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Article

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# Current and emerging developments in subseasonal to decadal prediction

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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 conferences[1] 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

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[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    variability[2] 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.

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[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

Among atmosphere-surface influences, land-atmosphere interactions have their greatest

impact on subseasonal time scales in forecasts where land is initialized (Dirmeyer et al. 2018a),

but also can contribute skill on weather prediction and multi-month time scales (Dirmeyer and

Halder 2016, 2017). The most broadly impactful land attribute is soil moisture (Koster et al.

2004, 2016), but anomalies in soil temperature (Y. Zhang et al. 2019; Yang et al. 2019), snow

cover (Jeong et al. 2012; Orsolini et al. 2013), and vegetation states (Williams et al. 2016) can all

have significant impacts. A number of recent studies have focused on non-local impacts of land

surface anomalies, showing for example that soil moisture anomalies can exert remote as well

as local influences in boreal summer through driving of quasi-stationary Rossby waves and

associated circulation anomalies (e.g., Teng et al. 2019; Wang et al. 2019). In addition, land

surface and subsurface temperatures in spring may exert delayed downstream influences on

precipitation (Xue et al. 2018), and evapotranspiration may remotely influence precipitation

over land (Wei and Dirmeyer 2019).

365

Atmosphere-ocean interactions, fundamental for S2D predictability, can also be influential on

S2S time scales. For example submonthly prediction skills for precipitation and temperature are

enhanced over certain land areas including parts of Australia, the Maritime Continent and the

contiguous United States when tropical sea surface temperature (SST) anomalies associated

with El Niño Southern Oscillation (ENSO) are present (Hudson et al. 2011; Li and Robertson

2015; DelSole et al. 2017). Extratropical SST anomalies also can impart S2S skill through

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.

17

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 (Toniazzo 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 at 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 research[3] 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

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[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 users[4].

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 demonstrat 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 at 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 Update[5] 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; Voldoire 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.

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**SIDEBAR 1:**

**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 representating 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 $CO_2$ flux mainly varies

1750    due to $pCO_2$ changes in the ocean. While thermal influences on $pCO_2$ 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.

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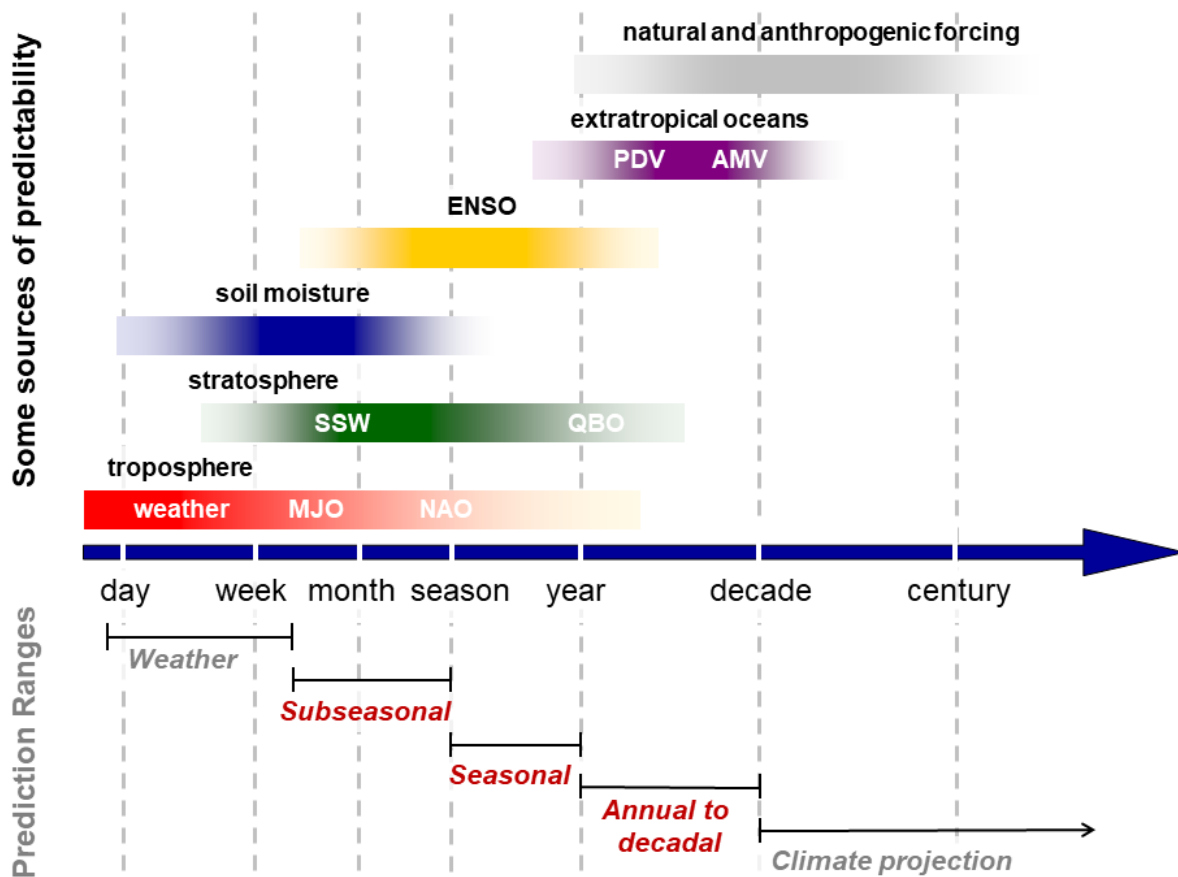
1771 **Fig. 1.** Schematic depiction of temporal ranges and sources of predictability for weather and climate

