



Current and emerging developments in subseasonal to decadal prediction

William J. Merryfield

*Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada,
Victoria, Canada*

Johanna Baehr

Institute of Oceanography, University of Hamburg, Hamburg, Germany

Lauriane Batté

CNRM, Université de Toulouse, Météo France, CNRS, Toulouse, France

Emily J. Becker

NOAA/NWS/NCEP/Climate Prediction Center/Innovim, LLC, College Park, Maryland

Amy H. Butler

*CIRES, University of Colorado Boulder, and Chemical Sciences Division, NOAA/ESRL, Boulder,
Colorado*

Caio A. S. Coelho

CPTEC/INPE Center for Weather Forecasts and Climate Studies, Cachoeira Paulista, Brazil

Gokhan Danabasoglu

Climate and Global Dynamics Laboratory, NCAR, Boulder, Colorado

Paul A. Dirmeyer

Center for Ocean–Land–Atmosphere Studies, George Mason University, Fairfax, Virginia

Francisco J. Doblas-Reyes

Barcelona Supercomputing Center and ICREA, Barcelona, Spain

Daniela I. V. Domeisen

Institute for Atmospheric and Climate Science, ETH Zürich, Zurich, Switzerland

Laura Ferranti

ECMWF, Reading, United Kingdom

Tatiana Ilynia

Max Planck Institute for Meteorology, Hamburg, Germany

Arun Kumar

Climate Prediction Center, NOAA/NWS/NCEP, College Park, Maryland

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44 Wolfgang A. Müller
45 *Max Planck Institute for Meteorology and Deutscher Wetterdienst, Hamburg, Germany*
46
47 Michel Rixen
48 *World Climate Research Programme, World Meteorological Organization, Geneva, Switzerland*
49
50 Andrew W. Robertson
51 *International Research Institute for Climate and Society (IRI), Columbia University, Palisades, NY*
52
53 Doug M. Smith
54 *Met Office Hadley Centre, Met Office, Exeter, UK*
55
56 Yuhei Takaya
57 *Department of Atmosphere, Ocean and Earth System Modeling Research, Meteorological*
58 *Research Institute, Japan Meteorological Agency, Tsukuba, Japan*
59
60 Matthias Tuma
61 *World Climate Research Programme, World Meteorological Organization, Geneva, Switzerland*
62
63 Frederic Vitart
64 *ECMWF, Reading, United Kingdom*
65
66 Christopher J. White
67 *Department of Civil and Environmental Engineering, University of Strathclyde, Glasgow, United*
68 *Kingdom*
69
70 Mariano S. Alvarez
71 *Universidad de Buenos Aires, Centro de Investigaciones del Mar y la Atmósfera, Institut Franco-*
72 *Argentin d'Estudes sur le Climat et ses Impacts, Buenos Aires, Argentina*
73
74 Constantin Ardilouze
75 *CNRM, Université de Toulouse, Météo France, CNRS, Toulouse, France*
76
77 Hannah Attard
78 *Embry-Riddle Aeronautical University-Worldwide, Daytona Beach, Florida*
79
80 Cory Baggett
81 *Department of Atmospheric Science, Colorado State University, Fort Collins, Colorado, and*
82 *NOAA/NWS/NCEP/Climate Prediction Center/Innovim, LLC, College Park, Maryland*
83
84 Magdalena A. Balmaseda
85 *ECMWF, Reading, United Kingdom*
86
87 Asmerom F. Beraki

88 *CSIR – Global Change, Climate and Air Quality Modelling, and Department of Geography,*
89 *Geoinformatics and Meteorology, University of Pretoria, Pretoria, South Africa*
90
91 Partha S. Bhattacharjee
92 *I.M. Systems Group, NOAA/NWS National Centers for Environmental Prediction, College Park,*
93 *Maryland*
94
95 Roberto Bilbao
96 *Barcelona Supercomputing Center, Barcelona, Spain*
97
98 Felipe M. de Andrade
99 *National Centre for Atmospheric Science, Department of Meteorology, University of Reading,*
100 *Reading, United Kingdom*
101
102 Michael J. DeFlorio
103 *Center for Western Weather and Water Extremes, Scripps Institution of Oceanography,*
104 *University of California, San Diego, California*
105
106 Leandro B. Díaz
107 *Universidad de Buenos Aires, Centro de Investigaciones del Mar y la Atmósfera, Institut Franco-*
108 *Argentin d’Estudes sur le Climat et ses Impacts, Buenos Aires, Argentina*
109
110 Muhammad Azhar Ehsan
111 *Earth System Physics Section, International Centre for Theoretical Physics, Trieste, Italy, and*
112 *Center of Excellence for Climate Change Research, King Abdulaziz University, Jeddah, Saudi*
113 *Arabia*
114
115 Georgios Fragkoulidis
116 *Institute for Atmospheric Physics, Johannes Gutenberg University, Mainz, Germany*
117
118 Sam Grainger
119 *Sustainability Research Institute, School of Earth and Environment, University of Leeds, Leeds,*
120 *United Kingdom*
121
122 Benjamin W. Green
123 *Cooperative Institute for Research in Environmental Sciences, University of Colorado, and*
124 *NOAA/OAR/ESRL/Global Systems Division, Boulder, Colorado*
125
126 Momme C. Hell
127 *Scripps Institution of Oceanography, La Jolla, California*
128
129 Johnna M. Infanti
130 *Cherokee Nation Strategic Programs, and NOAA/Office of Oceanic and Atmospheric*
131 *Research/Office of Weather and Air Quality, Silver Spring, Maryland*

132
133 Katharina Isensee
134 *Deutscher Wetterdienst, Offenbach, Germany*
135
136 Takahito Kataoka
137 *Japan Agency for Marine-Earth Science and Technology, Kanagawa, Japan*
138
139 Ben P. Kirtman
140 *University of Miami, Rosenstiel School for Marine and Atmospheric Sciences, Miami, Florida*
141
142 Nicholas P. Klingaman
143 *National Centre for Atmospheric Science, Department of Meteorology, University of Reading,*
144 *Reading, United Kingdom*
145
146 June-Yi Lee
147 *Research Center for Climate Sciences, Pusan National University and Center for Climate Physics,*
148 *Institute for Basic Science, Busan, Korea*
149
150 Kirsten Mayer
151 *Department of Atmospheric Science, Colorado State University, Fort Collins, Colorado*
152
153 Roseanna McKay,
154 *School of Earth, Atmosphere and Environment, Monash University, Melbourne, Australia*
155
156 Jennifer V Mecking
157 *Ocean and Earth Science, University of Southampton, Southampton, United Kingdom*
158
159 Douglas E. Miller
160 *University of Illinois at Urbana–Champaign, Urbana, Illinois*
161
162 Nele Neddermann
163 *Institute for Oceanography, CEN, Universität Hamburg, and International Max Planck Research*
164 *School on Earth System Modelling, Max Planck Institute for Meteorology, Hamburg, Germany*
165
166 Ching Ho Justin Ng
167 *Atmospheric and Oceanic Sciences (AOS), Princeton University, Princeton, New Jersey*
168
169 Albert Ossó
170 *NCAS-Climate, University of Reading, Reading, United Kingdom*
171
172 Klaus Pankatz
173 *Deutscher Wetterdienst, Offenbach, Germany and Max Planck Institut für Meteorologie,*
174 *Hamburg, Germany*
175

176 Simon Peatman
177 *School of Earth and Environment, University of Leeds, Leeds, United Kingdom*
178
179 Kathy Pegion
180 *George Mason University, Fairfax, Virginia*
181
182 Judith Perlwitz
183 *CIRES, University of Colorado Boulder, and Physical Sciences Division, NOAA/ESRL, Boulder,*
184 *Colorado*
185
186 G. Cristina Recalde-Coronel
187 *Department of Earth and Planetary Sciences, Johns Hopkins University, Baltimore, Maryland,*
188 *and Facultad de Ingeniería Marítima y Ciencias del Mar, Escuela Superior Politécnica del Litoral,*
189 *Guayaquil, Ecuador*
190
191 Annika Reintges
192 *GEOMAR Helmholtz Centre for Ocean Research, Kiel, Germany*
193
194 Christoph Renkl
195 *Department of Oceanography, Dalhousie University, Halifax, Canada*
196
197 Balakrishnan Solaraju-Murali
198 *Barcelona Supercomputing Center, Barcelona, Spain*
199
200 Aaron Spring
201 *Max Planck Institute for Meteorology, Hamburg, Germany*
202
203 Cristiana Stan
204 *Department of Atmospheric, Oceanic and Earth Sciences, George Mason University, Fairfax,*
205 *Virginia*
206
207 Y. Qiang Sun
208 *Atmospheric and Oceanic Sciences Program, Princeton University, Princeton, New Jersey*
209
210 Carly R. Tozer
211 *CSIRO Oceans and Atmosphere, Hobart, Tasmania, Australia*
212
213 Nicolas Vigaud
214 *International Research Institute for Climate and Society (IRI), Columbia University, Palisades, NY*
215
216 Steven Woolnough
217 *National Centre for Atmospheric Science, University of Reading, Reading, UK*
218
219 Stephen Yeager

220 *National Center for Atmospheric Research, Boulder, Colorado, USA*

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225 Corresponding author: William Merryfield (bill.merryfield@canada.ca)

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231 **Abstract**

232 Weather and climate variations on subseasonal to decadal timescales can have enormous

233 social, economic and environmental impacts, making skillful predictions on these timescales a

234 valuable tool for decision makers. As such, there is a growing interest in the scientific,

235 operational, and applications communities in developing forecasts to improve our

236 foreknowledge of extreme events. On subseasonal to seasonal (S2S) timescales, these include

237 high-impact meteorological events such as tropical cyclones, extratropical storms, floods,

238 droughts, and heat and cold waves. On seasonal to decadal (S2D) timescales, while the focus

239 broadly remains similar, (e.g., on precipitation, surface and upper ocean temperatures and their

240 effects on the probabilities of high-impact meteorological events), understanding the roles of

241 internal and externally-forced variability such as anthropogenic warming in forecasts also

242 becomes important.

243

244 The S2S and S2D communities share common scientific and technical challenges. These include

245 forecast initialization and ensemble generation; initialization shock and drift; understanding the

246 onset of model systematic errors; bias correction, calibration, and forecast quality assessment;

247 model resolution; atmosphere-ocean coupling; sources and expectations for predictability; and

248 linking research, operational forecasting, and end user needs. In September 2018 a coordinated
249 pair of international conferences, framed by the above challenges, was organized jointly by the
250 World Climate Research Programme (WCRP) and the World Weather Research Programme
251 (WWRP). These conferences surveyed the state of S2S and S2D prediction, ongoing research,
252 and future needs, providing an ideal basis for synthesizing current and emerging developments
253 in these areas that promise to enhance future operational services. This article provides such a
254 synthesis.

255

256 **Capsule**

257 Climate prediction on subseasonal to decadal time scales is a rapidly advancing field that is
258 synthesizing improvements in climate process understanding and modeling to improve and
259 expand operational services worldwide.

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270 **[Introductory text]**

271 Beyond the tremendous progress in weather forecasting witnessed in recent decades (Bauer et
272 al. 2015), predictive capabilities have expanded, increasingly seamlessly, to encompass climate
273 on subseasonal to decadal time scales (Fig. 1 and Kirtman et al. 2013). These advances have
274 been enabled by better observations, data assimilation schemes, and models originating both
275 from the weather prediction and long term climate simulation communities, together with
276 increased computational power supporting progressively higher resolution and larger
277 ensembles that allow uncertainties to be better estimated and in some cases reduced.

278
279 International efforts under the auspices of the World Weather Research Programme (WWRP)
280 and World Climate Research Programme (WCRP) have helped drive this progress through
281 coordinated research to improve the accuracy and utilization of weather and climate
282 predictions. Community research efforts under the WCRP led initially to climate predictions one
283 to two seasons ahead becoming part of the World Meteorological Organization (WMO)
284 operational infrastructure (Graham et al. 2011). More recently a joint WWRP and WCRP
285 Subseasonal to Seasonal Prediction Project has started tackling the so-called weather-climate
286 prediction desert from two weeks to a season (Robertson et al. 2018; Mariotti et al. 2018),
287 aiming to underpin new WMO operations on those time scales (Vitart et al. 2017), and the
288 NOAA-led SubX project has similar aims (Pegion et al. 2019). At longer ranges, WCRP-enabled
289 research has quantified predictability from a year to a decade, and corresponding WMO
290 operational infrastructure for annual-to-decadal climate prediction is now in place (World
291 Meteorological Organization 2018; Kushnir et al. 2019).

292

293 As each of these efforts has progressed it has become increasingly apparent that common
294 challenges exist across predictive time scales. These include understanding and adequately
295 representing in models processes that give rise to predictability in the Earth system, consisting
296 of the physical climate system—atmosphere, ocean, land and sea ice—together with associated
297 biogeochemical cycling, especially of carbon (upper part of Fig. 1); capturing and
298 communicating inherent uncertainties caused by the chaotic nature of weather and climate;
299 correcting for and reducing imperfections in models that may systematically degrade forecast
300 quality; and providing forecast information in a form that is applicable to decision making. At
301 the same time, opportunities for usefully predicting elements of the Earth system beyond long-
302 term means of standard meteorological variables , including land, ocean and sea ice properties
303 and risks of weather extremes, have come into focus. The ultimate collective endeavor is to
304 improve the prediction of the spatial–temporal continuum connecting weather to climate
305 through a coordinated, seamless and integrated Earth system approach for the benefit of
306 society.

