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

Christopher J. White,[a]* Daniela I. V. Domeisen,[b] Nachiketa Acharya,[c] Elijah A. Adefisan,[d]

Michael L. Anderson,[e] Stella Aura,[f] Ahmed A. Balogun,[g] Douglas Bertram,[a] Sonia Bluhm,[g]

David J. Brayshaw,[h] Jethro Browell,[i] Dominik Büeler,[j] Andrew Charlton-Perez,[h] Xandre

Chourio,[k] Isadora Christel,[l] Caio A. S. Coelho,[m] Michael J. DeFlorio,[n] Luca Delle Monache,[n]

Francesca Di Giuseppe,[o] Ana María García-Solórzano,[p] Peter B. Gibson,[n] Lisa Goddard,[k]

Carmen González Romero,[k] Richard J. Graham,[q] Robert M. Graham,[i] Christian M. Grams,[j]

Alan Halford,[h] W. T. Katty Huang,[h] Kjeld Jensen,[r] Mary Kilavi,[f] Kamoru A. Lawal,[s] Robert

W. Lee,[t] David MacLeod,[u] Andrea Manrique-Suñén,[l] Eduardo S. P. R. Martins,[v] Carolyn J.

Maxwell,[w] William J. Merryfield,[x] Ángel G. Muñoz,[l] Eniola Olaniyan,[s] George Otieno,[y] John

A. Oyedepo,[z] Lluís Palma,[l] Ilias G. Pechlivanidis,[aa] Diego Pons,[bb] F. Martin Ralph,[n] Dirceu S.

Reis Jr.,[cc] Tomas A. Remenyi,[dd] James S. Risbey,[g] Donald J. C. Robertson,[a] Andrew W.

Robertson,[k] Stefan Smith,[ee] Albert Soret,[l] Ting Sun,[h] Martin C. Todd,[ff] Carly R. Tozer,[g]

Francisco C. Vasconcelos Jr.,[v] Ilaria Vigo,[l] Duane E. Waliser,[gg] Fredrik Wetterhall,[o] Robert

G. Wilson,[w]

[a] *Department of Civil and Environmental Engineering, University of Strathclyde, Glasgow, U.K.*

[b] *Institute for Atmospheric and Climate Science, ETH Zürich, Zürich, Switzerland*

[c] *Center for Earth System Modeling, Analysis, and Data, Department of Meteorology and Atmospheric Science, Pennsylvania State University, State College, PA*

[d] *Department of Meteorology and Climate Science, Federal University of Tech Akure, Akure, Nigeria*

[e] *California Department of Water Resources, Sacramento, CO*

[f] *Kenya Meteorological Department, Nairobi, Kenya*

[g] *Oceans & Atmosphere, CSIRO, Hobart, Australia*

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25   [h] *Department of Meteorology, University of Reading, Reading, U.K.*

26   [i] *Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, U.K.*

27   [j] *Institute of Meteorology and Climate Research, Department of Troposphere Research, Karlsruhe Institute of*

28   *Technology, Karlsruhe, Germany*

29   [k] *International Research Institute for Climate and Society, The Earth Institute, Columbia University, New York,*

30   *NY*

31   [l] *Barcelona Supercomputing Center (BSC), Barcelona, Spain*

32   [m] *Center for Weather Forecast and Climate Studies, National Institute for Space Research, Cachoeira Paulista,*

33   *Brazil*

34   [n] *Center for Western Weather and Water Extremes, Scripps Institution of Oceanography, University of*

35   *California San Diego, San Diego, CA*

36   [o] *Forecast Department, European Centre for Medium-range Weather Forecasts, Reading, U.K.*

37   [p] *Escuela de Nutrición de la Facultad de Ciencias Químicas y Farmacia, Universidad de San Carlos,*