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

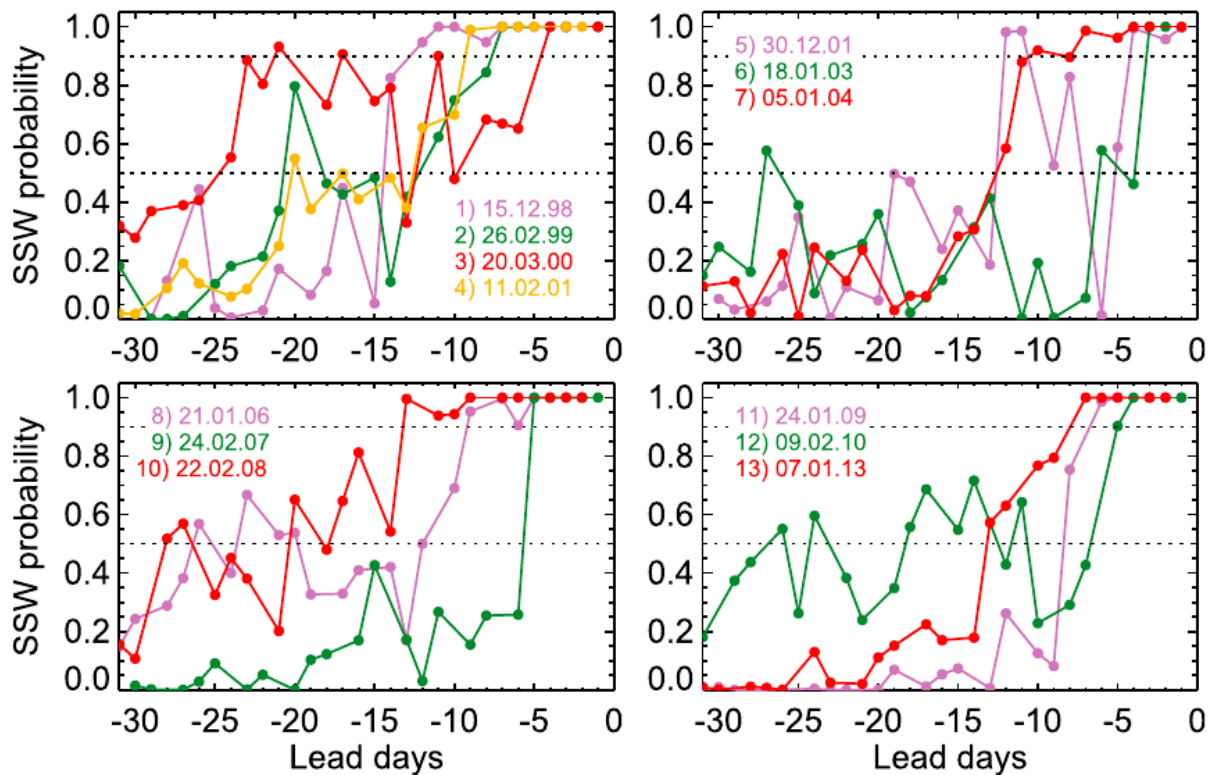1779 associated phenomena are discussed in the main text.

**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.)
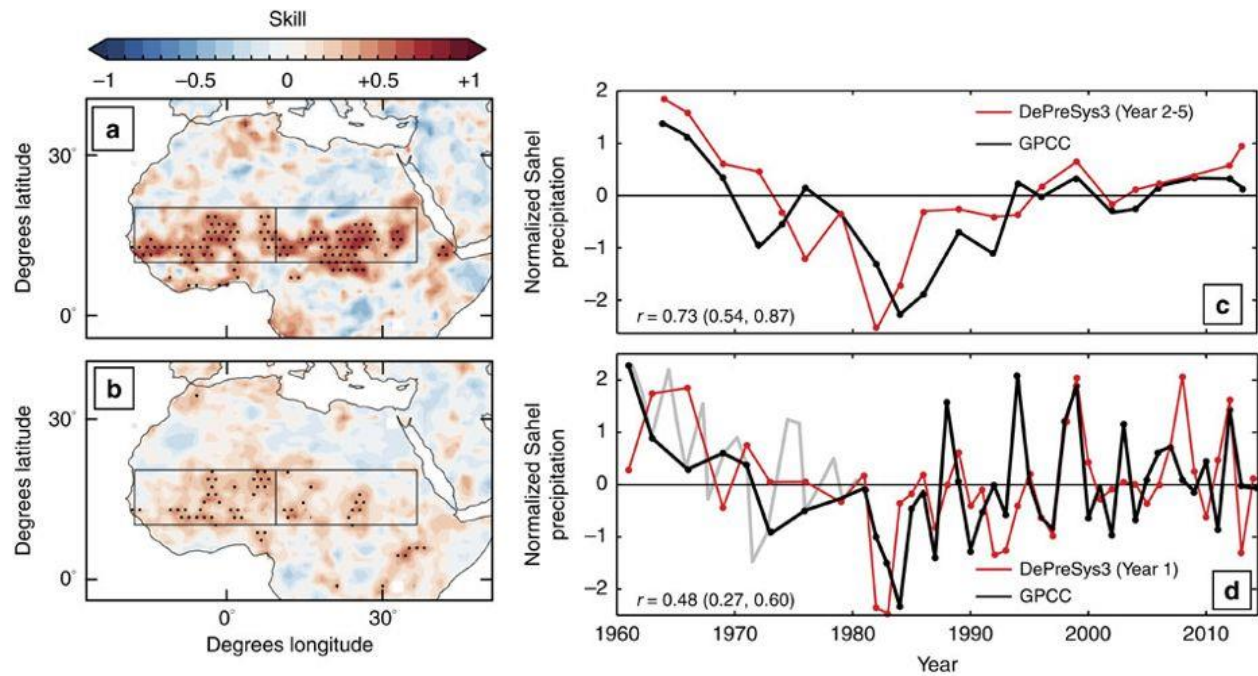
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**Fig. 3.** Skill for predicting linearly detrended Sahel summer rainfall in years 2-5 (upper panels) and year 1