307

308 In September 2018, international conferences¹ on subseasonal to seasonal prediction (S2S,
309 encompassing forecast ranges from two weeks to a season) and seasonal to decadal prediction (S2D,
310 encompassing ranges longer than a season, up to a decade) together with cross-cutting plenary

¹ The Second International Conference on Subseasonal to Seasonal Prediction (S2S) and Second International Conference on Seasonal to Decadal Prediction (S2D) were held 17-21 September 2018 at NCAR facilities in Boulder Colorado. These coordinated meetings involved 347 participants, including 92 early career scientists, from 38 countries, with a total of 368 oral and poster presentations. Further information including a complete list of contributions can be found at <https://www.wcrp-climate.org/s2s-s2d-2018-home>.

311 sessions were convened jointly by WWRP and WCRP. This represented a confluence of research
312 and operational climate prediction expertise and knowledge exchange across prediction time
313 scales that was unprecedented in scope. Selected outcomes, organized by themes
314 encompassing the challenges outlined above, are synthesized in this article.

315

316 **Mechanisms of predictability.**

317 *Subseasonal to Seasonal*

318 A major source of S2S predictability is the organization of tropical convection by the Madden
319 Julian Oscillation, or MJO (Woolnough, 2019), which is predicted skillfully by S2S project models
320 up to 3-4 weeks ahead (Vitart 2017). The MJO has worldwide impacts that depend on its
321 amplitude and phase, including modulation of tropical cyclone activity (Lee et al. 2018; Zhao et
322 al. 2019) and extratropical phenomena such as the East Asian summer monsoon (Li et al. 2018).
323 The associated tropical-extratropical teleconnections (Lin et al. 2019) impart S2S forecast skill
324 for many of these extratropical phenomena including Euro-Atlantic weather regimes, position
325 of the jet stream, atmospheric rivers (DeFlorio et al. 2019), and hail/tornado activity (Baggett et
326 al. 2018). However, good representations of the basic state both in the tropics and extratropics,
327 as well as tropical air-sea interactions and atmospheric convection (e.g., Yoo et al. 2015), are
328 necessary for these teleconnections to be correctly simulated by general circulation models
329 (Henderson et al. 2017).

330

331 S2S predictability also derives from the stratosphere through its relatively long time scales of
332 variability² and lagged influences on the troposphere (Kidston et al. 2015). Interactions
333 between the stratosphere and the troposphere from the tropics to the extratropics thus
334 provide a promising source of S2S prediction skill (Butler et al. 2019). For example, in the winter
335 Northern Hemisphere stratosphere the climatological westerly polar vortex exhibits extremes
336 in variability, including sudden stratospheric warmings (SSWs) that are driven largely by Rossby
337 waves from the troposphere. SSWs have lagged impacts on sea level pressure, surface
338 temperature and precipitation, including pronounced tendencies for cold anomalies over
339 northern Eurasia and warm anomalies over northeastern North America (e.g., Sigmond et al.
340 2013). Initializing forecasts during extreme stratospheric events provides increases in prediction
341 skill of surface climate in such regions up to 3-6 weeks later (Domeisen et al. 2019c). However,
342 the predictability of specific extreme stratospheric events is limited, ranging from a few days to
343 about two weeks (Fig. 2) for different SSWs (Karpechko 2018; Taguchi 2018, Domeisen et al.
344 2019a), although models show evidence of under-confident forecasts in the stratosphere on
345 S2S timescales (O'Reilly et al. 2019). Outstanding questions remain about the mechanisms of
346 stratosphere-troposphere coupling processes, in particular on the causes, variability, and trends
347 for the occurrence of SSW events (Ayarzaguena et al. 2018; Simpson et al. 2018) and why not
348 all SSW events have similar downward effects (e.g., Garfinkel et al. 2013, Maycock & Hitchcock,
349 2015). In addition, further research is needed to assess the degree to which prediction models
350 capture both the stratospheric variability and coupling processes.

² Including the quasi-biennial oscillation (QBO) of the tropical stratosphere, whose influences span a range of time scales and are addressed in the "Time scale interactions" subsection.

351

352 Among atmosphere-surface influences, land-atmosphere interactions have their greatest
353 impact on subseasonal time scales in forecasts where land is initialized (Dirmeyer et al. 2018a),
354 but also can contribute skill on weather prediction and multi-month time scales (Dirmeyer and
355 Halder 2016, 2017). The most broadly impactful land attribute is soil moisture (Koster et al.
356 2004, 2016), but anomalies in soil temperature (Y. Zhang et al. 2019; Yang et al. 2019), snow
357 cover (Jeong et al. 2012; Orsolini et al. 2013), and vegetation states (Williams et al. 2016) can all
358 have significant impacts. A number of recent studies have focused on non-local impacts of land
359 surface anomalies, showing for example that soil moisture anomalies can exert remote as well
360 as local influences in boreal summer through driving of quasi-stationary Rossby waves and
361 associated circulation anomalies (e.g., Teng et al. 2019; Wang et al. 2019). In addition, land
362 surface and subsurface temperatures in spring may exert delayed downstream influences on
363 precipitation (Xue et al. 2018), and evapotranspiration may remotely influence precipitation
364 over land (Wei and Dirmeyer 2019).

365

366 Atmosphere-ocean interactions, fundamental for S2D predictability, can also be influential on
367 S2S time scales. For example submonthly prediction skills for precipitation and temperature are
368 enhanced over certain land areas including parts of Australia, the Maritime Continent and the
369 contiguous United States when tropical sea surface temperature (SST) anomalies associated
370 with El Niño Southern Oscillation (ENSO) are present (Hudson et al. 2011; Li and Robertson
371 2015; DelSole et al. 2017). Extratropical SST anomalies also can impart S2S skill through
372 teleconnections, as shown for example by McKinnon et al. (2016) who identified a SST anomaly

373 pattern in the mid-latitude North Pacific that tends to precede heat waves and rainfall deficits
374 in the eastern United States by up to 50 days.

375
376 Sea ice strongly influences surface fluxes and lower atmospheric temperatures particularly in the
377 marginal ice zone, and provides a source of S2S predictability for polar and possibly midlatitude
378 regions (Chevallier et al. 2019). This motivates the development of S2S forecasts for sea ice,
379 which thus far have shown significant, albeit region-dependent skill for predicting intraseasonal
380 Arctic sea ice variability (Liu et al. 2018, Zampieri et al. 2018).

381
382 *Seasonal to decadal*

383 A primary general source of S2D atmospheric predictability is remote influences from a variety
384 of teleconnections (e.g., Yuan et al. 2018; Ruprich-Robert et al. 2018; Beverley et al. 2019).
385 Teleconnections associated with anomalous atmospheric circulation patterns arise from
386 changes to the Walker circulation usually driven by anomalous zonal SST gradients (Cai et al.
387 2019), and changes to the Hadley circulation usually driven by anomalous meridional SST
388 gradients, especially interhemispheric differences (Kang et al. 2018). These influences impact
389 tropical cyclones and rainfall, whereas anomalous upper level divergence due to tropical rainfall
390 anomalies leads to Rossby waves that impact the extratropics (Scaife et al. 2017; O'Reilly et al.
391 2018). Besides giving rise to atmosphere-ocean interactions that alter the atmospheric
392 circulation, SST anomalies can induce low-level temperature and moisture anomalies that are
393 advected elsewhere by climatological winds (Dunstone et al. 2018).

394

395 S2D atmospheric predictability arising from teleconnections requires that SST anomalies be
396 predictable. On seasonal timescales, tropical SST anomalies are dominated by ENSO (Yang et al.
397 2018), though there is some independent variability in the tropical Atlantic and Indian Oceans
398 that also drives teleconnections (e.g., Nnamchi et al. 2015; Lim et al. 2016). The impacts of
399 ENSO are sensitive to ENSO diversity (Capotondi et al. 2015), including the longitude at which
400 maximum SST anomalies occur (Yeh et al. 2018; Patricola et al. 2018). ENSO SST anomalies are
401 largely predictable out to a year particularly in winter and early spring (Barnston et al. 2017),
402 whereas predictability may extend to two years for some La Niña events (Di Nezio et al. 2017),
403 and to 1 ½ to two years for certain El Niño events (Luo et al. 2008).

404

405 Decadal SST variability occurs in both the Atlantic and Pacific oceans, often referred to as
406 Atlantic Multidecadal Variability (AMV) and Pacific Decadal Variability (PDV), e.g. Kushnir et al.
407 (2019). The causes of AMV are not fully understood, especially the relative roles of internal
408 variability and external forcing from aerosols. However, AMV is modulated to some extent by
409 the oceanic Atlantic Meridional Overturning Circulation (Yeager and Robson 2017), which
410 together with the North Atlantic subpolar gyre is influenced by deep ocean density anomalies
411 particularly in the Labrador Sea (Robson et al. 2016); these influences contribute to the
412 especially high multi-year predictability in the North Atlantic (Buckley et al. 2019). AMV couples
413 to the Hadley circulation, affecting hurricanes and Sahel rainfall as illustrated in Fig. 3 (Sheen et
414 al. 2017), and can initiate atmospheric Rossby waves with remote influences including
415 temperatures in parts of China (Monerie et al. 2018). AMV can influence PDV (Ruprich-Robert
416 et al. 2017), and vice-versa. PDV may also be influenced by off-equatorial heat content

417 anomalies in the western Pacific Ocean (Meehl et al. 2016). Decadal variability of deep
418 convection in the Southern Ocean influences temperatures in that region, potentially explaining
419 recent increases in Antarctic sea ice (L. Zhang et al. 2019).

420

421 S2D atmospheric predictability also arises from longer time scale processes over land, mainly
422 involving soil moisture (Chikamoto et al. 2017; Ardilouze et al. 2019) and vegetation (Weiss et
423 al. 2014; Bellucci et al. 2015). These highlight the need for land surface initialization
424 (Prodhomme et al. 2016a) and realistic vegetation models (Alessandri et al. 2017).

425

426 An additional source of S2D predictability is variations in radiative forcing, which provide
427 significant skill on multi-year timescales (Smith et al. 2019). Much of this skill arises from
428 changes in greenhouse gases, but anthropogenic aerosols may force decadal variations in AMV
429 (Booth et al. 2012) and PDV (Smith et al. 2016; Takahashi and Watanabe 2016). Solar variability
430 (Misios et al. 2019), and volcanic eruptions (Menegoz et al. 2018) including through their
431 influence on ENSO (Khodri et al. 2017; Wang et al. 2018) and possibly AMV and the North
432 Atlantic Oscillation (NAO; Swingedouw et al. 2017) affect climate on seasonal to decadal
433 timescales and are potentially important sources of predictability. However, the relative roles
434 of external radiative forcing and internal variability (W. Kim et al. 2018) continue to be
435 explored.

436

437 *Time scale interactions*

438 The Quasi-biennial Oscillation (QBO) is a downward-propagating ~28-month oscillation of
439 easterly and westerly zonal jets in the tropical stratosphere, driven by upward equatorial waves
440 from the troposphere (e.g., Kim and Chun 2015). In addition to having high predictability and
441 some teleconnected influence on winter surface climate (e.g., Scaife et al. 2014a), the QBO
442 modulates the amplitude, persistence, and rate of propagation of the boreal wintertime MJO
443 (Fig. 4) through its impact on tropical convection via changes in static stability near the
444 tropopause (Yoo and Son 2016, Nishimoto and Yoden 2017). MJO amplitude is better predicted
445 at longer leads during the easterly phase of the QBO (Marshall et al. 2017), likely as a result of
446 longer persistence of the MJO rather than its greater initial amplitude (Lim et al. 2019).

447

448 The modulation of SSW probability of occurrence by tropical sources of variability, such as the
449 QBO, ENSO, or MJO, may extend probabilistic predictability of stratospheric variability to a few
450 months or longer if these relationships can be adequately captured by prediction models
451 (Garfinkel & Schwartz 2017; Garfinkel et al. 2018; Domeisen et al. 2019a,b).

452

453 There is increasing evidence of additional interactions between various sources of S2S and S2D
454 predictability across time scales. One example is that seasonal time scale variations in ENSO
455 modulate the MJO (Chen et al. 2016) and its impact on the NAO (Lee et al. 2019) with
456 consequent influences on weather over remote regions. Another is that ENSO teleconnection
457 to the extratropics has varied over multi-decadal time scales spanning the past 100+ years
458 (O'Reilly 2018), possibly modulating ability to predict the NAO (Weishiemer et al. 2019),

459 although sampling variability can also give rise to such long-term changes in teleconnections
460 (Yun and Timmermann 2018).

461

462 **Modelling issues.**

463 *Subseasonal to Seasonal*

464 Because S2S operational prediction is a relatively new enterprise, considerable efforts focusing
465 on fundamental aspects of forecast system design are occurring at operational centers
466 worldwide (Takaya, 2019). One major emphasis consists of methods to represent the
467 uncertainty in initial conditions (bred vector, singular vector, ensemble data assimilation) and
468 model physics (stochastic physics, Leutbecher et al. 2018). In addition, configurations of real-
469 time forecasts and hindcasts, including ensemble size, ensemble strategy (lagged ensemble
470 with different initial times or burst ensemble with a common initial time) and hindcast period,
471 impact forecast quality and ability to evaluate the performance of the hindcast. Identifying
472 suitable compromises and trade-offs in forecast system design is a challenge under practical
473 constraints for operational activities (costs, priorities, timeliness) and demands further
474 research.

475

476 From the modelling perspective, multiple operational centers are moving towards a unified, or
477 “seamless” coupled forecast system that can be applied across timescales from days to seasons
478 or longer. More S2S models are incorporating ocean and sea-ice components, and becoming
479 increasingly complex and complete in representing coupled processes in the Earth system. On
480 the other hand, poor representation of model physics, in particular clouds (Morcrette et al.

