

## **The WWRP/WCRP S2S project and its achievements**

F. Vitart<sup>1\*</sup>, A. W. Robertson<sup>2</sup>, A. Brookshaw<sup>1</sup>, N. Caltabiano<sup>3</sup>, C. A. S. Coelho<sup>4</sup>, E. de Coning<sup>3</sup>, P. A. Dirmeyer<sup>5</sup>, D. I. V. Domeisen<sup>6,7</sup>, L. Hirons<sup>8</sup>, H. J. Kim<sup>9</sup>, H. Lin<sup>10</sup>, A. Kumar<sup>11</sup>, A. Molod<sup>12</sup>, J. Robbins<sup>13</sup>, Z. Segele<sup>11</sup>, C. M. Spillman<sup>14</sup>, C. Stan<sup>5</sup>, Y. Takaya<sup>15</sup>, S. Woolnough<sup>8</sup>, C. J. White<sup>16</sup> and T. Wu<sup>17</sup>

1. European Centre for Medium-range Weather Forecasts, Reading, UK
2. International Research Institute for Climate and Society (IRI), Columbia Climate School, New York, USA
3. World Meteorological Organization, World Weather Research Programme, Geneva, Switzerland
4. Centre for Weather Forecast and Climate Studies (CPTEC), National Institute for Space Research (INPE), Brazil
5. George Mason University, USA
6. University of Lausanne, Lausanne, Switzerland
7. ETH Zurich, Zurich, Switzerland
8. National Centre for Atmospheric Science, University of Reading, Reading, UK
9. APEC Climate Center, Busan, Korea
10. Environment and Climate Change Canada, Montreal, Canada
11. National Centers for Environmental Predictions, College Park, USA
12. NASA/GSFC, Greenbelt, USA
13. Met Office, Exeter, UK
14. Bureau of Meteorology, Melbourne, Victoria, Australia
15. Meteorological Research Institute, Japan Meteorological Agency, Tsukuba, Japan
16. University of Strathclyde, Glasgow, UK
17. China Meteorological Administration, Beijing, China

\*Corresponding author e-mail: Frederic Vitart, [Frederic.vitart@ecmwf.int](mailto:Frederic.vitart@ecmwf.int)

### **Abstract:**

The World Weather Research Programme (WWRP)/World Climate Research Programme (WCRP) Subseasonal to Seasonal Prediction (S2S) project was launched in 2013 with the primary goals of improving forecast skill and understanding sources of predictability on the subseasonal timescale (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 applications communities. This 10-year 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 towards 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 co-organized 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 Sub-seasonal Predictions Multi-Model Ensemble, which will provide real-time subseasonal multi-model 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. Skilful 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

## The WWRP/WCRP S2S project and its achievements

improve our understanding of subseasonal predictability and the performance of state-of-the-art subseasonal prediction models and multi-model ensembles.

**Keywords:** Subseasonal, multi-model ensemble, model evaluation/performance, predictability, Madden Julian Oscillation.

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

### 1. Introduction: The WWRP/WCRP S2S project

The WWRP/WCRP Subseasonal to Seasonal Prediction (S2S) project was launched in November 2013 as one of the three post-THORPEX (The Observing System Research and Predictability Experiment) activities of WWRP - together with the Polar Prediction Project (PPP) and the High Impact Weather project (HIWeather) - 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 WMO/WWRP/WCRP programmes to bridge the gap between medium-range (forecasts up to two 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., 2009). Originally planned for 5 years, the S2S project was extended for an additional 5 years (2018-2023). The first 5 years are referred to as S2S Phase 1 and the 5-year 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 two weeks to a season ahead. This article aims to summarise the main results and achievements of the S2S project focussing 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 Operations (R2O) collaborations, including the S2S Real-Time Pilot initiative. Another important activity during S2S Phase 2 was the S2S AI/ML Challenge (Section 7), designed to foster the use of machine learning (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; NMME; Kirtman et al., 2014; 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 multi-model ensemble database from current operational subseasonal forecasting systems, and to archive both forecasts and re-forecasts (also referred to as hindcasts). The S2S database (Vitart et al., 2017) includes availability of forecasts with a 3-week delay and re-forecasts from 13 operational and research centres. The S2S data is 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

## The WWRP/WCRP S2S project and its achievements

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 2 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 sub-surface 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-meter winds, was increased to 4 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 centres 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 multi-model 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 in <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.