(lower panels) in DePreSys hindcasts. Panels (a)-(b) show spatial distributions of anomaly correlation

coefficients with stippling indicating 95% significance. Panels (c)-(d) show time series of normalized

predicted and GPCC observed rainfall anomalies in the Sahel region outlined by the boxes in the maps,

with correlations and their 5–95% confidence intervals indicated. (From Sheen et al. 2017.)
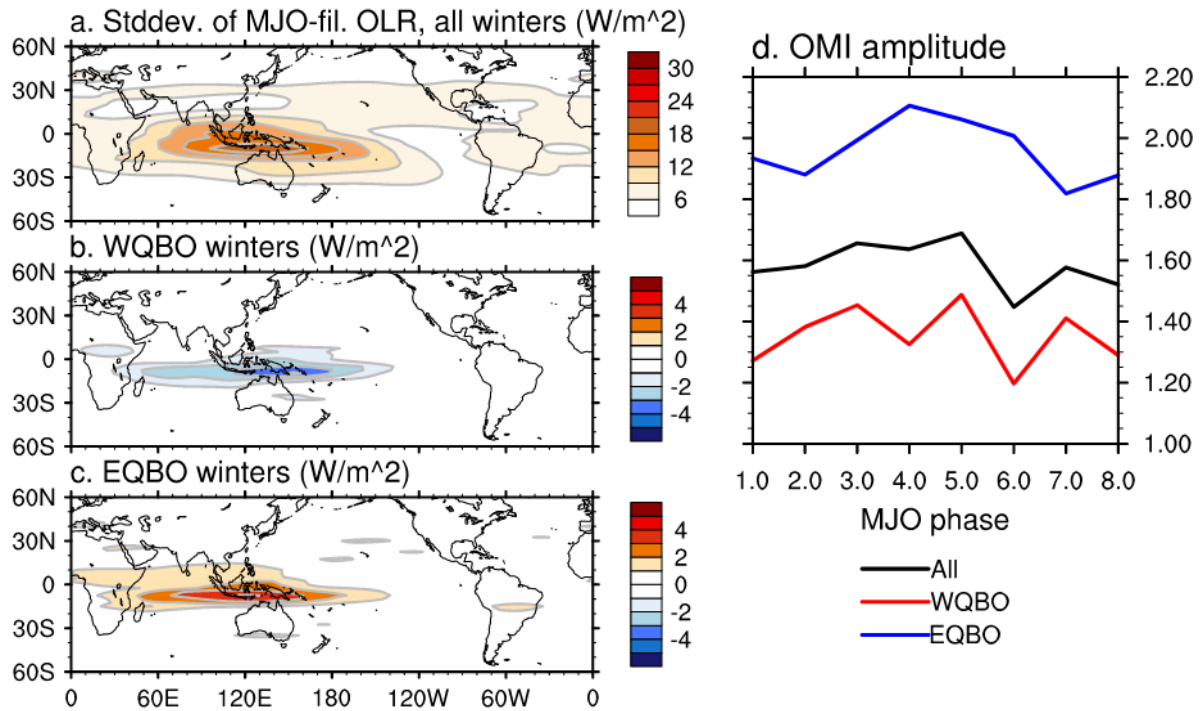
**Fig. 4.** Influence of QBO phase on MJO amplitude. (a) Standard deviation of wintertime outgoing

longwave radiation (OLR), filtered to retain temporal and spatial scales characteristic of the MJO, for all

winters in 1979 to 2012. Differences from these values in winters characterized by QBO westerly

(WQBO) and easterly (EQBO) phases are shown (b) and (c) respectively. (d) Amplitude of an OLR-based