481 2018), results in model drifts and biases in surface land and ocean temperatures, which is a
482 long-standing modeling issue that can degrade the skill of S2S predictions (Vitart and
483 Balmaseda, 2017). Improvements in cloud parameterizations (Stan and Straus, 2019) and in
484 representing the diurnal cycle of the atmospheric boundary layers are crucial for advancing S2S
485 modeling. The Earth system modeling approach poses another challenge to initialize the ocean
486 and sea ice components with high accuracy; for example there is a relatively large dispersion of
487 initialized sea ice fields in current S2S models (Chevallier et al. 2017, Zampieri et al. 2018).

488 Another important S2S modeling issue is predicting the MJO, owing to its importance as a
489 source of subseasonal predictability (H. Kim et al. 2018). Multi-model evaluations have shown
490 that S2S models have difficulties in representing MJO propagation across the Maritime
491 Continent. Process-oriented diagnostics (Maloney et al. 2019) have identified a dry bias in the
492 lower troposphere as one of the causes for the poor MJO propagation through weakening the
493 horizontal moisture gradient over the Indian Ocean and western Pacific (Lim et al. 2018) and
494 dampening the organization and propagation of the MJO. A recharge process whereby moisture
495 builds up in the lower troposphere during the suppressed convection phase of the MJO, and
496 that is key for MJO propagation around the Maritime Continent in boreal winter, is
497 underrepresented in S2S models due to the dry bias (Kim 2017). Ocean coupling is another
498 important process for the MJO (DeMott et al. 2015), and several studies have demonstrated
499 that ocean coupling can improve MJO propagation and enhance predictive skill in models.

500

501 Poor vertical resolution, low model lid height, inadequate orographic and non-orographic
502 gravity wave parameterizations, and biases in the tropospheric mean state (e.g., the location of

503 stationary Rossby waves) could limit the predictive skill from stratosphere-troposphere
504 coupling processes (Tripathi et al. 2015; Butler et al. 2016), but new generations of prediction
505 systems have rapidly improved in many of these areas. Future model development could
506 prioritize improved representation of orographic and non-orographic gravity wave drag and an
507 internally-generated QBO (Butchart et al. 2018). Better understanding of stratosphere-
508 troposphere coupling processes and the role of the stratosphere on surface skill could be
509 gained through case studies and stratospheric nudging experiments (Hansen et al. 2017).
510 Improved observations of the stratosphere (e.g., aerosols and chemistry) and other climate
511 components may improve S2S predictions. Finally, there is potential for modeling of
512 stratospheric ozone chemistry which provides surface temperature predictability on S2S time
513 scales due to its influence on high-latitude stratospheric circulation anomalies together with
514 their lagged surface impacts (Stone et al. 2019). Although that may currently be too resource-
515 intensive due to the many species and reactions that must be modeled, emerging machine-
516 learning techniques may provide pathways for incorporating chemistry-climate information into
517 S2S forecasts (Nowack et al. 2018).

518

519 *Seasonal to decadal*

520 Modeling issues for S2D prediction naturally overlap with those for S2S prediction. However,
521 the longer time scales of S2D prediction lead to a greater emphasis on representing slower
522 climate variations such as ENSO and AMV, and greater attention to reducing model biases in
523 the ocean that may take months to years to develop. Increased model resolution can reduce
524 model biases as illustrated in Fig. 5 (Jia et al. 2015; Müller et al. 2018), and improve skill

525 (Prodhomme et al. 2016b; Schuster et al. 2019; Infanti and Kirtman 2019), although the greater
526 computational cost is not always justified (Scaife et al. 2019). More fundamental strategies
527 involve analyzing/understanding model biases, before attempting to correct them a priori or a
528 posteriori. Such analysis methods include comparing hindcasts with observations and multi-
529 decadal historical or other simulations to distill causation for model errors, such as in the
530 tropical Pacific (Shonk et al. 2018) or Atlantic (Voldoire et al. 2019). Similarly, errors in modeled
531 variability or teleconnection patterns can be characterized by examining their evolution with
532 lead time. Model biases can be corrected both through simple methods such as statistical bias
533 correction and anomaly coupling (Tonizzo and Koseki, 2018), and more complex methods such
534 as supermodeling, through which multiple models exchange information during a climate
535 simulation (Shen et al. 2016).

536

537 Performance of S2D predictions is strongly tied to initialization of model components beyond
538 the lower atmosphere. For example, stratospheric initial conditions are a source of seasonal
539 winter NAO skill (e.g., O'Reilly et al. 2019; Nie et al. 2019) as illustrated in Fig. 6, and ocean
540 initial conditions are crucial for skillfully predicting ENSO (Balmaseda and Anderson 2009), as
541 well as decadal variability in the subpolar North Atlantic (Yeager and Robson, 2017; Borchert et
542 al. 2018). However, initialization using full-field observational values can lead to initial shocks
543 affecting skill (Kröger et al. 2018) and in such cases initialization combining observed anomalies
544 with the model's own climatology can be beneficial until underlying model errors can be
545 reduced (Volpi et al. 2017). Basic initialization strategies continue to be an active research area
546 particularly for decadal prediction (Brune et al. 2018), and methods extending to forecast runs

547 such as the ensemble dispersion filter which replaces the ensemble members with the
548 ensemble mean every three months (Kadlow et al. 2017) are also being explored. Comparisons
549 that apply different initialization methods to the same model can yield valuable insights
550 (Polkova et al. 2019); further issues specific to the initialization of the land, ocean, and sea ice
551 components are considered in the next section.

552
553 Tackling these diverse and persistent modeling issues effectively will require sustained effort, as
554 simple model-specific solutions may not cure the underlying problems, and ideally this should
555 involve coordination between the S2S/S2D prediction, climate modelling, and data assimilation
556 communities.

557
558 **Initialization issues.**

559 *Atmosphere initialization*

560 Accurate atmospheric model initialization is a basic requirement for numerical weather
561 prediction because atmospheric initial conditions are the primary source of predictability on
562 time scales less than a week or two (Fig. 1). It is enabled by sophisticated data assimilation
563 systems that are the result of decades of advancement (Bauer et al. 2015). Subseasonal and
564 seasonal prediction systems generally initialize their atmospheric components by such means,
565 with the additional requirement that historical observations must be assimilated similarly to
566 produce reanalyses that are used to initialize hindcasts. Because in situ and remotely sensed
567 atmospheric observations are relatively dense there is generally good agreement between
568 different reanalyses for the modern era implying relatively low uncertainty at heights below

569 about 10 hPa, although temporal inconsistencies can result from changes in observing systems
570 (Long et al. 2017). Because atmospheric initial conditions contribute less to predicability on
571 multi-annual time scales, some decadal prediction systems do not initialize the atmosphere
572 (e.g., Yeager et al. 2018).

573

574 *Land initialization*

575 Climatically important land variables such as soil moisture and snow can be initialized by driving
576 land surface models with observed atmospheric fields (e.g., Koster et al. 2009; Sospedra-
577 Alfonso et al. 2016a) or, more directly, assimilation of land observations principally from
578 satellites (Bilodeau et al. 2016; Muñoz-Sabater et al. 2019; Toure et al. 2018). Yet predictability
579 from land surface states is being harvested only to the extent that land initial conditions and
580 the relevant processes are represented realistically in forecast models (Koster et al. 2011;
581 Ardilouze et al. 2017). Historically, land surface and atmospheric models are developed
582 separately and their coupled behavior is not calibrated or validated (Dirmeyer et al. 2019), so
583 that coupled processes are often not represented accurately (Dirmeyer et al. 2018b).

584

585 There are also observational limitations. In situ measurements of soil moisture are of varying
586 quality and uneven distribution, and are not designed for real-time operational use (Dorigo et
587 al. 2011). Satellite soil moisture monitoring (Entekhabi et al. 2010; Kerr et al. 2010), provides
588 either very shallow or total column measurements including groundwater (Li et al. 2012), and is
589 subject to uncertainties caused by vegetation, etc. (Al-Yaari et al. 2017). By contrast, soil
590 moisture in forecast models is mainly a gross reservoir for the surface water balance, and its

591 variations do not represent all of the observed processes, particularly at sub-grid scales.
592 Therefore model soil moisture is only a crude representation of reality, although it still contains
593 useful information that can be largely consistent across different land models (Koster et al.
594 2009).

595

596 Climate forecasts can be improved by making high-quality land state observations an
597 operational priority for real-time reporting, and planning for long-term continuity in satellite
598 monitoring (Balsamo et al. 2018). This includes vegetation, especially as its interannual
599 variability and cycles of agricultural planting and harvest are not represented and can affect
600 surface fluxes and predictions (Alessandri et al. 2017). In addition, realistic snow initialization
601 can positively impact subseasonal predictions of surface temperatures (e.g., F. Li et al. 2019).
602 Along with coupled land-atmosphere model development (Santanello et al. 2018), such efforts
603 would facilitate improved predictions on weather to subseasonal time scales, as demonstrated
604 by numerous forecast model-based sensitivity studies such as that of Koster et al. (2011).

605

606 *Ocean and sea ice initialization*

607 The importance of initializing the oceans stems from their relatively long thermal and dynamical
608 time scales, through which they play an essential role in S2D climate predictability (Cassou et al.
609 2017). In addition, the oceans can influence S2S variability, for example through air-sea
610 interactions affecting the MJO (DeMott et al. 2015) and mesoscale eddy impacts on
611 atmospheric circulation (Saravanan and Chang 2019). Predicting future ocean evolution,
612 especially on S2D time scales, requires estimates of 3D ocean states for initialization. This in

613 turn requires a data assimilation method (usually in conjunction with a dynamical model) to
614 constrain ocean state estimates based on available observations. Similar considerations apply
615 to state estimates of sea ice. Comparisons of different ocean and sea ice state estimates as in
616 Fig. 7 can point to variables and regions for which they are most robust, as well as to where
617 uncertainties are relatively large (Balmaseda et al. 2015; Chevallier et al. 2017). Observing
618 system experiments in which certain observations are withheld have shown for example that
619 data from tropical ocean moorings positively impacts state estimates even when Argo float
620 data is also available (Fujii et al. 2015).

621
622 Recent enhancements in observing capabilities are enabling improvements in ocean and sea ice
623 state estimates, potentially leading to more accurate initial conditions and hence better
624 forecasts. For example, assimilation of satellite measurements of sea surface salinity (SSS) leads
625 to improvements in tropical Pacific ocean states and ENSO forecasts in experiments using an
626 intermediate-complexity coupled model (Hackert et al. 2019), whereas assimilation of satellite-
627 derived sea ice thickness (SIT) measurements has shown potential for improving sea ice
628 forecasts in operational seasonal forecasting systems (Chen et al. 2017; Blockley and Peterson,
629 2018). A major limitation is that these data sources have been available for less than a decade,
630 whereas considerably longer hindcast periods are required for forecast post-processing and skill
631 assessment, and temporal consistency of observational data used for initialization is required to
632 avoid artificial biases between hindcasts and forecasts. Forecasts thus continue to be initialized
633 typically without assimilation of SSS or SIT, from initial conditions that deviate appreciably from

634 available observations especially for SIT (Uotila et al. 2019). This motivates alternative
635 approaches for initializing SIT over multidecadal hindcast periods (Dirkson et al. 2017).

636

637 *Coupled data assimilation*

638 The atmosphere, land, ocean and sea ice components of climate prediction models have often
639 been initialized individually, without coupling. However, such an approach does not make
640 optimal use of observations, which may exert influences across the interfaces of the model
641 components. In addition, physical inconsistencies between the separately initialized
642 components may lead to rapid adjustments, or shocks. To overcome these limitations attention
643 has increasingly turned toward developing coupled data assimilation methods that treat
644 multiple components, such as atmosphere and ocean, simultaneously using observations from
645 each (Penny and Hamill 2017). Such methods are termed weakly or strongly coupled (Penny et
646 al. 2017). Weakly coupled methods apply assimilation independently to each model component
647 within the coupled model, so that the components may exchange information across their
648 interfaces. Such techniques have shown promise for reducing shocks (Mulholland et al. 2015),
649 and have begun to be applied operationally (e.g., Browne et al. 2019). Strongly coupled
650 methods apply assimilation to multiple model components in an integrated manner, so that
651 observations assimilated in one component can directly influence others. Such methods
652 remain experimental and thus far have been applied mainly in simplified models (e.g., Penny et
653 al. 2019).

654

655 **Ensemble predictions and forecast information.**

656 *Subseasonal to Seasonal*

657 In contrast to ensemble weather forecasts, a consolidated verification strategy for S2S
658 predictions is not yet established, and developing such a framework that encompasses
659 important forecast attributes such as accuracy, association, discrimination, reliability, and
660 resolution has thus emerged as a priority (Coelho et al. 2018). (Accuracy measures error, or
661 distance between forecast and observed values; association measures strength of the linear
662 relationship between forecast and observation as through temporal or spatial correlations;
663 discrimination measures by how much forecasts differ given different outcomes; reliability
664 measures how well forecast probabilities correspond to observed frequencies of occurrence;
665 resolution measures by how much outcomes differ given different forecast probabilities.
666 Forecast quality encompasses all these attributes, whereas skill indicates quality relative to
667 some benchmark such as persisted anomalies or climatological probabilities.) As for seasonal
668 predictions, a purpose of S2S hindcasts is to provide a larger sample for more confident
669 verification statistics than real time forecasts because they cover more years. However,
670 because S2S hindcasts are initialized using re-analysis and most often have a smaller ensemble
671 size, their verification generally underestimates real-time forecast quality. Operational centres
672 are encouraged to compute and monitor verification statistics based both on hindcasts and
673 real-time forecasts.

