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The WWRP/WCRP S2S Project and Its Achievements

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KEYWORDS: Teleconnections; Ensembles; Forecast verification/skill; Hindcasts; Operational forecasting; Probability forecasts/models/distribution

ABSTRACT: The World Weather Research Programme (WWRP)/World Climate Research Programme (WCRP) Subseasonal to Seasonal (S2S) Prediction project was launched in 2013 with the primary goals of improving forecast skill and understanding sources of predictability on the subseasonal time scale (from 2 weeks to a season) around the globe. Particular emphasis was placed on high-impact weather events, on developing coordination among operational centers, and on promoting the use of subseasonal forecasts by the application communities. This 10-yr project ended in December 2023. A key accomplishment was the establishment of a database of subseasonal forecasts, called the S2S database. This database enhanced collaboration between the research and operational communities, enabled studies on a wide range of topics, and contributed to significant advances toward a better understanding of subseasonal predictability and windows of opportunity that contributed to improvements in forecast skill. It was used to train machine learning methods and test their performance in the S2S artificial intelligence/machine learning (AI/ML) prize challenge. The S2S project coorganized several coordinated research experiments to advance understanding of subseasonal predictability and the Real-Time Pilot Initiative that provided real-time access to subseasonal data for 15 application projects. A sequence of training courses sustained over 10 years enhanced the capacity of national meteorological services in the Global South to make subseasonal forecasts. A major legacy of the S2S project was the establishment and designation of the World Meteorological Organization (WMO) Global Producing Centres and Lead Centre for Subseasonal Prediction Multi-Model Ensemble, which will provide real-time subseasonal multimodel ensemble (MME) products to national and regional meteorological services.

SIGNIFICANCE STATEMENT: There is a growing interest in the research and application communities for subseasonal forecasts which cover the time range from 2 weeks to a season and fill the gap between medium-range weather and long-range seasonal forecasts. Skillful subseasonal prediction provides an important opportunity to inform decision-makers of, for example, changes in risks of extreme events or opportunities for optimizing resource management decisions. The WWRP/WCRP S2S project, mostly through the development of a large dataset of subseasonal ensemble predictions, known as the S2S database, helped improve our understanding of subseasonal predictability and the performance of state-of-the-art subseasonal prediction models and multimodel ensembles.

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The WWRP/WCRP S2S project contributed to a better understanding and communication of subseasonal predictions.

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1. Introduction: The WWRP/WCRP S2S project

The World Weather Research Programme (WWRP)/World Climate Research Programme (WCRP) Subseasonal to Seasonal (S2S) Prediction project was launched in November 2013 as one of the three post-The Observing System Research and Predictability Experiment (THORPEX) activities of WWRP—together with the Polar Prediction Project (PPP) and the High Impact Weather (HIWeather) project—and was the first major joint research project between WWRP and WCRP. A motivation of the S2S project was to capitalize on the expertise across both the weather and climate research communities and World Meteorological Organization (WMO)/WWRP/WCRP programs to bridge the gap between medium-range (forecasts up to 2 weeks) and seasonal forecasting (forecast for the next seasons), which was seen as critical for coordinated future development of the Global Framework for Climate Services (GFCS) (Hewitt et al. 2012). Originally planned for 5 years, the S2S project was extended for an additional 5 years (2018–23). The first 5 years are referred to as S2S phase 1, and the 5-yr extension is referred to as S2S phase 2. Detailed reports on S2S phase 1 and 2 activities are available from WMO website (https://www.wcrp-climate.org/WCRP-publications/2018/WCRP-Report-No6-2018-S2S-P1.pdf and https://library.wmo.int/records/item/68643-wwrp-wcrp-subseasonal-prediction-project-s2s-phase-2-final-report). In this article, subseasonal refers to the time range from 2 weeks to a season ahead. This article aims to summarize the main results and achievements of the S2S project focusing on activities organized within the project. For the many studies triggered by the project, we refer to, for example, the overview articles by White et al. (2022) and Domeisen et al. (2022).

The primary aims of the S2S project were to establish the S2S database (section 2), assess the predictive capabilities of state-of-the-art operational subseasonal forecasts (section 3), and identify gaps in the science and capabilities with respect to forecasts on these lead times. The subseasonal time range is particularly challenging for making predictions since it fills the gap between medium-range weather forecasting which is an atmospheric initial value problem and seasonal forecasting which is a boundary condition problem. The availability of the S2S database led to many research studies on advancing understanding of subseasonal predictability and improving prediction capabilities (section 4). Section 5 discusses the ability of the S2S models to predict extreme events, and section 6 reviews the S2S project's contribution to facilitating research-to-operation (R2O) collaborations, including the S2S Real-Time Pilot Initiative. Another important activity during S2S phase 2 was the S2S artificial intelligence/machine learning (AI/ML) challenge (section 7), designed to foster the use of ML methods for improved subseasonal prediction harnessing the large amount of forecast data in the S2S database. Outreach activities (workshops, training courses) are reviewed in section 8. Finally, the legacies of this project and outstanding science issues are discussed in section 9.

2. The S2S database

While databases of medium-range forecasts (TIGGE; Swinbank 2016) and seasonal forecasts [DEMETER; Palmer et al. 2004; North American Multimodel Ensemble (NMME); Kirtman et al. 2014; Climate-System Historical Forecast Project (CHFP); Tompkins et al. 2017] were developed in the early 2000s, no database existed for subseasonal forecasts. An important S2S project motivation was to create a multimodel ensemble database from current operational subseasonal forecasting systems and to archive both forecasts and reforecasts (RFCs) (also referred to as hindcasts). The S2S database (Vitart et al. 2017) includes availability of forecasts with a 3-week delay and reforecasts from 13 operational and research centers. The S2S data are publicly available from two official S2S archiving centers at the European Centre for Medium-Range Weather Forecasts (ECMWF) and the China Meteorological Administration (CMA) as well as from the International Research Institute for Climate and Society (IRI) at Columbia University. The main characteristics of the database, when launched in 2015, are described in Vitart et al. (2017). Currently, the S2S database contains over 260 terabytes of data compared to about 22 terabytes in 2015, with over 2200 users from more than 90 countries who have downloaded about two petabytes of data from ECMWF. Although the subseasonal time range extends up to day 90, the S2S database contains forecasts only up to day 60 for practical reasons.

The initial list of atmospheric parameters in the archive (Vitart et al. 2017) was later expanded to include nine ocean subsurface and sea ice variables (DeMott et al. 2021). Documentation of land component models and their initialization were added, the frequency of some parameters, such as 10-m winds, was increased to four times daily, and two additional models, from the Chinese Academy of Sciences (CAS, China) and the Center for Weather Forecast and Climate Studies (CPTEC, Brazil), were added. Most operational centers have upgraded their subseasonal systems since 2015 (e.g., Vitart et al. 2022a). Some of these changes include increased ensemble size and frequency of the forecasts. An important achievement of the S2S project was to align the dates of production of contributed real-time forecasts so that all the S2S database partners now produce a subseasonal real-time forecast every Thursday. This consistency, introduced in January 2018, was a crucial step, making it possible to produce multimodel ensemble subseasonal forecasts. Table 1 shows a summary of the main characteristics of the S2S models available in November 2024. More details on the latest configuration of the S2S models, as well as an history of the model changes, are available online (https://confluence.ecmwf.int/display/S2S/Models).

The S2S database has opened up the opportunity for researchers to use ensemble data for a wide range of studies, including comparative forecast verification studies of subseasonal predictability and dynamical processes, as well as application development, with a growing number of S2S database related articles published in the peer reviewed literature (360 at the time of writing) and a book (Robertson and Vitart 2019). Selected highlights of these studies will be presented in the next sections.

