



# Advances in the application and utility of subseasonal-to-seasonal predictions

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## ABSTRACT

The subseasonal-to-seasonal (S2S) predictive timescale, encompassing lead times ranging from 2 weeks to a season, is at the frontier of forecasting science. Forecasts on this timescale 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 socio-economic 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 co-generation 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 timescale.

## CAPSULE

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.

## 97 **Introduction**

98 The subseasonal-to-seasonal (S2S) predictive timescale, encompassing forecast ranges  
99 from 2 weeks to a season, is a rapidly maturing discipline. The S2S timescale is a frontier of  
100 forecasting science, with emerging recognition for both the need and the potential utility of  
101 forecasts on this timescale (White et al. 2017; Merryfield et al. 2020; Mariotti et al. 2020). It  
102 is now over a decade since Brunet et al. (2010) recommended that the weather and climate  
103 communities, under the auspices of World Weather Research Programme (WWRP) and  
104 World Climate Research Programme (WCRP), collaborate to jointly tackle the challenge of  
105 providing skillful and useable S2S forecasts. Significant advancements have been made in  
106 this time, including the joint WWRP/WCRP Subseasonal to Seasonal Prediction Project<sup>1</sup>  
107 (Robertson et al. 2018), which is advancing the science in identifying and simulating key  
108 sources of S2S predictability and identifying ‘windows of opportunity’ (Vitart 2014; Mariotti  
109 et al. 2020), quantifying and reducing inherent uncertainties, and working towards their  
110 future operationalization (Robertson et al. 2014; Vitart et al. 2017; Lang et al. 2020). As S2S  
111 prediction science continues to mature, the availability of extended-range forecasts provides  
112 opportunities for enhanced application-focused capabilities to complement existing services  
113 and develop new ones. Applications of S2S forecasts are increasingly being explored and  
114 assessed across a range of sectors (White et al. 2017), with efforts also underway to test their  
115 application in real-time through the S2S Real-Time Pilot Initiative<sup>2</sup> (Robbins 2020).

116 There remains, however, a ‘knowledge-value’ gap, where evidence of the potential socio-  
117 economic benefits of S2S forecasts supported by demonstrations of their utility across a  
118 number of sectors, has been limited to date. The 2018 international conference on S2S  
119 prediction in Boulder, reported in Merryfield et al. (2020), brought together research,

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<sup>1</sup> WWRP/WCRP ‘Subseasonal to Seasonal Prediction Project’ (<http://s2sprediction.net/>)

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

120 operational prediction and application expertise to help identify such gaps and provide  
121 pathways to address them. Several recommendations were identified for action, including the  
122 creation of a summary of application-focused S2S case studies that highlight past and  
123 ongoing projects to encourage and promote better engagement with end users and  
124 stakeholders. As user needs vary greatly between different sectors and regions, the wider  
125 community is increasingly working together on the co-generation of S2S predictions, yet  
126 such application-focused studies are typically either reported as a ‘side story’ to S2S  
127 predictability studies, or are simply not publishable in their own right. However, to guide  
128 further user-driven decision-making products and support the continued development and  
129 utility of S2S forecasts and related services, these efforts need to be catalogued and widely  
130 disseminated.

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

## 141 **Sectoral case studies**

142 *Public health*

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

#### 152 1) MORTALITY PREDICTIONS DURING EXTREME COLD WEATHER EVENTS IN THE U.K.

153 *Authors: Andrew J. Charlton-Perez, Christian M. Grams, Dominik Büeler, Robert W.*  
154 *Lee, W. T. Katty Huang, Ting Sun*

155 Extreme weather, such as cold and heat waves, often increases human mortality in  
156 temperate countries (e.g., Anderson and Bell 2009; Rytı et al. 2016). Anomalous mortality  
157 can be particularly high during events that last several weeks, meaning mortality predictions  
158 on S2S timescales are of specific interest. Here we examine the application of S2S forecasts  
159 for predicting mortality in the U.K. during a recent cold wave event in 2018, colloquially  
160 ‘The Beast from the East’, by combining a statistical mortality model (Vicedo-Cabrera et al.  
161 2019) with 2m temperature (T2m) and weather regime (Michelangeli et al. 1995; Grams et al.  
162 2020) predictions from S2S forecasts. The event was characterized by two intense cold waves  
163 peaking on February 28 and March 18, 2018, in the U.K. (Fig. 1a), which were both  
164 associated with a cold Greenland Blocking weather regime (cf. Grams et al. 2017) (Fig. 1c).  
165 The statistical model, estimating temperature-related mortality from observed T2m, indicates  
166 more than 300 mortalities per day attributable to the event’s cold temperatures (Fig. 1b),

167 totaling an estimated burden of 9,568 deaths during March that largely exceeded the 20-year  
168 average. During the peak of the cold wave in the first week of March, the excess daily  
169 mortality compared to the 20 year average (cf. differences of blue lines in Fig. 1b) matches  
170 the mortality attributable to cold weather (black line in Fig. 1b)

171 We explore how far in advance the European Centre for Medium-Range Weather  
172 Forecasting (ECMWF) extended-range (Vitart 2004; Vitart et al. 2008; Vitart et al. 2014)  
173 S2S ensemble forecasts<sup>3</sup>, available from the S2S global repository, indicated the first cold  
174 wave to occur at the end of February. The T2m forecast converges towards a cold scenario  
175 after the February 13 initialization, which is indicated by the substantial drop in the ensemble  
176 mean and the gradual reduction in ensemble spread (Fig. 1d). The consideration of weather  
177 regime forecasts provides additional insight into the predictability of the large-scale  
178 conditions determining the cold temperatures. Both Scandinavian Blocking and Greenland  
179 Blocking probabilities were relatively high in the S2S forecasts from February 05 (Fig. 1e);  
180 as these regimes typically coincide with colder than average temperatures in the U.K., the  
181 forecast thus indicates a possible cold scenario up to 3 weeks in advance. Nevertheless, the  
182 regime prediction is rather uncertain until a Sudden Stratospheric Warming (e.g., Lee et al.  
183 2019) occurs on February 12, indicated by the gradual increase in the probability for the two  
184 blocking regimes and the decrease in the probability for the typically mild cyclonic regimes.

185 These results reveal the potential for predicting mortality on an operational basis when  
186 combining a statistical mortality model with S2S forecasts. Our analysis shows that a  
187 sophisticated combination of both temperature and weather regime information from S2S  
188 forecasts as predictors might generate useful operational mortality forecasts, such as national  
189 or regional mortality exceedance probabilities, that could support National Health Service

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<sup>3</sup> ECMWF extended-range forecasts (<https://www.ecmwf.int/en/forecasts/documentation-and-support/extended-range-forecasts>)



190 decision-making (e.g., NHS Improvement 2018). This builds on previous investigations that  
191 systematically linked weather regimes with the likelihood of high mortality (Charlton-Perez  
192 et al. 2019; Huang et al. 2020). Engagements with national health boards and public health  
193 agencies in the U.K. through webinars and one-on-one interviews indicate interest by  
194 stakeholders (particularly once the capability of S2S forecasts is clearly communicated)<sup>4</sup>.  
195 However, the lack of operational planning focused on S2S timescales and health services'  
196 limited capacity to react to moderate probability events are challenges that need to be  
197 overcome.

## 198 2) MALARIA OCCURRENCE PREDICTION IN NIGERIA

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200 *Kamoru A. Lawal*

201 Malaria is one of the largest contributors to disease in Nigeria. Humans contract the  
202 malaria parasite through mosquitos (Githeko and Ndegwa 2001; Jones and Morse 2010), the  
203 distribution and survival of which is largely influenced by environmental and atmospheric  
204 factors such as temperature and rainfall (Abiodun et al. 2016; Asare and Amekudzi 2017).  
205 The vector-borne disease community model of ICTP, Trieste (VECTRI) (Tompkins and  
206 Ermert 2013), a distributed open-source dynamical malaria model that resolves the growth  
207 stages of the egg-larvae-pupa in addition to the gonotrophic and the sporogonic cycles, has  
208 demonstrated predictive skill over different regions in Africa using both modelled and  
209 observed climatic drivers (Tompkins and Ermert 2013; Asare et al. 2016; Asare and  
210 Amekudzi 2017). The Nigerian Meteorological Agency (NiMet) and the National Weather  
211 and Hydrological Centers (NWHC) are collaborating with researchers globally<sup>5</sup> to develop a

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<sup>4</sup> 'Addressing the resilience needs of the UK health sector: climate service pilots' project, part of the UK Climate Resilience Programme (<https://www.ukclimateresilience.org/projects/addressing-the-resilience-needs-of-the-uk-health-sector-climate-service-pilots/>)

<sup>5</sup> 'GCRF African SWIFT' project (<https://africanswift.org/>)

212 sustainable African weather forecasting and application system. Under these auspices, NiMet  
213 has developed a real-time monitoring system based on temperature and rainfall conditions for  
214 malaria transmission and has been issuing early warning forecasts for the potential  
215 occurrence of malaria on the S2S timescale (2-6 weeks) using VECTRI. Despite the potential  
216 benefits of forecasting malaria distribution in west Africa on the S2S timescale (Olaniyan et  
217 al. 2018), the utility of S2S forecasts in the operational early warning system has yet to be  
218 explored in this region.

