECMWF S2S precipitation forecasts from the S2S global repository were evaluated to assess their performance at producing inflow predictions for the Orós reservoir in Ceará State up to 45 days ahead between January and April 2018 (Fig. 4). The verification study focuses on 15 weekly forecasts as if issued every Thursday from 18 January to 26 April. The quality of these forecasts has been evaluated at three time-mean horizons, 15, 30, and 45 days ahead from the initialization date. ECMWF S2S forecasts initialized once a week during the January–April 1998–2017 period were used to feed a hydrological model to produce flow forecasts into the Orós reservoir. These forecasts were then postprocessed through an empirical quantile mapping procedure using observed (1998–2017) flows to generate mean flow forecasts for 2018. All 11 available ECMWF hindcast ensemble members were used for postprocessing. Figure 4b shows the correlation between the 11-member ensemble mean flow forecasts and the corresponding observations computed over the 1998–2017 hindcast period for each initialization date and time mean horizons. Correlation values between 0.70 and 0.90 indicate reasonable forecast association ability. Figure 4c shows boxplots of 51-member postprocessed ensemble flow forecasts for 2018 (for 30-day means) along with the observed flow and climatological 50th and 80th percentiles (dashed lines), which provided a good description of the observed flow for most initialization dates.

These results illustrate the utility of inflow forecasts based on S2S precipitation forecasts in addition to the existing seasonal flow forecast system to support water management decisions and the triggering of emergency responses (e.g., construction of pipelines and wells) for municipalities at risk in Ceará State. Although this study illustrates the utility of S2S forecasts to guide IDCG's decisions, additional activities are needed to demonstrate their long-term value, such as one-on-one meetings with IDCG members to provide details about the developed S2S time-scale inflow forecasting system, an assessment of past performance of this system, and the opening of a two-way dialogue with users to enable suggestions for future improvements and product codevelopment.

Water management in western United States (authors: Michael J. DeFlorio, Peter B. Gibson, Duane E. Waliser, F. Martin Ralph, Michael L. Anderson, and Luca Delle Monache). The Center for Western Weather and Water Extremes (CW3E) and the National Aeronautics

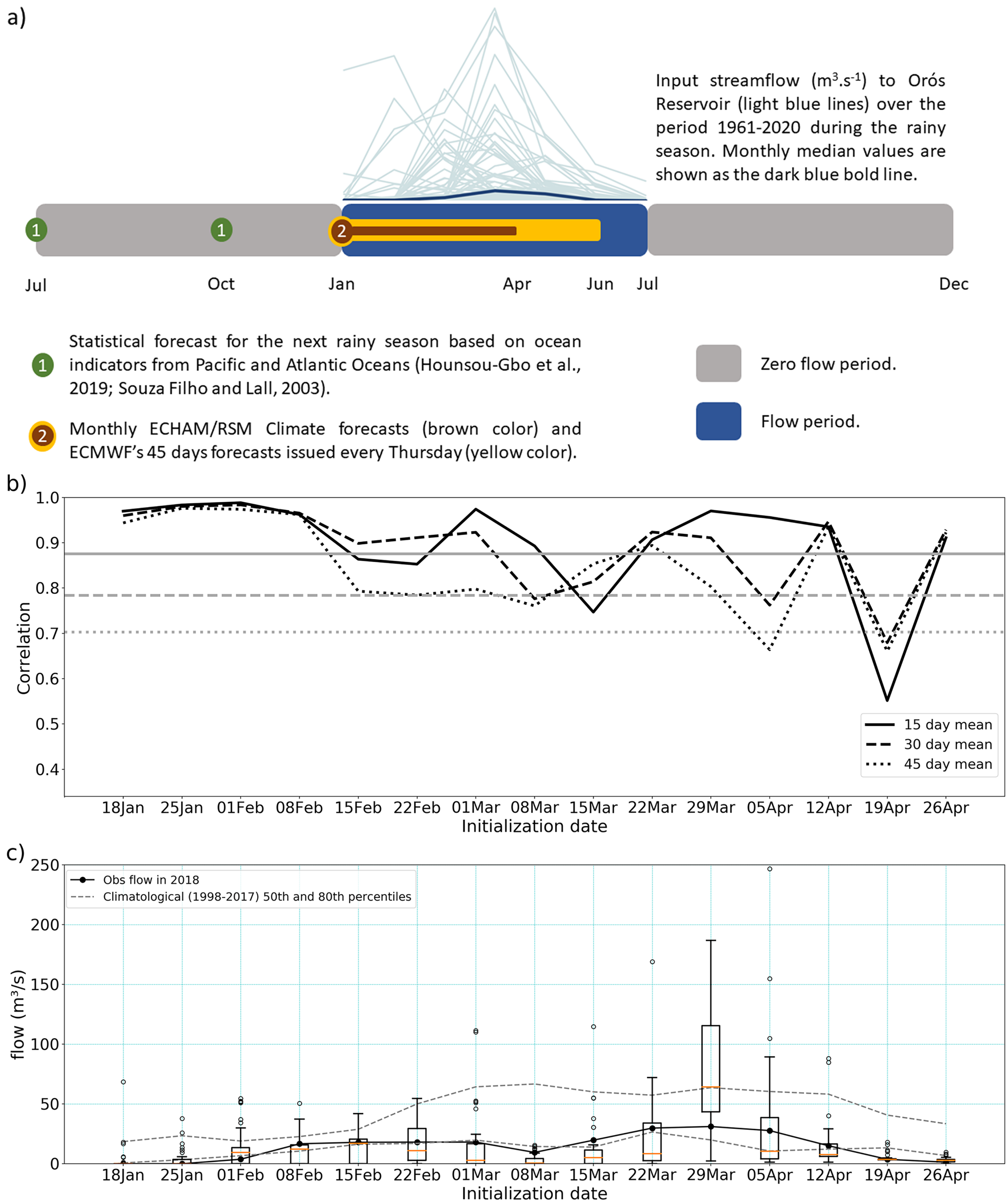

Fig. 4. **Water management in Ceará State, showing (a) Ceará State flow forecast system schematic depicting January–April (rainy period) forecasts. Produced with 1) statistical models using previous July and October equatorial Pacific and Atlantic indices, and 2) daily precipitation forecasts from dynamical global and regional seasonal forecast models updated monthly from January to April for feeding a hydrological model to generate monthly flow forecasts (brown), and with ECMWF subseasonal precipitation forecasts produced every Thursday for the following 45 days for feeding a hydrological model to generate daily flow forecasts during the January–May period (yellow). The blue (gray) bar illustrates the wet (dry) period; (b) correlations between cross-validated 11-member ensemble-mean flow forecasts postprocessed through empirical quantile mapping and the corresponding observed flow over the 1998–2017 hindcast period for three time horizons (15-, 30-, and 45-day means). Flow forecasts were produced with a hydrological model (Lopes 1999) fed with daily precipitation ECMWF S2S forecasts initialized every Thursday (15 dates between 18 Jan and 26 Apr). The solid, dashed, and dotted**

horizontal gray lines represent the correlation values computed aggregating all available forecasts (300 pairs of forecasts and observations) for the three time horizons; (c) 30-day-mean postprocessed flow forecasts for 2018 (boxplots of 51 member ensembles) produced with a hydrological model fed with daily precipitation ECMWF subseasonal forecasts initialized every Thursday (between 18 Jan and 26 Apr). The red line in the boxplots represents the median p_{50} (50th percentile), the upper box border represents the upper quartile p_{75} (75th percentile), and the lower border the lower quartile p_{25} (25th percentile). The whiskers at the top of each box extend to p_{75} + 1.5IQR, where IQR is the interquartile range (p_{75}–p_{25}). The whiskers at the bottom of each box extend to p_{25} – 1.5IQR. Values outside the whiskers are plotted with open circles. The black line represents the 2018 observed flow, and the dashed lines the climatological (1998–2017) 50th and 80th percentiles.

and Space Administration Jet Propulsion Laboratory (NASA JPL), supported by the California Department of Water Resources (CA DWR), formed a partnership to improve the S2S prediction of precipitation to benefit water management in the western United States. The main objective of this team is to produce experimental S2S prediction products for atmospheric rivers (ARs), ridging events, and precipitation, supported by research and hindcast skill assessments. Although the main quantity of interest for stakeholders is total precipitation (i.e., available water), ARs and ridging events are a focal point due to their strong influence on the presence (and absence, respectively) of precipitation in the western United States during wintertime and their intrinsic predictability. The primary sector and stakeholder for which this effort is particularly relevant is western U.S. water resource management and CA DWR, respectively.