674

675 As has been demonstrated for seasonal prediction, S2S multi-model ensembles (MMEs)
676 generally outperform individual models (Vigaud et al. 2017; Pegion et al. 2019). Currently, the

677 S2S and SubX MME projects are providing testbeds for research³ as well as a foundation for
678 operational use (Vitart and Robertson 2019; Pegion et al. 2019). One focus for exploiting such
679 datasets is developing calibration procedures, post-processing steps that improve the
680 properties of probabilistic forecasts, to enable S2S ensemble forecasts to provide reliable
681 probabilities for particular conditions occurring or thresholds being exceeded, especially for
682 extreme events. The varied current choices among S2S project modelling systems for hindcast
683 and near real time initialization dates, hindcast period and ensemble size is, however, limiting
684 advances in developing multi-model calibration and combination procedures. In addition, the
685 value of these datasets for research would be enhanced if more comprehensive stratospheric
686 data were to be available across models.

687
688 S2S ensemble forecasts have shown promise in providing useful predictions and early warnings
689 for high impact climate and weather events including severe heat waves and cold spells, as well
690 as regional probabilities of the occurrence of tropical storms as illustrated in Fig. 8 (Vitart and
691 Robertson 2018). Examples include severe cold conditions over Europe associated with the
692 negative phase of the NAO, whose useful predictability into week 3 is enhanced by tropical–
693 extratropical teleconnections resulting from MJO activity (Ferranti et al. 2018), and atmospheric
694 rivers, plumes of intense water vapor transport that often trigger weather and hydrologic
695 extremes and are especially predictable at lead times of 3 to 5 weeks during certain MJO and
696 QBO phase combinations (Baggett et al. 2017). While modest overall skill at ranges longer than

³ Hindcast and near real-time forecast data are available from S2S at www.s2sprediction.net and from SubX at <http://iridl.ldeo.columbia.edu/SOURCES/.Models/.SubX/>.

697 a week has been found for S2S predictions of springtime Sahelian heat waves including
698 measures of heat stress, such conditions following a strong El Nino were accurately forecast,
699 pointing to the tropical Pacific as a source of predictability for extremes in that region (Batté et
700 al. 2018).

701

702 A global precipitation hindcast quality assessment of the S2S prediction project models (Fig. 9)
703 was performed by de Andrade et al. (2019). Sub-seasonal prediction quality is modulated by
704 the MJO, QBO, ENSO in the tropics, changes in large-scale flow in the extra-tropics and
705 stratospheric tropical and extratropical variability (Butler et al. 2019). It is therefore important
706 to estimate the predictive skill of such events and identify their impacts on predictions of
707 weather and weather extremes. Evaluating the conditional prediction quality associated with
708 the key low frequency variability modes is instrumental for better understanding S2S
709 predictability mechanisms. For example, MJO predictive skill in the S2S MME ranges between
710 12 to 36 days and is affected both by the MJO amplitude and phase errors (Vitart 2017; Lim et
711 al. 2018; H. Kim et al. 2018). Communicating these variations in forecast quality, including if the
712 forecasts are no better than climatology, is extremely important as users with such knowledge
713 can better utilize and benefit from the forecast information. Furthermore, capitalizing on
714 “windows of opportunity” when skill is especially high increases the value of S2S forecasts
715 (Mariotti et al. 2020), and motivates their frequent initialization (ideally daily).

716

717 *Seasonal to decadal*

718 Limited forecast quality in current S2D ensemble prediction systems motivates research
719 initiatives that focus on extracting skillful and reliable information from the large amounts of
720 forecast and hindcast data available to potential users⁴.

721

722 One emerging theme of such research is that S2D prediction systems sometimes underestimate
723 the predictable signal (Eade et al. 2014; Scaife and Smith 2018). As a result, very large ensembles
724 that effectively filter out unpredictable noise demonstrate higher skill in predicting phenomena
725 such as the winter NAO (Scaife et al. 2014b; Dunstone et al. 2016) and seasonal to multi-annual
726 regional precipitation variations (Dunstone et al. 2018; Yeager et al. 2018) than was previously
727 thought possible. While very large ensemble sizes hold value for isolating weak predictable
728 signals, much smaller ensemble sizes are sufficient for skillful prediction of tropical SST, for which
729 signal to noise ratios are much larger (Zhu et al. 2015). The causes of unrealistically low modeled
730 predictable signals (sometimes called the “signal to noise paradox”) remain under investigation.
731 Two hypotheses stemming from hindcast experiments are that winter NAO skill is enhanced by
732 skillful prediction of a QBO teleconnection that is too weak in models (O’Reilly et al. 2019), and
733 that transient eddy feedbacks are too weak in models (Scaife et al. 2019). Others based on simple
734 models suggest that the NAO predictable signal is too weak because climate models switch

⁴ Seasonal hindcast data from the WCRP Climate-system Historical Forecast Project (CHFP; Tompkins et al. 2017) are available at <http://chfps.cima.fcen.uba.ar/access.php>, and from the North American Multi-Model Ensemble (NMME, Kirtman et al. 2014) including real-time forecasts at <https://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/>. Decadal hindcast data from the WCRP Coupled Model Intercomparison Project Phases 5 and 6 are available via <https://esgf-node.llnl.gov/projects/cmip5/> and <https://esgf-node.llnl.gov/projects/cmip6/>.

735 between NAO regimes too rapidly (Strommen and Palmer 2019), or exhibit less persistent NAO
736 variability than is observed (Zhang and Kirtman 2019).

737
738 In the case of the winter NAO which is a key source of variability over the mid-latitude North
739 Atlantic and Europe, another approach to extract relevant information from over-dispersive
740 ensembles that leads to improved skill is to subsample ensemble members that are close to a
741 “first guess” statistical prediction of the NAO (Dobrynin et al. 2018); subsampling has shown
742 potential for improving European summer forecasts as well (Neddermann et al. 2019).

743
744 Estimating and realizing the predictability of key modes of variability is still a major challenge at
745 S2D time scales. ENSO is considered one of the most predictable phenomena on multi-seasonal
746 time scales, but longer-range skill has been viewed as limited. However, multi-year ensemble
747 predictions have shown evidence of skill in predicting long-lasting La Niña events that follow
748 warm events up to 24 months ahead (DiNezio et al. 2017; Luo et al. 2017). Challenges in the
749 initialization of such longer time scale predictions remain, as evidenced by multi-year predictions
750 in which skill for SST and precipitation over land improves with lead time in some areas,
751 suggesting that short-term adjustments following initialization may tend to degrade skill (Yeager
752 et al. 2018).

753
754 Calibration of ensemble forecasts is a necessary step to reduce the areas for which S2D forecasts
755 are unreliable and potentially misleading. Combinations of several forecasting systems such as
756 the North American Multi-Model Ensemble (NMME, Kirtman et al. 2014) are now routinely used

757 to increase ensemble reliability and improve forecast skill. Several recent efforts have explored
758 weighted multi-model calibration methods to combine ensembles from different models in order
759 to improve probabilistic seasonal forecasts for temperature and precipitation anomalies as well
760 as forecast of extremes (Becker 2017). Calibration methods have also been developed for
761 ensemble decadal hindcasts to adjust both the bias and ensemble spread with a parametric
762 dependency on lead time and initialization time (Pasternack et al. 2018). Such methods are found
763 to improve both the conditional bias and probabilistic skill of decadal hindcasts.

764

765 **Climate forecasts for decision making.**

766 *Subseasonal to Seasonal*

767 Many decisions are made on the S2S forecasting timescale, which sits between weather
768 forecasts and S2D climate outlooks; therefore the continued development of S2S forecasts has
769 the potential to benefit many sectors of society (Fig. 10). S2S forecasting is a rapidly maturing
770 discipline, with emerging recognition for both the need and the potential use of forecasts on
771 this timescale (White et al. 2017). While S2S forecasts are increasingly being used in
772 government as well as a range of sectors including agriculture, energy, finance, health and
773 water resource management – more engagement between S2S forecasters and end users is
774 needed to increase the wider awareness and uptake of S2S forecasts.

775

776 Although scientific knowledge gaps, computational capacity, and gaps in observations and
777 modeling currently limit the use of S2S forecasts to some degree, by increasingly placing
778 decision makers at the forefront of S2S forecast development, an improved dialogue between

779 S2S forecasters, developers and end users will accelerate the awareness and application of S2S
780 forecasts to real-world decision-making.

781

782 To support the increased use of S2S forecasts for decision-making, the following
783 recommendations were identified for action following the Boulder conference:

- 784 ● A summary of existing stakeholder case studies is planned to be created to demonstrate past
785 and ongoing ‘success stories’, and support better engagement with end users and
786 stakeholders. As the S2S forecast needs and associated performance varies greatly between
787 different sectors and users, the wider community is increasingly working together on the co-
788 design and production of S2S predictions in order to better meet user needs. Several
789 applications of S2S forecasts are now being developed in different disciplines, such as the
790 EU-funded S2S4E project in the energy sector, a quasi-operational excess heat outlook
791 system in the health sector (Lowe et al. 2016), and S2S hydrologic prediction in the water
792 management sector. These efforts need to be catalogued and disseminated to guide further
793 user-driven decision-support products, and to support the continued development of S2S
794 forecast, verification metrics and related services.
- 795 ● Systematically assessing the relative skill (or lack thereof) of forecasting a series of historical
796 high-impact events, such as heat waves, extreme rainfall events, or wildfires, on the S2S
797 timescale would be a useful way to help demonstrate the potential of S2S forecasts to
798 decision-makers across multiple sectors. At present, such case studies are often ad-hoc and
799 typically not published in the wider literature; however, a collaborative effort that brings
800 together a set of demonstrable case studies, involving both forecasters and end users, would

801 fill this gap. For example, a series of ‘tailored narratives’, or ‘storylines’ (approaches that
802 construct stories of plausible, non-probabilistic climatic futures that relate to a specific
803 person or sector to counter perceived barriers; e.g., Hazeleger *et al.* 2015), may aid in the
804 understanding of what S2S forecasts may deliver in the future.

- 805 ● To support the co-design, uptake and use of S2S forecasts, S2Sapp.net is currently being
806 established as a new network of researchers, modellers and practitioners – an ‘open to all’
807 global community with a shared aim of exploring and promoting cross-sectoral services and
808 applications of this new generation of forecasts from across government, academia, and the
809 private sector.

810

811 *Seasonal to decadal*

812 Research efforts are assessing the value of S2D forecast information for many applications, and
813 initiatives such as the WMO’s Global Seasonal Climate Update⁵ and Annual to Decadal Climate
814 Update (Kushnir *et al.* 2019) are making such information more widely available. However,
815 consultation with decision makers is essential in order to tailor forecast information to the needs
816 and expectations of users.

817

818 Fisheries management is one application for which S2D forecast information holds promise
819 (Tommasi *et al.* 2017). This is due to reasonable skill for ocean prediction in regions of interest,
820 coupled with strong influences of S2D climate variability on fish populations. Case studies

⁵ <https://public.wmo.int/en/our-mandate/climate/global-seasonal-climate-update>

821 employing fisheries management decision frameworks have shown that SST forecast information
822 can potentially increase fishery yields while reducing the risk of population collapse from
823 combined effects of environmental factors and overfishing. However, significant challenges
824 remain for fully realizing this potential. These include a need for improved initialization and
825 reduced model errors in key ocean regions such as the US Northeast continental shelf, dynamical
826 downscaling in cases where important spatial scales are not resolved by global models, and
827 sufficiently accurate observational data for hindcast verification on these scales. In addition,
828 incorporating biogeochemistry and marine ecosystem components into prediction systems will
829 expand their potential capabilities, while posing additional verification challenges.

830

831 Another current focus of application-oriented research is water management. Global climate
832 prediction models have been shown to have skill in predicting the next winter season's snowpack
833 throughout much of the western US, where spring snowmelt is an essential water resource
834 (Kapnick et al. 2018; Sospedra-Alfonso et al. 2016b). Because temperature influences snowmelt
835 and runoff efficiency, skill in seasonal temperature forecasts can provide improved skill for
836 seasonal water supply forecasts in this region (Lehner et al. 2017). Seasonal forecast skill has also
837 been demonstrated for monsoon rainfall (e.g., Jain et al. 2019) and drought (Hao et al. 2018) with
838 potential to inform water management decisions in many regions of the globe. Decadal forecasts
839 potentially can meet planning horizon needs but currently are less familiar to water managers
840 than seasonal forecasts and long-term climate projections. Efforts to apply decadal climate
841 information for water management decisions have included assessing the role of decadal modes
842 of variability, and using statistically downscaled decadal predictions as hydrological model inputs.

843 Developing information that is credible and compatible with existing decision frameworks is an
844 important consideration (Towler et al. 2018).

845
846 Additional sectors for which S2D forecasts are being assessed for decision making include
847 agriculture (Klemm and McPherson, 2017), energy (demand & wind power generation, Clark et
848 al. 2017; Lledó et al. 2019), tropical cyclone (Bergman et al. 2019) and coastal flooding (Widlansky
849 et al. 2017) preparedness, Arctic marine transportation (Stephenson and Pincus 2018), wildfire
850 risk (Turco et al. 2019), and food security (Funk et al. 2019).

851
852 Initiatives to develop and deliver climate forecast information range in scale from international,
853 regional and national (e.g., Marotzke et al. 2016), to individual users, all of which aim to provide
854 forecast information having practical value for decision makers. In all cases, it is crucially
855 important that uncertainties are adequately quantified and conveyed in order to avoid any false
856 sense of certainty and to build trust in forecast information providers, although sometimes this
857 requires overcoming a preference of users for deterministic information. Additional
858 considerations are that expectations of users need to be conditioned to generally modest levels
859 of skill, but that this information can nonetheless be advantageous when applied consistently in
860 the long term. The likelihood that climate forecast information gets used increases when efforts
861 are made to build relationships with potential users, and dialogs are opened to enable forecast
862 products to be co-designed (Kolstad et al. 2019).