3. Prediction skill assessment of S2S forecasts

The skill of the S2S models to predict weekly mean anomalies of 2-m temperature was assessed using the ranked probability skill score (RPSS; Epstein 1969) and the fifth major global reanalysis produced by ECMWF (ERA5; Hersbach et al. 2020) for verification. Several

Table 1. Main characteristics of the 12 S2S models contributing to the S2S database (status in November 2024). (from left to right) The modeling center responsible for the forecasts, the ensemble size and frequency of the real-time forecasts, the RFC period, initialization frequency, and ensemble size. Ocean coupling indicates if the atmospheric component is coupled to a dynamical ocean model. Sea ice coupling indicates if an active dynamical sea ice model is included or not.

Models	Ensemble Size	Frequency	RFC Period	RFC Frequency	RFC Size	Ocean Coupling	Sea Ice Coupling
CMA	4	2 per week	Past 15 year	2 per week	4	Yes	Yes
CNR-ISAC	41	Weekly	2001–20	Every 5 days	8	No	No
CNRM	35	Weekly	1993–2017	Every 7 days	10	Yes	Yes
CPTEC	11	2 per week	1999–2018	Every 7 days	11	No	No
ECCC	21	2 per week	2001–20	2 per week	4	Yes	Yes
ECMWF	101	Daily	Past 20 year	Every 2 days	11	Yes	Yes
HMCR	41	Weekly	1991–2020	Weekly	11	No	No
IAP-CAS	49	Daily	1999–2018	Daily	4	Yes	Yes
JMA	5	Daily	1991–2020	1 per month	5	Yes	Yes
KMA	8	Daily	1993–2016	4 per month	7	Yes	Yes
NCEP	16	Daily	1999–2010	Daily	4	Yes	Yes
UKMO	4	Daily	1993–2016	4 per month	7	Yes	Yes

S2S models display skill above climatology (RPSS larger than 0) up to week 4.5 (day 26–32), while the simple multimodel ensemble mean (same weight to all models) is close to but does not outperform the best model (see Fig. 1 over the northern extratropics). However, multimodel combinations can benefit subseasonal prediction for regional precipitation (Vigaud et al. 2017, 2019) or phenomena like sudden stratospheric warmings and their impacts (Karpechko et al. 2018). RPSS maps for 2-m air temperature and total precipitation of the

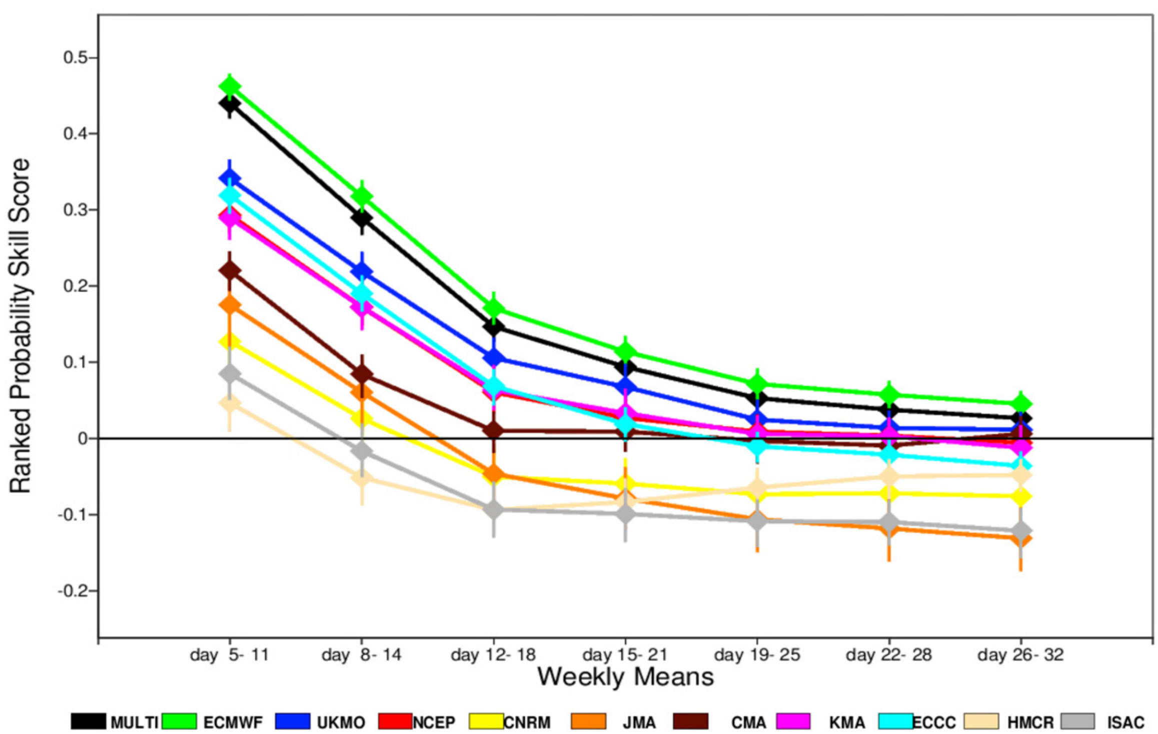


Fig. 1. RPSS of 2-m temperature over the northern extratropics (north of 30°N) for each S2S model as a function of the lead time (overlapping weekly periods in days). The scores have been computed from all the tercile probabilities produced every Thursday from 2018 to 2023 (308 cases). The black line shows the RPSS of the MME built by simply averaging the probabilities from each model with equal weight. Higher values of the RPSS indicate higher skill. Positive (negative) values of the RPSS indicate skill above (below) that of climatology.