38   *Guatemala City, Guatemala*

39   [q] *Formerly of Met Office, Exeter, U.K.*

40   [r] *Applied Research, British Telecommunications plc, London, U.K.*

41   [s] *Numerical Weather Prediction, Nigerian Meteorological Agency, Abuja, Nigeria*

42   [t] *National Centre for Atmospheric Science, Department of Meteorology, University of Reading, Reading, U.K.*

43   [u] *School of Geographical Sciences, University of Bristol, Bristol, U.K.*

44   [v] *Ceará State Meteorology and Water Resources Foundation, Fortaleza, Brazil*

45   [w] *Hydro Tasmania, Hobart, Australia*

46   [x] *Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada, Victoria,*

47   *Canada*

48   [y] *IGAD Climate Prediction and Applications Centre, Nairobi, Kenya*

49   [z] *Federal University of Agriculture Abeokuta, Abeokuta, Nigeria*

50   aa *Hydrology R&D, Swedish Meteorological and Hydrological Institute, Norrköping, Sweden*

51   bb *Department of Anthropology and Geography, Colorado State University, Fort Collins, CO*

52   cc *Department of Civil and Environmental Engineering, University of Brasilia, Brasilia, Brazil*

53   dd *School of Geography, Planning and Spatial Sciences, University of Tasmania, Hobart, Australia*

54   ee *School of the Built Environment, University of Reading, Reading, U.K.*

55   ff *University of Sussex, Brighton, U.K.*

56   gg *Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA*

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69   *Corresponding author*: Dr Christopher J. White, chris.white@strath.ac.uk, Department of

70   Civil and Environmental Engineering, University of Strathclyde, James Weir Building, 75

71   Montrose Street, Glasgow, G1 1XJ, U.K.

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72   ABSTRACT

73   The subseasonal-to-seasonal (S2S) predictive timescale, encompassing lead times ranging

74   from 2 weeks to a season, is at the frontier of forecasting science. Forecasts on this timescale

75   provide opportunities for enhanced application-focused capabilities to complement existing

76   weather and climate services and products. There is, however, a 'knowledge-value' gap,

77   where a lack of evidence and awareness of the potential socio-economic benefits of S2S

78   forecasts limits their wider uptake. To address this gap, here we present the first global

79   community effort at summarizing relevant applications of S2S forecasts to guide further

80   decision-making and support the continued development of S2S forecasts and related

81   services. Focusing on 12 sectoral case studies spanning public health, agriculture, water

82   resource management, renewable energy and utilities, and emergency management and

83   response, we draw on recent advancements to explore their application and utility. These case

84   studies mark a significant step forward in moving from *potential* to *actual* S2S forecasting

85   applications. We show that by placing user needs at the forefront of S2S forecast

86   development – demonstrating both skill and utility across sectors – this dialogue can be used

87   to help promote and accelerate the awareness, value and co-generation of S2S forecasts. We

88   also highlight that while S2S forecasts are increasingly gaining interest among users,

89   incorporating probabilistic S2S forecasts into existing decision-making operations is not

90   trivial. Nevertheless, S2S forecasting represents a significant opportunity to generate useful,

91   usable and actionable forecast applications for and with users that will increasingly unlock

92   the potential of this forecasting timescale.

93   CAPSULE

94   A global community exploration of the application and utility of S2S predictions,

95   comprising 12 case studies from across public health, agriculture, water resource

96   management, energy and utilities, and emergency management.

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Introduction

The subseasonal-to-seasonal (S2S) predictive timescale, encompassing forecast ranges from 2 weeks to a season, is a rapidly maturing discipline. The S2S timescale is a frontier of forecasting science, with emerging recognition for both the need and the potential utility of forecasts on this timescale (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 towards 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).

There remains, however, a 'knowledge-value' gap, where evidence of the potential socio-economic 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,

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[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)

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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.

Sectoral case studies

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142   *Public health*

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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; Ryti 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),

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

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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)[4].