863

864 **Cross-cutting issues in S2S and S2D prediction.**

865 *Initialization shock and model error*

866 Model biases are an endemic modeling issue that is common across S2S and S2D prediction
867 time scales and influence all aspects of the prediction systems – complicating ingestion of
868 assimilated observations, degrading skill, and necessitating post-processing steps such as bias
869 correction and calibration for product development and delivery.

870

871 Model biases begin to develop on fast time scales and lead to drifts from the climate
872 represented by the initial conditions to that of a model's biased equilibrium state. It has been
873 extremely hard to understand the mechanisms behind these drifts, and further, pathways for
874 their diagnosis are not clear although some progress is being made (Sanchez-Gomez et al. 2015;
875 Shonk et al. 2018; Voltaire et al. 2019). Such difficulties arise due to non-linear interaction
876 between various physical processes that are parameterized, and because biases could be non-
877 local in their origin. Long time scales before models' equilibrium states are attained make
878 understanding the causes of drifts even harder. The Boulder meeting recognized that the
879 S2S/S2D prediction community needs to pay particular attention to developing pathways for
880 understanding the onset of model biases and put together mechanisms (such as summer
881 schools) to train the next generation of scientists with interest and expertise in climate
882 modeling and model diagnostics.

883

884 Initialization shocks that arise from imbalances in initial states with respect to the formulation
885 of the model and can be caused by limitations of observations and data assimilation as well as
886 model biases were also recognized as a major issue, particularly in the context of decadal

887 predictions. Initialization shocks result in the degradation of initial information that may be the
888 primary source of predictability for the subsequent forecast. Even after considerable research
889 and investment in decadal predictions it is still not clear what may be best approaches, such as
890 between full field vs. anomaly initialization, to retain predictive information in the initial state
891 while minimizing the influence of initial shocks on the subsequent forecast. The continuing
892 prominence of model drift and initial shocks as important issues reinforces a long held
893 sentiment that these are outstanding problems that need to be studied more systematically if
894 progress in translating inherent predictability into prediction skill is to be made.

895

896 *S2S and S2D research interactions*

897 The examples of interaction among modes of variability across S2S and S2D time scales noted
898 earlier emphasize the fact that continued interaction and communication across the S2S and
899 S2D research communities will be important to make progress. Furthering our understanding of
900 time-scale interactions will require investments in process level understanding of these
901 phenomena and will not only benefit our understanding about their lower-frequency variations
902 but will also contribute to improved process level diagnostics of model simulations. Better
903 understanding of time-scale interactions is likely to require the use of a hierarchy of models,
904 such as simple linear models to investigate the characteristics of tropical-extratropical
905 interactions (including their influence on storm tracks), to diagnose possible causes for errors in
906 their representation in complex GCMs (Dias et al. 2019).

907

908 Another aspect of research interactions across time scales is quantifying the fidelity of models
909 in S2S and S2D prediction as well as projections of climate on longer time scales based on their
910 simulation and prediction of shorter time-scale phenomena. The advantage of such an
911 approach is that much larger samples for predictions of shorter time-scale phenomena are
912 available, and an assessment of the reliability of such predictions can be used to build
913 confidence in prediction on longer time-scales. Theoretical basis for extrapolating the reliability
914 of forecasts across different time scales may also require the use of a hierarchy of models
915 (Weisheimer and Palmer 2014; Christensen and Berner 2019).

916

917 *Research and operations*

918 Post-processing to improve forecast quality is an important area of research that bears directly
919 on operational activities. Post-processing is necessary because biases in forecasts can be as
920 large as the predicted signal, and therefore require the use of bias correction and calibration
921 techniques to adjust real-time predictions before their delivery to the users. These
922 requirements are shared across sub-seasonal to decadal prediction time-scales, however
923 because of different levels of experience (seasonal predictions having the longest history) the
924 opportunity for cross-community interactions was recognized. Some aspects for post-
925 processing are specific to time-scale, for example, bias correction for decadal predictions
926 requires methods to account for the non-stationarity of climate, and research needs to develop
927 such methods were stressed.

928

929 Necessity for post-processing requires an extensive set of hindcasts to accompany real-time
930 predictions. Because of limited resources, decisions about hindcast period, ensemble size and
931 forecast start dates are not straightforward and call for further guidance from the research
932 community. Such questions about the operational infrastructure for long-range prediction
933 systems, including ensemble generation techniques and recommendations for harmonizing
934 hindcast and real time forecast production, provide an opportunity to link operational and
935 research communities that was highlighted during the conference.

936

937 Product development and communicating forecasts to the user community is also a common
938 thread across the S2S and S2D communities. Communication of probabilistic forecast
939 information (including confidence in the forecast based on past verifications) to users for their
940 decision making has been a challenge, and once again there is much to be gained from lessons
941 learned from the experiences of different communities. Similar challenges and opportunities
942 also exist in the context of product development that incorporate user needs based on an
943 ongoing dialog from the very start of the process. In addition, users often wish to have
944 information on smaller spatial scales than are represented in global climate models. For such
945 applications either statistical or dynamical downscaling is possible and can be effective in
946 reducing local climatological biases, although clear demonstrations that downscaling can
947 improve the skill of climate predictions remain elusive (e.g., Manzanas et al. 2018).

948

949 In summary, research needs for further development of operational infrastructure, product
950 generation and communication of probabilistic forecasts were themes often repeated during
951 the conference.

952

953 **Conclusions and the future of subseasonal to decadal prediction**

954 This paper has outlined many commonalities in the prediction of weather and climate across
955 time scales and Earth system components, and through the value cycle from basic research to
956 operational delivery.

957

958 The Earth's weather and climate is inherently chaotic and challenges the best currently
959 available modeling capabilities. There remains however untapped skill, and realizing this skill
960 will require improvements on numerous fronts. These include fundamental understanding of
961 fine-scale processes, leading toward their robust parameterization; accurately representing
962 property exchanges across Earth system components through realistic coupling limiting
963 systematic errors; sustained Earth observing systems and advanced data assimilation methods
964 enabling balanced initial conditions that avoid shocks and mitigate model drifts; and innovative
965 numerical and ensemble generation techniques to address model scalability issues. Additional
966 important avenues toward improved services include development of probabilistic information
967 for high impact weather and climate events including unprecedented extremes, and optimal
968 post-processing and data fusion to add value to multi-model ensembles, among many others.

969

970 These challenges are broad but so are opportunities for steady progress, ranging from curiosity-
971 driven science to the systematic model evaluation and improvement in a collaborative and
972 open research/operational environment.

973

974 The joint WWRP-WCRP conferences in Boulder clearly demonstrated the benefit in bringing
975 relevant stakeholders together to cross-fertilize their experience, knowledge, respective issues
976 and working cultures, which will surely help frame a new and vibrant research portfolio, and
977 inspire the next generation of science leaders to ensure that society has access to the best
978 possible weather and climate prediction science.

979

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1693 **SIDEBAR 1:**

1694 **Hindcast and forecast quality assessment (or, “the unexamined life is not worth living”).**

1695 Besides helping to inform decision making, the careful assessment of forecast quality is critical
1696 to guiding forecasting improvements, but has many and varied considerations. Simply
1697 answering the question “is this forecast better than that one?” is complicated, as the
1698 appropriate skill metric or means for comparison is not always obvious. Some recent studies
1699 have focused on newer statistical methods for comparing one forecast to another. One
1700 relatively simple approach is the random walk test (DelSole and Tippett 2016), illustrated in Fig.
1701 SB1. This method is applicable to a wide range of measures such as a score based on the earth
1702 mover’s distance metric (Düsterhus 2019), while also being robust and fair in its discrimination.

1703

1704 The utility of forecast assessment can be illustrated through two very different applications of
1705 seasonal forecasts: sea-ice and hurricanes. The assessment of seasonal sea ice forecasts is
1706 complicated by the low quality of sea-ice observations, but nevertheless reveals that initializing
1707 sea-ice thickness using observational data sets generally improves the prediction of Arctic sea-
1708 ice extent and edges (Blockley et al. 2018). Comparison of multi-annual forecasts of Atlantic
1709 hurricane activity obtained by direct tracking of storms in decadal hindcasts and through a
1710 hybrid approach combining predicted SSTs and observed statistical relations finds that each
1711 approach is skillful, especially hybrid forecasts based on a SST index for AMV (Caron et al.
1712 2018).

1713

1714 A robust assessment of model performance should include the model's simulation of climate
1715 modes and teleconnection patterns such as ENSO, MJO and NAO, since they are major sources
1716 of predictability and errors representing their patterns or strength (e.g., Yang and DelSole
1717 2012; Vitart 2017) can degrade skill in affected regions (Gleixner et al. 2017; Lu et al. 2017). In
1718 cases where modeled teleconnection patterns are imperfect, forecast skill may be improved by
1719 means of statistical methods that use model forecasts of relevant climate modes such as ENSO
1720 as predictors (e.g., Strazzo et al. 2019). It remains desirable, however, for models to improve so
1721 that their simulated teleconnection patterns are sufficiently realistic that such corrections are
1722 not needed.

1723

1724 **SIDEBAR 2:**

1725 **Frontiers in Earth system prediction.**

1726 New frontiers in S2D prediction have been enabled by Earth system models (ESMs, Flato 2011)
1727 that represent the carbon and other biogeochemical cycles in addition to the physical climate
1728 system. These frontiers include prediction of ocean and land carbon sinks and biogeochemistry
1729 and their important contribution to global carbon storage, as well as ecosystem services. The
1730 world's oceans are a fundamental regulator of global carbon storage and variability. The
1731 strength of ocean carbon uptake, together with uptake of carbon by the land, determines the
1732 fraction of anthropogenic emissions remaining in the atmosphere, and hence modulates
1733 present and future warming. Observed global mean ocean carbon uptake shows variability on
1734 decadal time scales that can be represented by ESMs in which physical climate variables are
1735 assimilated (H. Li et al. 2019).

1736

1737 ESM simulations indicate that internal variability of the ocean carbon uptake on decadal
1738 timescales is as large as the forced climate change trend (Li and Ilyina 2018), pointing to the
1739 potential importance and utility of decadal carbon cycle predictions. Decadal predictions from a
1740 number of ESMs are assessing the predictability of the ocean and land carbon sinks and other
1741 ocean tracers such as dissolved oxygen. These forecasts are part of the Decadal Climate
1742 Prediction Project (Boer et al. 2016) and international programs such as the World Climate
1743 Research Programme's Grand Challenge on Carbon Feedbacks (Ilyina and Friedlingstein 2016).
1744 Initial results based on individual models have demonstrated potential predictive skill, assessed
1745 through verification against the assimilating reconstructions that provide initial conditions, for
1746 ocean carbon uptake in certain regions such as the North Atlantic reaching up to 7 or more
1747 years (Li et al. 2016; Lovenduski et al. 2019), and skill in predicting actual variations estimated
1748 from observations (Fig. SB2) has been demonstrated (Li et al. 2019).

1749 ESM-based studies also point to the drivers of this predictability. Air-sea CO₂ flux mainly varies
1750 due to pCO₂ changes in the ocean. While thermal influences on pCO₂ play a role in shorter term
1751 predictability, predictability beyond 3 years is maintained mainly by nonthermal influences of
1752 ocean circulation and biological modification of surface dissolved inorganic carbon and
1753 alkalinity (Li et al. 2019; Lovenduski et al. 2019).

1754

1755 Investigations in progress are finding potential for multi-annual prediction of additional
1756 biogeochemical fields such as net primary productivity and interior dissolved oxygen
1757 concentrations. In addition, potential predictability and skill for terrestrial carbon uptake have

1758 also begun to be assessed, with promising initial results (N. Lovenduski 2019, personal
1759 communication). These examples demonstrate that skillful multi-year prediction is likely
1760 achievable for biogeochemical and ecological Earth system components, and open prospects
1761 for the utilization of such information although significant challenges including the paucity of
1762 long term observational data for initialization and verification will need to be overcome.