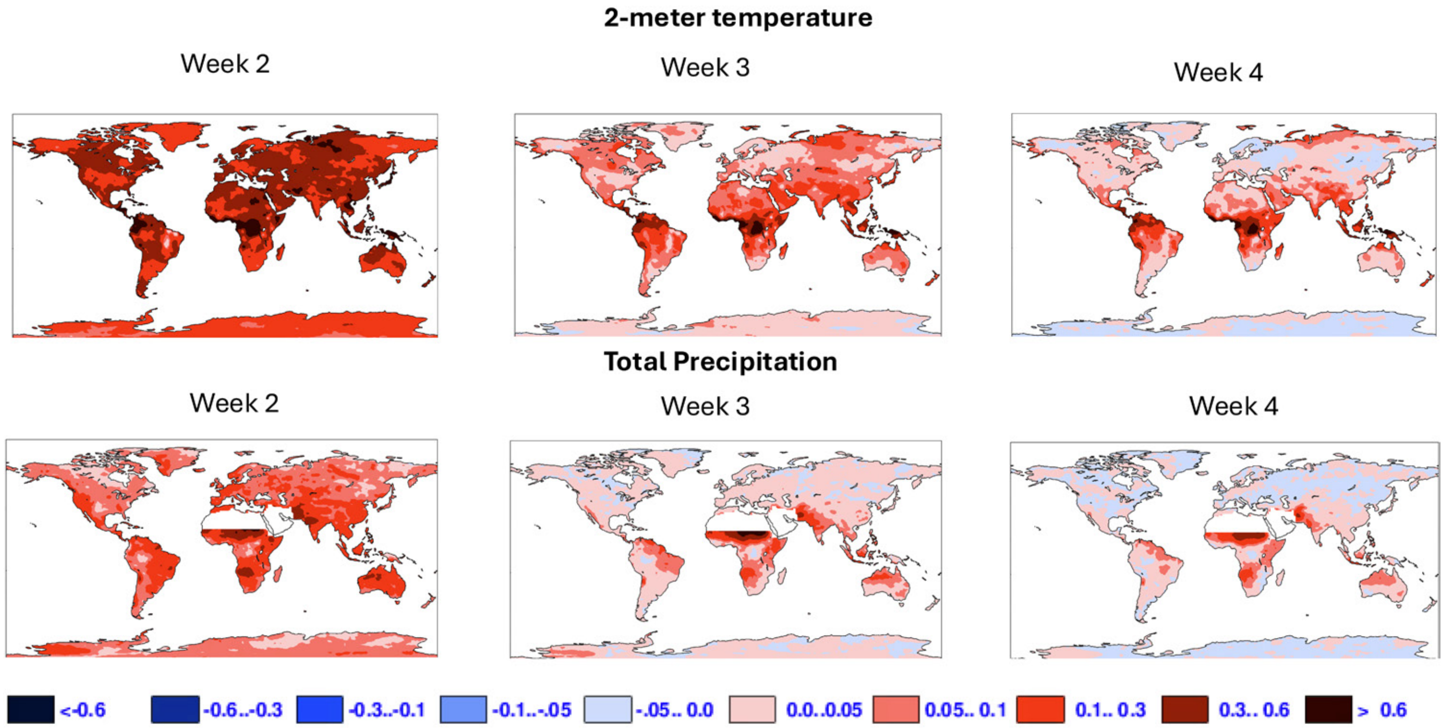


Fig. 2. **RPSS of (top) 2-m air temperature and (bottom) precipitation computed from the S2S MME forecast produced once a week (every Thursday) over the period 2018–23 for different lead times. A positive (negative) value or red (blue) color indicates skill above (below) climatology. For precipitation, the Saharan region was masked due to too low climatological precipitation to define tercile boundaries.**

S2S multimodel ensemble over the period 2018–23 (Fig. 2) show that the multimodel ensemble is more skillful than climatology calculated over the common period 2003–10 up to week 4 for 2-m temperature and week 3 for precipitation over most land areas, suggesting potential usefulness of these forecasts for subseasonal applications. While RPSS decreases with lead time as expected, the decrease is much slower in the tropics than at high latitudes, so that by week 3, most of the skill is located in the tropical regions as found for seasonal predictions (Kumar et al. 2011). Figures 1 and 2 show the limit of practical predictability (ability to predict with current methods) of S2S models on average over the 6-yr period. However, there are periods of time, referred to as "windows of opportunity for skillful forecasts" (Mariotti et al. 2020), when the S2S intrinsic predictability (physical limit of predictability) is higher (e.g., Spaeth et al. 2024).

Most forecast systems have been upgraded during the S2S project, so these results may not reflect the precise current performances. The inclusion of these model upgrades in the S2S database provides an opportunity to measure progress in subseasonal prediction since the launch of the S2S database. For instance, the skill in predicting the Madden–Julian oscillation (MJO) has improved since 2015 for most S2S models (Fig. 3). On average, there has been a gain of 3 days of predictive skill for the MJO between 2015 and 2023, which suggests a remarkable improvement in subseasonal predictive skill in the tropics. In the northern extratropics, the North Atlantic Oscillation (NAO) and Pacific–North American (PNA) pattern forecast skill horizons have increased, respectively, from 10.4 and 14.2 days in 2015 to 11.5 and 15.1 days in 2023, which represents a gain of about 1 day of forecast skill during the 8-yr period. Skill improvements up to week 4 can also be observed in the real-time multimodel ensemble forecasts over the period 2021–23 compared to 2018–20 (Fig. 4), although the verification period is not the same and subseasonal forecast skill can display strong interannual variability due to El Niño–Southern Oscillation (ENSO) for instance. These improvements in forecast skill can be partly explained by improvements in the model physics and configurations. Most S2S models have finer horizontal and vertical

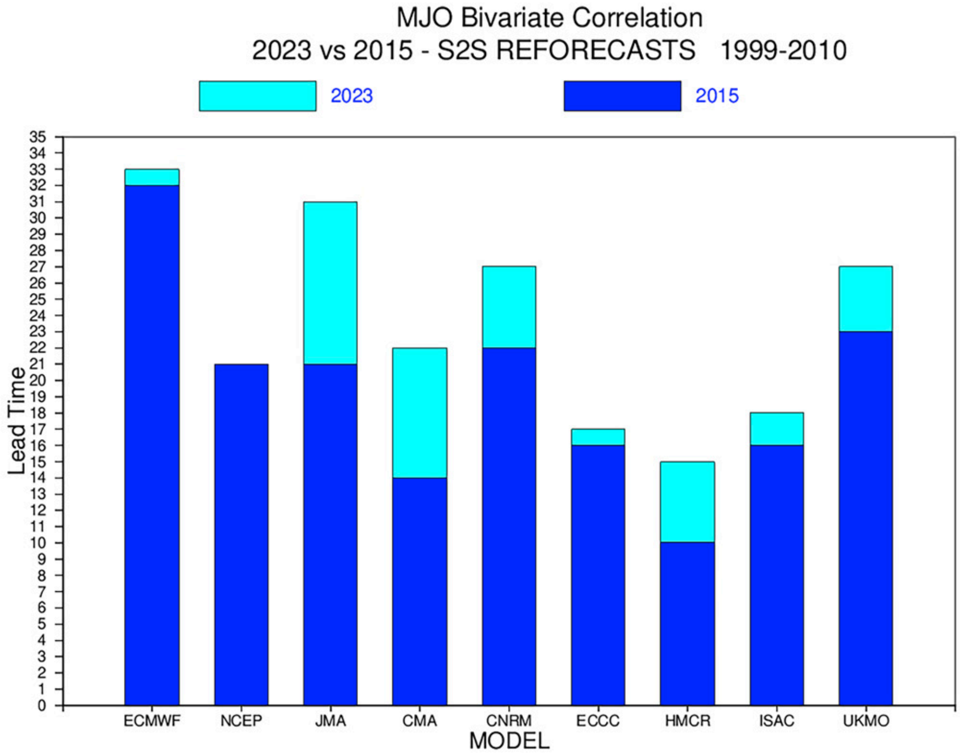


Fig. 3. MJO forecast skill measured as the lead time (*y* axis) when the MJO bivariate correlation between the ensemble-mean RFCs of the MJO index (Wheeler and Hendon 2004) and reanalysis (ERA5) reaches 0.5. The forecast skill has been computed over the common RFC period from November to March (1999–2010). Cyan bars (dark blue bars) indicate the performances of the operational models used in 2023 (2015).

atmospheric resolutions and increased ensemble size since 2015. In addition, several models [e.g., Environment and Climate Change Canada (ECCC), JMA], which were atmosphere only in 2015, are now coupled to an ocean and sea ice model.