219 Here we explore the potential benefits of S2S forecasts for the hyper-endemic malaria  
220 zones in Nigeria using the VECTRI model. Observed daily temperature and rainfall datasets  
221 were obtained from the Nigerian Meteorological Agency, together with ensemble hindcasts  
222 from ECMWF (VarEPS, based on IFS version 41r1), China Meteorological Administration  
223 (CMA) (BCC-CPS-S2Sv1 version 1) and UK Met Office (UKMO) (GloSea4) from the S2S  
224 global repository. Clinically reported malaria cases were obtained from of the ‘Roll Back  
225 Malaria’ program<sup>6</sup>. Two evaluations were undertaken between 2013 and 2017: firstly,  
226 reported (observed) malaria cases were used to evaluate the skill of the VECTRI model using  
227 an estimated entomological inoculation rate (EIR) as a measure of exposure to infectious  
228 mosquitoes; secondly, the skill of the S2S predictions in driving the VECTRI model. The EIR  
229 from the observed-driven VECTRI model was then compared with the EIR from the S2S-  
230 driven VECTRI model. Preliminary results show that the estimated EIR from the S2S-driven  
231 VECTRI model (and as also seen in the observed-driven VECTRI model) increases from the  
232 Gulf of Guinea to the Sahel as a function of the population profiles, with the ensemble means  
233 of both the CMA and ECMWF S2S ensembles showing correlations with the observed-driven  
234 EIR ranging from 0.7 to 0.85. A correlation of approximately 0.9 was found over all regions  
235 from the UMKO model.

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<sup>6</sup> ‘Roll Back Malaria’ program (<https://endmalaria.org/>)

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

### 243 3) AN EARLY-ACTION SYSTEM FOR ACUTE UNDERNUTRITION IN GUATEMALA

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246 The World Food Programme indicates the prevalence of stunting in children younger than  
247 5 years old in Guatemala reaches 46.5% nationally, with peaks of 90% in the hardest-hit  
248 municipalities (WFP 2020). Food insecurity in Guatemala is driven by both climate and non-  
249 climate factors, and its pathways are often complex (Beveridge et al. 2019). Additionally,  
250 70% of the impoverished population in Guatemala lives in rural areas, where agricultural  
251 production is mainly rain-fed (Lopez-Ridaura et al. 2019). Climate factors contribute to acute  
252 undernutrition in children under 5, especially in the Dry Corridor, a region already highly  
253 vulnerable to climate-related impacts.

254 Since September 2018, the National Secretariat for Food Security and Nutrition (SESAN)  
255 has been using a monitoring system called ‘Sala Situacional’, to allow for an early-action  
256 system for food security. Some limitations, though, have been identified: the expert-based  
257 criteria and the survey-based method are labor intensive, and its outputs are more aligned  
258 with a monitoring system than an early warning system. These challenges limit the use of the  
259 system as a forecasting tool, since it does not provide enough forecast lead time for decision-

260 makers to maneuver and distribute the resources available to better deal with food insecurity.  
261 To address these issues, an objective, automated forecast system that incorporates S2S  
262 forecasts that supports SESAN's current monitoring system is presented and discussed. Using  
263 the 'Sala Situacional' approach as the base, the International Research Institute for Climate &  
264 Society (IRI) worked with SESAN to co-develop a system to forecast the number of cases of  
265 acute undernutrition for children under 5 per department.

266 The forecast system follows the NextGen methodology (Muñoz et al. 2019, 2020; WMO  
267 2020) and promotes ecosystems of climate services (a climate services landscape that  
268 increases resilience to crises via optimal orchestration of available resources; see Goddard et  
269 al. 2020), considering the role of both climate and non-climate factors in statistical models of  
270 increasing complexity. Observed total rainfall (or lack thereof) can be used as a predictor of  
271 acute undernutrition in children under 5, with lags (or lead times) ranging 3-6 months  
272 depending on the geographical location. A combination of observed rainfall and calibrated  
273 rainfall forecasts produced by the S2S prediction project (Vitart and Robertson 2018) were  
274 found to provide monthly predictions of acute undernutrition for up to 5 months in advance –  
275 a lead time identified by SESAN as useful since it would allow the National Government to  
276 deploy resources effectively. Calibration was found to be required in order to guarantee that  
277 the S2S forecasts could reproduce the observed (statistical) characteristics of acute  
278 undernutrition. The best predictive models were found to exhibit good forecast discrimination  
279 (as measured by the two-alternative forced-choice metric; Mason and Weigel 2009) for  
280 almost all departments in Guatemala, with the system forecast skill being highest over the  
281 eastern Dry Corridor (Fig. 2).

282 Although the interannual and seasonal characteristics (e.g., timing) of acute  
283 undernutrition are well captured by models using rainfall as the only predictor, the inclusion  
284 of non-climate predictors, such as the price of maize, beans and coffee, and user-defined

285 probability of exceedance of thresholds, were found to increase forecast skill and usability. In  
286 other words, the inclusion of non-climate predictors, which are consistent with the conceptual  
287 model of drivers for food security in Guatemala developed by SESAN, helps to reproduce the  
288 main features beyond the annual cycle and interannual variability of the undernutrition  
289 timeseries by better capturing peaks at monthly timescales.

## 290 *Agriculture*

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

## 297 4) RAINY SEASON ONSET TIMING IN KENYA

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299 *Todd, Stella Aura*

300 Approximately 98% of Kenya's agricultural systems are rain-fed (Republic of Kenya  
301 2017). Prediction of rainy season onset timing is therefore a key requirement for assisting  
302 farmers in timely land preparation and planting. The Kenya Meteorological Department  
303 (KMD) provides season onset predictions based on inferences from statistical and dynamical  
304 seasonal forecast systems. A real-time trial of the utility of S2S forecasts was undertaken by  
305 KMD to assess their usefulness in strengthening these operational onset predictions, at lead  
306 times of up to 4 weeks, for improved agricultural decision-making, crop yield and food

307 security. The trial was part of the ‘Forecast-based Preparedness Action’ (ForPac) project<sup>7</sup>,  
308 conducted over 5 rainy seasons in the period 2018-2020.

309 Met Office GloSea5 (MacLachlan et al. 2015) S2S forecasts<sup>8</sup> were provided to KMD in  
310 the form of weekly guidance bulletins with a supporting narrative. KMD used the guidance  
311 primarily for pre-operational evaluation purposes, however, in some cases where confidence  
312 in the predictions was high (e.g., consistency over consecutive lead times), the information  
313 was used in operational forecasts to the Kenyan public, including farming communities. The  
314 bulletin was provided weekly throughout each rainy season, beginning 3 to 4 weeks ahead of  
315 the climatological start of the season. Products included maps of forecast probabilities for  
316 tercile categories of weekly-averaged precipitation at weeks 1-4 ahead and forecasts of the  
317 Madden-Julian Oscillation (MJO), a key driver of sub-seasonal rainfall in the region  
318 (Berhane and Zaitchik 2014), using phase and amplitude diagrams (Wheeler and Hendon  
319 2004). The prediction skill and GloSea5’s representation of the MJO phase teleconnections,  
320 which are generally well captured (MacLeod et al. 2021a), were also provided. Two March-  
321 May (MAM) rainy seasons and three October-December (OND) rainy seasons were sampled  
322 in the trial, each containing marked rainfall anomalies, including one with a widespread  
323 notable delay in rainfall onset (MAM 2019) and one with a marked early rainfall onset (OND  
324 2019). In both of these highly impactful cases, predicted tercile category rainfall probabilities  
325 for the early weeks of the seasons were consistent with the observed onset anomaly,  
326 including at week 4 of early forecasts, with the forecast signal strengthening as the lead time  
327 shortened.

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<sup>7</sup> ‘Towards Forecast-based Preparedness Action (ForPac)’ project  
(<http://www.shear.org.uk/research/ForPac.html>)

<sup>8</sup> Met Office GloSea5 seasonal prediction system (<https://www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/climate-models/glosea5>)

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

#### 341 5) AGRICULTURAL MANAGEMENT IN BIHAR, INDIA

342 *Authors: Nachiketa Acharya, Andrew W. Robertson, Lisa Goddard*

343 A probabilistic S2S forecast system was developed for the state of Bihar, one of the most  
344 climate-sensitive states in India. Precipitation forecasts were issued in real-time during the  
345 June-September 2018 monsoon to explore the potential value of the S2S forecasts for small-  
346 holder farmers who operate farms of less than five acres<sup>9</sup>. Four districts were selected – two  
347 in the northern plains (flood-prone) and two in the southern plains (drought-prone). The  
348 project was a collaboration between IRI, University of Arizona, Indian Meteorological  
349 Department (IMD), Regional Integrated Multi-Hazard Early Warning System for Africa and  
350 Asia (RIMES), and the Government of Bihar, India.