A key pillar of this applied research endeavor is to collaborate with CA DWR's stakeholders regarding the target predictand, methodology, and data used for research along with the experimental product display and description for experimental S2S forecast products. Our team, which also includes collaborators at IRI, University of California, Los Angeles, The University of Arizona, and University of Colorado, has interacted regularly with stakeholders from CA DWR to facilitate communication and help with the development of the forecast products. This interaction ensures that the research and forecast product development are meeting the specific needs of end users while maintaining high standards for both quality of research and utility of the forecast products for the applications community. These experimental S2S forecast products, together with continued investment from CA DWR into S2S research, stand to benefit end users at CA DWR by providing information at subseasonal lead times to support flood risk management, emergency response, and situational awareness (DeFlorio et al. 2021).

Figure 5 summarizes two CW3E/JPL experimental S2S applications that utilize data from the S2S global repository: the week 3 AR activity outlook (Fig. 5a) and the weeks 3–4 ridging outlook (Fig. 5b). This figure shows an example of particular forecast for AR activity and ridging made on 21 September 2020. In Fig. 5a, the bottom panel shows the anomaly forecast field (top minus middle panels) for above or below average AR days per week for the 6–12 October week-3 verification period in the NCEP forecast system. In Fig. 5b, forecast probabilities for each ridge type (north, south, and west) during the 5–19 October weeks 3–4 verification period are shown. If >50% of ensemble members in the NCEP forecast system predict above-normal ridge frequency, the right panel maps are displayed to show the likelihood of wetter or drier conditions based on how each ridge type typically influences precipitation (Gibson et al. 2020a). Both outlooks are updated weekly and made available on the CW3E S2S forecast website.[12] Skill assessments of the NCEP and ECMWF hindcasts from the S2S repository are provided in DeFlorio et al. (2019a,b) and

[12] CW3E Subseasonal to Seasonal (S2S) Experimental Forecasts (https://cw3e.ucsd.edu/s2s_forecasts/).

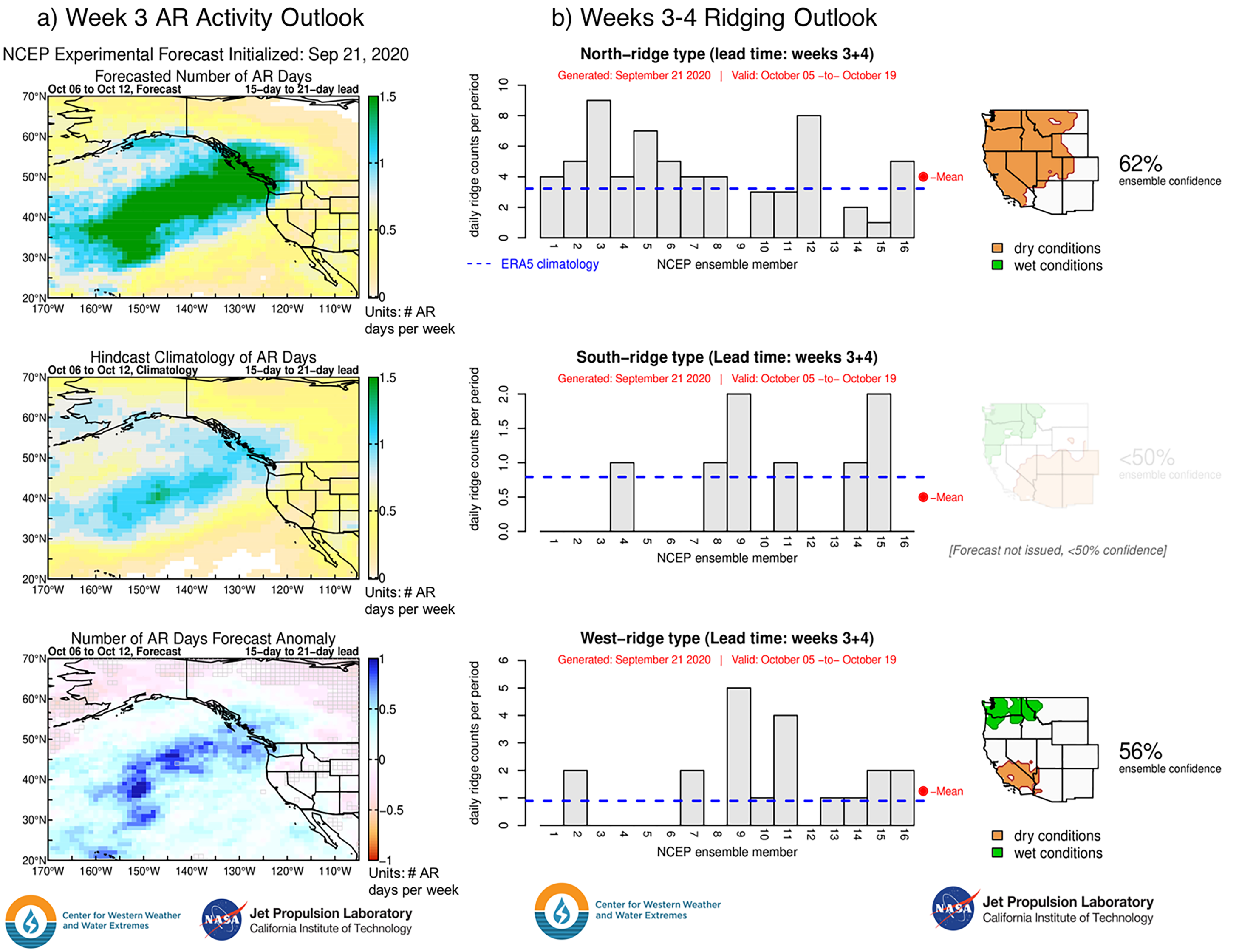

Fig. 5. Water management in western United States, showing (a) CW3E/JPL week 3 AR activity outlook. Forecast initialized 21 Sep 2020 and verified 6–12 Oct 2020. (top) The forecasted number of AR days to occur during the week 3 verification period; (middle) the NCEP hindcast climatology of AR days during the 6–12 Oct week in the hindcast record; (bottom) the anomaly forecast field (top minus middle panels). Hindcast skill assessment provided in DeFlorio et al. (2019a,b). (b) CW3E/JPL weeks 3–4 experimental ridging outlook. Forecast initialized on 21 Sep 2020 and verified 5–19 Oct 2020. (left) Occurrence frequency of each ridge type (bars) compared to climatology (horizontal line) for each of the model ensemble members. (top) North, (middle) south, and (bottom) west ridge forecasts, respectively. (right) If over 50% of the ensemble members predict more ridging than expected (for this time of year), then maps indicate the likelihood of wetter or drier conditions based on how each ridge type typically influences precipitation. We note that summing across ridge types for a given ensemble member does not necessarily equal 14 daily counts as there can be days in the 2-week forecast verifying period where none of the three ridge types are predicted to occur. Methodology for calculating ridge types is provided in Gibson et al. (2020a); hindcast skill assessment is provided in Gibson et al. (2020b).

Gibson et al. (2020b). These forecast products have been regularly consulted by our stakeholders at CA DWR, both in internal CA DWR meetings and in collaborative meetings between CA DWR stakeholders and our research team.