1763

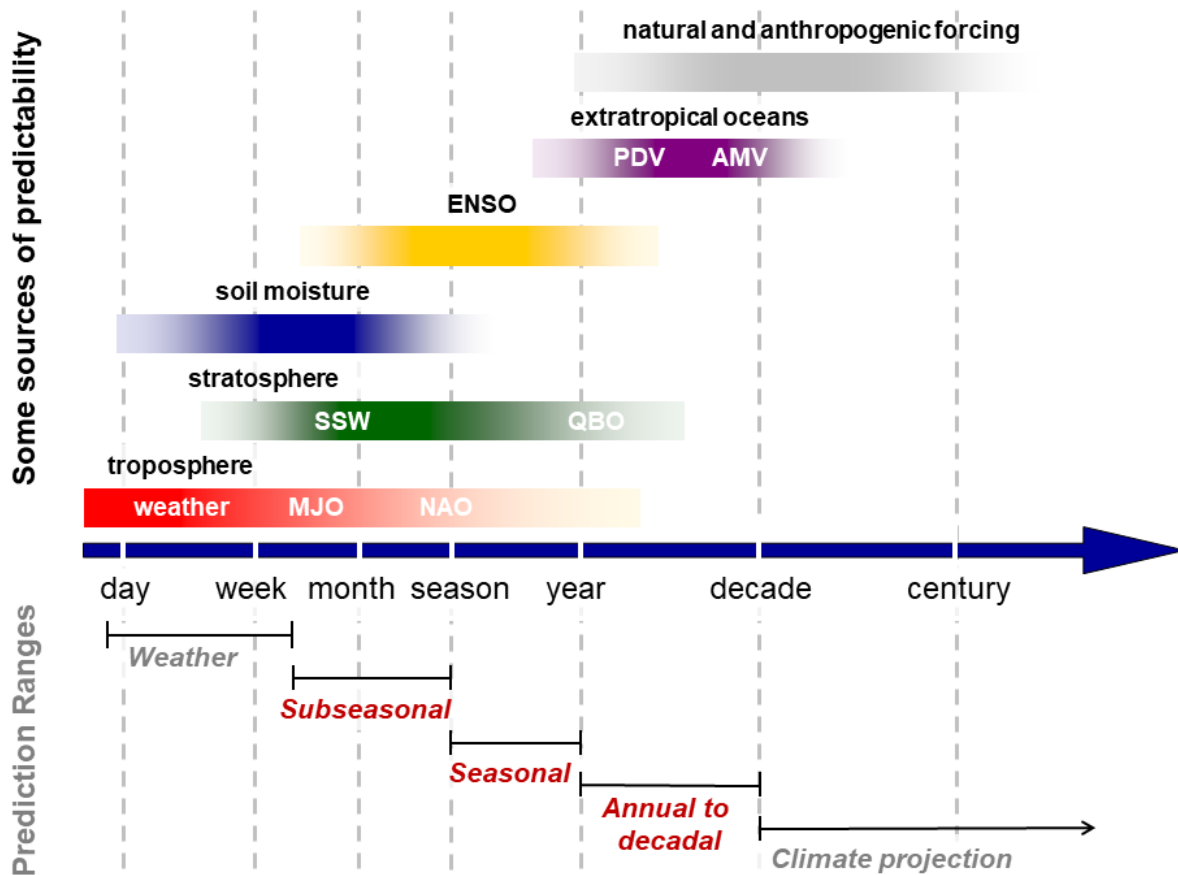
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1771 **Fig. 1.** Schematic depiction of temporal ranges and sources of predictability for weather and climate

1772 prediction. The subseasonal range encompasses the S2S time scales, and the seasonal and annual-to-

1773 decadal ranges the S2D time scales, that are considered in this paper. Longer multi-decadal and

1774 centennial ranges derive predictability mainly from forcing scenarios rather than initial conditions, and

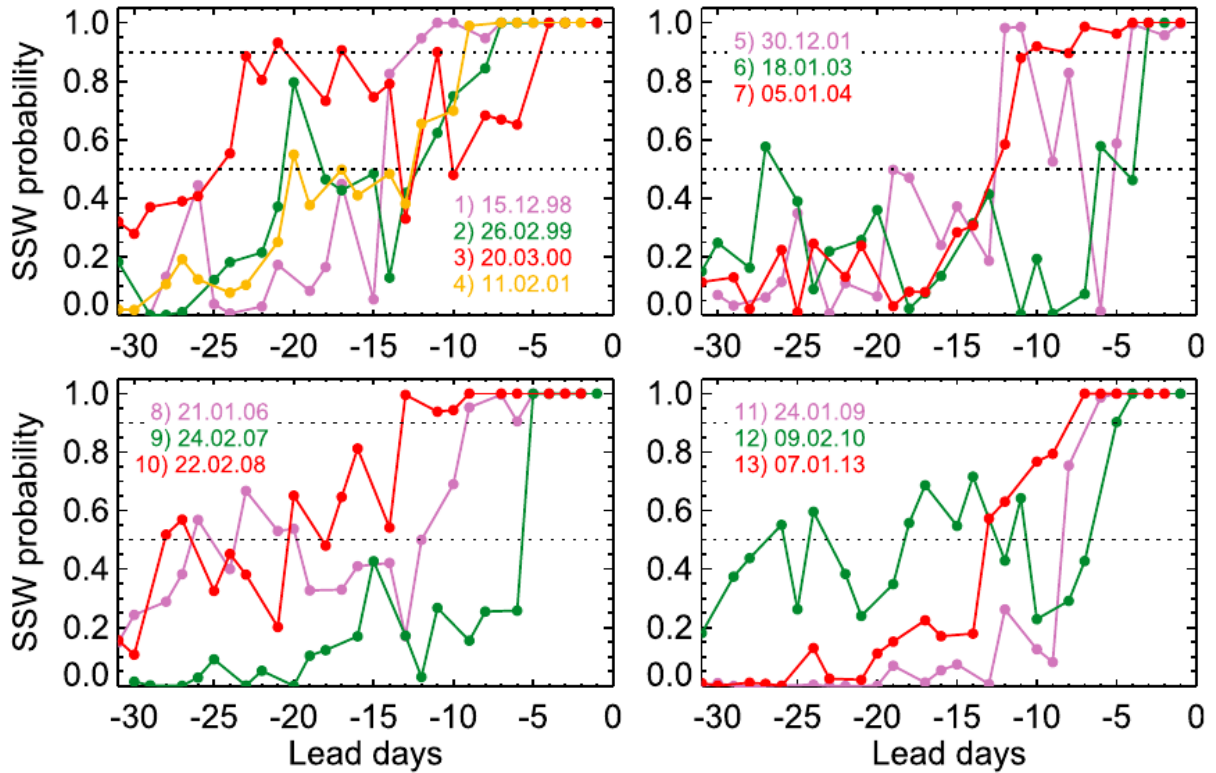
1775 are typically represented through climate projections originating from historical simulations begun in

1776 preindustrial times rather than predictions initialized from more recent observation-based climate

1777 states. Some important sources of predictability and approximate time scales over which they are most

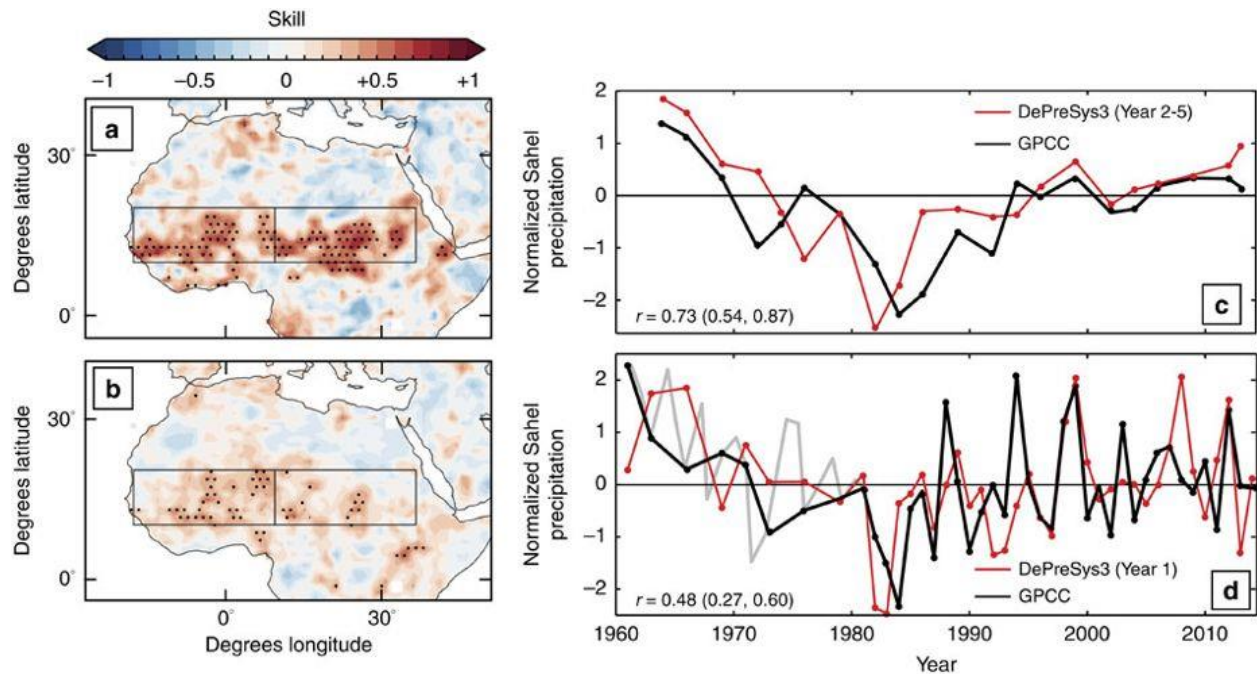
1778 influential on surface climate are indicated in the upper portion of the figure; acronyms are defined and

1779 associated phenomena are discussed in the main text.



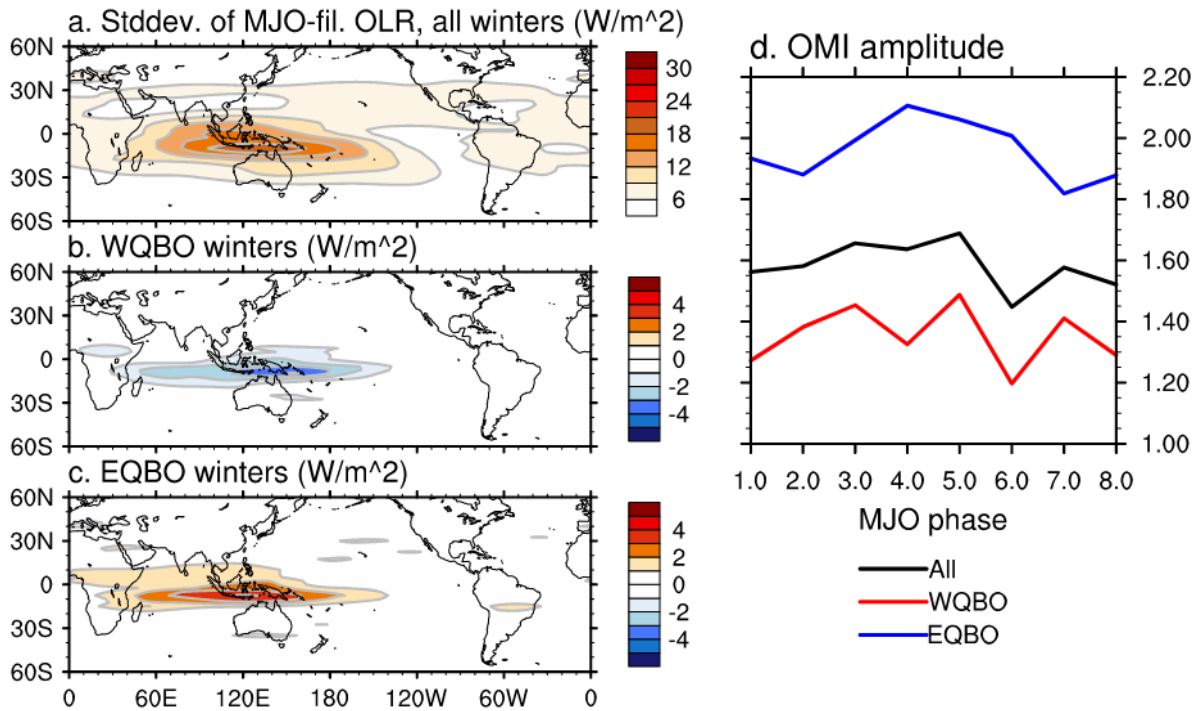
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Fig. 2. Forecast probabilities of 13 SSW that occurred on the indicated dates as a function of lead time, based on ensemble hindcasts from the ECMWF monthly forecasting system. Most of the SSWs are predicted between 8 and 12 days lead time with a probability of 0.5–0.9, which is considerably larger than the average frequency of SSW occurrence. (From Karpechko 2018.)