<u>MODELS</u>	<u>ENSEMBLE SIZE</u>	<u>FREQUENCY</u>	<u>RFC PERIOD</u>	<u>RFC FREQUENCY</u>	<u>RFC SIZE</u>	<u>OCEAN COUPLING</u>	<u>SEA-ICE COUPLING</u>
<u>CMA</u>	<u>4</u>	<u>2 per week</u>	<u>Past 15 years</u>	<u>2 per week</u>	<u>4</u>	<u>Yes</u>	<u>Yes</u>
<u>CNR-ISAC</u>	<u>41</u>	<u>Weekly</u>	<u>2001-2020</u>	<u>Every 5 days</u>	<u>8</u>	<u>No</u>	<u>No</u>
<u>CNRM</u>	<u>35</u>	<u>Weekly</u>	<u>1993-2017</u>	<u>Every 7 days</u>	<u>10</u>	<u>Yes</u>	<u>Yes</u>
<u>CPTEC</u>	<u>11</u>	<u>2 per week</u>	<u>1999-2018</u>	<u>Every 7 days</u>	<u>11</u>	<u>No</u>	<u>No</u>
<u>ECCC</u>	<u>21</u>	<u>2 per week</u>	<u>2001-2020</u>	<u>2 per week</u>	<u>4</u>	<u>Yes</u>	<u>Yes</u>
<u>ECMWF</u>	<u>101</u>	<u>Daily</u>	<u>Past 20 years</u>	<u>Every 2 days</u>	<u>11</u>	<u>Yes</u>	<u>Yes</u>
<u>HMCR</u>	<u>41</u>	<u>Weekly</u>	<u>1991-2020</u>	<u>Weekly</u>	<u>11</u>	<u>No</u>	<u>No</u>
<u>IAP-CAS</u>	<u>49</u>	<u>Daily</u>	<u>1999-2018</u>	<u>Daily</u>	<u>4</u>	<u>Yes</u>	<u>Yes</u>
<u>JMA</u>	<u>5</u>	<u>Daily</u>	<u>1991-2020</u>	<u>1 per month</u>	<u>5</u>	<u>Yes</u>	<u>Yes</u>
<u>KMA</u>	<u>8</u>	<u>Daily</u>	<u>1993-2016</u>	<u>4 per month</u>	<u>7</u>	<u>Yes</u>	<u>Yes</u>
<u>NCEP</u>	<u>16</u>	<u>Daily</u>	<u>1999-2010</u>	<u>Daily</u>	<u>4</u>	<u>Yes</u>	<u>Yes</u>
<u>UKMO</u>	<u>4</u>	<u>Daily</u>	<u>1993-2016</u>	<u>4 per month</u>	<u>7</u>	<u>Yes</u>	<u>Yes</u>

*Table 1: Main characteristics of the 12 S2S models contributing to the S2S database (status in November 2024). Columns from left to right indicate the modelling center responsible for the forecasts, the ensemble size and frequency of the real-time forecasts, the re-forecast (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.*

### **3. Prediction skill assessment of S2S forecasts**

The skill of the S2S models to predict weekly mean anomalies of 2-meter temperature was assessed using the Ranked Probability Skill Score (RPSS, Epstein 1969) and the ECMWF Reanalysis v5 (ERA5, Hersbach 2020) for verification. Several S2S models display skill above climatology (RPSS larger than 0) up to week 4.5 (day 26-32), while the simple multi-model 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, multi-model 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-meter air temperature and total precipitation of the S2S multi-model ensemble over the period 2018-2023 (Fig. 2) show that the multi-model ensemble is more skilful than climatology calculated over the common period 2003-2010 up to week 4 for 2-meter 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., 2010). Figures 1 and 2 show the limit of practical predictability (ability to predict with current methods) of S2S models on average over the six-year period. However, there are periods of time, referred to as “windows of opportunity for skilful forecasts” (Mariotti et al., 2020) when the S2S intrinsic predictability (physical limit of predictability) is higher (e.g. Spaeth et al, 2024).