Renewable energy and utilities. Understanding weather-related risk is vital for renewable energy pricing, production, transmission, and usage. Energy demand and risk-based scenarios based on S2S predictions are now being explored to support the management of anticipated energy peaks and other weather-related risks. In this section, we explore an S2S forecast-based renewable energy decision-support tool, hydropower inflow predictions and scenario planning in Scotland and Australia, and weather risk management for telecommunications in the United Kingdom.

A decision-support tool for the renewable energy sector (authors: Andrea Manrique-Suñén, Isadora Christel, Ilaria Vigo, Lluís Palma, Ilias G. Pechlivanidis, and Albert Soret). The S2S4E[13] project explored the usefulness of S2S forecasts to anticipate renewable energy production and demand several weeks to months ahead (Soret et al. 2019). A decision-support tool (DST) that provides S2S predictions of climate variables and renewable energy–related indices was codeveloped with users. The spatial coverage of the majority of the forecasts is global with some products provided for the pan-European domain. The DST is fed with forecasts from the ECMWF S2S forecast system (2-m mean, maximum, and minimum temperature, 10-m wind speed, precipitation, solar radiation, and mean sea level pressure). It provides weekly S2S forecasts for up to 4 weeks lead time via a visual interface that includes a skill score that evaluates the quality of the forecast with respect to a climatological forecast reference (fair-ranked probability skill score for the tercile probabilities and fair Brier skill score for the extreme probabilities; Wilks 2011; Ferro 2014). The raw forecasts are bias adjusted to remove the model mean bias with respect to ERA5 (Hersbach et al. 2020). The computation of a robust climatology is crucial to ensure an effective bias adjustment of subseasonal forecasts (Manrique-Suñén et al. 2020).

[13] "Sub-seasonal to Seasonal climate forecasting for Energy" project (https://s2s4e.eu/dst).

The DST provides forecast indices per energy sector: hydropower (maximum snow and inflows at the catchment scale), wind energy (three capacity factors for three different turbine types), solar energy (capacity factor), and energy balance (electricity demand, wind energy production, and demand minus wind energy production per country). Energy companies use the S2S forecasts to inform operation and maintenance decisions, optimize water levels in the reservoirs, and hedge against climate variability (e.g., by trading energy futures).

The cogeneration and operationalization of the DST involved scientists, designers, and communication and industry specialists. The inclusion of three energy companies as consortium partners [Electricité de France (EDF), EDP Renováveis SA, and Energie Baden-Württemberg AG (EnBW)] provided opportunities for collaboration at all stages of the project, and ensured their needs were addressed in the codevelopment of the DST. In the design phase, user input was crucial to devise a structured, complete, and concise interface. Focus groups, workshops, interviews, usability testing, and eye tracking were some of the techniques used (Calvo et al. 2022). During the operational phase, monthly meetings were held with partners to understand how the tool was being employed. This allowed a continuous feedback that served to include small modifications or additional functionalities. A key challenge in the development of the DST was introducing the concept of "skill" to users. To orientate the user, a qualitative skill classification was devised: "no skill" (skill < 0%), "fair" (0% < skill < 15%), "good" (15% < skill < 30%) and "very good" (30% < skill). This helped users to evaluate expected quality. Nevertheless, in order to attribute trust to a probabilistic forecast, users need to combine the skill information with a measure of uncertainty (related to the ensemble spread) provided by the forecast probability. This remains an open challenge in the field of uncertainty communication in climate services.

Hydropower inflow predictions in Scotland, United Kingdom (authors: Robert M. Graham, Jethro Browell, Christopher J. White, and Douglas Bertram). In Scotland, reservoir inflow forecasts for hydropower generation are primarily dependent on weather forecasts rather than initial hydrological conditions. This is due to steep topography and low groundwater storage capacity (Svensson 2015). SSE Renewables, a U.K. energy generation company, have a hydropower portfolio of 1,459 MW across Scotland, enough to supply approximately 1 million U.K. homes. Hydropower operators at SSE currently use deterministic inflow forecasts, covering periods up to 2 weeks ahead, and an expert meteorologist provides longer range outlooks based on S2S forecasts. A team of hydropower operators from SSE Renewables and researchers from the fields of meteorology, energy forecasting and hydrology at the University of Strathclyde codeveloped probabilistic S2S inflow forecasts for selected hydropower reservoirs in Scotland and further evaluated the potential economic value of these forecasts. SSE were involved from the initial concept stage of the project to its closure.

Inflow forecasts were derived from ECMWF S2S forecasts from the S2S global repository. Benchmark inflow forecasts for a case study reservoir were created by training a linear regression of the S2S precipitation forecasts onto the historical inflow record. These were then postprocessed, following methods similar to Scheuerer (2014), to produce calibrated probabilistic inflow forecasts (Graham et al. 2021). We evaluated the inflow forecasts for 11 lead times, including weekly mean inflow rate forecasts from week 1 (days 1–7) to week 6 (days 36–42), and extended mean inflow rate forecasts from 2 (days 1–14) to 6 weeks (days 1–42) ahead. After postprocessing, the probabilistic weekly mean inflow forecasts demonstrated skill up to week 6, though skill in weeks 3 to 6 is low relative to weeks 1 and 2. Furthermore, the 6-week-average (days 1–42) inflow rate forecasts displayed greater skill than weekly mean inflow forecasts for week 2 (days 8–14). In contrast, the raw S2S precipitation forecasts and benchmark inflow forecasts held statistical skill only to forecast week 2, the typical skill horizon in midlatitudes for probabilistic ensemble forecasts (Branković et al. 1990).

The economic value of the inflow forecasts was explored using a stylized cost model based on the classical "news vendor" optimization problem (Khouja 1999), following the principle of maintaining a target water level in the reservoir. Within this framework, the probabilistic inflow forecasts consistently reduced costs relative to the use of climatological forecasts, even for forecast week 6 (days 36–42). However, deterministic inflow forecasts, based on the median of the probabilistic forecast distribution, often resulted in poor operational decisions and increased costs relative to the use of climatological forecasts from week 2 (days 8–14) onward.

The project concluded that S2S probabilistic forecasts can improve water management decisions for hydropower reservoirs up to 6 weeks ahead. However, postprocessing and forecast calibration is an essential step to realize skill in the S2S range. The demonstration of the potential for the S2S inflow forecasts to increase economic value and improve decision-making was particularly welcomed by the industry collaborators. The partnership was not without its challenges, however; understanding how the "value" of the S2S forecasts could be fully realized and applied in operation would require closer and continued collaboration between the researchers, hydropower operators, and in-house meteorologists.

Scenario planning for hydropower operations in Tasmania, Australia (authors: Carly R. Tozer, Sonia Bluhm, Carolyn J. Maxwell, Tomas A. Remenyi, James S. Risbey, and Robert G. Wilson). El Niño–Southern Oscillation (ENSO) and Indian Ocean dipole (IOD) are recognized as key large-scale drivers of Australia's climate variability (Risbey et al. 2009). The cooccurrence of El Niño and positive IOD events has been associated with dry conditions across the country (Meyers et al. 2007; Ummenhofer et al. 2011). One such occurrence was in 2015, which coincided with below average winter and spring rainfall across parts of southern Australia. Tasmania experienced statewide rainfall deficits and the lowest spring rainfall on record in western Tasmania (Karoly et al. 2016). Hydro Tasmania, which manages multiple hydropower facilities, primarily located across western Tasmania, produces hydroelectricity for both Tasmania and mainland Australia. The record low rainfall in 2015 contributed to an energy supply challenge for Hydro Tasmania, leading to a subsequent operational review. In 2019,