MJO index (OMI) as a function of MJO phase for WQBO, EQBO and all winters. (From Yoo and Son 2016.)
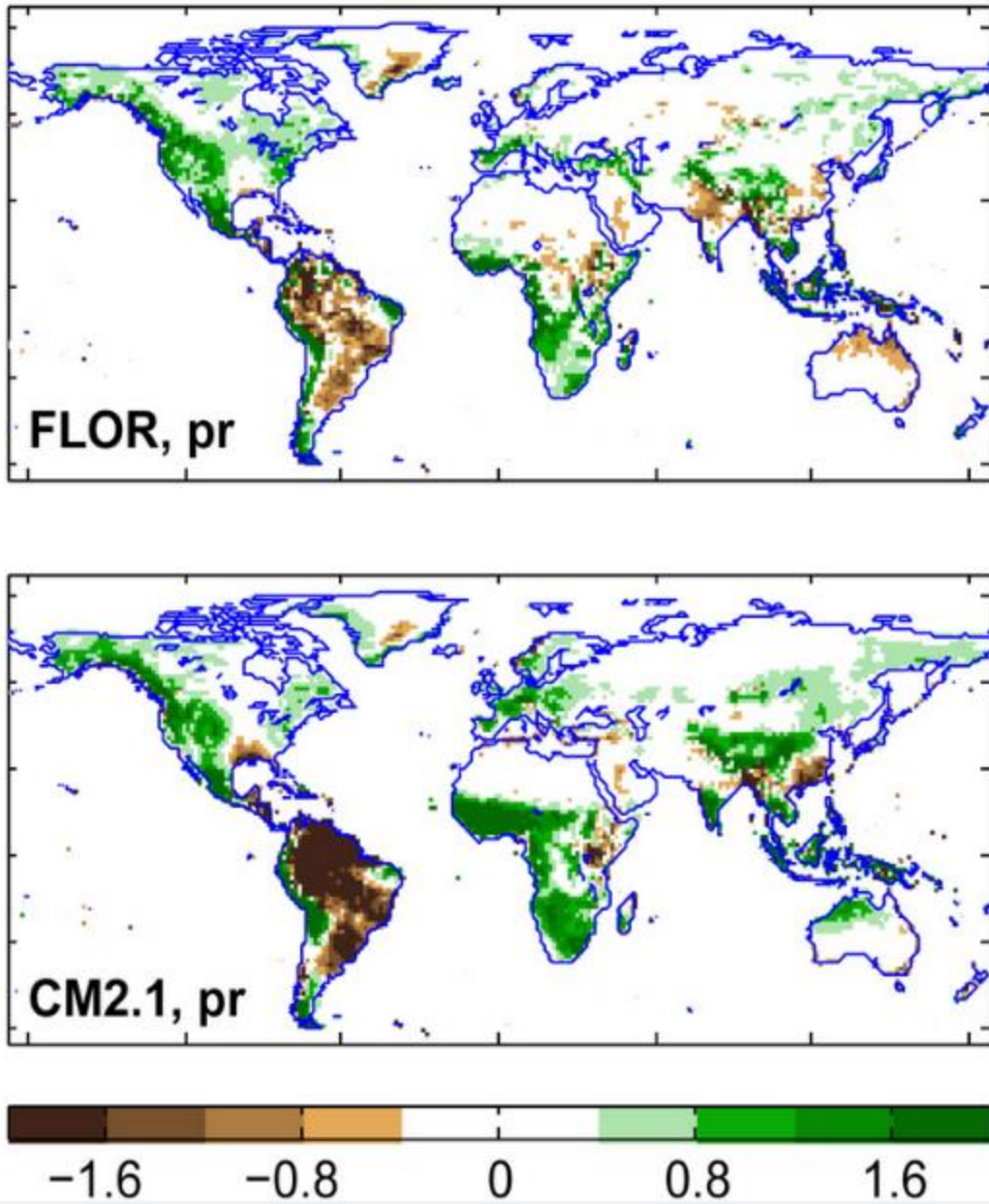
**Fig. 5.** Impact of resolution on precipitation biases in GFDL seasonal prediction models. Atmospheric resolution is approximately 50 km with 32 levels in FLOR (upper panel), and approximately 200 km with 24 levels in CM2.1 (lower panel), whereas ocean resolution is approximately 100 km in both models. Higher atmospheric resolution in FLOR reduces precipitation biases in numerous regions including much of the tropics. Annual mean biases over land in mm day$^{-1}$ based on 1981-2010 CMAP observations are shown. (After Jia et al. 2015.)
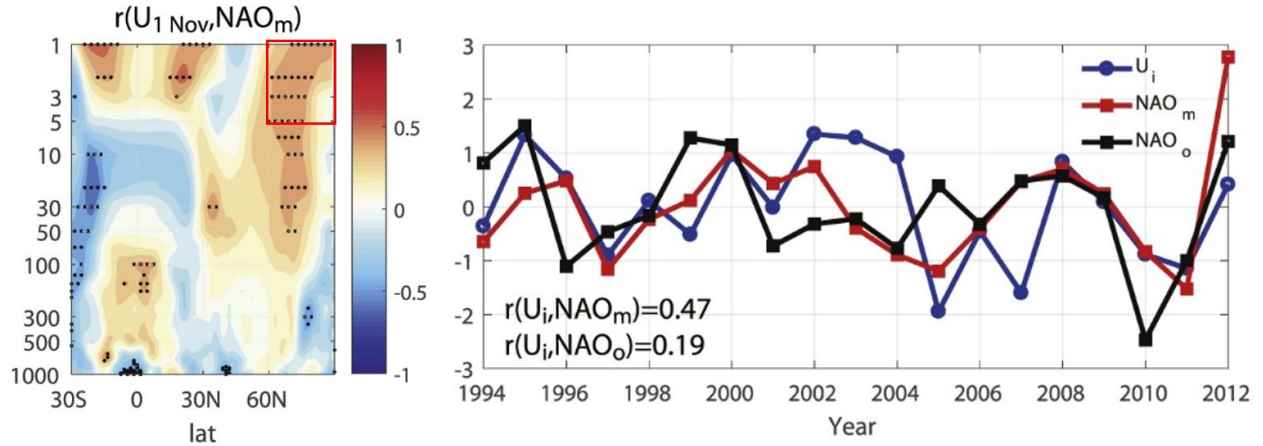
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1809    **Fig. 6** Connection between stratospheric initial conditions and predicted winter NAO for UK Met Office

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.)