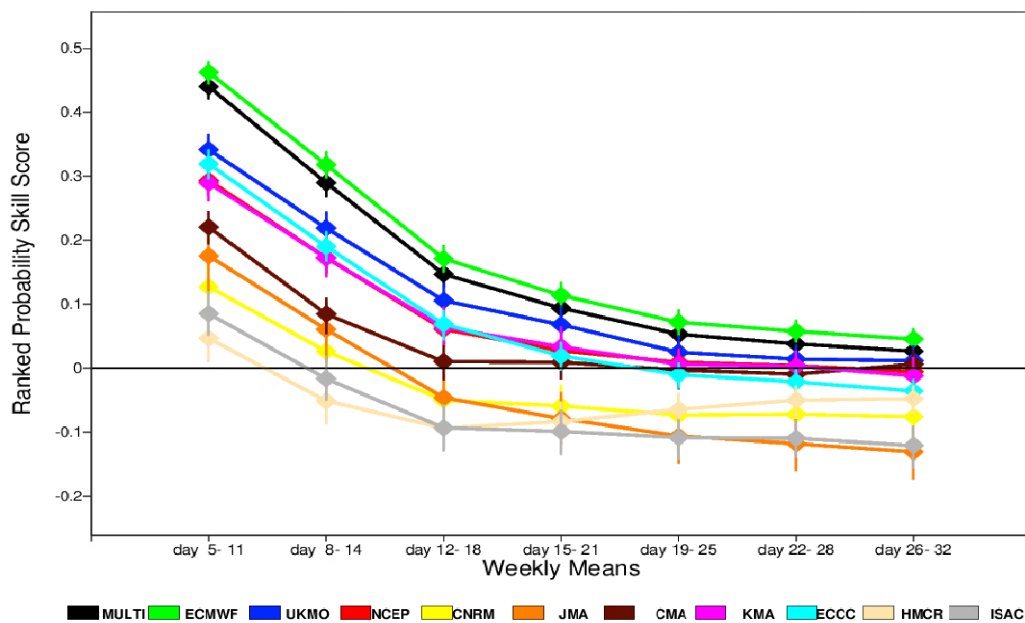
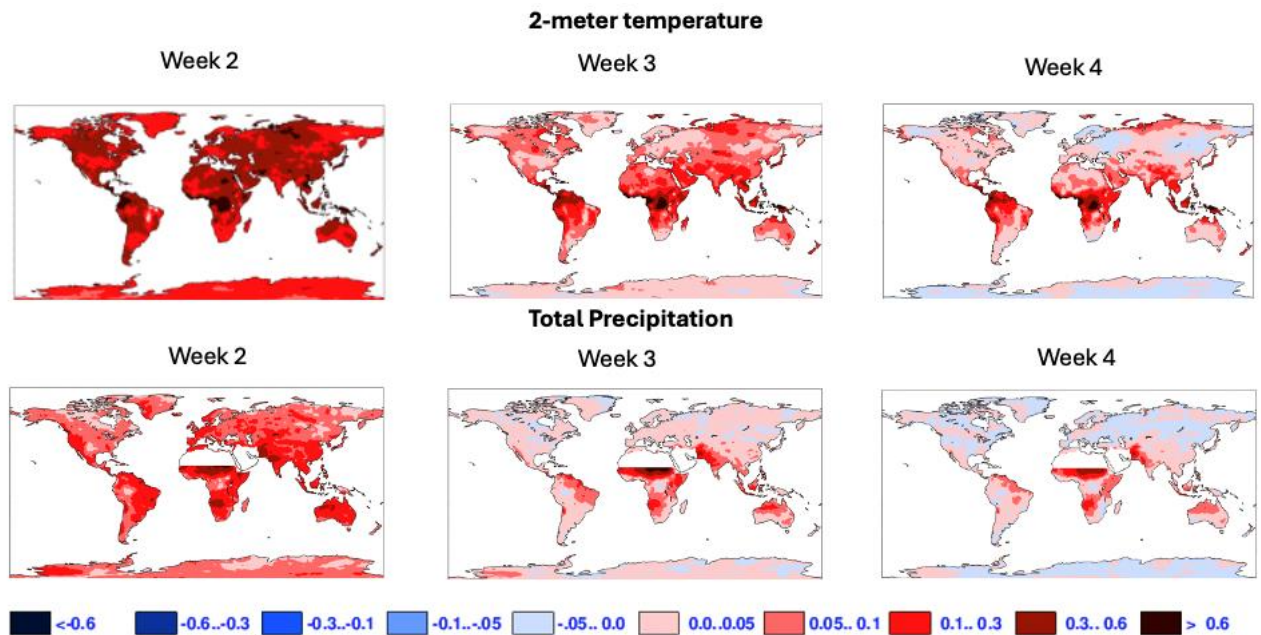