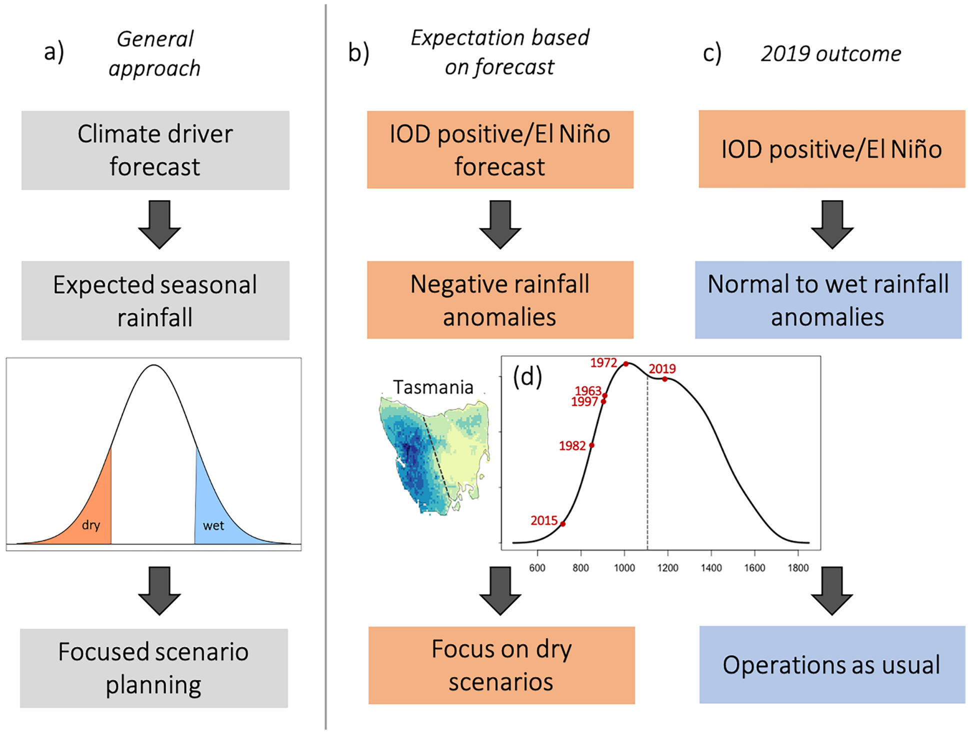

Fig. 6. Scenario planning for hydropower operations in Tasmania showing (a) a general scenario planning approach, where a climate driver forecast is received from which there is an expectation around the seasonal rainfall response focused toward operational scenario planning; (b) dry scenario planning in response to IOD positive–El Niño forecast and the expectation of negative (dry) rainfall anomalies in western Tasmania; (c) 2019 example outcome; (d) probability density function of total winter/spring rainfall (in mm) in western Tasmania for each year from 1900 to 2019. The years marked in red indicate past IOD positive–El Niño events and the associated winter/spring rainfall anomalies. Dashed line indicates median winter/spring rainfall. Western Tasmania is considered the region west of the dashed black line (inset map).

a reappearance of this combination of climate drivers looked likely, with S2S forecasts issued in April and May 2019 pointing toward the development of El Niño and positive IOD over winter and spring (e.g., Bureau of Meteorology 2019). The positive "super-IOD" (Doi et al. 2020) event has since been linked to rainfall deficits and bushfires across Australia (van Oldenborgh et al. 2021).

Hydro Tasmania collaborated with the Commonwealth Scientific and Industrial Research Organisation (CSIRO) as part of a project to understand the use and potential utility of climate forecasts, including identifying Hydro Tasmania's operations and decision-making processes, and the climate variables of importance for forecast evaluation. The application of climate forecasts within Hydro Tasmania's operations is through operational scenario planning (Fig. 6a). Potential operational outcomes are produced in response to forecast information and evaluated against historical data. In the case of the 2019 El Niño–positive IOD forecast, Hydro Tasmania's operational scenario planning options were focused on dry conditions as this was the expectation based on past experiences (Figs. 6b,d). As the year progressed, Hydro Tasmania monitored the subseasonal climate driver forecasts issued by Australia's Bureau of Meteorology in concert with rainfall received in western Tasmania, in a "watch and act" process. When it became clear that the rainfall deficits experienced in 2015 were not being repeated in 2019 (Fig. 6d) no major changes to operations were enacted (Fig. 6c).

Using S2S forecasts of climate drivers to inform scenario planning—as opposed to the direct input of forecast information into operational systems—implicitly acknowledges that there is uncertainty in S2S forecasts, and that teleconnections between large-scale climate drivers and regional rainfall are complex. There are typically multiple drivers at play on different time scales, which is the case in Tasmania (Risbey et al. 2009; Tozer et al. 2018), meaning a skillful forecast of a particular climate driver may not lead to a skillful rainfall forecast. The forecast may also not directly change a decision, but it can influence which scenarios to reassess. Scenario planning puts Hydro Tasmania in a stronger position to identify options and make appropriate decisions should a dry scenario play out, or continue normal operations if it does not.

Weather risk management for U.K. fixed-line telecommunications (authors: David Brayshaw, Alan Halford, Stefan Smith, and Kjeld Jensen). The physical infrastructure associated with fixed-line telecommunication systems, which are critical for many aspects of modern service-based economies, is subject to significant weather exposure. In the United Kingdom, weather-related line faults are commonly associated with service disruptions (e.g., BT 2018); however, rapid evolution of the infrastructure (e.g., growth in broadband) limits the availability of historical data for both weather risk assessment and impact-based prediction. A jointly supervised project (Halford 2018) by the University of Reading and a leading U.K. communications services company, BT PLC, sought to address these challenges by creating a robust long-term historic fault-rate record for the U.K. telecommunications system with a multiweek fault-rate forecasting system to support line-maintenance scheduling. In brief, historic fault rates from 1979 to 2017 were constructed using a multiple linear regression fault-rate model which was applied to weather inputs from ERA-Interim (Dee et al. 2011), i.e., a time series of estimated fault rates assuming the historic weather impacted upon the U.K. telecoms system of 2017 was produced [refer to Brayshaw et al. (2020) for details]. S2S "forecasts" spanning 1996–2015 for the same U.K. telecoms system were then generated using ECMWF S2S ensemble hindcasts (11 ensemble members). Here, and in the original study (Brayshaw et al. 2020), there was an emphasis on the quantitative estimation of end-user "value" from skillful S2S forecasts that can be summarized by the schematic:

$$\text{S2S forecasts(weather)} \Rightarrow \text{Impact model(line faults)} \Rightarrow \text{Decision model(cost)}$$

S2S forecasts were identified as potentially offering predictive skill and opportunities for user value through efficient scheduling of staffing resources (restorative maintenance versus provision of new line connections). A strategy was agreed that combined a tercile-based S2S forecast of the North Atlantic Oscillation (NAO), with fault-rate distributions from the long-term synthetic fault-rate record corresponding to the occurrence of each NAO tercile. The resulting forecast system was shown to have skill in predicting weekly fault rates up to 4 weeks ahead in winter, based on 11-member ECMWF S2S hindcasts spanning 1996–2015 (Vitart and Robertson 2018).

A decision-simulation model utilizing the fault-rate forecast in maintenance scheduling was then developed to estimate forecast value. This demonstrated that the fault-rate forecast system could be used to improve both short-term and long-term management strategies, e.g., either meeting week-to-week performance targets (a simulated ~5%–10% improvement) or achieving the same level of performance but at lower long-term cost (a simulated ~1% reduction in resource levels). Though these estimates are likely an upper bound to that which would be achievable in practice, the savings are potentially significant with the penalty for failing to meet repair targets reaching up to ~GBP 1 million day^{-1} and annual staffing costs of around GBP 500 million (see Brayshaw et al. 2020).

The success of the project is attributable to the extensive collaboration between the academics and BT PLC staff from the outset. This not only enabled the rapid codevelopment of statistical fault-rate and decision-support models, but also deepened engagement in both directions (as BT staff, rather than the academic team, held the expertise regarding the fault-rate modeling and maintenance scheduling). Beyond successfully demonstrating skill on S2S lead times, the project emphasized that the skill of the fault-rate forecast does not in itself guarantee value to the end user, e.g., a forecast may have skill but may hold little value if the outcome has no relevant consequences and/or the user is unable to act upon it.