4. Sources of predictability

The S2S database has provided an important resource to better understand predictability in S2S models. To encourage its use, several subprojects were organized around research topics: MJO, stratosphere, land, ocean, ensemble generation, and aerosols. The outcomes of these activities are summarized below and reported in more detail in online (https://library.wmo.int/records/item/68643-wwrp-wcrp-subseasonal-prediction-project-s2s-phase-2-final-report).

a. MJO and teleconnections. As shown in Fig. 3, S2S models have skill in predicting the evolution of the MJO 2–4 weeks in advance depending on the model (Vitart 2017; Lim et al. 2018). However, the skill in predicting the northward propagation in boreal summer [boreal summer intraseasonal oscillation (BSISO)] does not exceed 2 weeks (Jie et al. 2017). Despite significant improvements in the representation and prediction of the MJO, S2S models underestimate its impact in the North Pacific and Euro-Atlantic sector (Stan et al. 2022; Vitart 2017; Skinner et al. 2022). This issue represents an important barrier for skillful subseasonal predictions over the northern extratropics, although Kent et al. (2023) found that the impact of these teleconnection errors on NAO monthly prediction skill might be modest. A joint activity between the WCRP/Research Board Working Group on Numerical Experimentation's (WGNE; https://wgne.net/) MJO Task Force and WMO S2S teleconnection subproject resulted in a set of standardized diagnostics and metrics to characterize the MJO teleconnections and to understand the associated key dynamical processes (Wang et al. 2020a,b; Stan et al. 2022). Reproducing the magnitude of the extratropical response to the MJO remains

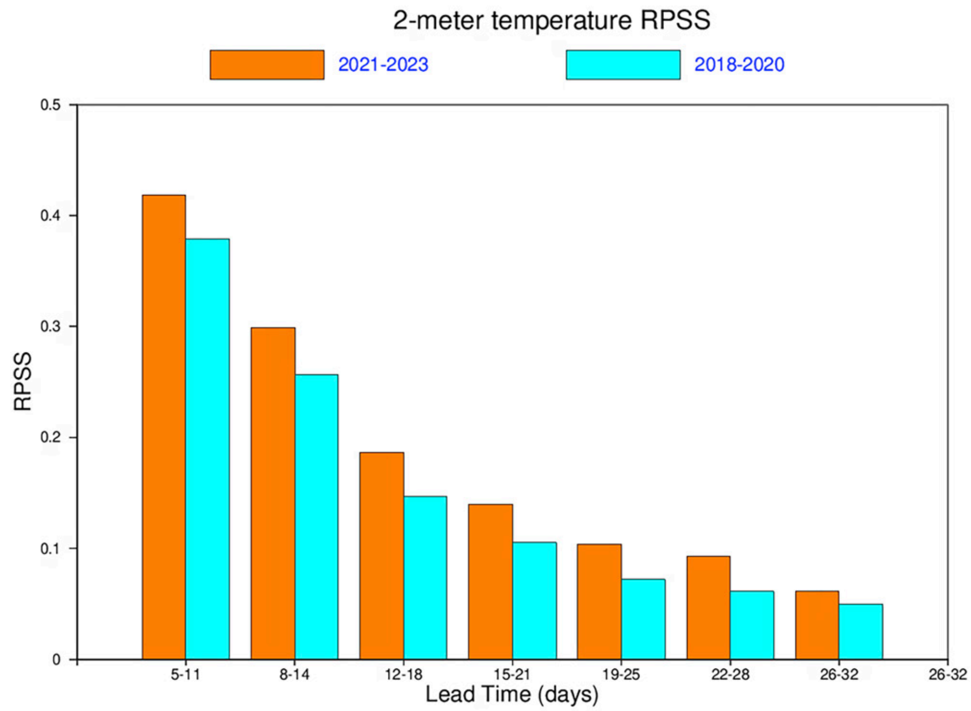


Fig. 4. **RPSS of weekly mean 2-m air temperature anomalies from the S2S MME as a function of forecast lead time. The scores have been computed over land points, globally. The orange (cyan) bars indicate the skill scores for the period 2021–23 (2018–20).**

a challenge for the subseasonal forecast systems and additional studies must be conducted to find sources of this underestimation including the development of additional process-level diagnostics.

b. Stratosphere. An important source of subseasonal predictability is the stratospheric polar vortex, especially for the Northern Hemisphere winter and spring (Butler et al. 2019; Scaife et al. 2022). Figure 5 shows the surface temperature response to both weak and strong polar vortex events in comparison between the S2S models and ERA-Interim reanalysis. Domeisen et al. (2020a) found that sudden stratospheric warmings are predictable only 1–2 weeks in advance, but once they occur, they can provide improved predictive skill in certain regions at subseasonal (weeks 3–6) lead times for both surface

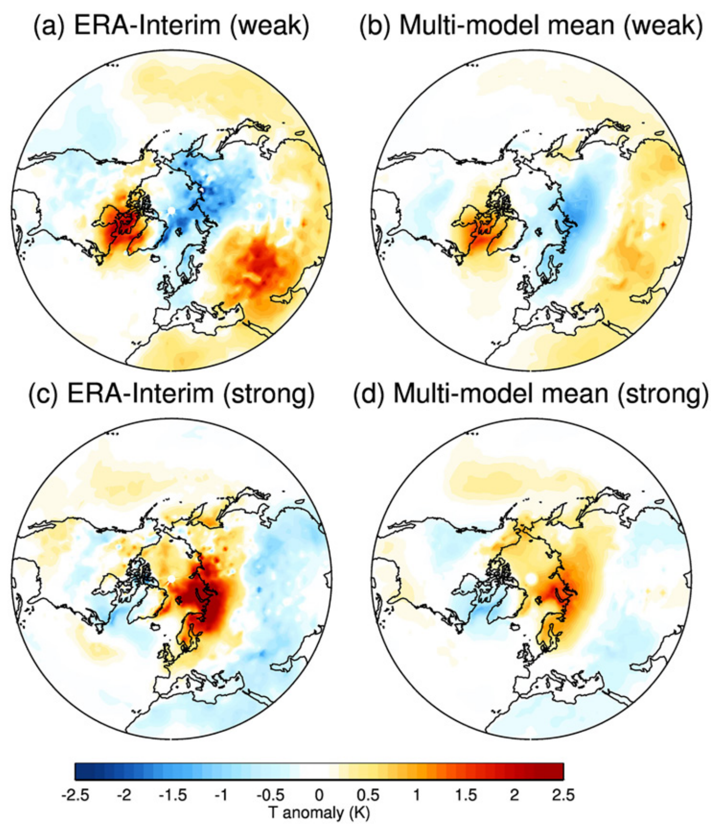


Fig. 5. **Composite of 2-m temperature anomalies (K) for weeks 3–4 for (top) weak vortex states and (bottom) strong vortex states. (b),(d) The ensemble mean for forecasts initialized during weak/strong vortex states. (a),(c) The equivalent anomalies for ERA-Interim where each date present in the multimodel mean in (b) and (d) has been given an equivalent weighting (from Domeisen et al. 2020b).**

climate (Domeisen et al. 2020b) as well as extreme events (Domeisen and Butler 2020). Systems with a higher model top generally show better predictive skill compared to models with a lower model top (Domeisen et al. 2020a). S2S models still suffer from important biases in the stratosphere, including a too warm global stratosphere, too strong/cold wintertime polar vortices, too cold extratropical tropopause regions (Lawrence et al. 2022), biases in the downward coupling from the stratosphere (Nebel et al. 2024), and biases in tropospheric stationary waves that impact upward wave propagation (Schwartz et al. 2022). The seasonality and regionality of these biases point to radiative and dynamical processes that are poorly simulated in some systems, particularly those with lower model tops. Understanding these biases may allow for future improvement of these processes in subseasonal forecasting systems. Targeted stratospheric nudging experiments using the S2S model database have emerged as a spin-off initiative from the S2S project and the Stratospheric Network for the Assessment of Predictability (SNAP) with the goal of testing the stratospheric influence on the troposphere for both hemispheres (Hitchcock et al. 2022).