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<sup>9</sup> ‘International Research Applications Project (IRAP)’ project (<https://cpo.noaa.gov/Meet-the-Divisions/Climate-and-Societal-Interactions/IRAP>)

351 Real-time National Centers for Environmental Prediction (NCEP) CFSv2 (Saha et al.  
352 2014) S2S forecasts<sup>10</sup>, calibrated against observed gridded rainfall fields from the IMD  
353 using canonical correlation analysis, were generated each month during June-September  
354 2018. The forecasts were limited to two weeks in advance as the calibrated probabilistic  
355 forecasts for weeks 3-4 were concentrated around climatological probabilities (0.33), which  
356 was a limitation of the forecast's potential utility. The 2018 monsoon recorded a large rainfall  
357 deficit over Bihar (~25% below its long-term average) with 11 of the 18 weeks registering  
358 deficits. The real-time S2S forecast captured the signal of the weaker monsoon in 2018 over  
359 Bihar, including the delayed monsoon onset and the observed break phase in August at the  
360 week 2 lead time. The quantitative verification of the district-level hindcasts and real-time  
361 forecasts over the monsoon season in 2018 is evaluated in Robertson et al. (2019) and  
362 Acharya (2018).

363 To assess the usability and utility of the real-time S2S forecasts to the user community,  
364 'field schools' involving ~300 farmers were conducted prior to the monsoon in May 2018.  
365 The curriculum extended beyond the presentation of climate forecasts to include contextual  
366 information on climate systems and variability, the technology of forecasting, and the range  
367 of adaptations available under specific forecast conditions. During the monsoon season, real-  
368 time forecasts were displayed through a virtual 'maproom'<sup>11</sup>. Text summaries based on the  
369 forecast maps were sent to two of Bihar's State Agricultural Universities (SAUs) – one for  
370 the flood districts and the other for the drought districts – who translated the forecast  
371 summary into the local language (Hindi). These were disseminated through a non-  
372 governmental organization (NGO) directly to farmers via text message (Fig. 3). A user  
373 survey was conducted at the end of the 2018 monsoon season across the four districts to find

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<sup>10</sup> NCEP CFSv2 seasonal forecasts ([https://www.cpc.ncep.noaa.gov/products/CFSv2/CFSv2\\_body.html](https://www.cpc.ncep.noaa.gov/products/CFSv2/CFSv2_body.html))

<sup>11</sup> IRI Bihar Climate Maproom (<http://iridl.ldeo.columbia.edu/maproom/Agriculture/bihar.html#tabs-2>)



374 out how farmers used the S2S forecasts for farm-level planning and decisions (October  
375 2018). The survey found that almost half of the farmers that participated in the field school  
376 used the forecasts to change their farming practices and irrigation schedules compared to  
377 previous years. Farmers used the late arrival of the 2018 monsoon (~16 days), which was  
378 well captured across Bihar by the S2S forecast, to delay the sowing of rice and other crops  
379 until closer to the monsoon onset. They also changed to a less water-demanding variety of  
380 paddy rice in response to expectations of a weaker monsoon.

### 381 *Water resource management*

382 Forecast information on S2S timescales is crucial for managing water resources,  
383 especially in times of flood or drought. Combined S2S meteorological, climatological and  
384 hydrological forecast systems provide valuable water resource information to reduce  
385 economic, social and environmental damages (White et al. 2015), particularly in climate-  
386 sensitive regions (Ralph et al. 2020). Here, we explore water resource management S2S  
387 forecasting applications in Brazil and the western U.S..

### 388 6) WATER MANAGEMENT IN CEARÁ STATE, BRAZIL

389 *Authors: Francisco C. Vasconcelos Jr., Dirceu S. Reis Jr., Caio A. S. Coelho, Eduardo S.*  
390 *P. R. Martins*

391 A combination of seasonal climate and hydrological models has been used for ~15 years  
392 by Ceará State Meteorology and Water Resources Foundation (FUNCEME) and Ceará State  
393 Water Resources Management Company to support reservoir operations by forecasting  
394 inflows for key regional basins in Brazil, for both water resources planning and drought risk  
395 response. Current efforts on improving the seasonal forecast system include the use of an  
396 interannual statistical model and both global and regional dynamical models, but forecast use  
397 on S2S timescales is still in its infancy (Fig. 4a). The Inter-agency Drought Contingency

398 Group (IDCG) is responsible for monitoring and predicting the State drought status within a  
399 30-day planning horizon for 184 municipalities, including triggering emergency warnings  
400 and responses for municipalities at risk. In the absence of operational S2S forecasts, these 30-  
401 day ahead scenarios are based on seasonal forecasts updated monthly.

402 In this study, ECMWF S2S precipitation forecasts from the S2S global repository were  
403 evaluated to assess their performance at producing inflow predictions for the Orós reservoir  
404 in Ceará State up to 45-days ahead between January-April 2018 (Fig. 4). The verification  
405 study focuses on 15 weekly forecasts as if issued every Thursday from January 18 to April  
406 26. The quality of these forecasts has been evaluated at three time-mean horizons, 15, 30 and  
407 45 days ahead from the initialization date. ECMWF S2S forecasts initialized once a week  
408 during the Jan-Apr 1998-2017 period were used to feed a hydrological model to produce flow  
409 forecasts into the Orós reservoir. These forecasts were then post-processed through an  
410 empirical quantile mapping procedure using observed (1998-2017) flows to generate mean  
411 flow forecasts for 2018. All 11 available ECMWF hindcast ensemble members were used for  
412 post-processing. Fig. 4b shows the correlation between the 11-member ensemble mean flow  
413 forecasts and the corresponding observations computed over the 1998-2017 hindcast period  
414 for each initialization date and time mean horizons. Correlation values between 0.70 and 0.90  
415 indicate reasonable forecast association ability. Fig. 4c shows boxplots of 51-member post-  
416 processed ensemble flow forecasts for 2018 (for 30-day means) along with the observed flow  
417 and climatological 50th and 80th percentiles (dashed lines), which provided a good  
418 description of the observed flow for most initialization dates.

419 These results illustrate the utility of inflow forecasts based on S2S precipitation forecasts  
420 in addition to the existing seasonal flow forecast system to support water management  
421 decisions and the triggering of emergency responses (e.g., construction of pipelines and  
422 wells) for municipalities at risk in Ceará State. Although this study illustrates the utility of

423 S2S forecasts to guide IDCG's decisions, additional activities are needed to demonstrate their  
424 long-term value, such as one-on-one meetings with IDCG members to provide details about  
425 the developed S2S timescale inflow forecasting system, an assessment of past performance of  
426 this system, and the opening of a two-way dialogue with users to enable suggestions for  
427 future improvements and product co-development.

#### 428 7) WATER MANAGEMENT IN WESTERN U.S.

429 *Authors: Michael J. DeFlorio, Peter B. Gibson, Duane E. Waliser, F. Martin Ralph,*  
430 *Michael L. Anderson, Luca Delle Monache*

431 The Center for Western Weather and Water Extremes (CW3E) and the National  
432 Aeronautics and Space Administration Jet Propulsion Laboratory (NASA JPL), supported by  
433 the California Department of Water Resources (CA DWR), formed a partnership to improve  
434 the S2S prediction of precipitation to benefit water management in the western U.S.. The  
435 main objective of this team is to produce experimental S2S prediction products for  
436 atmospheric rivers (ARs), ridging events, and precipitation, supported by research and  
437 hindcast skill assessments. Although the main quantity of interest for stakeholders is total  
438 precipitation (i.e., available water), ARs and ridging events are a focal point due to their  
439 strong influence on the presence (and absence, respectively) of precipitation in the western  
440 U.S. during wintertime, and their intrinsic predictability. The primary sector and stakeholder  
441 for which this effort is particularly relevant is western U.S. water resource management and  
442 CA DWR, respectively.

443 A key pillar of this applied research endeavor is to collaborate with CA DWR's  
444 stakeholders regarding the target predictand, methodology, and data used for research along  
445 with the experimental product display and description for experimental S2S forecast  
446 products. Our team, which also includes collaborators at IRI, University of California at Los

447 Angeles, University of Arizona, and University of Colorado, has interacted regularly with  
448 stakeholders from CA DWR to facilitate communication and help with the development of  
449 the forecast products. This interaction ensures that the research and forecast product  
450 development are meeting the specific needs of end users while maintaining high standards for  
451 both quality of research and utility of the forecast products for the applications community.  
452 These experimental S2S forecast products, together with continued investment from CA  
453 DWR into S2S research, stand to benefit end users at CA DWR by providing information at  
454 subseasonal lead times to support flood risk management, emergency response, and  
455 situational awareness (DeFlorio et al. 2021).