**Ensemble Spread of the 1993-2010 Mean**
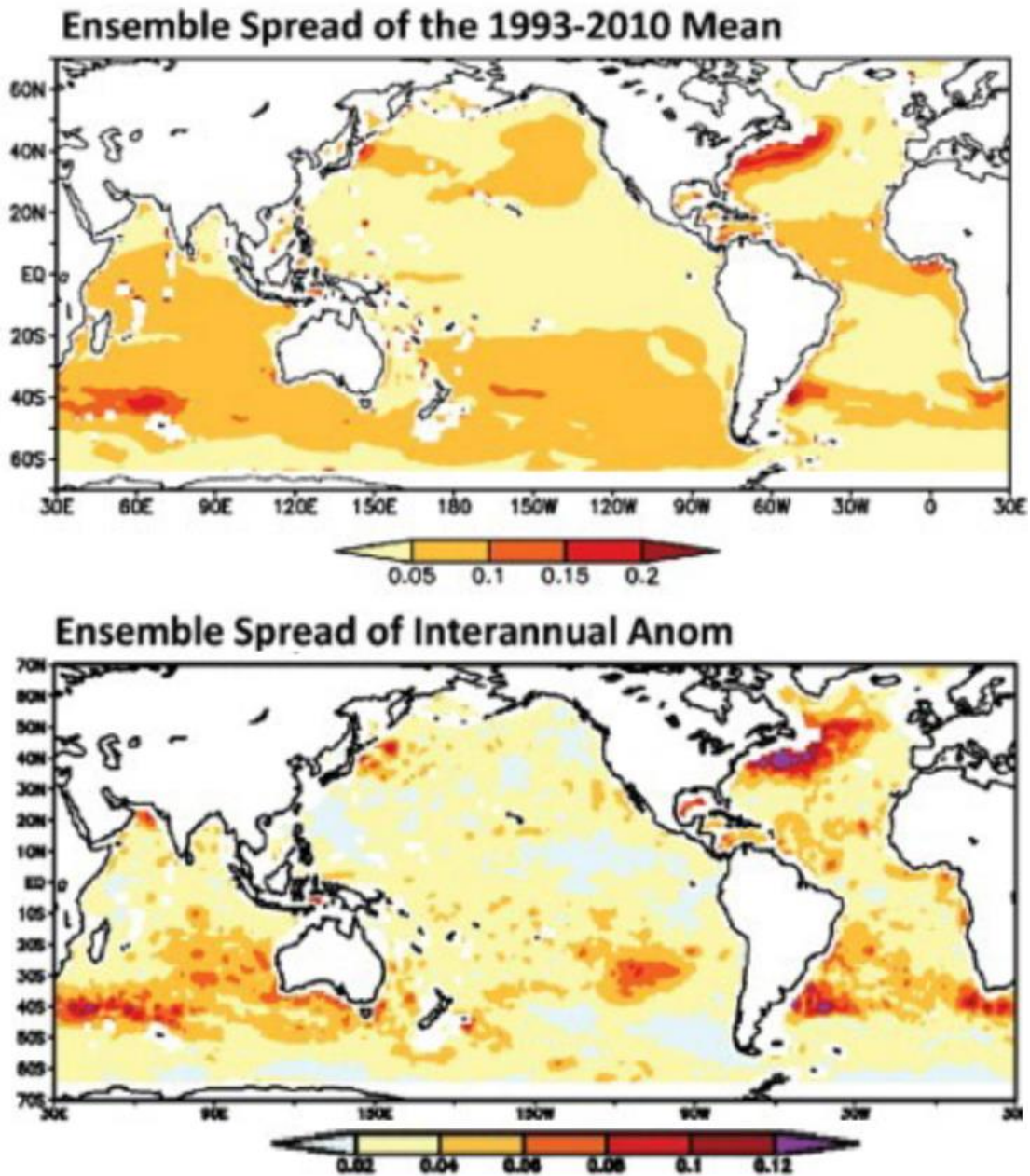
**Ensemble Spread of Interannual Anom**

Fig. 7. Consistency across an ensemble of ocean state estimates of depth-averaged salinity over 0–

700m, from the Ocean Reanalyses Intercomparison Project. Ensemble standard deviations in both the

1993-2010 means (upper panel) and interannually varying monthly anomalies (lower panel) tend to be

largest in eddy active regions such as the Gulf Stream, and less well-observed regions such as the

Southern Ocean. These differences across state estimates are reflective of uncertainties in ocean initial