Disaster early warnings and emergency management. Skillful and reliable extended-range forecasts of extreme events, such as floods and droughts, offer significant opportunities for improved disaster preparedness and risk reduction, including tracking the progress of the slowly evolving, large-scale climate modes and supporting the transition from long-range outlooks to weather forecasts to provide early warnings and inform emergency management activities (Tadesse et al. 2016). In this section, we explore the use of S2S forecasts for flood forecasting across Europe.

European flood forecasting (authors: Francesca Di Giuseppe and Fredrik Wetterhall). The European Flood Awareness System (EFAS)[14] is operated by the Copernicus Emergency Management System (CEMS), and functions as a common pan-European tool to provide coherent early warnings of flood events. A set of decision rules based on forecast persistency and magnitude are defined to identify points on Europe's river network where flooding is likely to happen. The authorities responsible for flood forecasting in the specific location are then sent flood notifications ahead of such events. EFAS uses medium-range forecasts, typically up to a 10-day lead time, but for rare and potentially widespread flood events a system working on the S2S time scale (10–30 days) would extend the early warning window to help pinpoint regions in need of attention. EFAS recently added a twice weekly extended-range ensemble forecast with 51 members up to 6 weeks (aggregated into weekly averages) based on ECMWF S2S forecasts (Wetterhall and Di Giuseppe 2018). These forecasts are currently only for supplementary information and not used to issue warnings. Since the predictability for extreme events on S2S lead times can be uncertain (Domeisen et al. 2022), decision rules for preventive actions would have to be designed with this increased uncertainty in mind in comparison with the medium-range forecasts.

[14] EFAS (www.efas.eu), part of the European Commissions' Emergency Management System (CEMS) (https://emergency.copernicus.eu/).

In this study, we revisit a major flooding event that took place in southeastern Europe in May 2014 to explore the potential added value in the decision-making process of S2S hydrological forecasts. During the event, large areas of southeastern and central Europe experienced exceptionally intense rainfall which led to widespread flooding where over 60 people died and more than a million inhabitants were affected (Stadtherr et al. 2016). The EFAS system indicated exceedance of the 20-yr return period more than a week ahead of the event and was able to issue notifications with a 4–5-day lead time. However, this information could potentially have been even more useful if an even earlier indication of the event was available. In this revised analysis, we look at how far back a signal for these conditions was present in the S2S forecasts. The fraction of ensemble members that predicted the exceedance of the "decision" threshold is considered as the probability of an event occurring for the period preceding and following the event (1 April–30 June in this case) and as a function of lead times up to 46 days ahead. Considering that extreme conditions are difficult to detect at longer lead times as the forecast naturally reverts to climatology as predictability decreases, a 30% chance at lead times > 10 days is generally taken as an indication a forthcoming event. In this study, the main event had a persistent signal up to 25 days before the event in the S2S forecasts, highlighting the importance and potential utility of the S2S time scale for prewarning. To put this into the context of decision-making, a full cost–loss scenario analysis of the historical period is needed to establish the correct level of probability and lead time to issue prealerts for severe events. Further, the decision-making process in the region would need to be trained to utilize the added information.

Discussion

We demonstrate here that S2S forecasts are increasingly being used across the public health, agriculture, water resource management, renewable energy and utilities, and emergency management and response sectors in both the developed and emerging economies. As identified across our 12 application-focused case studies (Table 1), current decision-making is generally based on either short- to medium-range (often deterministic) or seasonal forecasts. The S2S forecasting time scale is therefore a new concept for many users. While the additional value of S2S forecasts for decision-making is increasingly gaining interest among users, as shown here, incorporating probabilistic ensemble S2S forecasts into existing operations is not trivial. S2S forecasts do not produce a "go–no go" answer of what a user should do; instead they provide additional, supplementary "situational awareness" information that can be used to drive decision-making and risk-based management processes on weekly to monthly forecast horizons. Seasonal to decadal forecasts face the same challenge. What the presented case studies clearly suggest, however, is that the kind of widespread national and international investment witnessed in service development on seasonal and climate time scales is also needed on the S2S time scale.

In addition to the limited awareness and demonstration of the potential benefits of the S2S time scale across sectors to date, a lack of "in house" expertise in how to effectively apply S2S forecasts and, to some extent, a lack of access to S2S forecasts, have also been barriers to widespread adoption of S2S forecasts. This is the "knowledge–value" gap, highlighting the challenge and need of translating S2S forecast *skill* into forecast *value* (e.g., Giuliani et al. 2020). For S2S predictions to have utility, there needs to be an signal in the forecast that emerges beyond the noise in the system (Mariotti et al. 2020). However, across the case studies presented here, there are varying interpretations of what "skill" is from a scientific or user perspective and what magnitude of signal is needed for a forecast to add value for a user. For any forecast application, user-focused questions such as "What is the minimum level of skill (or perhaps "certainty") that can still be useful?" and "Is the required level of skill actually attainable for the variables, region, and application of interest?" are as essential to the concept of forecast utility as is verifying forecast skill (e.g., Crochemore et al. 2021). Here, we highlight that the answers to these and similar questions can only be determined via user engagement and continued partnership. This approach helps determine whether S2S forecast information can be better utilized through approaches such as multiple scenario planning "storyline" frameworks with a comparison to recent historical events (e.g., hydropower operations in Tasmania), or supplemented by statistical postprocessing (e.g., hydropower inflows in Scotland), or through additional impact-based models (e.g., malaria occurrence in Nigeria). Some of the most effective real-time/operational applications presented here are where S2S forecasts have been communicated to end users and contributed to "situational awareness" using an early "horizon scanning" approach of upcoming extreme events. This is true in the case of farmers determining the planting and management of crops, informed by the timing of the monsoon in Bihar, and the rainy season onset in Kenya. The codevelopment of the S2S4E project's decision-support tool for the renewable energy sector also provides a particularly useful and insightful discussion around forecast skill, value, trust, and communication, with all of the cross-sectoral case studies presented here confirming the need for the cogeneration of forecast products. This clearly identifies and communicates the strengths and limitations of forecasts in support of improved forecast utility.

We acknowledge, however, that S2S forecasting is still a maturing discipline, with several of the studies here being at the "proof of concept" stage so their scope is somewhat limited or that issues to their further implementation and/or operationalization remain. There is also a distinction between case studies that use S2S forecasts directly (e.g., precipitation and temperature fields) compared to those exploring the large-scale climate drivers to identify additional sources of skill (e.g., ENSO, NAO, MJO). While we present application case studies that span different sectors from around the world, there is also a notable focus on water-related applications. This is perhaps not surprising—there is an experienced user base spanning the water-related sectors, meaning the "knowledge–value" gap is perhaps not as significant here compared to other disciplines. For example, the agriculture sector is already familiar with using seasonal outlooks (e.g., Verbist et al. 2010), and flood management is the forefront of providing risk-based anticipatory warnings in response to forecasts. Impact-based flood and drought forecasts, for example, have huge potential to help shape these dialogues (Merz et al. 2020) and have been deployed in a number of the water-related studies shown here. Water therefore presents perhaps the best opportunity to demonstrate the utility of S2S forecasts to bridge the gap between the weather and climate forecasting time scales.

It is, however, the collective body of evidence provided by *all* of these multisectoral case studies that marks a significant step forward from White et al. (2017) in moving from *potential* to *actual* S2S forecasting applications. By placing user needs and applications at the forefront of S2S forecast development—demonstrating both skill and utility across sectors—in unison with ongoing scientific endeavors to improve forecasting systems and identify sources of skill, it is hoped that this dialogue will help promote and accelerate the awareness, value and cogeneration of S2S forecasts to real-world decision-making. Increasing the ability of users to engage simply and transparently with S2S forecasts, and to employ new technologies such as machine learning and artificial intelligence tools to build and augment impact models, would help to further accelerate this process. Crucially, this study provides a platform toward the creation of a global community of researchers and users with a shared aim of exploring and promoting applications of this new generation of forecasts. S2S forecasting represents a significant opportunity to generate useful, usable, and actionable forecast information and services for and with users for a range of sectoral applications on previously untapped predictive time scales.