c. Land. Soil moisture prediction skill was evaluated in the S2S database by Zhu et al. (2019). They found lower prediction skill than most atmospheric variables, indicating that more effort should be made to improve the subseasonal forecasting of land processes. The greatest potential impact for improved subseasonal forecasts based on the harvest of predictability from the land surface lies in episodes of drought and extreme heat. Recent research has demonstrated that dry soils can generate positive feedbacks on both phenomena (Miralles et al. 2019; Schumacher et al. 2019; Dirmeyer et al. 2021; Ford and Labosier 2017; Hirsch et al. 2019) and that accurate soil initialization benefits subseasonal prediction skill (Seo et al. 2019). A crucial factor is the identification of locally critical values for soil moisture below which surface heat fluxes and maximum temperatures become hypersensitive to further soil drying (Benson and Dirmeyer 2021). Subseasonal prediction skill in winter has been attributed in part to the feedback processes between land and atmosphere via snow radiative (Xue et al. 2021) as well as delayed hydrologic feedbacks (Xu and Dirmeyer 2013). Snow-cover skill has been evaluated in subseasonal forecasts (Diro and Lin 2020), and influence of snow cover on the subseasonal predictability was investigated (Takaya et al. 2024). Diro and Lin (2020) found that the prediction skill of snow water equivalent is generally higher than the skill of 2-m air temperature at week 3 and week 4 lead times.

d. Ocean. The inclusion of ocean and sea ice variables in the S2S database helped improve the understanding of the role of ocean–atmosphere coupled processes for subseasonal prediction (e.g., Qin et al. 2022) and evaluate the ability of some coupled forecast systems to predict societally relevant ocean variables for certain regions and under certain conditions. For instance, Zampieri et al. (2018) found that some S2S models were able to predict Arctic sea ice edge extension more than a month in advance, which could be useful for shipping activity in an increasingly ice-free Arctic Ocean. Another study focused on subseasonal prediction skill of coastal sea level along the North American west coast, which has implications for fisheries and coastal flooding (Amaysa et al. 2022).

e. Ensemble generation. Numerical prediction on subseasonal time scales always contains the uncertainty arising from the chaotic nature of the Earth system and the uncertainty in the estimate of initial conditions and model formulation. The numerical weather prediction uncertainty is assessed by performing multiple predictions from slightly different initial conditions and with stochastically perturbed parameters or multiple models. Vitart and Takaya (2021), comparing the prediction skill in different ensemble configurations, found that the daily lagged approach, using combinations of ensembles starting from initial conditions up to 4 days old, can be beneficial for the subseasonal prediction. Predicting the uncertainty in subseasonal predictions is challenging for several reasons: subseasonal predictions have relatively large random and systematic errors and low skill compared to medium-range ensemble predictions. Ideally, the spread of the ensemble, which measures the plausible ranges of ensemble forecasts, should be related to the skill of the forecasting system. Larger (smaller) ensemble spread should provide lower (higher) confidence in the skill of the forecast. Several studies (e.g., Murphy 1988; Buizza 1997) found a positive correlation between spread and root-mean-square error (RMSE) between the ensemble mean and the verification data for forecast lead times of less than a week or so. An evaluation of the spread–skill relationship in the ECMWF S2S model provided promising results: the spread–skill relationship can be captured reasonably well in week-4 850-hPa zonal wind forecasts (Fig. 6) over the northern extratropics, with a correlation of 0.59. In addition, the ensemble spread displays predictability with a correlation of about 0.5 between the spreads calculated from two separate subsets of the ensemble. These results suggests that the ensemble spread might be a useful indicator of forecast skill at this time range, as for medium-range prediction.

f. Aerosols. Atmospheric composition plays a crucial role in both numerical weather and climate prediction, influencing the absorption, scattering, and emission of solar radiation and thermal infrared radiation. However, most S2S models still prescribe climatological aerosols. Therefore, WGNE, the S2S project, and WMO Global Atmosphere Watch (GAW) organized a coordinated experiment to evaluate the impact of interactive aerosols on subseasonal prediction skill. The aim was to simulate the direct and (optionally) indirect effects of aerosols in five different models, allowing for comparisons between simulations with climatological aerosols and those incorporating the effect of aerosol interactively. Preliminary results indicate significant impact of interactive aerosols on week 4 biases over some regions, such as South–east South America (not shown).

g. Weather regimes. Many studies used the S2S database for predictability studies in the extratropics, focusing on weather regime predictability and their links to teleconnections. Some of them evaluated the S2S prediction skill of North American (e.g., Vigaud et al. 2018; Robertson et al. 2020) or European (e.g., Ferranti et al. 2018; Büeler et al. 2021; Osman et al. 2023b)

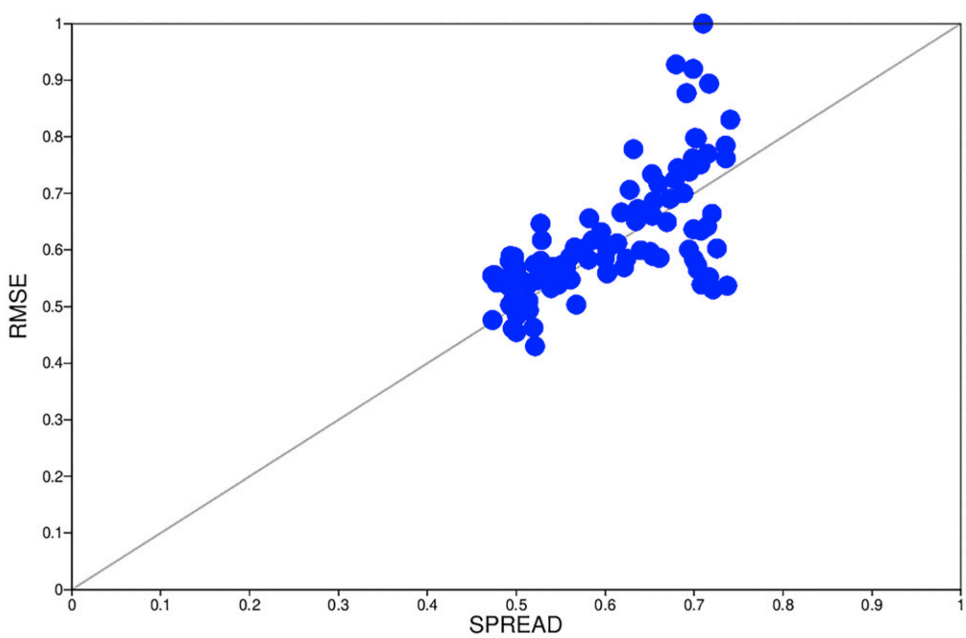


Fig. 6. Scatterplot of RMSE and spread for averages of 850-hPa zonal wind in week 4 from all the operational ECMWF real-time forecasts produced during extended winter (November–March) (2017–18).

weather regimes. Charlton-Perez et al. (2018), and Domeisen et al. (2020c) investigated the influence of the stratosphere on European weather regimes.

h. Modeling issues. In addition to the S2S model shortcomings mentioned above, several issues common to most models from the S2S database have been identified. For instance, Quinting and Vitart (2019) showed that all S2S models tend to underestimate blocking frequency over the northeastern Atlantic/European sector, while overestimating blocking over Scandinavia and eastern Europe. Some studies highlighted the positive impact of increased atmospheric horizontal resolution on blocking as well as on the representation of the MJO teleconnections (Vitart 2017) or an increased vertical resolution on stratospheric processes (e.g., Wicker et al. 2023). The S2S database also helped assessing the use of subseasonal forecasts to force high-resolution regional models for improved subseasonal prediction of local extreme events (e.g., Risanto et al. 2024).

5. Prediction of extremes

During the S2S project, there have been significant advances in the understanding and assessment of predictability of extreme events. Domeisen et al. (2022) provided an overview of subseasonal predictability for case studies of some of the most prominent extreme events across the globe using the ECMWF S2S prediction system: heat waves, cold spells, heavy precipitation events, and tropical and extratropical cyclones (Fig. 7a).