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

199   *Authors: Eniola Olaniyan, Elijah A. Adefisan, Ahmed A. Balogun, John A. Oyedepo,*

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[5] to develop a

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[4] '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/)
[5] 'GCRF African SWIFT' project (https://africanswift.org/)

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

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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

244   *Authors: Carmen González Romero, Ángel G. Muñoz, Ana María García-Solórzano,*

245   *Xandre Chourio, Diego Pons*

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-

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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

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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

298   *Authors: Richard J. Graham, Mary Kilavi, David MacLeod, George Otieno, Martin C.*

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

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307   security. The trial was part of the 'Forecast-based Preparedness Action' (ForPAc) project[7],

308   conducted over 5 rainy seasons in the period 2018-2020.

309   Met Office GloSea5 (MacLachlan et al. 2015) S2S forecasts[8] 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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[7] 'Towards Forecast-based Preparedness Action (ForPAc)' project
(http://www.shear.org.uk/research/ForPAc.html)
[8] 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[9]. 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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[9] '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[10], 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'[11]. 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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[10] NCEP CFSv2 seasonal forecasts (https://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)

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

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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

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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

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

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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[13] 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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[13] '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

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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

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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

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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 (Karoly 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

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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

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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

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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)[14] 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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[14] EFAS (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.

Discussion

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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

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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

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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	Telecommuni-cation 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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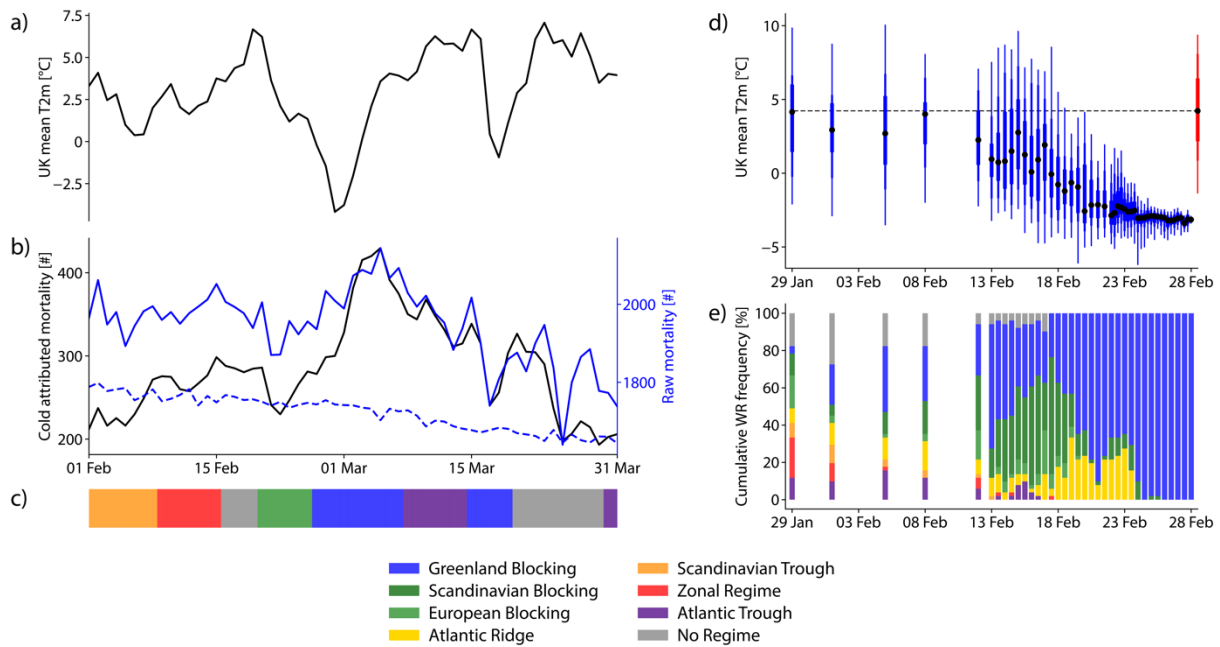
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1103   **Figure 1** Mortality during extreme cold weather events in the U.K., showing: a) HadUK-Grid