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Data availability statement. The joint WWRP–WCRP Subseasonal to Seasonal Prediction Project (e.g., Robertson et al. 2014) created a global repository of experimental or operational near-real-time S2S forecasts and reforecasts (hindcasts) from 11 international meteorological institutions, cohosted by ECMWF and CMA (Vitart et al. 2017). These data are publicly accessible by researchers and users (https://apps.ecmwf.int/datasets/data/s2s and http://s2s.cma.cn/index). With the exception of the fourth case study, which uses GloSea5 forecasts (MacLachlan et al. 2015), all case studies use selected S2S forecasts and reforecasts that are available from this repository, providing a consistent basis for S2S forecast skill assessment and evaluation of their utility.

References

Abiodun, G. J., R. Maharaj, P. Witbooi, and K. O. Okosun, 2016: Modeling and analyzing the impact of temperature and rainfall on mosquito population dynamics over Kwazulu-Natal Province, South Africa. *Int. J. Biomath.*, **10**, 1750055, https://doi.org/10.1142/S1793524517500553.

Acharya, N., 2018: Calibration of probabilistic ensemble forecasts for Indian summer monsoon rainfall: A non-Gaussian approach. *Eighth Int. Workshop on Climate Informatics*, Boulder, CO, NCAR, 104–106, https://doi.org/10.5065/D6BZ64XQ.

Anderson, B. G., and M. L. Bell, 2009: Weather-related mortality: How heat, cold, and heat waves affect mortality in the United States. *Epidemiology*, **20**, 205–213, https://doi.org/10.1097/EDE.0b013e318190ee08.

Asare, E. O., and L. K. Amekudzi, 2017: Assessing climate driven malaria variability in Ghana using a regional scale dynamical model. *Climate*, **5**, 20, https://doi.org/10.3390/cli5010020.

——, A. M. Tompkins, and A. A. Bomblies, 2016: Regional model for malaria vector developmental habitats evaluated using explicit, pond-resolving surface hydrology simulations. *PLOS ONE*, **11**, e0150626, https://doi.org/10.1371/journal.pone.0150626.

Berhane, F., and B. Zaitchik, 2014: Modulation of daily precipitation over East Africa by the Madden–Julian oscillation. *J. Climate*, **27**, 6016–6034, https://doi.org/10.1175/JCLI-D-13-00693.1.

Beveridge, L., and Coauthors, 2019: Experiences and drivers of food insecurity in Guatemala's dry corridor: Insights from the integration of ethnographic and household survey data. *Front. Sustain. Food Syst.*, **3**, 65, https://doi.org/10.3389/fsufs.2019.00065.

Branković, Č., T. N. Palmer, F. Molteni, S. Tibaldi, and U. Cubasch, 1990: Extended-range predictions with ECMWF models: Time-lagged ensemble forecasting. *Quart. J. Roy. Meteor. Soc.*, **116**, 867–912, https://doi.org/10.1002/qj.49711649405.

Brayshaw, D. J., A. Halford, S. Smith, and K. Jensen, 2020: Quantifying the potential for improved management of weather risk using sub-seasonal forecasting: The case of UK telecommunications infrastructure. *Meteor. Appl.*, **27**, e1849, https://doi.org/10.1002/met.1849.

Brunet, G., and Coauthors, 2010: Collaboration of the weather and climate communities to advance subseasonal-to-seasonal prediction. *Bull. Amer. Meteor. Soc.*, **91**, 1397–1406, https://doi.org/10.1175/2010BAMS3013.1.

BT, 2018: BT Group PLC annual report and form 20-F. BT Group Doc., 320 pp., www.bt.com/bt-plc/assets/documents/investors/financial-reporting-and-news/annual-reports/2018/bt-annual-report-form-20-f-2018.pdf.

Bureau of Meteorology, 2019: Long-range sea surface temperature outlooks. Bureau of Meteorology, accessed 19 August 2020, www.bom.gov.au/climate/ocean/outlooks/#tabs=Graphs&region=IOD.

Calvo, L., I. Christel, M. Terrado, F. Cucchietti, and M. Pérez-Montoro, 2022: Users' cognitive load: A key aspect to successfully communicate visual climate information. *Bull. Amer. Meteor. Soc*., **103**, E1–E16, https://doi.org/10.1175/BAMS-D-20-0166.1.

Charlton-Perez, A. J., R. W. Aldridge, C. M. Grams, and R. Lee, 2019: Winter pressures on the UK health system dominated by the Greenland blocking weather regime. *Wea. Climate Extremes*, **25**, 100218, https://doi.org/10.1016/j.wace.2019.100218.

Clements, J., A. Ray, and G. Anderson, 2013: The value of climate services across economic and public sectors: A review of relevant literature. USAID Rep., 54 pp., www.climate-services.org/wp-content/uploads/2015/09/CCRD-Climate-Services-Value-Report_FINAL.pdf.

Crochemore, L., C. Cantone, I. G. Pechlivanidis, and C. Photiadou, 2021: How does seasonal forecast performance influence decision-making? Insights from a serious game. *Bull. Amer. Meteor. Soc.*, **102**, E1682–E1699, https://doi.org/10.1175/BAMS-D-20-0169.1.

Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.*, **137**, 553–597, https://doi.org/10.1002/qj.828.

DeFlorio, M. J., D. E. Waliser, B. Guan, F. M. Ralph, and F. Vitart, 2019a: Global evaluation of atmospheric river subseasonal prediction skill. *Climate Dyn.*, **52**, 3039–3060, https://doi.org/10.1007/s00382-018-4309-x.

——, and Coauthors, 2019b: Experimental subseasonal-to-seasonal (S2S) forecasting of atmospheric rivers over the western United States. *J. Geophys. Res. Atmos.*, **124**, 11 242–11 265, https://doi.org/10.1029/2019JD031200.

——, F. M. Ralph, D. E. Waliser, J. Jones, and M. L. Anderson, 2021: Better subseasonal-to-seasonal forecasts for water management. *Eos*, **102**, https://doi.org/10.1029/2021EO159749.

Doi, T., S. Behera, and T. Yamagata, 2020: Predictability of the super IOD event in 2019 and its link with El Niño Modoki. *Geophys. Res. Lett.*, **47**, e2019GL086713, https://doi.org/10.1029/2019GL086713.

Domeisen, D., and Coauthors, 2022: Advances in the subseasonal prediction of extreme events: Relevant case studies across the globe. *Bull. Amer. Meteor. Soc*., https://doi.org/10.1175/BAMS-D-20-0221.1, in press.

Ferro, C. A. T., 2014: Fair scores for ensemble forecasts. *Quart. J. Roy. Meteor. Soc.*, **140**, 1917–1923, https://doi.org/10.1002/qj.2270.

Gibson, P. B., D. E. Waliser, B. Guan, M. J. DeFlorio, F. M. Ralph, and D. L. Swain, 2020a: Ridging associated with drought in the western and southwestern United States: Characteristics, trends, and predictability sources. *J. Climate*, **33**, 2485–2508, https://doi.org/10.1175/JCLI-D-19-0439.1.

——, ——, A. Goodman, M. J. DeFlorio, L. Delle Monache, and A. Molod, 2020b: Subseasonal-to-seasonal hindcast skill assessment of ridging events related to drought over the western United States. *J. Geophys. Res. Atmos.*, **125**, e2020JD033655, https://doi.org/10.1029/2020JD033655.

Githeko, A. K., and W. Ndegwa, 2001: Predicting malaria epidemics in the Kenyan highlands using climate data: A tool for decision makers. *Global Change Hum. Health*, **2**, 54–63, https://doi.org/10.1023/A:1011943131643.

Giuliani, M., L. Crochemore, I. Pechlivanidis, and A. Castelletti, 2020: From skill to value: Isolating the influence of end user behavior on seasonal forecast assessment. *Hydrol. Earth Syst. Sci.*, **24**, 5891–5902, https://doi.org/10.5194/hess-24-5891-2020.