456 Fig. 5 summarizes two CW3E/JPL experimental S2S applications that utilize data from  
457 the S2S global repository: the week 3 AR activity outlook (Fig. 5a), and the weeks 3-4  
458 ridging outlook (Fig. 5b). This figure shows an example of particular forecast for AR activity  
459 and ridging made on September 21, 2020. In Fig. 5a, the bottom panel shows the anomaly  
460 forecast field (top minus middle panels) for above or below average AR days per week for  
461 the October 06-12 week-3 verification period in the NCEP forecast system. In Fig. 5b,  
462 forecast probabilities for each ridge type (North, South, and West) during the October 05-19  
463 weeks 3-4 verification period are shown. If > 50% of ensemble members in the NCEP  
464 forecast system predict above normal ridge frequency, the right panel maps are displayed to  
465 show the likelihood of wetter or drier conditions based on how each ridge type typically  
466 influences precipitation (Gibson et al. 2020a). Both outlooks are updated weekly and made  
467 available on the CW3E S2S forecast website<sup>12</sup>. Skill assessments of the NCEP and ECMWF  
468 hindcasts from the S2S repository are provided in DeFlorio et al. (2019a,b) and Gibson et al.  
469 (2020b). These forecast products have been regularly consulted by our stakeholders at CA

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<sup>12</sup> CW3E Subseasonal to Seasonal (S2S) Experimental Forecasts ([https://cw3e.ucsd.edu/s2s\\_forecasts/](https://cw3e.ucsd.edu/s2s_forecasts/))

470 DWR, both in internal CA DWR meetings and in collaborative meetings between CA DWR  
471 stakeholders and our research team.

## 472 *Renewable energy and utilities*

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

### 479 8) A DECISION-SUPPORT TOOL FOR THE RENEWABLE ENERGY SECTOR

480 *Authors: Andrea Manrique-Suñén, Isadora Christel, Ilaria Vigo, Lluís Palma, Ilias G.*  
481 *Pechlivanidis, Albert Soret*

482 The S2S4E<sup>13</sup> project explored the usefulness of S2S forecasts to anticipate renewable  
483 energy production and demand several weeks to months ahead (Soret et al. 2019). A  
484 decision-support tool (DST) that provides S2S predictions of climate variables and renewable  
485 energy-related indices was co-developed with users. The spatial coverage of the majority of  
486 the forecasts is global with some products provided for the pan-European domain. The DST  
487 is fed with forecasts from the ECMWF S2S forecast system (2 m mean / max / min  
488 temperature, 10m wind speed, precipitation, solar radiation and mean sea level pressure). It  
489 provides weekly S2S forecasts for up to 4 weeks lead time via a visual interface that includes  
490 a skill score that evaluates the quality of the forecast with respect to a climatological forecast  
491 reference (fair Ranked Probability Skill Score for the tercile probabilities and fair Brier Skill  
492 Score for the extreme probabilities; Wilks 2011; Ferro et al. 2014). The raw forecasts are bias

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<sup>13</sup> 'Sub-seasonal to Seasonal climate forecasting for Energy' project (<https://s2s4e.eu/dst>)

493 adjusted to remove the model mean bias with respect to ERA5 reanalysis (Hersbach et al.  
494 2020). The computation of a robust climatology is crucial to ensure an effective bias  
495 adjustment of subseasonal forecasts (Manrique-Suñén et al. 2020).

496 The DST provides forecast indices per energy sector: hydropower (maximum snow and  
497 inflows at the catchment scale), wind energy (3 capacity factors for 3 different turbine types),  
498 solar energy (capacity factor) and energy balance (electricity demand, wind energy  
499 production, and demand minus wind energy production per country). Energy companies use  
500 the S2S forecasts to inform operation and maintenance decisions, optimize water levels in the  
501 reservoirs, and hedge against climate variability (e.g., by trading energy futures).

502 The co-generation and operationalization of the DST involved scientists, designers,  
503 communication and industry specialists. The inclusion of three energy companies as  
504 consortium partners (EDF Electricité de France, EDP Renováveis SA, and ENBW Energie  
505 Baden-Württemberg AG) provided opportunities for collaboration at all stages of the project,  
506 and ensured their needs were addressed in the co-development of the DST. In the design  
507 phase, user input was crucial to devise a structured, complete and concise interface. Focus  
508 groups, workshops, interviews, usability testing and eye-tracking were some of the  
509 techniques used (Calvo et al. 2021). During the operational phase, monthly meetings were  
510 held with partners to understand how the tool was being employed. This allowed a  
511 continuous feedback that served to include small modifications or additional functionalities.  
512 A key challenge in the development of the DST was introducing the concept of ‘skill’ to  
513 users. To orientate the user, a qualitative skill classification was devised : ‘no skill’ (skill <  
514 0%), ‘fair’ (0 < skill < 15%), ‘good’ (15% < skill < 30%) and ‘very good’ (30% < skill). This  
515 helped users to evaluate expected quality. Nevertheless, in order to attribute trust to a  
516 probabilistic forecast, users need to combine the skill information with a measure of

517 uncertainty (related to the ensemble spread) provided by the forecast probability. This  
518 remains an open challenge in the field of uncertainty communication in climate services.

#### 519 9) HYDROPOWER INFLOW PREDICTIONS IN SCOTLAND, U.K.

520 *Authors: Robert M. Graham, Jethro Browell, Christopher J. White, Douglas Bertram*

521 In Scotland, reservoir inflow forecasts for hydropower generation are primarily dependent  
522 on weather forecasts rather than initial hydrological conditions. This is due to steep  
523 topography and low groundwater storage capacity (Svensson 2015). SSE Renewables, a UK  
524 energy generation company, have a hydropower portfolio of 1,459MW across Scotland,  
525 enough to supply approximately 1 million UK homes. Hydropower operators at SSE  
526 currently use deterministic inflow forecasts, covering periods up to 2 weeks ahead, and an  
527 expert meteorologist provides longer range outlooks based on S2S forecasts. A team of  
528 hydropower operators from SSE Renewables and researchers from the fields of meteorology,  
529 energy forecasting and hydrology at the University of Strathclyde co-developed probabilistic  
530 S2S inflow forecasts for selected hydropower reservoirs in Scotland and further evaluated the  
531 potential economic value of these forecasts. SSE were involved from the initial concept stage  
532 of the project to its closure.

533 Inflow forecasts were derived from ECMWF S2S forecasts from the S2S global  
534 repository. Benchmark inflow forecasts for a case study reservoir were created by training a  
535 linear regression of the S2S precipitation forecasts onto the historical inflow record. These  
536 were then post-processed, following methods similar to Scheuerer (2014), to produce  
537 calibrated probabilistic inflow forecasts (Graham et al. 2021). We evaluated the inflow  
538 forecasts for 11 lead times, including weekly mean inflow rate forecasts from week 1 (days 1-  
539 7) to week 6 (days 36-42), and extended mean inflow rate forecasts from 2 (days 1-14) to 6  
540 weeks (days 1-42) ahead. After post-processing, the probabilistic weekly mean inflow

541 forecasts demonstrated skill up to week 6, though skill in weeks 3 to 6 is low relative to  
542 weeks 1 and 2. Furthermore, the six-week average (days 1-42) inflow rate forecasts displayed  
543 greater skill than weekly mean inflow forecasts for week 2 (days 8-14). In contrast, the raw  
544 S2S precipitation forecasts and benchmark inflow forecasts held statistical skill only to  
545 forecast week 2, the typical skill horizon in mid-latitudes for probabilistic ensemble forecasts  
546 (Branković et al. 1990).

547 The economic value of the inflow forecasts was explored using a stylized cost model  
548 based on the classical ‘News Vendor’ optimization problem (Khouja 1999), following the  
549 principle of maintaining a target water level in the reservoir. Within this framework, the  
550 probabilistic inflow forecasts consistently reduced costs relative to the use of climatological  
551 forecasts, even for forecast week 6 (days 36-42). However, deterministic inflow forecasts,  
552 based on the median of the probabilistic forecast distribution, often resulted in poor  
553 operational decisions and increased costs relative to the use of climatological forecasts from  
554 week 2 (days 8-14) onwards.

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

563 10) SCENARIO PLANNING FOR HYDROPOWER OPERATIONS IN TASMANIA, AUSTRALIA



564 *Authors: Carly R. Tozer, Sonia Bluhm, Carolyn J. Maxwell, Tomas A. Remenyi, James S.*  
565 *Risbey, Robert G. Wilson*

566 The El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) are recognized  
567 as key large-scale drivers of Australia's climate variability (Risbey et al. 2009). The co-  
568 occurrence of El Niño and positive IOD events has been associated with dry conditions  
569 across the country (Meyers et al. 2007; Ummenhofer et al. 2011). One such occurrence was  
570 in 2015, which coincided with below average winter and spring rainfall across parts of  
571 southern Australia. Tasmania experienced statewide rainfall deficits and the lowest spring  
572 rainfall on record in western Tasmania (Károly et al. 2016). Hydro Tasmania, which manages  
573 multiple hydropower facilities, primarily located across western Tasmania, produces hydro-  
574 electricity for both Tasmania and mainland Australia. The record low rainfall in 2015  
575 contributed to an energy supply challenge for Hydro Tasmania, leading to a subsequent  
576 operational review. In 2019, a reappearance of this combination of climate drivers looked  
577 likely, with S2S forecasts issued in April and May 2019 pointing towards the development of  
578 an El Niño and positive IOD over winter and spring (e.g., Bureau of Meteorology 2019). The  
579 positive 'super-IOD' (Doi et al. 2020) event has since been linked to rainfall deficits and  
580 bushfires across Australia (van Oldenborgh et al. 2021).