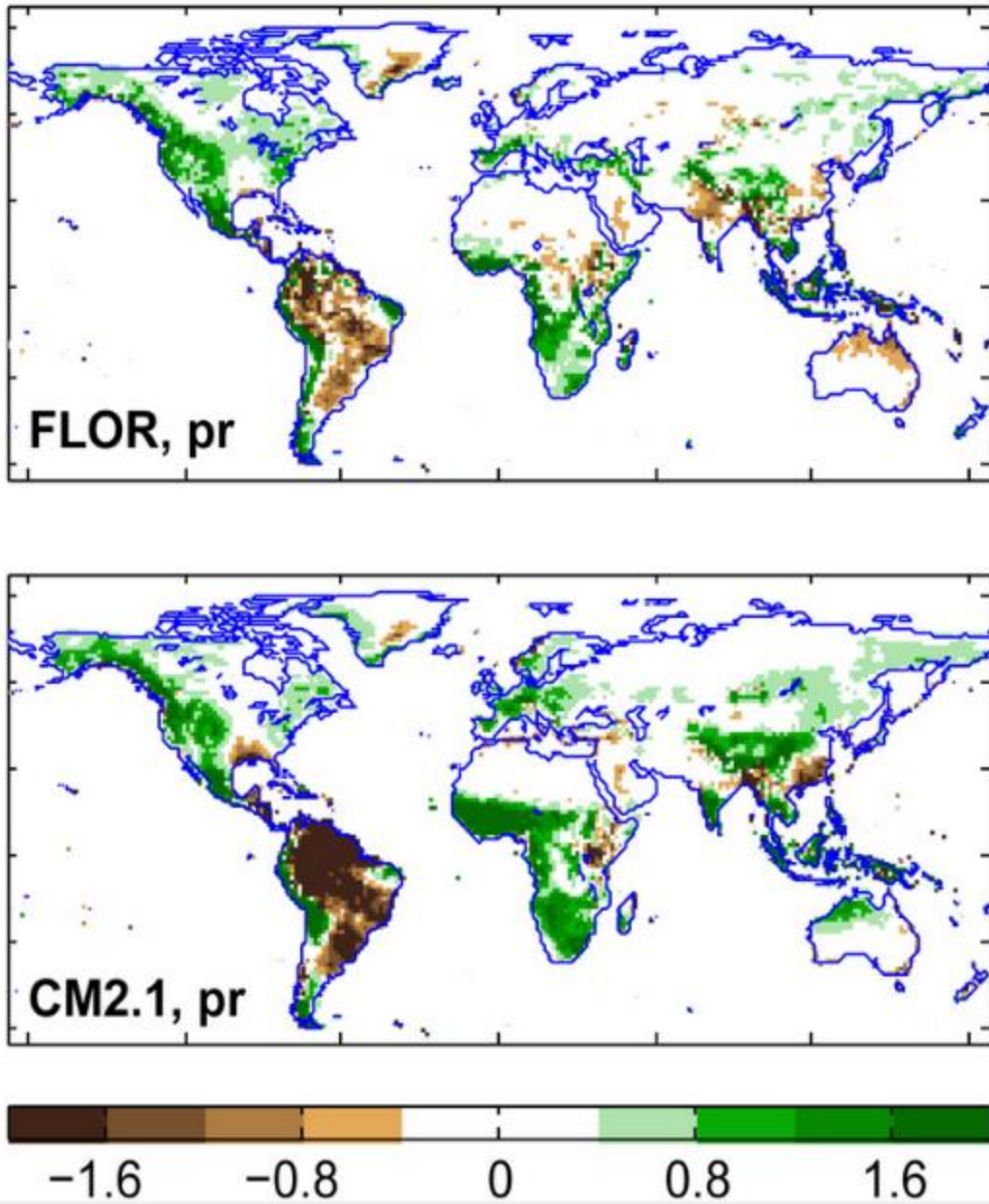


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1788 **Fig. 3.** Skill for predicting linearly detrended Sahel summer rainfall in years 2-5 (upper panels) and year 1
 1789 (lower panels) in DePreSys hindcasts. Panels (a)-(b) show spatial distributions of anomaly correlation
 1790 coefficients with stippling indicating 95% significance. Panels (c)-(d) show time series of normalized
 1791 predicted and GPCCC observed rainfall anomalies in the Sahel region outlined by the boxes in the maps,
 1792 with correlations and their 5–95% confidence intervals indicated. (From Sheen et al. 2017.)

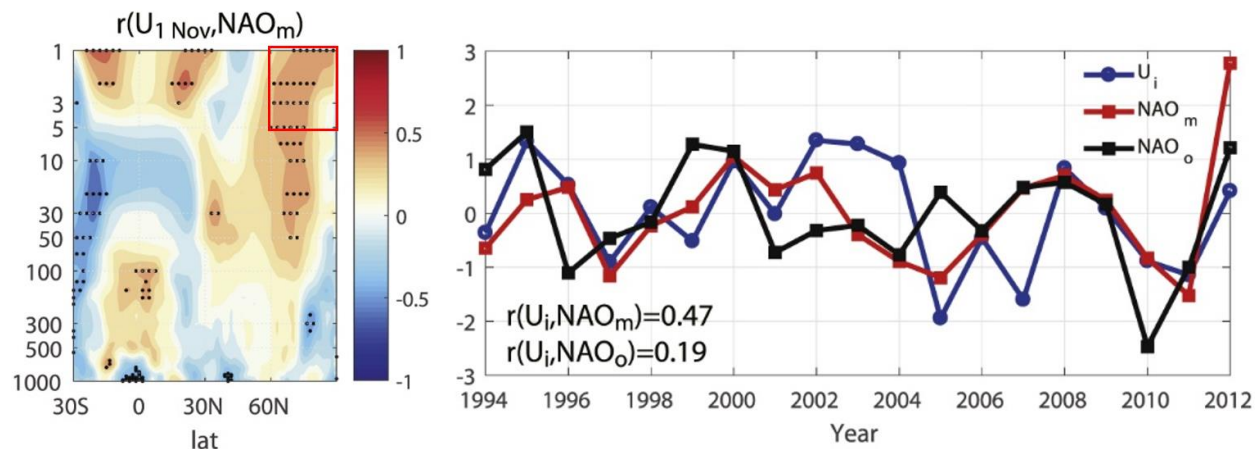


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 1795 **Fig. 4.** Influence of QBO phase on MJO amplitude. (a) Standard deviation of wintertime outgoing
 1796 longwave radiation (OLR), filtered to retain temporal and spatial scales characteristic of the MJO, for all
 1797 winters in 1979 to 2012. Differences from these values in winters characterized by QBO westerly
 1798 (WQBO) and easterly (EQBO) phases are shown (b) and (c) respectively. (d) Amplitude of an OLR-based
 1799 MJO index (OMI) as a function of MJO phase for WQBO, EQBO and all winters. (From Yoo and Son 2016.)



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1802 **Fig. 5.** Impact of resolution on precipitation biases in GFDL seasonal prediction models. Atmospheric
 1803 resolution is approximately 50 km with 32 levels in FLOR (upper panel), and approximately 200 km with
 1804 24 levels in CM2.1 (lower panel), whereas ocean resolution is approximately 100 km in both models.
 1805 Higher atmospheric resolution in FLOR reduces precipitation biases in numerous regions including much
 1806 of the tropics. Annual mean biases over land in mm day^{-1} based on 1981-2010 CMAP observations are
 1807 shown. (After Jia et al. 2015.)



1808

1809 **Fig. 6** Connection between stratospheric initial conditions and predicted winter NAO for UK Met Office

1810 GloSea5 predictions initialized 1 November 1995-2012. Left: correlation between initial zonal wind

1811 anomaly on 1 November and ensemble mean model-predicted surface NAO index (NAO_m) during DJF.

1812 Black dots represent values significant at $\alpha = 0.05$ confidence based on one-tailed test, and mean values

1813 within the red box define an index U_i . Right: Annual standardized U_i (blue), NAO_m (red) and observed

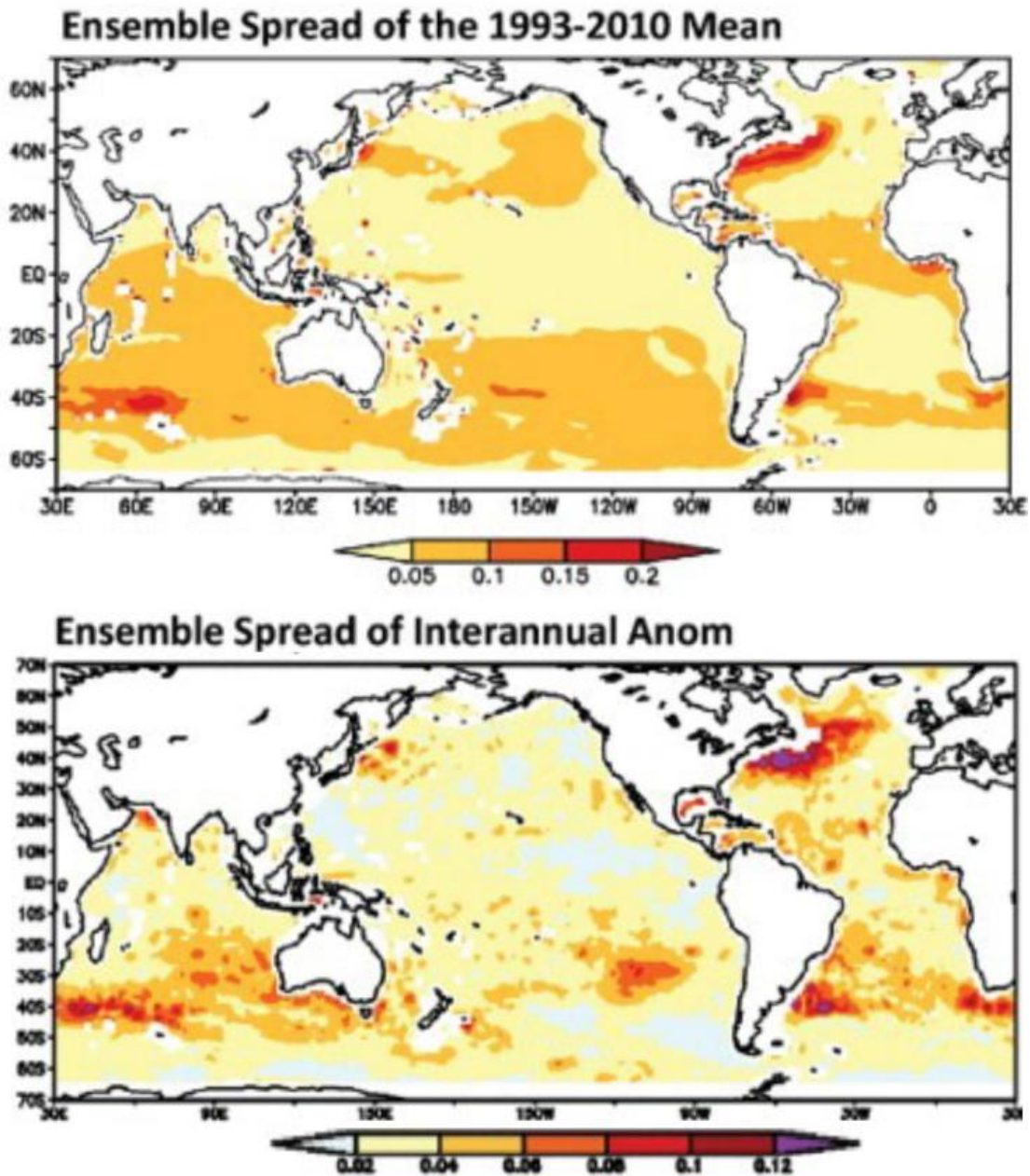
1814 surface NAO index, NAO_o (black). The correlation of U_i with NAO_m , indicated at lower left, is significant at

1815 $\alpha = 0.05$ confidence whereas the lower correlation of U_i with NAO_o is not unexpected based on signal to

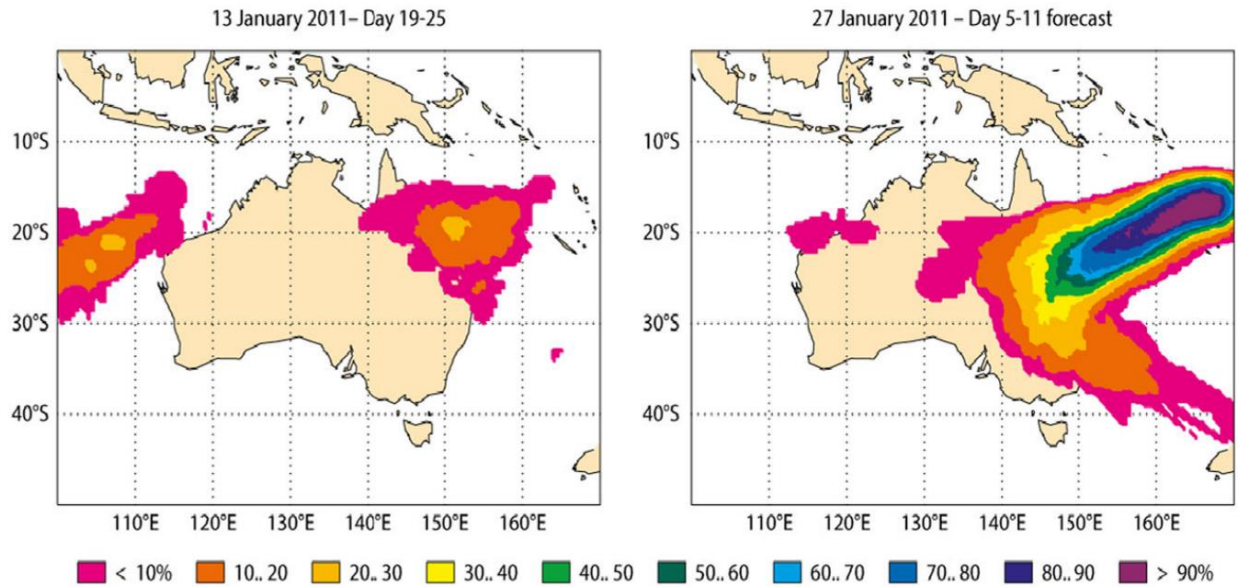
1816 noise considerations and that there is only one realization of observations. The larger correlation of

1817 predicted and observed winter NAO values $r(NAO_m, NAO_o)=0.62$ suggests that additional sources of

1818 predictability exist. (After Nie et al. 2019.)



1819
 1820 **Fig. 7.** Consistency across an ensemble of ocean state estimates of depth-averaged salinity over 0–
 1821 700m, from the Ocean Reanalyses Intercomparison Project. Ensemble standard deviations in both the
 1822 1993-2010 means (upper panel) and interannually varying monthly anomalies (lower panel) tend to be
 1823 largest in eddy active regions such as the Gulf Stream, and less well-observed regions such as the
 1824 Southern Ocean. These differences across state estimates are reflective of uncertainties in ocean initial
 1825 conditions. (After Balmaseda et al. 2015.)



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1827 **Fig. 8.** Elevated probabilities of tropical cyclone occurrence during 31 January to 6 February 2011, based
 1828 on ECMWF ensemble forecasts forecast starting 13 January with 18 day lead time (left), and 27 January
 1829 with 4 day lead time (right). Destructive Cyclone Yasi made landfall in northeastern Australia on 3
 1830 February 2011 as a destructive category 5 storm. (Adapted from Vitart and Robertson 2018).