These case studies clearly illustrated the potential for event-dependent advance warnings for a wide range of extreme events. The recent example of the devastating flooding over south Brazil in 2024, illustrating the potential usefulness of subseasonal prediction as early warning, is shown in Fig. 8. Recent research has shown the potential for subseasonal prediction of heat waves (e.g., Tian et al. 2017; Wulff and Domeisen 2019; Vitart and Robertson 2018; Pyrina and Domeisen 2023; Lin et al. 2022), cold waves (e.g., Kautz et al. 2020; Karpechko et al. 2018), extreme precipitation events (e.g., Muñoz et al. 2019; Wang et al. 2022), tropical cyclones (Lee et al. 2020), and atmospheric rivers (DeFlorio et al. 2019).

6. From research to operation and applications

To assess the potential value of subseasonal forecasts for applications and identify the main obstacles in their use and operationalization (White et al. 2017), the S2S project initiated the Real-Time Pilot Initiative in 2019. In this initiative, real-time access to the S2S database was given to 15 application development projects involving both subseasonal forecast developers and users over the period 2020–22, removing the 3-week delay. Codevelopment between scientists and the end users of climate information is known to be critical for developing effective climate services, and exploring the use of forecasts in real time is essential to these interactions. The aim was not to advise or direct the projects but to observe how these projects worked with users to deliver relevant outcomes, by means of surveys and semistructured interviews. In one example, researchers from the University of Reading collaborated with National Meteorological and Hydrological Services (NMHSs) in Ghana, Kenya, Nigeria, and Senegal as well as the WMO Regional Climate Centers (RCCs) to create bespoke forecast products with users to support their decision-making and increase the subseasonal forecasting capacity of the NMHSs and RCCs. For example, the meningitis-emergence vigilance maps in Fig. 9, jointly produced with the African Centre of Meteorological Applications for Development (ACMAD), are based on week-1 and week-2 forecasts constructed from S2S data. While not usually thought of as the subseasonal range, the weekly averaging is typical of a subseasonal forecast, and these forecasts could be extended to longer leads depending on skill and user needs. Further examples for such applications are available in White et al. (2022) that surveyed the use and utility of S2S prediction across a large set of sectoral applications case

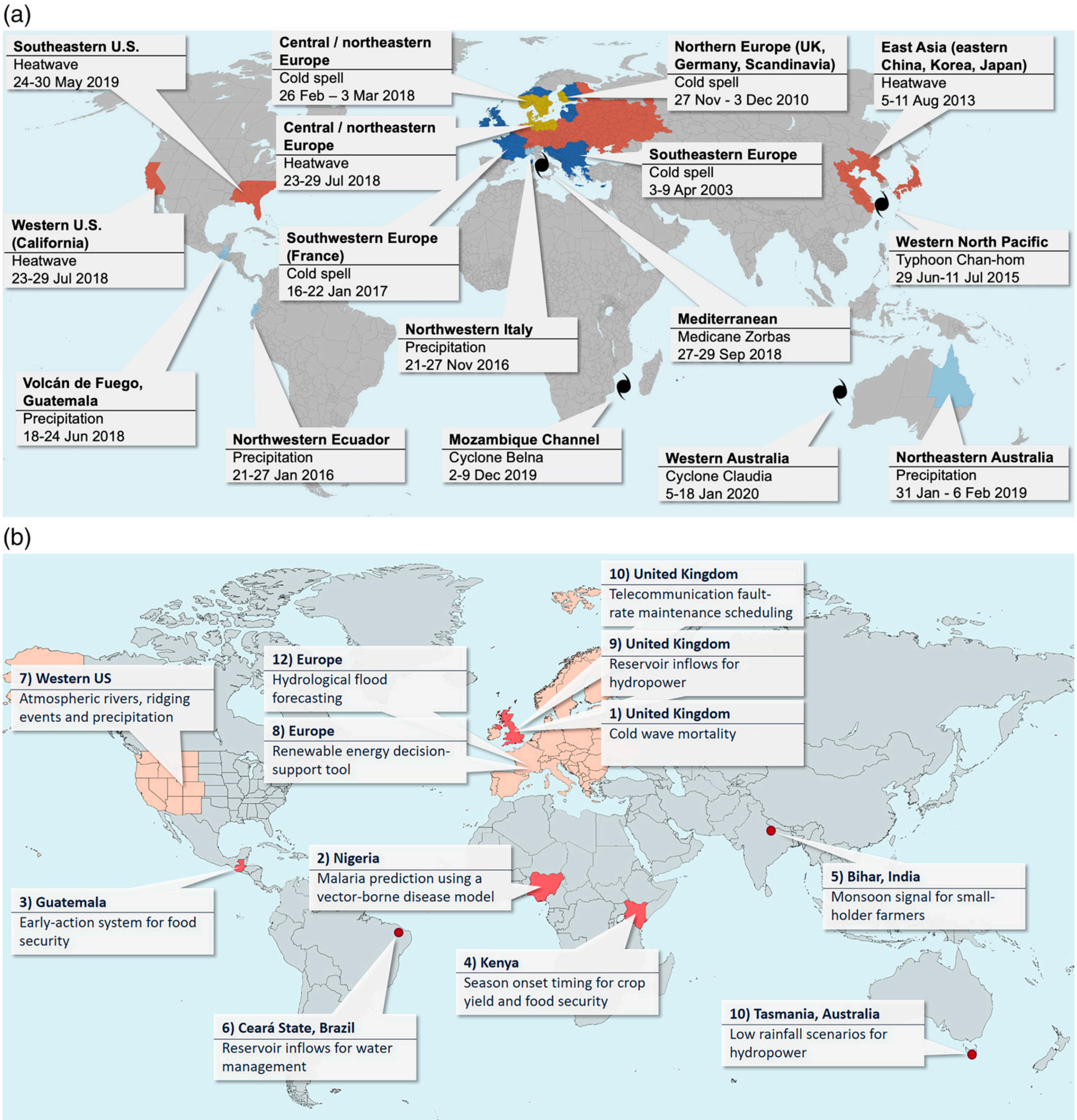


Fig. 7. **(a) Location of the extreme event case studies with predictability on subseasonal time scales documented in Domeisen et al. (2022). (b) Location of sectoral case studies with related subseasonal application and/or product in White et al. (2022) (from S2S newsletters 18 and 19, http://www.s2sprediction.net/static/newsletter).**

studies (Fig. 7b) and in the special issue on "Subseasonal to decadal predictions in support of climate services" (Osman et al. 2023a).

7. Machine learning for subseasonal prediction

The S2S database with its large volume of data promises to be a valuable resource for developing and testing AI/ML methods (e.g., Kim et al. 2021; van Straaten et al. 2022). To evaluate the potential of ML methods for improved subseasonal prediction, the WWRP/WCRP S2S project