581 Hydro Tasmania collaborated with the Commonwealth Scientific and Industrial Research  
582 Organisation (CSIRO) as part of a project to understand the use and potential utility of  
583 climate forecasts, including identifying Hydro Tasmania's operations and decision-making  
584 processes, and the climate variables of importance for forecast evaluation. The application of  
585 climate forecasts within Hydro Tasmania's operations is through operational scenario  
586 planning (Fig. 6a). Potential operational outcomes are produced in response to forecast  
587 information and evaluated against historical data. In the case of the 2019 El Niño/positive  
588 IOD forecast, Hydro Tasmania's operational scenario planning options were focused on dry

589 conditions as this was the expectation based on past experiences (Fig. 6b,d). As the year  
590 progressed, Hydro Tasmania monitored the subseasonal climate driver forecasts issued by  
591 Australia's Bureau of Meteorology in concert with rainfall received in western Tasmania, in a  
592 'watch and act' process. When it became clear that the rainfall deficits experienced in 2015  
593 were not being repeated in 2019 (Fig. 6d) no major changes to operations were enacted (Fig.  
594 6c).

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

#### 605 11) WEATHER RISK MANAGEMENT FOR U.K. FIXED-LINE TELECOMMUNICATIONS

606 *Authors: David Brayshaw, Alan Halford, Stefan Smith, Kjeld Jensen*

607 The physical infrastructure associated with fixed-line telecommunication systems, which  
608 are critical for many aspects of modern service-based economies, is subject to significant  
609 weather exposure. In the U.K., weather-related line-faults are commonly associated with  
610 service disruptions (e.g., BT 2018), however, rapid evolution of the infrastructure (e.g.,  
611 growth in broadband) limit the availability of historical data for both weather risk assessment  
612 and impact-based prediction. A jointly supervised project (Halford 2018) by the University of

613 Reading and a leading UK communications services company, BT plc, sought to address  
614 these challenges by creating a robust long-term historic fault-rate record for the UK  
615 telecommunications system with a multi-week fault rate forecasting system to support line-  
616 maintenance scheduling. In brief, historic fault-rates from 1979-2017 were constructed using  
617 a multiple linear regression fault-rate model which was applied to weather-inputs from ERA-  
618 Interim (Dee et al. 2011), i.e., a time-series of estimated fault rates assuming the historic  
619 weather impacted upon the UK telecoms system of 2017 was produced (refer to Brayshaw et  
620 al. 2020 for details). S2S ‘forecasts’ spanning 1996-2015 for the same UK telecoms system  
621 were then generated using ECMWF S2S ensemble hindcasts (11 ensemble members). Here,  
622 and in the original study (Brayshaw et al. 2020), there was an emphasis on the quantitative  
623 estimation of end-user ‘value’ from skillful S2S forecasts that can be summarized by the  
624 schematic:

625           S2S forecast (weather) => Impact model (line faults) => Decision model (cost)

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

634       A decision-simulation model utilizing the fault-rate forecast in maintenance scheduling  
635 was then developed to estimate forecast value. This demonstrated that the fault-rate forecast  
636 system could be used to improve both short-term and long-term management strategies, e.g.,  
637 either meeting week-to-week performance targets (a simulated ~5-10% improvement) or

638 achieving the same level of performance but at lower long-term cost (a simulated ~1%  
639 reduction in resource levels). Though these estimates are likely an upper bound to that which  
640 would be achievable in practice, the savings are potentially significant with the penalty for  
641 failing to meet repair targets reaching up to ~£1 million/day and annual staffing costs of  
642 around £500 million (see Brayshaw et al. 2020).

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

#### 651 *Disaster early warnings and emergency management*

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

#### 658 12) EUROPEAN FLOOD FORECASTING

659 *Authors: Francesca Di Giuseppe, Fredrik Wetterhall*

660 The European Flood Awareness System (EFAS)<sup>14</sup> is operated by the Copernicus  
661 Emergency Management System (CEMS), and functions as a common pan-European tool to  
662 provide coherent early warnings of flood events. A set of decision rules based on forecast  
663 persistency and magnitude are defined to identify points on Europe's river network where  
664 flooding is likely to happen. The authorities responsible for flood forecasting in the specific  
665 location are then sent flood notifications ahead of such events. EFAS uses medium-range  
666 forecasts, typically up to 10 days lead time, but for rare and potentially widespread flood  
667 events a system working on the S2S timescale (10-30 days) would extend the early warning  
668 window to help pinpoint regions in need of attention. EFAS recently added a twice weekly  
669 extended-range ensemble forecast with 51 members up to 6 weeks (aggregated into weekly  
670 averages) based on ECMWF S2S forecasts (Wetterhall and Di Giuseppe 2018). These  
671 forecasts are currently only for supplementary information and not used to issue warnings.  
672 Since the predictability for extreme events on S2S lead times can be uncertain (Domeisen et  
673 al. 2021), decision rules for preventive actions would have to be designed with this increased  
674 uncertainty in mind in comparison with the medium-range forecasts.

675 In this study, we revisit a major flooding event that took place in southeastern Europe in  
676 May 2014 to explore the potential added-value in the decision-making process of S2S  
677 hydrological forecasts. During the event, large areas of south-eastern and central Europe  
678 experienced exceptionally intense rainfall which led to widespread flooding where over 60  
679 people died and more than a million inhabitants were affected (Stadtherr et al. 2016). The  
680 EFAS system indicated exceedance of the 20-year return period more than a week ahead of  
681 the event and was able to issue notifications 4-5 days lead time. However, this information  
682 could potentially have been even more useful if an even earlier indication of the event was

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

683 available. In this revised analysis, we look at how far back a signal for these conditions was  
684 present in the S2S forecasts. The fraction of ensemble members that predicted the exceedance  
685 of the ‘decision’ threshold is considered as the probability of an event occurring for the  
686 period preceding and following the event (April 01 to June 30 in this case) and as a function  
687 of lead times up to 46 days ahead. Considering that extreme conditions are difficult to detect  
688 at longer lead times as the forecast naturally reverts to climatology as predictability  
689 decreases, a 30% chance at lead times >10 days is generally taken as an indication a  
690 forthcoming event. In this study, the main event had a persistent signal up to 25 days before  
691 the event in the S2S forecasts, highlighting the importance and potential utility of the S2S  
692 time scale for pre-warning. To put this into the context of decision-making, a full cost-loss  
693 scenario analysis of the historical period is needed to establish the correct level of probability  
694 and lead time to issue pre-alerts for severe events. Further, the decision-making process in the  
695 region would need to be trained to utilize the added information.

## 696 **Discussion**

697 We demonstrate here that S2S forecasts are increasingly being used across the public  
698 health, agriculture, water resource management, renewable energy and utilities, and  
699 emergency management and response sectors in both the developed and emerging economies.  
700 As identified across our 12 application-focused case studies (Table 1), current decision-  
701 making is generally based on either short-to-medium range (often deterministic) or seasonal  
702 forecasts. The S2S forecasting timescale is therefore a new concept for many users. While the  
703 additional value of S2S forecasts for decision-making is increasingly gaining interest among  
704 users, as shown here, incorporating probabilistic ensemble S2S forecasts into existing  
705 operations is not trivial. S2S forecasts do not produce a “go/no go” answer of what a user  
706 should do; instead they provide additional, supplementary ‘situational awareness’ information

707 that can be used to drive decision-making and risk-based management processes on weekly to  
708 monthly forecast horizons. Seasonal to decadal forecasts face the same challenge. What the  
709 presented case studies clearly suggest, however, is that the kind of widespread, national and  
710 international investment witnessed in service development on seasonal and climate timescales  
711 is also needed on the S2S timescale.