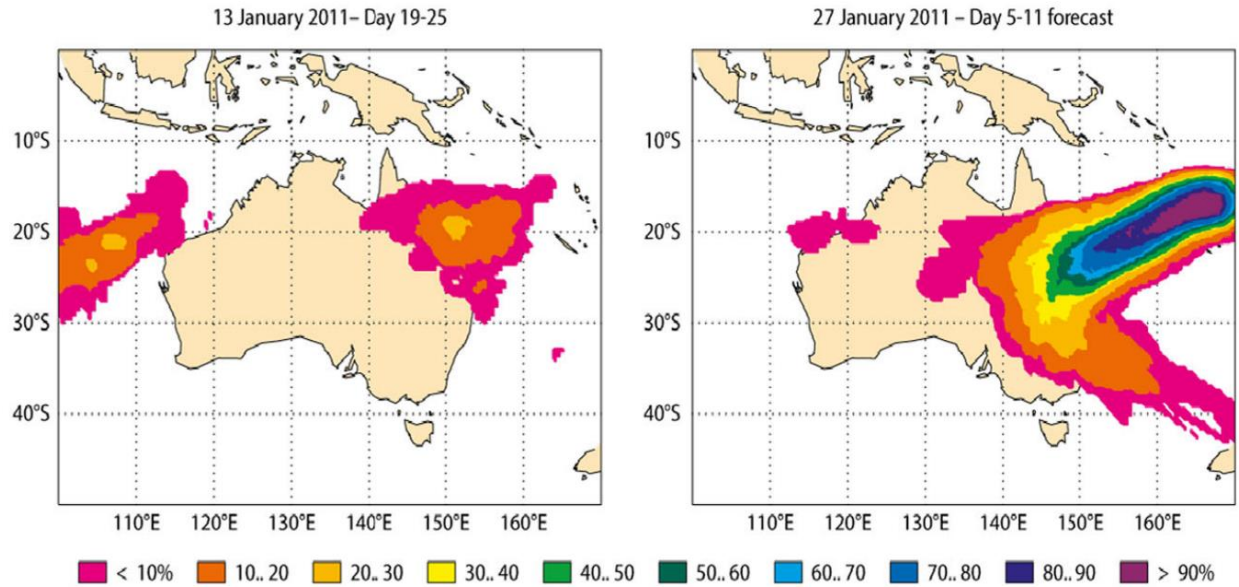conditions. (After Balmaseda et al. 2015.)

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**Fig. 8.** Elevated probabilities of tropical cyclone occurrence during 31 January to 6 February 2011, based

on ECMWF ensemble forecasts forecast starting 13 January with 18 day lead time (left), and 27 January

with 4 day lead time (right). Destructive Cyclone Yasi made landfall in northeastern Australia on 3

February 2011 as a destructive category 5 storm. (Adapted from Vitart and Robertson 2018).
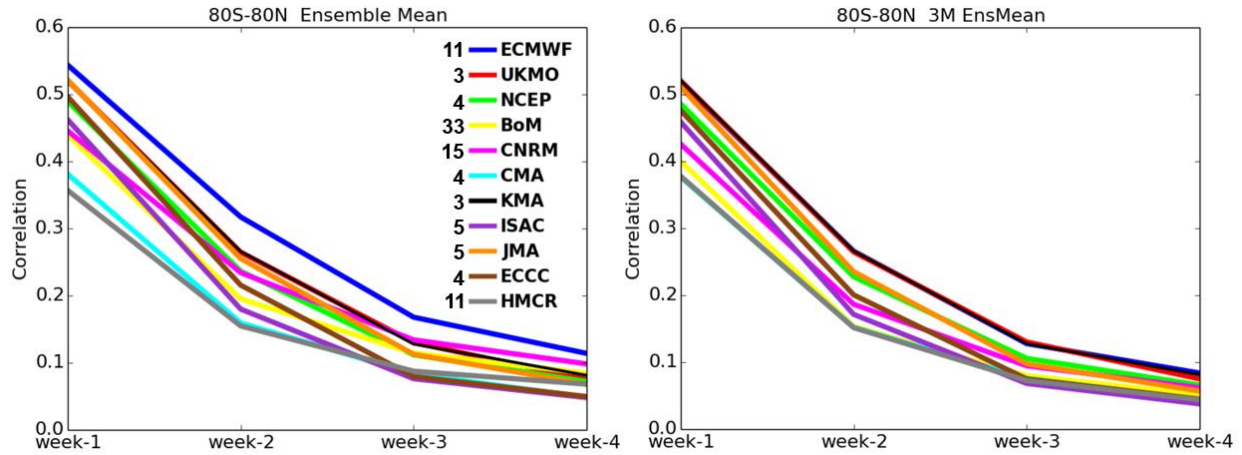
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**Fig. 9.** Global averages of correlations between hindcast and observed precipitation anomalies over the 80°S to 80°N latitudinal band for weeks 1-4 for S2S project models initialized from November to March, 1999–2009. Left: Hindcast quality assessment based on ensemble means using the full ensemble size for each model, as indicated in the figure legend. Right: Hindcast quality assessment based on ensemble means using three ensemble members for each model. The reduced spread of the lines shown in the right panel when ensemble sizes are identical compared to the spread of the lines shown in the left panel demonstrates the value of the use of larger ensembles for subseasonal precipitation forecasting. (Adapted from de Andrade et al. 2019.)
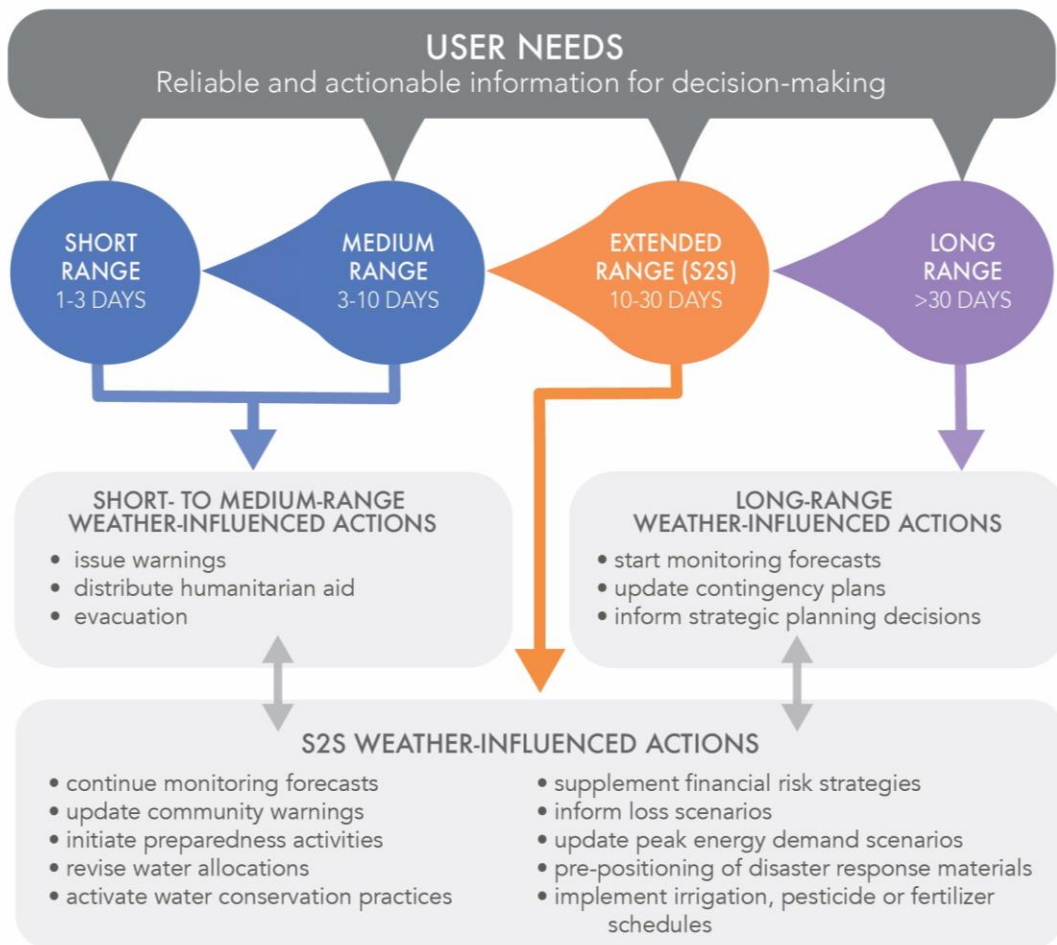
**USER NEEDS**
Reliable and actionable information for decision-making