Goddard, L., and Coauthors, 2020: Climate services ecosystems in times of COVID-19. *WMO Bull.*, **69**, 39–46, https://public.wmo.int/en/resources/bulletin/climate-services-ecosystems-times-of-covid-19.

Graham, R. M., J. Browell, D. Bertram, and C. J. White, 2021: The application of sub-seasonal to seasonal (S2S) predictions for hydropower forecasting. arXiv, https://arxiv.org/abs/2108.06269.

Grams, C. M., R. Beerli, S. Pfenninger, I. Staffell, and H. Wernli, 2017: Balancing Europe's wind-power output through spatial deployment informed by weather regimes. *Nat. Climate Change*, **7**, 557–562, https://doi.org/10.1038/nclimate3338.

——, L. Ferranti, and L. Magnusson, 2020: How to make use of weather regimes in extended-range predictions for Europe. *ECMWF Newsletter*, No. 165, ECMWF, Reading, United Kingdom, 14–19, www.ecmwf.int/en/newsletter/165/meteorology/how-make-use-weather-regimes-extended-range-predictions-europe.

Halford, A., 2018: Forecasting weather impacts on the United Kingdom telecommunication network. Ph.D. thesis, University of Reading, 233 pp.

Hersbach, H., and Coauthors, 2020: The ERA5 global reanalysis. *Quart. J. Roy. Meteor. Soc.*, **146**, 1999–2049, https://doi.org/10.1002/qj.3803.

Huang, W. T. K., A. Charlton-Perez, R. W. Lee, R. Neal, C. Sarran, and T. Sun, 2020: Weather regimes and patterns associated with temperature-related excess mortality in the UK: A pathway to sub-seasonal risk forecasting. *Environ. Res. Lett.*, **15**, 124052, https://doi.org/10.1088/1748-9326/abcbba.

Jones, A. E., and A. P. Morse, 2010: Application and validation of a seasonal ensemble prediction system using a dynamic malaria model. *J. Climate*, **23**, 4202–4215, https://doi.org/10.1175/2010JCLI3208.1.

Karoly, D., M. Black, M. Grose, and A. King, 2016: The roles of climate change and El Niño in the record low rainfall in October 2015 in Tasmania, Australia [in "Explaining Extreme Events of 2015 from a Climate Perspective"].

Bull. Amer. Meteor. Soc., **97** (12), S127–S130, https://doi.org/10.1175/BAMS-D-16-0139.1.

Khouja, M., 1999: The single-period (news-vendor) problem: Literature review and suggestions for future research. *Omega*, **27**, 537–553, https://doi.org/10.1016/S0305-0483(99)00017-1.

Kilavi, M., and Coauthors, 2018: Extreme rainfall and flooding over central Kenya including Nairobi City during the long-rains season 2018: Causes, predictability, and potential for early warning and actions. *Atmosphere*, **9**, 472, https://doi.org/10.3390/atmos9120472.

Lang, A. L., K. Pegion, and E. A. Barnes, 2020: Introduction to special collection: "Bridging weather and climate: Subseasonal-to-seasonal (S2S) prediction." *J. Geophys. Res. Atmos.*, **125**, e2019JD031833, https://doi.org/10.1029/2019JD031833.

Lee, S. H., A. J. Charlton-Perez, J. C. Furtado, and S. J. Woolnough, 2019: Abrupt stratospheric vortex weakening associated with North Atlantic anticyclonic wave breaking. *J. Geophys. Res. Atmos.*, **124**, 8563–8575, https://doi.org/10.1029/2019JD030940.

Lopes, J. E. G., 1999: Soil Moisture Accounting Procedure (SMAP) model manual. Accessed 12 March 2021, http://pha.poli.usp.br/LeArq.aspx?id_arq=3596.

Lopez-Ridaura, S., L. Barba-Escoto, C. Reyna, J. Hellin, B. Gerard, and M. van Wijk, 2019: Food security and agriculture in the western highlands of Guatemala. *Food Secur.*, **11**, 817–833, https://doi.org/10.1007/s12571-019-00940-z.

MacLachlan, C., and Coauthors, 2015: Global Seasonal forecast system version 5 (GloSea5): A high-resolution seasonal forecast system. *Quart. J. Roy. Meteor. Soc.*, **141**, 1072–1084, https://doi.org/10.1002/qj.2396.

MacLeod, D., and Coauthors, 2021a: Drivers and subseasonal predictability of heavy rainfall in equatorial East Africa and relationship with flood risk. *J. Hydrometeor.*, **22**, 887–903, https://doi.org/10.1175/JHM-D-20-0211.1.

——, and Coauthors, 2021b: Are Kenya Meteorological Department heavy rainfall advisories useful for forecast-based early action and early preparedness for flooding? *Nat. Hazards Earth Syst. Sci.*, **21**, 261–277, https://doi.org/10.5194/nhess-21-261-2021.

Manrique-Suñén, A., N. Gonzalez-Reviriego, V. Torralba, N. Cortesi, and F. J. Doblas-Reyes, 2020: Choices in the verification of S2S forecasts and their implications for climate services. *Mon. Wea. Rev.*, **148**, 3995–4008, https://doi.org/10.1175/MWR-D-20-0067.1.

Mariotti, A., and Coauthors, 2020: Windows of opportunity for skillful forecasts subseasonal to seasonal and beyond. *Bull. Amer. Meteor. Soc.*, **101**, E608–E625, https://doi.org/10.1175/BAMS-D-18-0326.1.

Mason, S. J., and A. P. Weigel, 2009: A generic forecast verification framework for administrative purposes. *Mon. Wea. Rev.*, **137**, 331–349, https://doi.org/10.1175/2008MWR2553.1.

Merryfield, W. J., and Coauthors, 2020: Current and emerging developments in subseasonal to decadal prediction. *Bull. Amer. Meteor. Soc.*, **101**, E869–E896, https://doi.org/10.1175/BAMS-D-19-0037.1.

Merz, B., and Coauthors, 2020: Impact forecasting to support emergency management of natural hazards. *Rev. Geophys.*, **58**, e2020RG000704, https://doi.org/10.1029/2020RG000704.

Meyers, G., P. McIntosh, L. Pigot, and M. Pook, 2007: The years of El Niño, La Niña, and interactions with the tropical Indian Ocean. *J. Climate*, **20**, 2872–2880, https://doi.org/10.1175/JCLI4152.1.

Michelangeli, P., R. Vautard, and B. Legras, 1995: Weather regimes: Recurrence and quasi stationarity. *J. Atmos. Sci.*, **52**, 1237–1256, https://doi.org/10.1175/1520-0469(1995)052<1237:WRRAQS>2.0.CO;2.

Ministry of Agriculture, Livestock and Fisheries, 2017: Kenya climate smart agriculture strategy 2017–2026. Kenya Ministry of Agriculture, Livestock and Fisheries Rep., 53 pp., www.adaptation-undp.org/resources/plans-and-policies-relevance-naps-least-developed-countries-ldcs/kenya-climate-smart.

Muñoz, Á. G., and Coauthors, 2019: NextGen: A next-generation system for calibrating, ensembling and verifying regional seasonal and subseasonal forecasts. *2019 Fall Meeting*, San Francisco, CA, Amer. Geophys. Union, Abstract A23U-3024.

——, X. Chourio, A. Rivière-Cinnamond, M. A. Diuk-Wasser, P. A. Kache, E. A. Mordecai, L. Harrington, and M. C. Thomson, 2020: AeDES: A next-generation monitoring and forecasting system for environmental suitability of Aedes-borne disease transmission. *Sci. Rep.*, **10**, 12640, https://doi.org/10.1038/s41598-020-69625-4.

NHS Improvement, 2018: NHS review of winter 2017/18. NHS Doc. SL 16/18, 27 pp.

Olaniyan, E., E. A. Adefisan, F. Oni, E. Afiesimama, A. A. Balogun, and K. A. Lawal, 2018: Evaluation of the ECMWF sub-seasonal to seasonal precipitation forecasts during the peak of West Africa monsoon in Nigeria. *Front. Environ. Sci.*, **6**, 4, https://doi.org/10.3389/fenvs.2018.00004.