712 In addition to the limited awareness and demonstration of the potential benefits of the  
713 S2S timescale across sectors to date, a lack of ‘in house’ expertise in how to effectively apply  
714 S2S forecasts and, to some extent, a lack of access to S2S forecasts, have also been barriers to  
715 widespread adoption of S2S forecasts. This is the ‘knowledge-value’ gap, highlighting the  
716 challenge and need of translating S2S forecast *skill* into forecast *value* (e.g., Giuliani et al.  
717 2020). For S2S predictions to have utility, there needs to be an signal in the forecast that  
718 emerges beyond the noise in the system (Mariotti et al. 2020). However, across the case  
719 studies presented here, there are varying interpretations of what ‘skill’ is from a scientific or  
720 user perspective and what magnitude of signal is needed for a forecast to add value for a user.  
721 For any forecast application, user-focused questions such as “What is the minimum level of  
722 skill (or perhaps ‘certainty’) that can still be useful?”, and “Is the required level of skill  
723 actually attainable for the variables, region and application of interest?” are as essential to the  
724 concept of forecast utility as is verifying forecast skill (e.g., Crochemore et al. 2021). Here,  
725 we highlight that the answers to these and similar questions can only be determined via user  
726 engagement and continued partnership. This approach helps determine whether S2S forecast  
727 information can be better utilized through approaches such as multiple scenario planning  
728 ‘storyline’ frameworks with a comparison to recent historical events (e.g., hydropower  
729 operations in Tasmania, Australia), or supplemented by statistical post-processing (e.g.,  
730 hydropower inflows in Scotland, U.K.), or through additional impact-based models (e.g.,  
731 Malaria occurrence in Nigeria). Some of the most effective real-time / operational

732 applications presented here are where S2S forecasts have been communicated to end-users  
733 and contributed to ‘situational awareness’ using an early ‘horizon scanning’ approach of up-  
734 coming extreme events. This is true in the case of farmers determining the planting and  
735 management of crops, informed by the timing of the monsoon in Bihar, India, and the rainy  
736 season onset in Kenya. The co-development of the S2S4E project’s decision-support tool for  
737 the renewable energy sector also provides a particularly useful and insightful discussion  
738 around forecast skill, value, trust and communication, with all of the cross-sectoral case  
739 studies presented here confirming the need for the co-generation of forecast products. This  
740 clearly identifies and communicates the strengths and limitations of forecasts in support of  
741 improved forecast utility.

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



756 here. Water therefore presents perhaps the best opportunity to demonstrate the utility of S2S  
757 forecasts to bridge the gap between the weather and climate forecasting timescales.

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

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#### 811 DATA AVAILABILITY

812 The joint WWRP/WCRP Subseasonal to Seasonal Prediction Project (e.g., Robertson et  
813 al. 2014) created a global repository of experimental or operational near real-time S2S  
814 forecasts and reforecasts (hindcasts) from eleven international meteorological institutions, co-  
815 hosted by ECMWF and CMA (Vitart et al. 2017). These data are publicly accessible by  
816 researchers and users (<https://apps.ecmwf.int/datasets/data/s2s> and <http://s2s.cma.cn/index>).  
817 With the exception of case study 4), which uses GloSea5 forecasts (MacLachlan et al. 2015)),  
818 all case studies use selected S2S forecasts and reforecasts that are available from this  
819 repository, providing a consistent basis for S2S forecast skill assessment and evaluation of  
820 their utility.

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1091

1093 **Table 1** Description of sectoral case studies with notable prior or related studies where  
 1094 applicable. Note: not all case studies are based on previously-published work; for some, this  
 1095 is the first time they have been documented (shown as n/a). In other cases, such as study 2  
 1096 and 4, the studies listed describe key motivations, partially related components of the case  
 1097 study, or prediction of events different to that of the main study theme and should not be  
 1098 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 U.K.	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	n/a
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, India	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, Brazil	Water resource management	Reservoir inflows for water management	n/a
7) Water management in western U.S.	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)



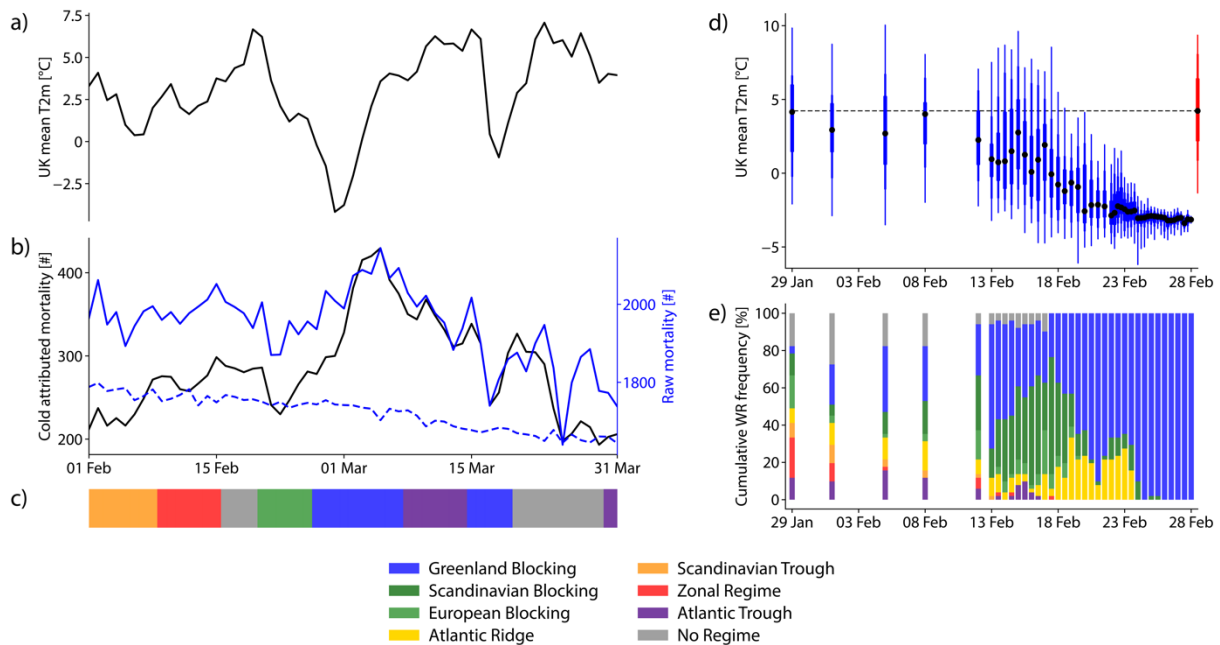
9) Hydropower inflow predictions in Scotland, U.K.	Renewable energy and utilities	Reservoir inflows for hydropower	Graham et al. (2021)
10) Scenario planning for hydropower operations in Tasmania, Australia	Renewable energy and utilities	Low rainfall scenarios for hydropower	n/a
11) Weather risk management 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)

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## FIGURES

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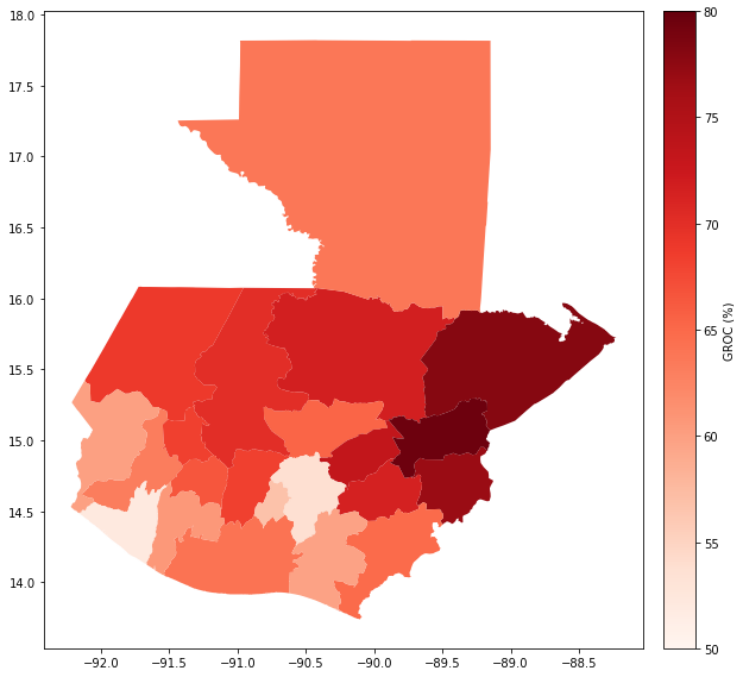


1102

1103 **Figure 1** Mortality during extreme cold weather events in the U.K., showing: a) HadUK-Grid  
 1104 mean 2m temperature (T2m) observations for the two cold waves in February and March  
 1105 2018; b) estimated U.K. mortality attributable to the cold weather (black line), observed raw  
 1106 total mortality (blue line), and 1998-2017 average (dashed line); c) Observed weather regime  
 1107 evolution (based on ECMWF analysis) during the same period for a life cycle definition of  
 1108 seven weather regimes (cf. Grams et al. 2017); d) ECMWF extended- and medium-range  
 1109 U.K. mean T2m ensemble forecasts valid for February 28, 2018 00 UTC (y-axis) as a  
 1110 function of forecast initial time (x-axis), with the blue box-and-whiskers showing the 99th,  
 1111 75th, 50th, 25th, and 1st percentiles, the black dots the control forecast, and the red box-and-  
 1112 whiskers the model climatology for February 28, 2018 00 UTC (plotting tool provided by  
 1113 Linus Magnusson, ECMWF); e) Same as d) but for the predicted probabilities of the active  
 1114 weather regime (regime projection  $> 1$  sigma) in the ensemble indicated by the corresponding  
 1115 color (gray indicates the ‘no regime’ category representing an atmospheric state not  
 1116 resembling any of the seven regimes).