**SHORT RANGE**
1-3 DAYS

**MEDIUM RANGE**
3-10 DAYS

**EXTENDED RANGE (S2S)**
10-30 DAYS

**LONG RANGE**
>30 DAYS

**SHORT- TO MEDIUM-RANGE WEATHER-INFLUENCED ACTIONS**
- issue warnings
- distribute humanitarian aid
- evacuation

**LONG-RANGE WEATHER-INFLUENCED ACTIONS**
- start monitoring forecasts
- update contingency plans
- inform strategic planning decisions

**S2S WEATHER-INFLUENCED ACTIONS**
- continue monitoring forecasts
- update community warnings
- initiate preparedness activities
- revise water allocations
- activate water conservation practices

- supplement financial risk strategies
- inform loss scenarios
- update peak energy demand scenarios
- pre-positioning of disaster response materials
- implement irrigation, pesticide or fertilizer schedules

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.

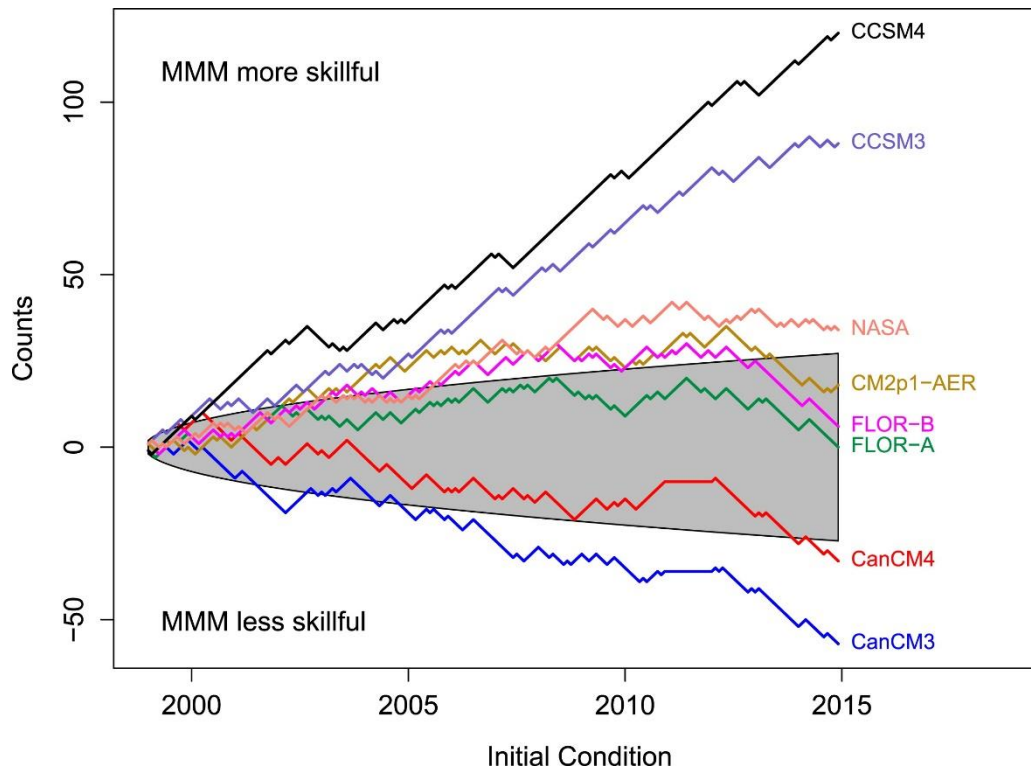1850  (After White et al. 2017.)