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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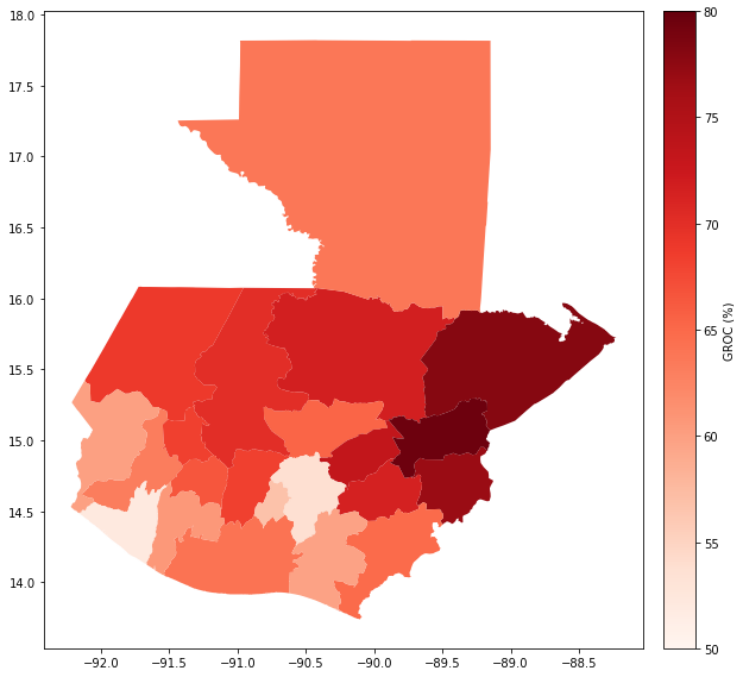
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Figure 2 Skill assessment for the early-action system for acute undernutrition in Guatemala,

showing: The Generalized Relative Operating Characteristics (GROC) skill metric for cases

of acute undernutrition for children under five 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 lags/lead times between rainfall

and acute undernutrition for each department.

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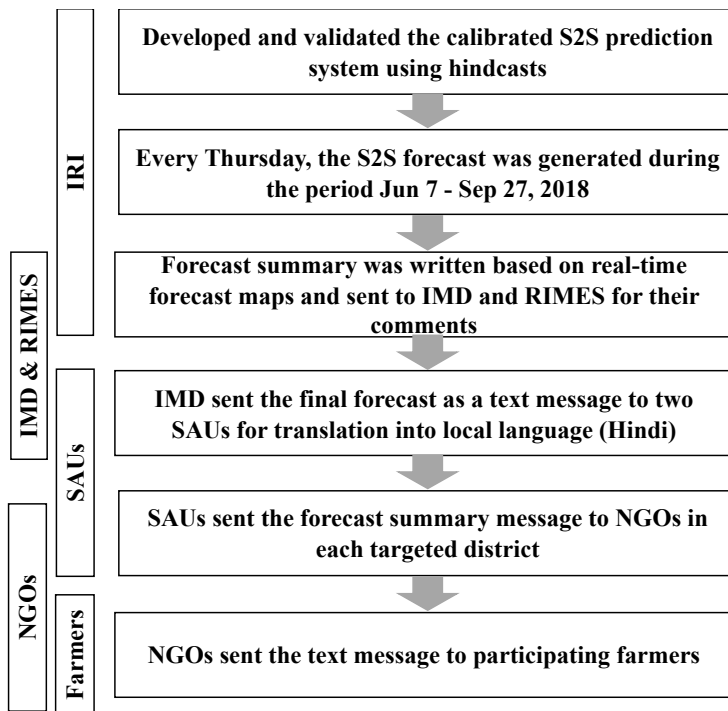
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1133   **Figure 3** Agricultural management in Bihar, India, showing: A flowchart of the forecast