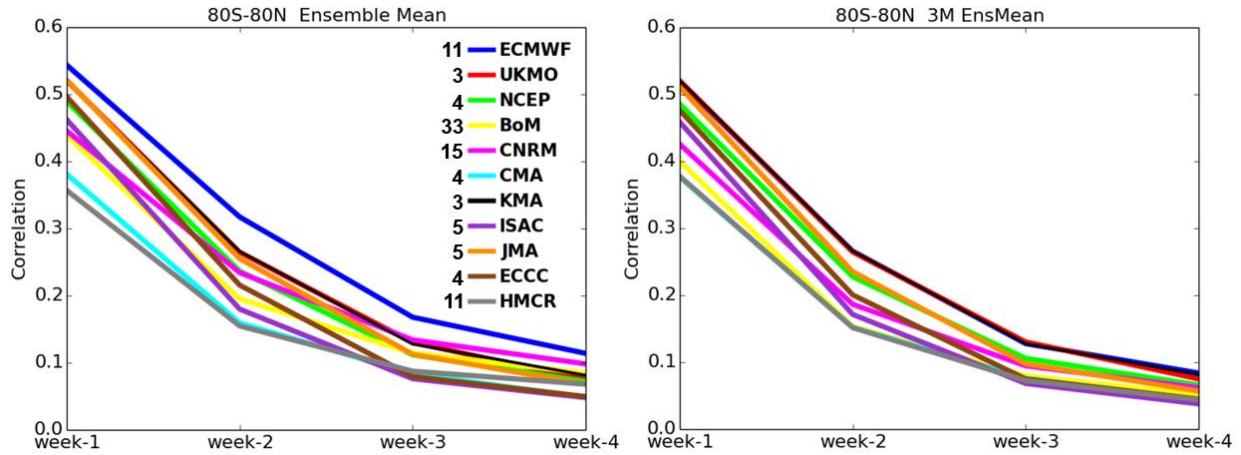
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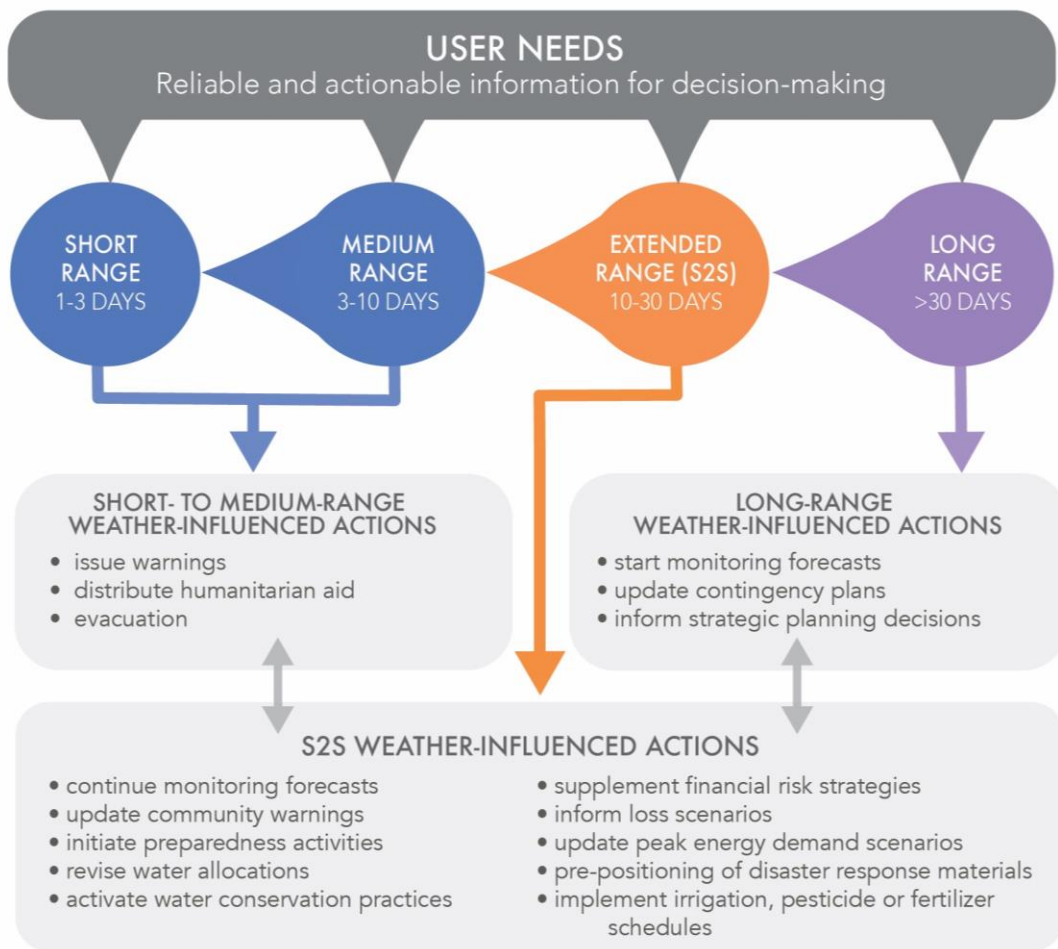
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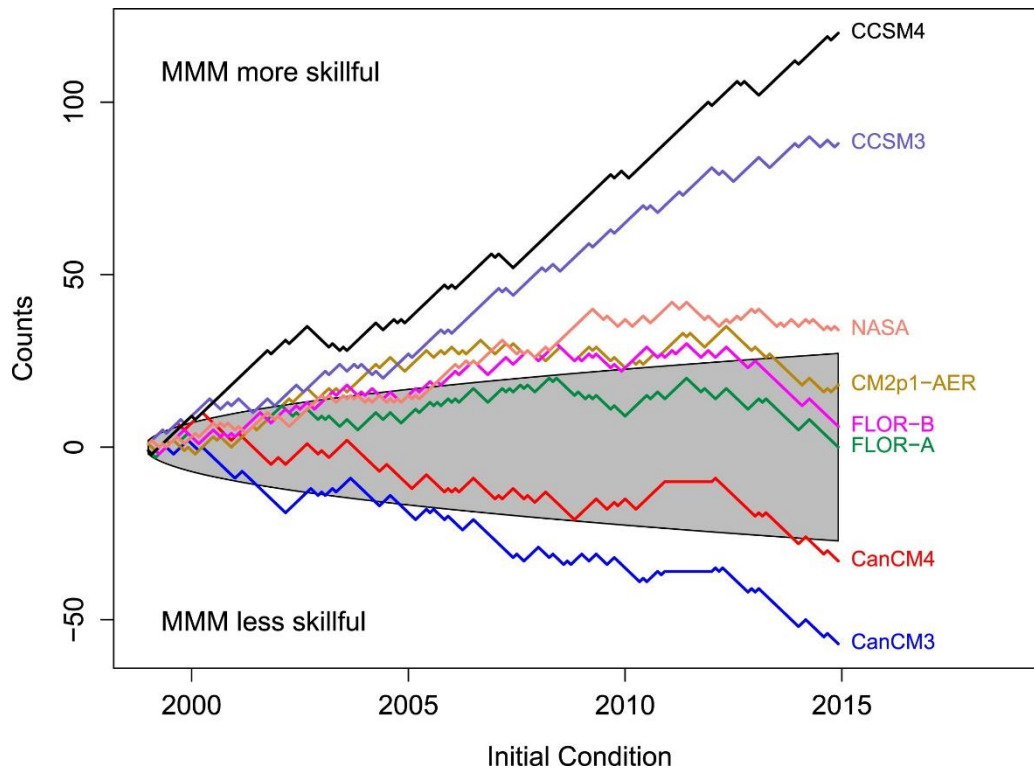


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1838 **Fig. 9.** Global averages of correlations between hindcast and observed precipitation anomalies over the
 1839 80°S to 80°N latitudinal band for weeks 1-4 for S2S project models initialized from November to March,
 1840 1999–2009. Left: Hindcast quality assessment based on ensemble means using the full ensemble size for
 1841 each model, as indicated in the figure legend. Right: Hindcast quality assessment based on ensemble
 1842 means using three ensemble members for each model. The reduced spread of the lines shown in the
 1843 right panel when ensemble sizes are identical compared to the spread of the lines shown in the left
 1844 panel demonstrates the value of the use of larger ensembles for subseasonal precipitation forecasting.
 1845 (Adapted from de Andrade et al. 2019.)

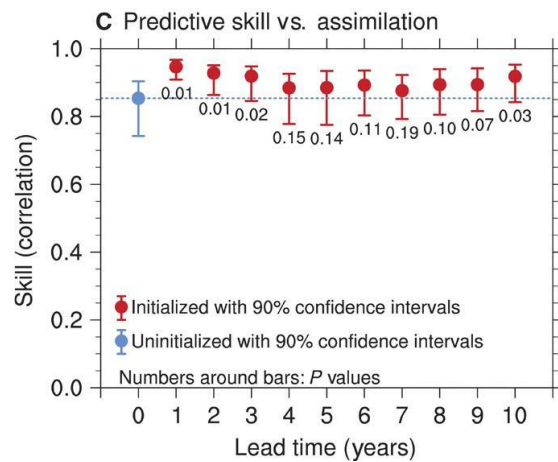
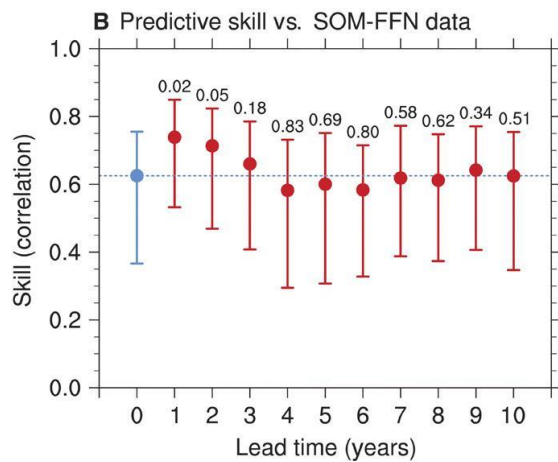
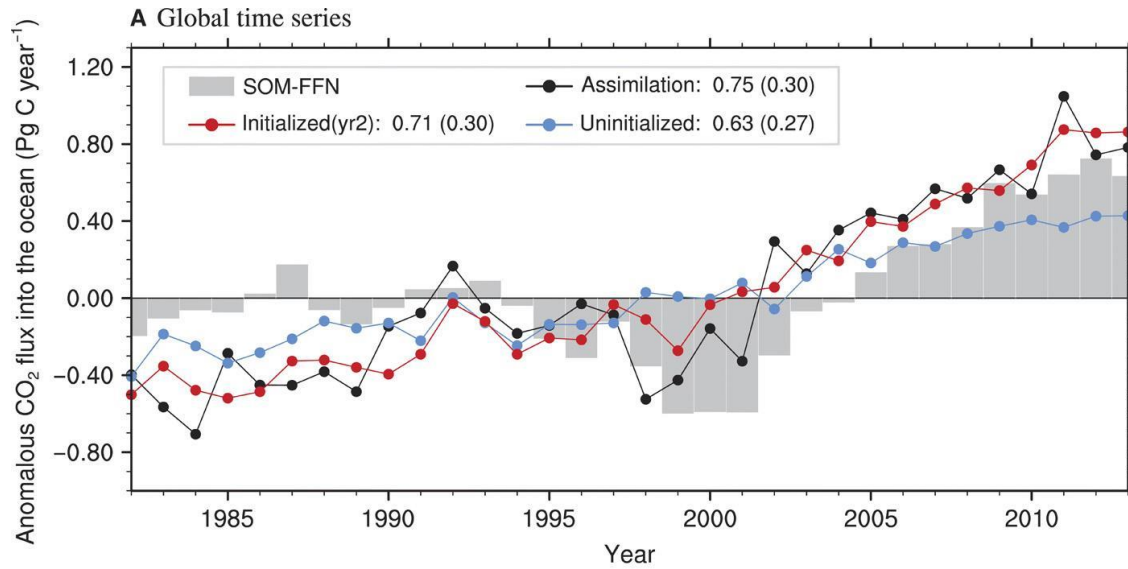


1846
 1847 **Fig. 10.** Schematic illustration of relationships between a S2S forecast range of 10-30 days and other
 1848 prediction timescales, including examples of actionable information that can enable decision making by
 1849 various sectors. Indicated actions are examples that are not exclusive to a particular forecast range.
 1850 (After White et al. 2017.)



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1853 **Fig. SB1.** Random walk test comparing monthly mean forecasts of the Niño 3.4 index for equatorial
 1854 Pacific SST at 2.5-month lead, between the multi-model mean (MMM) and individual models in the
 1855 NMME. Counts (vertical axis) increase by 1 when MMM squared error is smaller than that an individual
 1856 model (MMM more accurate) and decrease by 1 otherwise (individual model more accurate), and are
 1857 accumulated forward for all initial months and years (horizontal axis). Accumulated counts above or
 1858 below the shaded region indicate skill differences according to the squared error metric that are
 1859 significant with >95% confidence (MMM more skillful above the shaded region and individual model
 1860 more skillful below). Niño 3.4 anomalies are relative to 1982–98 climatological values, and span each
 1861 month in 1999–2015. (From DelSole and Tippett 2016.)



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Fig. SB2. Temporal evolution and predictive skill of global CO₂ flux into the ocean from the MPI-ESM-HR decadal prediction system. (A) Annual values of anomalous CO₂ flux into the ocean from data-based estimates (SOM-FFN; gray) and MPI-ESM uninitialized simulations (blue), year 2 of initialized decadal predictions (red) and data-constrained assimilation run (black). Anomaly correlations and root-mean-square errors (in parentheses) verifying against SOM-FFN data are indicated. (B) Anomaly correlation skill for global CO₂ flux into the ocean, verifying against SOM-FFN. The blue dot and dashed line show the uninitialized skill for which lead time is not relevant, and the red dots initialized skill for different forecast years, with 90% confidence intervals and P values based on a bootstrap approach indicated. (C) Like (B), but verifying against the assimilation run. (After Li et al. 2019.)