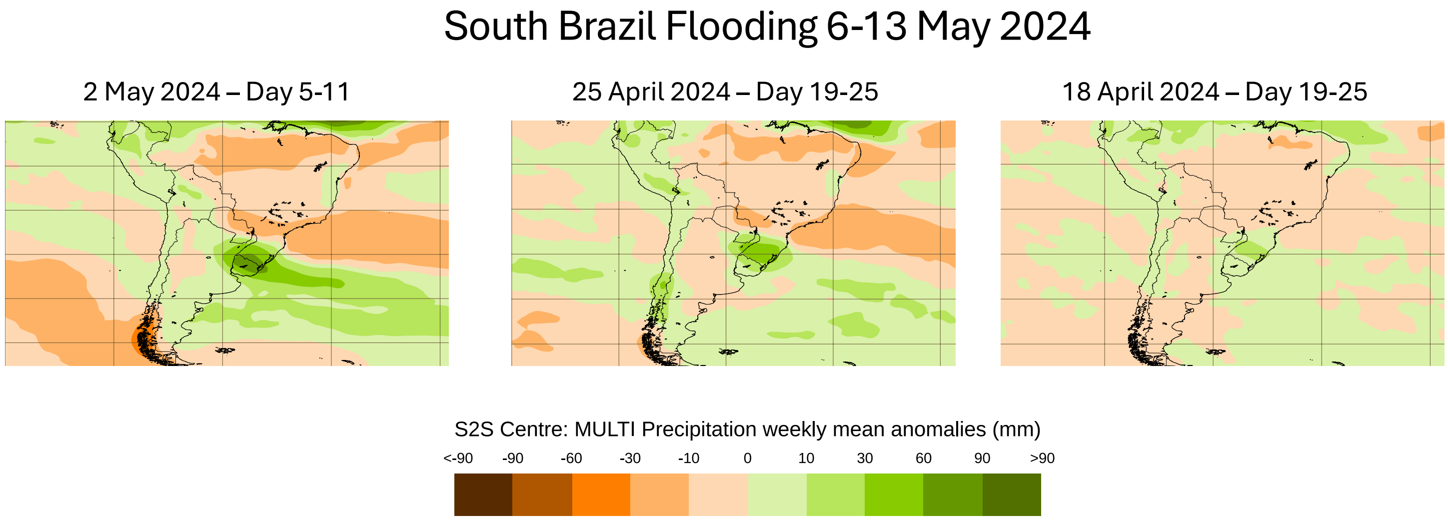


Fig. 8. **Weekly mean precipitation prediction anomalies from the S2S MME combination (from the WMO LC-SSPMME website: https://charts.ecmwf.int/wmo/) at different lead times and verifying on 6–13 May 2024.**

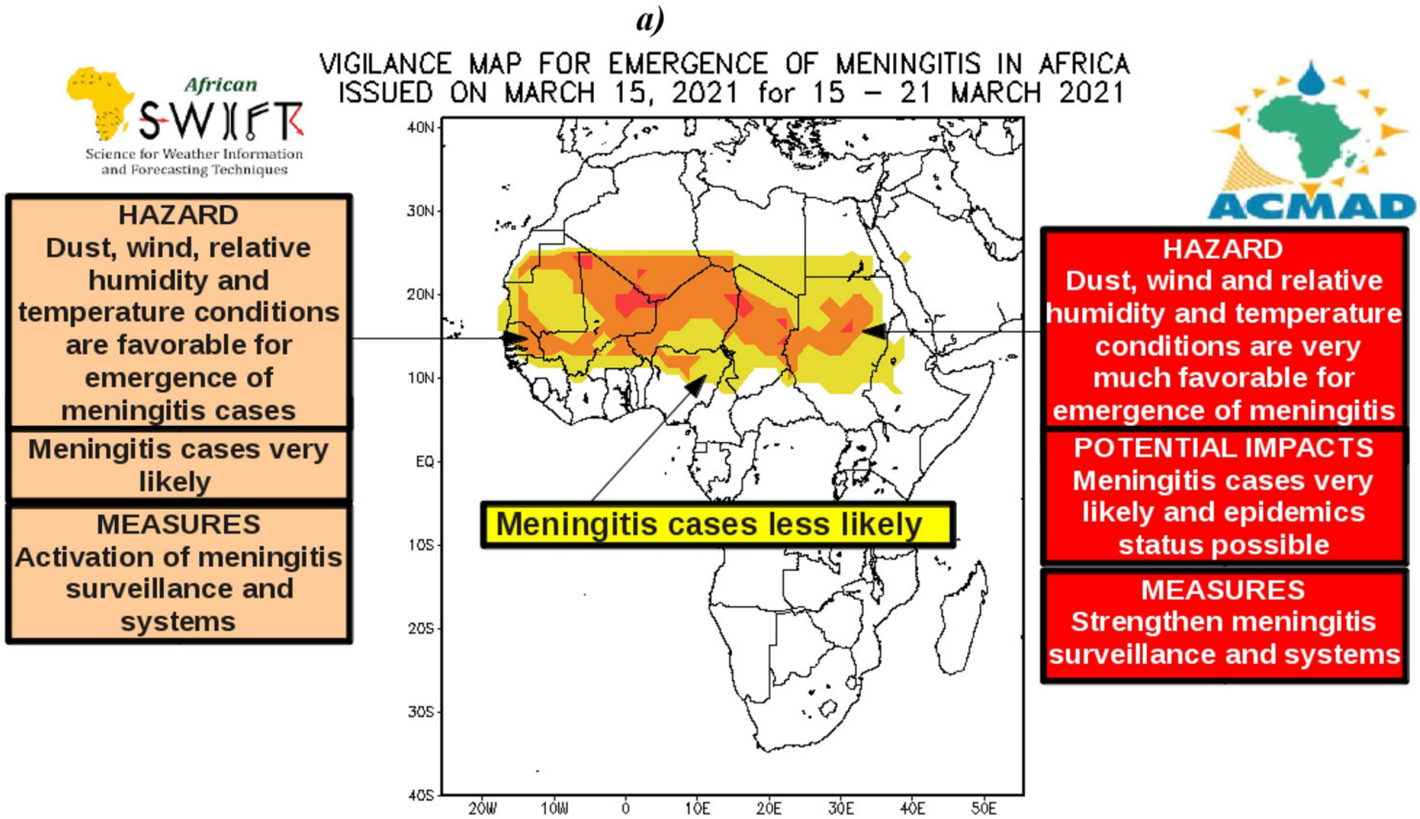
organized an AI/ML prize challenge (Vitart et al. 2022) in 2022 in collaboration with the Swiss Data Science Center (SDSC) and ECMWF. The three winners of this competition used ML methods for postprocessing S2S models and produced more skillful predictions of temperature and precipitation than the benchmark which calibrated subseasonal predictions from ECMWF. In this competition, methods using ML as a replacement of the subseasonal dynamical model (data-driven methods) were not as successful as the methods using ML for postprocessing the dynamical model outputs. However, since this competition, data-driven methods have progressed significantly, and some of them (e.g., Chen et al. 2023) are already competitive for targeted variables and analyses compared to state-of-the-art dynamical subseasonal models. A new challenge would be useful to compare the benefits of these new data-driven methods compared to the use of improved AI/ML postprocessing methods.

8. Outreach and capacity development

An important aspect of the S2S project was to promote subseasonal research, forecasting, and application development and to develop capacity particularly among early career scientists and in the Global South. A total of 47 workshops/sessions at conferences [e.g., the S2S Extremes Workshop at IRI in 2016, United States; the S2S/subseasonal to decadal (S2D) conferences in Boulder in 2018 (Merryfield et al. 2020); S2S Summit at Reading University, United Kingdom, in 2023 (Woolnough et al. 2024)] were organized by the S2S project, and 25 training workshops were held for national meteorological services and young scientists, on topics of subseasonal predictability, prediction methods, verification, and applications. Practical sessions have included accessing and downloading data from the S2S database and analyzing skill and case studies of the subseasonal predictability of high-impact weather events in the participants' countries. Instructors have been drawn from the S2S steering group and beyond, often with S2S members codeveloping the curricula. These outreach activities, organized with the help of the International Coordination Office (ICO) for the S2S project, which was hosted by the Korea Meteorological Administration (KMA) and the Asia–Pacific Economic Cooperation (APEC) Climate Center (APCC), allowed the subseasonal communities to exchange the latest issues and outcomes of the S2S project.