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.
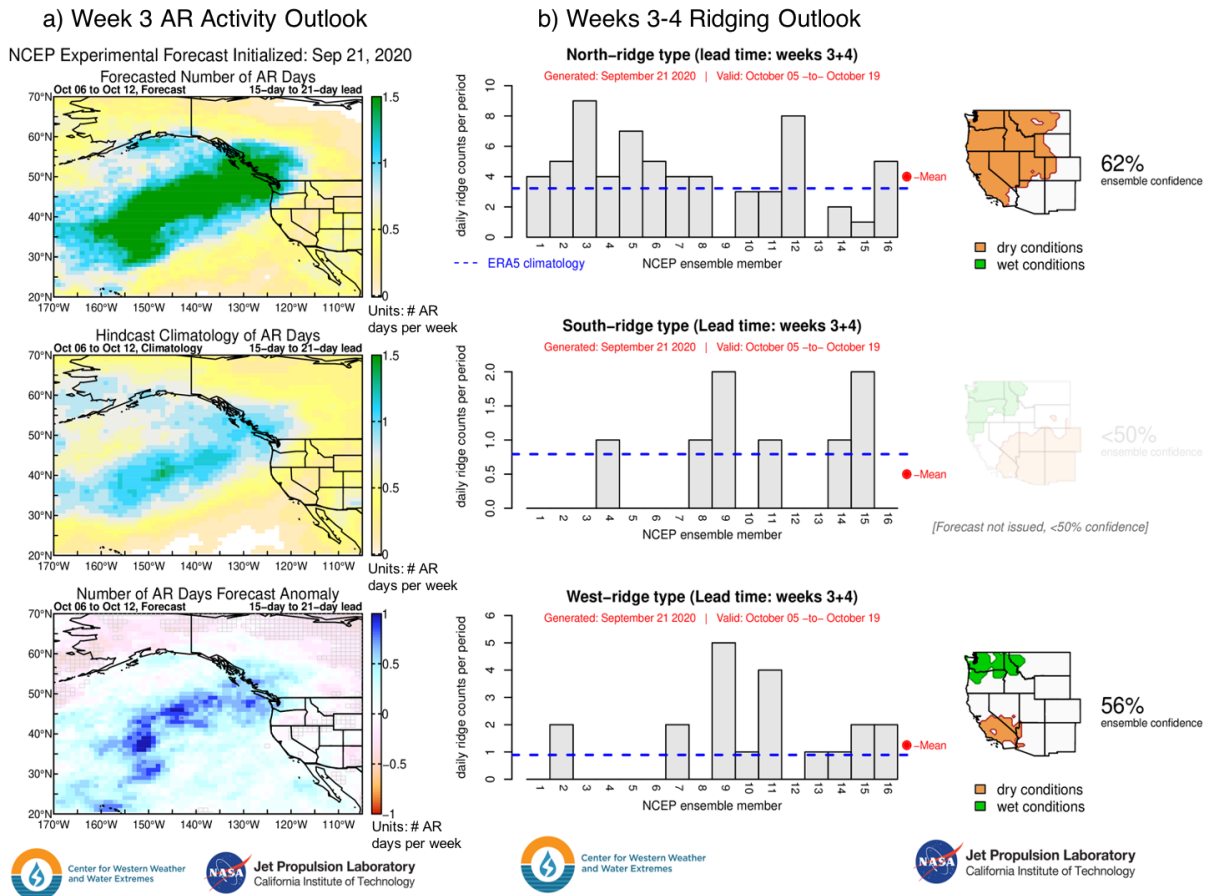
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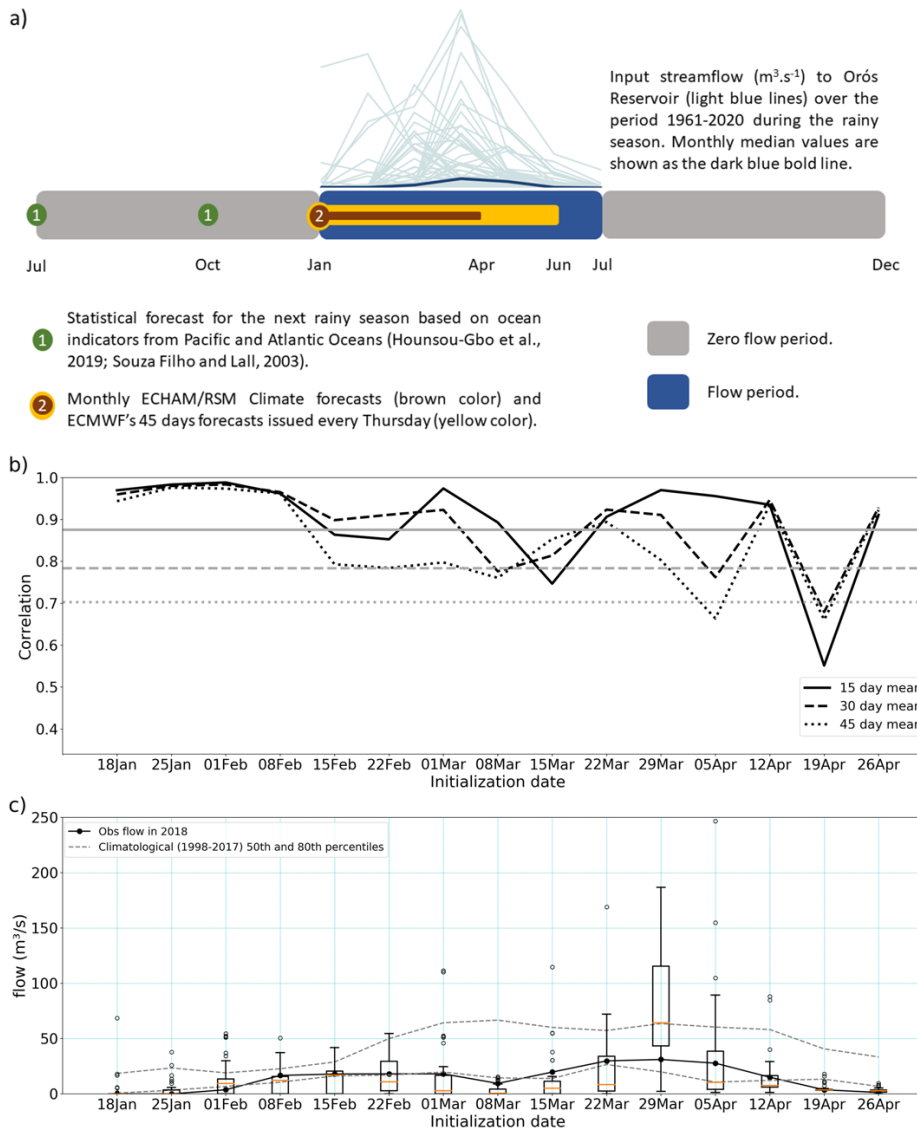
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1142 **Figure 4** Water management in Ceará State, Brazil, showing: a) Ceará State flow forecast