**Fig. SB1.** Random walk test comparing monthly mean forecasts of the Niño 3.4 index for equatorial

Pacific SST at 2.5-month lead, between the multi-model mean (MMM) and individual models in the

NMME. Counts (vertical axis) increase by 1 when MMM squared error is smaller than that an individual

model (MMM more accurate) and decrease by 1 otherwise (individual model more accurate), and are

accumulated forward for all initial months and years (horizontal axis). Accumulated counts above or

below the shaded region indicate skill differences  according to the squared error metric that are

significant with >95% confidence (MMM more skillful above the shaded region and individual model

more skillful below). Niño 3.4 anomalies are relative to 1982–98 climatological values, and span each

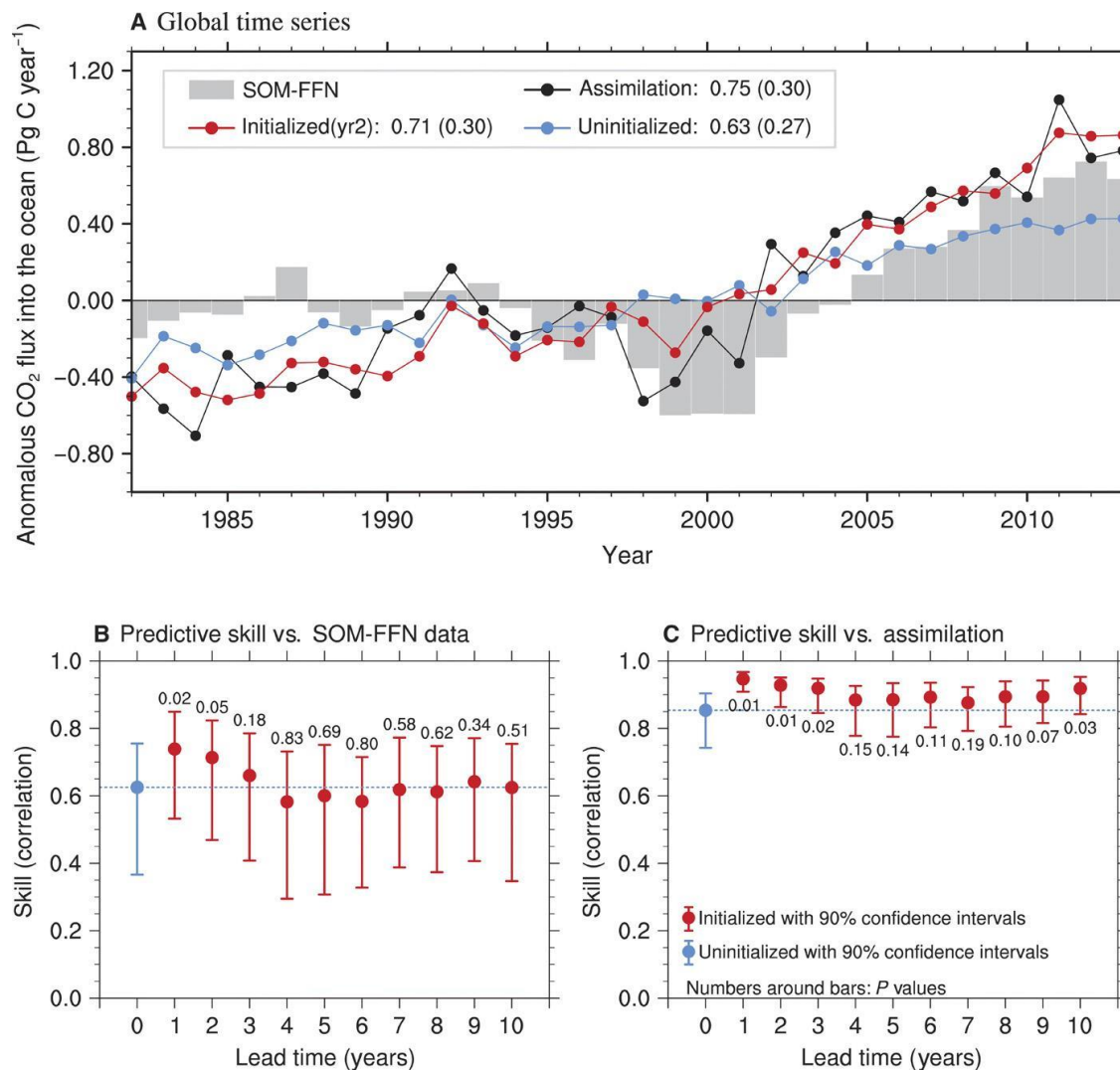month in 1999-2015. (From DelSole and Tippett 2016.)

**Fig. SB2.** Temporal evolution and predictive skill of global $CO_2$ flux into the ocean from the MPI-ESM-HR

decadal prediction system. (A) Annual values of anomalous $CO_2$ 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 $CO_2$ 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.)