9. Legacy of the WWRP/WCRP S2S project

The S2S project brought together a large community of researchers, operational centers, and potential users of climate services targeting the subseasonal range where anticipatory



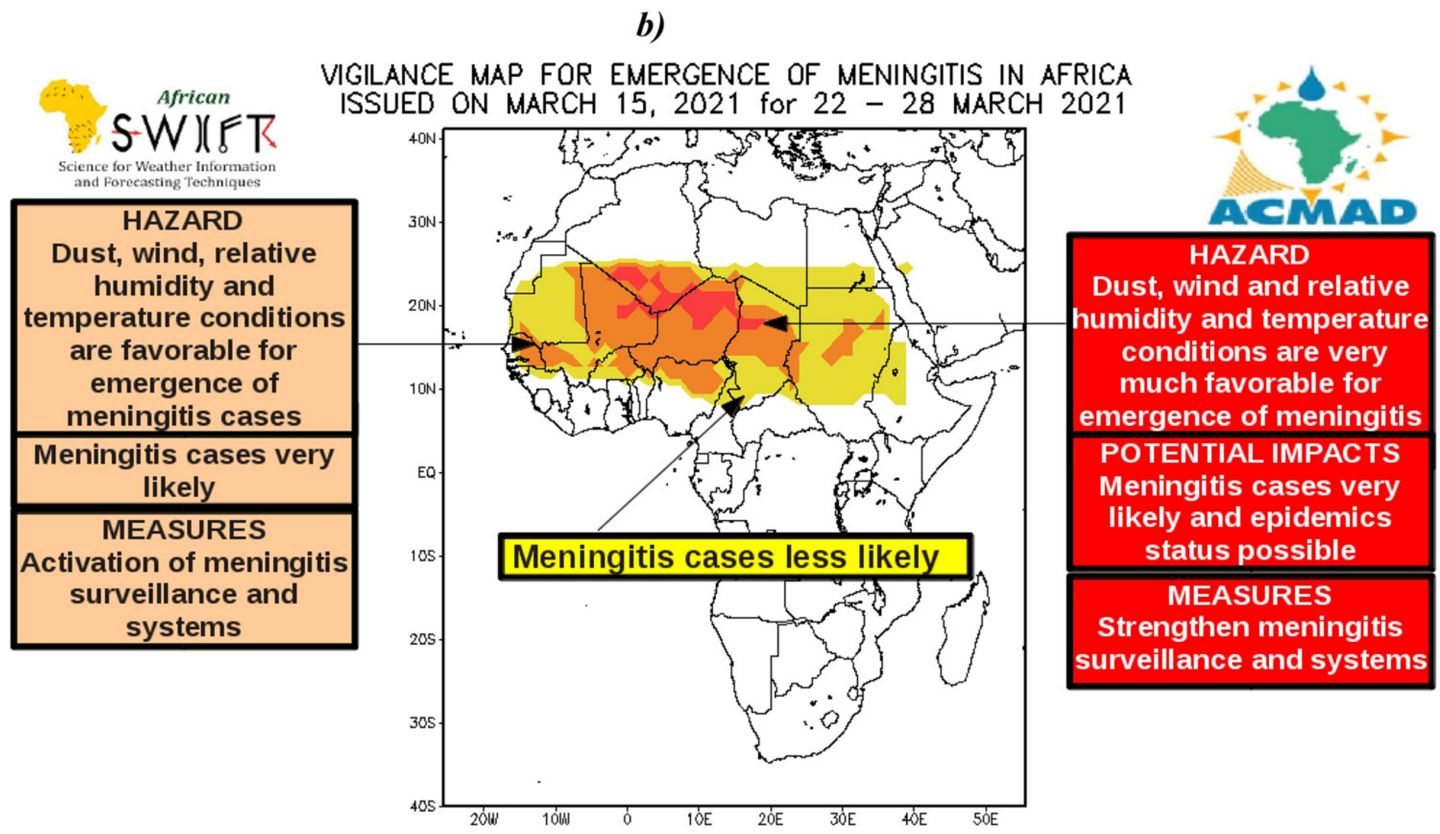


Fig. 9. Vigilance map of meningitis cases over Africa produced on 15 Mar 2021 and valid for (a) week from 15 to 21 Mar 2021 and (b) week from 22 to 28 Mar 2021. The vigilance map is computed based on temperature, relative humidity, and surface dust concentrations forecast from the ECMWF model. Climate variables are from the S2S database, and surface dust concentration is from the Barcelona Supercomputer Center (BSC) (from Dione et al. 2022).

action can be taken based on early warnings of weather and climate extremes, helping societies manage climate impacts. The field of subseasonal forecasting is now well established. A direct project legacy is the establishment and designation of the WMO Global Producing Centres for subseasonal predictions (GPC-SSP) and the WMO Lead Centre for Subseasonal Prediction Multi-Model Ensemble (LC-SSPMME) hosted at ECMWF, which will provide access to near-real-time S2S data and multimodel products (including verification products following established WMO standards) from a subset of the S2S data providers. Near-real-time multimodel charts are already available online (https://charts.ecmwf.int/wmo/charts). The S2S database will continue to be maintained and updated for at least 5 additional years. A major obstacle preventing the uptake of S2S data by applications developers has been the 3-week delay in the access to real-time data. In a recent move toward open data, several S2S data providers have agreed to reduce this delay to 48 h.

In 2024, WWRP launched the Subseasonal Applications for Agriculture and Environment (SAGE) project which will build on the success of the S2S project and follow its recommendations, with an increased focus on the use of subseasonal forecasts to support decision-making, and continued research on processes and modeling to improve forecast skill. Within WCRP, subseasonal activities will be promoted particularly in connection to longer time scales, within the Working Group on Subseasonal to Interdecadal Prediction (WGSIP), which is part of the Earth System Modeling and Observation (ESMO) core project, and in the other WCRP core projects, including Atmospheric Processes And their Role in Climate (APARC) and Global Energy and Water Exchanges project (GEWEX), as well as Regional Information for Society (RifS).

The S2S project has helped advance subseasonal predictive capabilities and understanding of sources of subseasonal predictability, together with better knowledge of the scientific challenges in subseasonal prediction. One of the most important challenges and a major hurdle toward more skillful subseasonal forecasts is to address the too weak teleconnections in the S2S models. These errors, present in all S2S models [e.g., Vitart 2017 and Stan et al. 2022 for MJO teleconnections; Garfinkel et al. 2022; Williams et al. 2023; Molteni and Brookshaw 2023 for ENSO; Anstey et al. 2022 for the quasi-biennial oscillation (QBO); and Domeisen et al. 2020a for MJO, QBO, and ENSO teleconnections through the stratosphere], might also contribute to the too weak signal to noise ratio in midlatitudes and the "signal to noise paradox" in seasonal forecasts (Scaife and Smith 2018; Garfinkel et al. 2024). There is also a need for better understanding the interactions between teleconnections (e.g., between MJO and ENSO), particularly in the context of a changing climate. The advances in ML, used as a tool to provide online or offline model error corrections, as a way to better understand subseasonal predictability (explainable AI) or as a replacement of dynamical S2S models, provide promising opportunities for improving subseasonal forecast skill. An ongoing critical challenge is the incorporation of subseasonal probabilistic forecasts into decision-making processes. The S2S Real-Time Pilot was a first step to better understand the subseasonal value chain. The new WWRP SAGE project as well as the establishment of the GPC-SSP and LC-SSPMME should improve and increase the uptake of subseasonal operational predictions as part of climate services for better adaptation to climate change.

A wide range of information about the S2S project and the database is available on the website (www.s2sprediction.net) up to at least the end of 2025.

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Data availability statement. The datasets analyzed in this article are publicly available from the S2S database (https://apps.ecmwf.int/datasets/data/s2s, http://s2s.cma.cn/index and https://iridl.ldeo.columbia.edu/index.html).

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