Ralph, F. M., D. E. Waliser, M. D. Dettinger, J. J. Rutz, M. L. Anderson, I. V. Gorodetskaya, B. Guan, and W. Neff, 2020: The future of atmospheric river research and applications. *Atmospheric Rivers*, F. Ralph et al., Eds., Springer, 219–247, https://doi.org/10.1007/978-3-030-28906-5_8.

Risbey, J., M. Pook, P. McIntosh, M. Wheeler, and H. Hendon, 2009: On the remote drivers of rainfall variability in Australia. *Mon. Wea. Rev.*, **137**, 3233–3253, https://doi.org/10.1175/2009MWR2861.1.

Robbins, J., 2020: Progress on the S2S real time pilot initiative. *S2S Newsletter*, No. 14, S2S International Coordination Office, Jeju, South Korea, 1–2, www.s2sprediction.net/file/newsletter/S2S_Newsletter14_July_2020.pdf.

Robertson, A. W., A. Kumar, M. Peña, and F. Vitart, 2014: Improving and promoting subseasonal to seasonal prediction. *Bull. Amer. Meteor. Soc.*, **96**, ES49–ES53, https://doi.org/10.1175/BAMS-D-14-00139.1.

——, S. J. Camargo, A. Sobel, F. Vitart, and S. Wang, 2018: Summary of workshop on sub-seasonal to seasonal predictability of extreme weather and climate. *npj Climate Atmos. Sci.*, **1**, 20178, https://doi.org/10.1038/s41612-017-0009-1.

——, and Coauthors, 2019: Subseasonal forecasts of the 2018 Indian summer monsoon over Bihar. *J. Geophys. Res. Atmos.*, **124**, 13 861–13 875, https://doi.org/10.1029/2019JD031374.

Ryti, N. R. I., Y. Guo, and J. J. K. Jaakkola, 2016: Global association of cold spells and adverse health effects: A systematic review and meta-analysis. *Environ. Health Perspect.*, **124**, 12–22, https://doi.org/10.1289/ehp.1408104.

Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System version 2. *J. Climate*, **27**, 2185–2208, https://doi.org/10.1175/JCLI-D-12-00823.1.

Scheuerer, M., 2014: Probabilistic quantitative precipitation forecasting using ensemble model output statistics. *Quart. J. Roy. Meteor. Soc.*, **140**, 1086–1096, https://doi.org/10.1002/qj.2183.

Soret, A., and Coauthors, 2019: Sub-seasonal to seasonal climate predictions for wind energy forecasting. *J. Phys.: Conf. Ser.*, **1222**, 012009, https://doi.org/10.1088/1742-6596/1222/1/012009.

Stadtherr, L., D. Coumou, V. Petoukhov, S. Petri, and S. Rahmstorf, 2016: Record Balkan floods of 2014 linked to planetary wave resonance. *Sci. Adv.*, **2**, e1501428, https://doi.org/10.1126/sciadv.1501428.

Svensson, C., 2015: Seasonal river flow forecasts for the United Kingdom using persistence and historical analogues. *Hydrol. Sci. J.*, **61**, 19–35, https://doi.org/10.1080/02626667.2014.992788.

Tadesse, T., T. Haigh, N. Wall, A. Shiferaw, B. Zaitchik, S. Beyene, G. Berhan, and J. Petr, 2016: Linking seasonal predictions to decision-making and disaster management in the greater Horn of Africa. *Bull. Amer. Meteor. Soc.*, **97**, ES89–ES92, https://doi.org/10.1175/BAMS-D-15-00269.1.

Tompkins, A. M., and V. Ermert, 2013: A regional-scale, high resolution dynamical malaria model that accounts for population density, climate and surface hydrology. *Malar. J.*, **12**, 65, https://doi.org/10.1186/1475-2875-12-65.

Tozer, C., J. Risbey, T. O'Kane, D. Monselesan, and M. Pook, 2018: The relationship between wave trains in the Southern Hemisphere storm track and rainfall extremes over Tasmania. *Mon. Wea. Rev.*, **146**, 4201–4230, https://doi.org/10.1175/MWR-D-18-0135.1.

Ummenhofer, C., and Coauthors, 2011: Indian and Pacific Ocean influences on southeast Australian drought and soil moisture. *J. Climate*, **24**, 1313–1336, https://doi.org/10.1175/2010JCLI3475.1.

van Oldenborgh, G. J., and Coauthors, 2021: Attribution of the Australian bushfire risk to anthropogenic climate change. *Nat. Hazards Earth Syst. Sci.*, **21**, 941–960, https://doi.org/10.5194/nhess-21-941-2021.

Verbist, K., A. W. Robertson, W. M. Cornelis, and D. Gabriels, 2010: Seasonal predictability of daily rainfall characteristics in central northern Chile for dry-land management. *J. Appl. Meteor. Climatol.*, **49**, 1938–1955, https://doi.org/10.1175/2010JAMC2372.1.

Vicedo-Cabrera, A. M., F. Sera, and A. Gasparrini, 2019: Hands-on tutorial on a modeling framework for projections of climate change impacts on health. *Epidemiology*, **30**, 321–329, https://doi.org/10.1097/EDE.0000000000000982.

Vitart, F., 2004: Monthly forecasting at ECMWF. *Mon. Wea. Rev.*, **132**, 2761–2779, https://doi.org/10.1175/MWR2826.1.

——, 2014: Evolution of ECMWF sub-seasonal forecast skill scores. *Quart. J. Roy. Meteor. Soc.*, **140**, 1889–1899, https://doi.org/10.1002/qj.2256.

——, and A. W. Robertson, 2018: The Subseasonal to Seasonal Prediction Project (S2S) and the prediction of extreme events. *Climate Atmos. Sci.*, **1**, 3, https://doi.org/10.1038/s41612-018-0013-0.

——, and Coauthors, 2008: The new VarEPS-monthly forecasting system: A first step towards seamless prediction. *Quart. J. Roy. Meteor. Soc.*, **134**, 1789–1799, https://doi.org/10.1002/qj.322.

——, and Coauthors, 2014: Sub-seasonal predictions. European Centre for Medium-Range Weather Forecasts Tech. Memo. 738, 47 pp.

——, and Coauthors, 2017: The Subseasonal to Seasonal (S2S) Prediction Project database. *Bull. Amer. Meteor. Soc.*, **98**, 163–173, https://doi.org/10.1175/BAMS-D-16-0017.1.

Wetterhall, F., and F. Di Giuseppe, 2018: The benefit of seamless forecasts for hydrological predictions over Europe. *Hydrol. Earth Syst. Sci.*, **22**, 3409–3420, https://doi.org/10.5194/hess-22-3409-2018.

WFP, 2020: WFP Guatemala country brief, April 2020. UN WFP Rep., 2 pp., https://reliefweb.int/report/guatemala/wfp-guatemala-country-brief-april-2020.

Wheeler, M. C., and H. H. Hendon, 2004: An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. *Mon. Wea. Rev.*, **132**, 1917–1932, https://doi.org/10.1175/1520-0493(2004)132<1917:AARMMI>2.0.CO;2.

White, C. J., S. W. Franks, and D. McEvoy, 2015: Using subseasonal-to-seasonal (S2S) extreme rainfall forecasts for extended-range flood prediction in Australia. *Proc. IAHS*, **370**, 229–234, https://doi.org/10.5194/piahs-370-229-2015.

——, and Coauthors, 2017: Potential applications of subseasonal-to-seasonal (S2S) predictions. *Meteor. Appl.*, **24**, 315–325, https://doi.org/10.1002/met.1654.

Wilks, D. S., 2011: *Statistical Methods in the Atmospheric Sciences*. 3rd ed. Elsevier, 676 pp.

WMO, 2020: Guidance on operational practices for objective seasonal forecasting. WMO Rep. WMO-1246, 106 pp., https://library.wmo.int/doc_num.php?explnum_id=10314.