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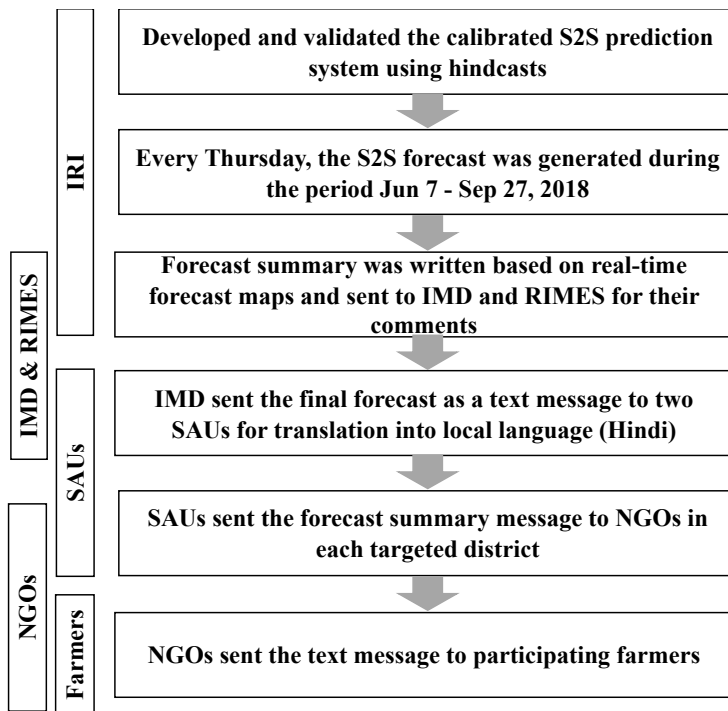
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1120 **Figure 2** Skill assessment for the early-action system for acute undernutrition in Guatemala,  
1121 showing: The Generalized Relative Operating Characteristics (GROC) skill metric for cases  
1122 of acute undernutrition for children under five in each department in Guatemala. GROC  
1123 measures forecast discrimination, or how well the system discriminates between different  
1124 categories (below normal, normal or above normal values). This NextGen forecast system  
1125 uses total monthly rainfall as a predictor of monthly cases of acute undernutrition for children  
1126 under 5 years old. Values ~50% indicate discrimination as good as climatology, and values  
1127 above (below) 50% indicate better (worse) discrimination than climatology. The skill shown  
1128 corresponds to the average skill for the following target month (example, January, if the  
1129 forecast is made in December), and considers the different lags/lead times between rainfall  
1130 and acute undernutrition for each department.

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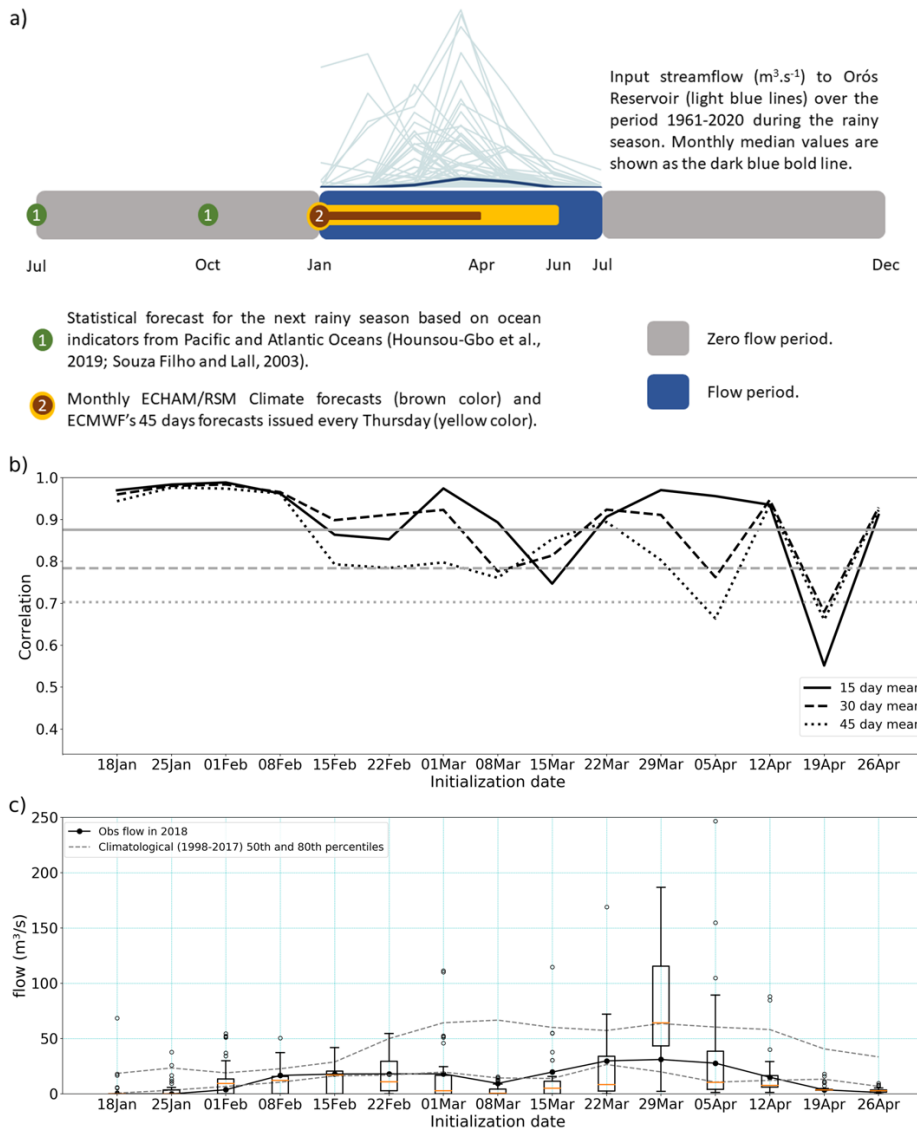


1132

1133 **Figure 3** Agricultural management in Bihar, India, showing: A flowchart of the forecast  
 1134 generation and dissemination. Interactions between the institutions and actors involved are  
 1135 indicated. NGO: non-governmental organization; IMD: India Meteorological Department;  
 1136 RIMES: Regional Integrated Multi-Hazard Early Warning System for Africa and Asia; SAU:  
 1137 State Agricultural Universities; IRI: International Research Institute for Climate and Society.

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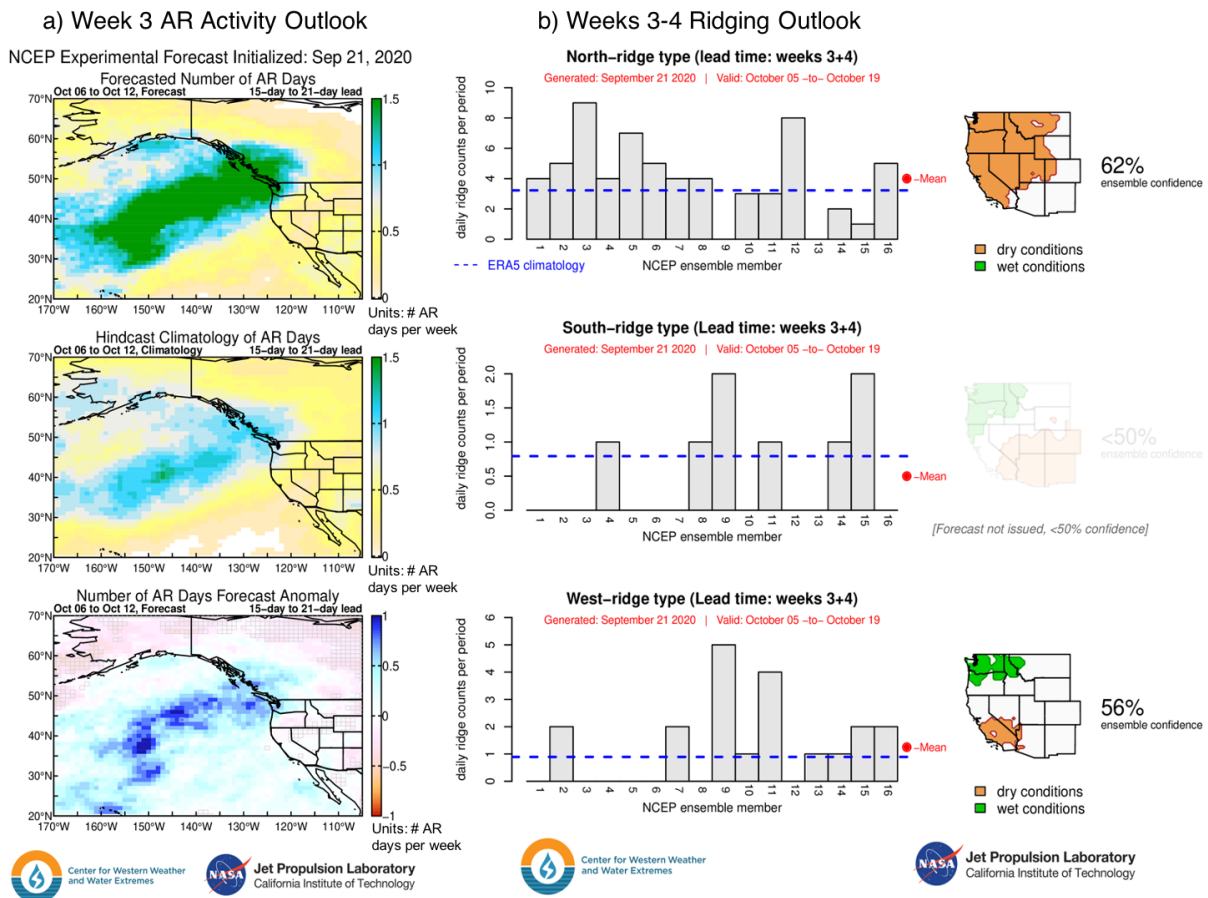
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1141