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.

1167

a) Week 3 AR Activity Outlook

NCEP Experimental Forecast Initialized: Sep 21, 2020

b) Weeks 3-4 Ridging Outlook

Figure 5 Water management in western U.S., showing: a) CW3E/JPL week 3

AR activity outlook. Forecast initialized September 21, 2020 and verified October 06-12,

2020. Top panel shows the forecasted number of AR days to occur during the week 3

verification period; middle panel shows the NCEP hindcast climatology of AR days during

the October 06-12 week in the hindcast record; bottom panel shows 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

September 21, 2020 and verified October 05-19, 2020. Left column shows the occurrence

frequency of each ridge type (bars) compared to climatology (horizontal line) for each of the

model ensemble members. The top, middle, and bottom row display the North, South, and

West ridge forecasts, respectively. If over 50% of the ensemble members predict more

ridging than expected (for this time of year), then the right column 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

55

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).

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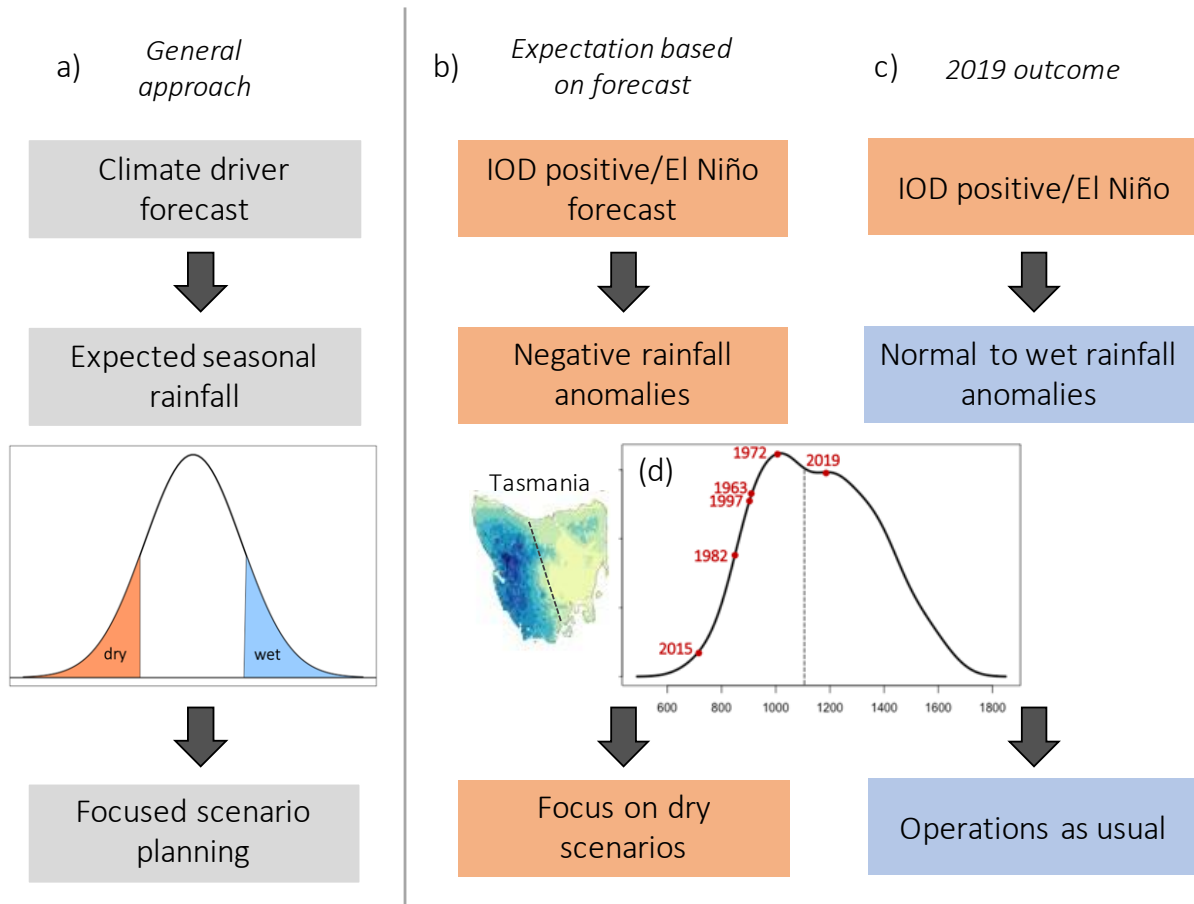
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1190   **Figure 6** Scenario planning for hydropower operations in Tasmania, Australia, showing: a) A

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).

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