1142 **Figure 4** Water management in Ceará State, Brazil, showing: a) Ceará State flow forecast  
 1143 system schematic depicting January to April (rainy period) forecasts. Produced with (1)  
 1144 statistical models using previous July and October equatorial Pacific and Atlantic indices, and  
 1145 (2) daily precipitation forecasts from dynamical global and regional seasonal forecast models  
 1146 updated monthly from January to April for feeding a hydrological model to generate monthly  
 1147 flow forecasts (brown), and with ECMWF sub-seasonal precipitation forecasts produced  
 1148 every Thursday for the following 45 days for feeding a hydrological model to generate daily  
 1149 flow forecasts during the January to May period (yellow). The blue (grey) bar illustrates the  
 1150 wet (dry) period; b) Correlations between cross-validated 11 members ensemble mean flow  
 1151 forecasts post-processed through empirical quantile mapping and the corresponding observed

1152 flow over the 1998-2017 hindcast period for three time horizons (15, 30 and 45 day means).  
1153 Flow forecasts were produced with a hydrological model (Lopes 1999) fed with daily  
1154 precipitation ECMWF S2S forecasts initialized every Thursday (15 dates between January 18  
1155 and April 26). The solid, dashed and dotted horizontal grey lines represent the correlation  
1156 values computed aggregating all available forecasts (300 pairs of forecasts and observations)  
1157 for the three time horizons; c) 30 day mean post-processed flow forecasts for 2018 (boxplots  
1158 of 51 member ensembles) produced with a hydrological model fed with daily precipitation  
1159 ECMWF sub-seasonal forecasts initialized every Thursday (between January 18 and April  
1160 26). The red line in the boxplots represents the median  $p_{50}$  (50th percentile), the upper box  
1161 border represents the upper quartile  $p_{75}$  (75th percentile), and the lower border the lower  
1162 quartile  $p_{25}$  (25th percentile). The whiskers at the top of each box extend to  $p_{75} + 1.5IQR$ ,  
1163 where IQR is the interquartile range ( $p_{75}-p_{25}$ ). The whiskers at the bottom of each box extend  
1164 to  $p_{25}-1.5IQR$ . Values outside the whiskers are plotted with open circles. The black line  
1165 represents the 2018 observed flow, and the dashed lines the climatological (1998-2017) 50th  
1166 and 80th percentiles.  
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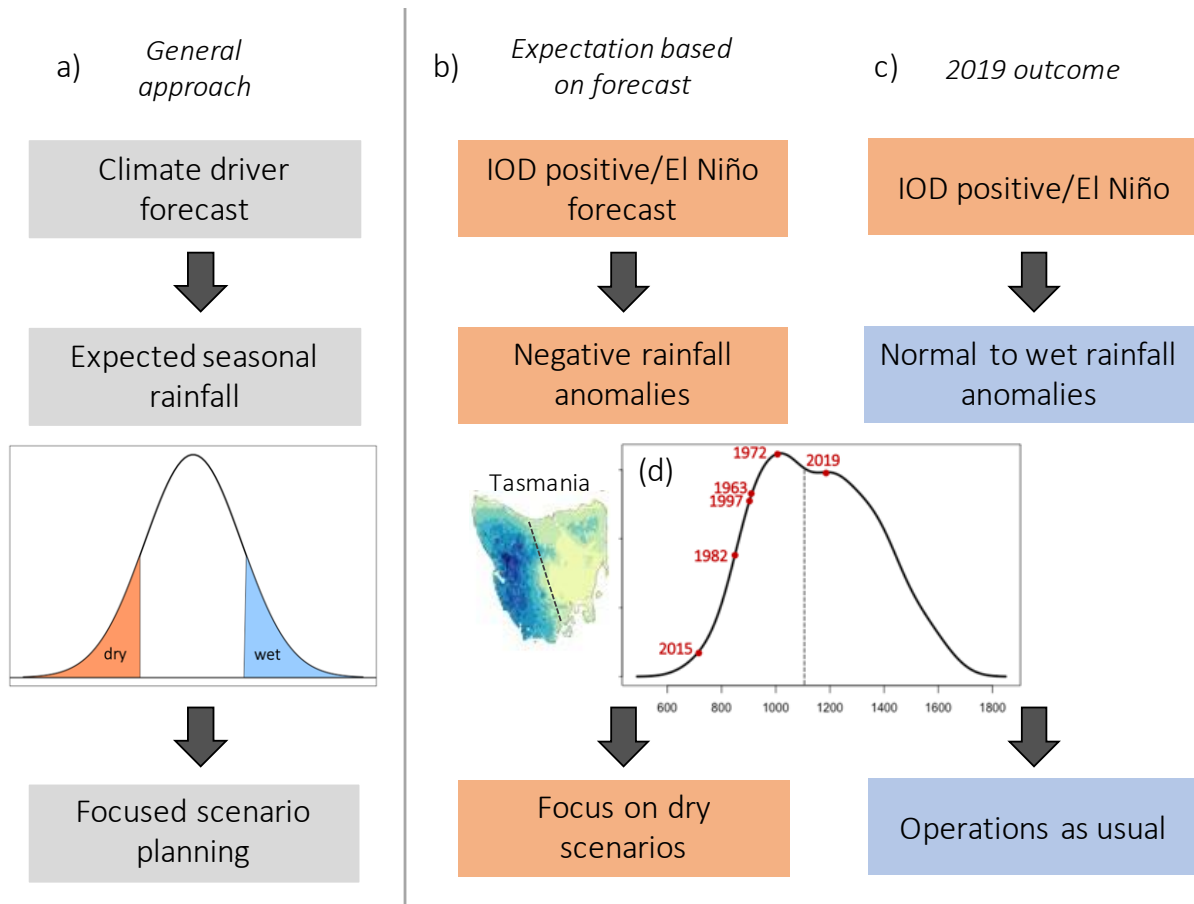


1169

1170 **Figure 5** Water management in western U.S., showing: a) CW3E/JPL week 3  
 1171 AR activity outlook. Forecast initialized September 21, 2020 and verified October 06-12,  
 1172 2020. Top panel shows the forecasted number of AR days to occur during the week 3  
 1173 verification period; middle panel shows the NCEP hindcast climatology of AR days during  
 1174 the October 06-12 week in the hindcast record; bottom panel shows the anomaly forecast  
 1175 field (top minus middle panels). Hindcast skill assessment provided in DeFlorio et  
 1176 al. (2019a,b); b) CW3E/JPL weeks 3-4 experimental ridging outlook. Forecast initialized on  
 1177 September 21, 2020 and verified October 05-19, 2020. Left column shows the occurrence  
 1178 frequency of each ridge type (bars) compared to climatology (horizontal line) for each of the  
 1179 model ensemble members. The top, middle, and bottom row display the North, South, and  
 1180 West ridge forecasts, respectively. If over 50% of the ensemble members predict more  
 1181 ridging than expected (for this time of year), then the right column maps indicate the  
 1182 likelihood of wetter or drier conditions based on how each ridge type typically influences  
 1183 precipitation. We note that summing across ridge types for a given ensemble member does  
 1184 not necessarily equal 14 daily counts as there can be days in the 2 week forecast verifying

1185 period where none of the three ridge types are predicted to occur. Methodology for  
1186 calculating ridge types is provided in Gibson et al. (2020a); hindcast skill assessment is  
1187 provided in Gibson et al. (2020b).





1189

1190 **Figure 6** Scenario planning for hydropower operations in Tasmania, Australia, showing: a) A  
 1191 general scenario planning approach, where a climate driver forecast is received from which  
 1192 there is an expectation around the seasonal rainfall response focused towards operational  
 1193 scenario planning; b) Dry scenario planning in response to IOD positive/El Niño forecast  
 1194 and the expectation of negative (dry) rainfall anomalies in western Tasmania; (c) 2019  
 1195 example outcome; (d) Probability density function of total winter/spring rainfall (in mm) in  
 1196 western Tasmania for each year from 1900-2019. The years marked in red indicate past IOD  
 1197 positive/El Niño events and the associated winter/spring rainfall anomalies. Dashed line  
 1198 indicates median winter/spring rainfall. Western Tasmania is considered the region west of  
 1199 the dashed black line (inset map).

1200