Figure 1: Ranked probabilistic skill score (RPSS) of 2-meter temperature over the northern extratropics (North of 30N) for each S2S model as a function of the lead time (overlapping weekly periods in days). The scores have been computed from all the tercile probabilities produced every Thursday from 2018 to 2023 (308 cases). The black line shows the RPSS of the multi-model ensemble 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.*



*Figure 2: RPSS of 2-meter air temperature (top panels) and precipitation (bottom panels) computed from the S2S multi-model ensemble forecast produced once a week (every Thursday) over the period 2018-2023 for different lead times. A positive (negative) value or red (blue) colour indicates skill above (below) climatology. For precipitation, the Saharan region was masked due to too low climatological precipitation to define tercile boundaries.*

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 pattern (PNA) 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-year period. Skill improvements up to week 4 can also be observed in the real-time multi-model ensemble forecasts over the period 2021-2023 compared to 2018-2020 (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 atmospheric resolutions and increased ensemble size since 2015. In addition, several models (e.g. ECCO, JMA) which were atmosphere-only in 2015, are now coupled to an ocean and sea-ice model.

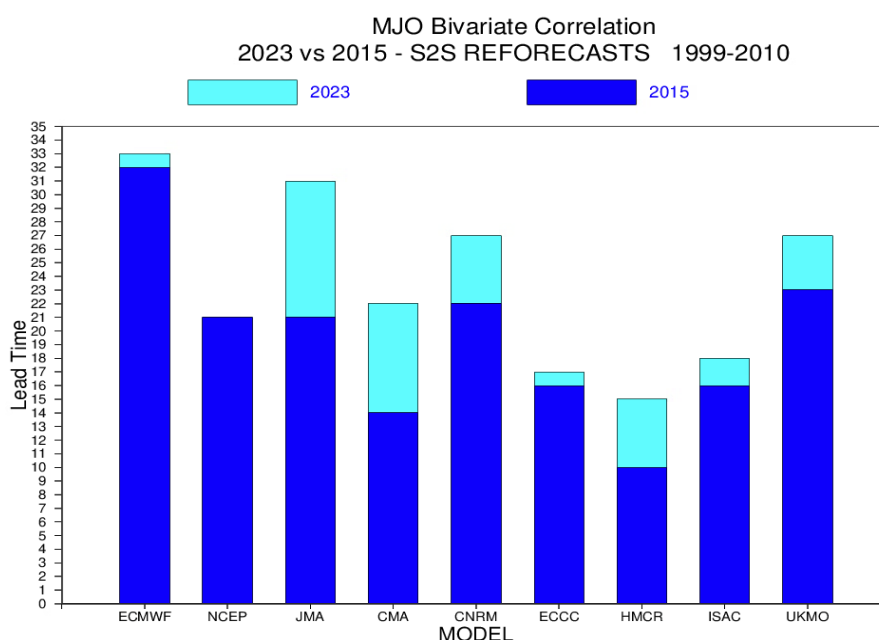
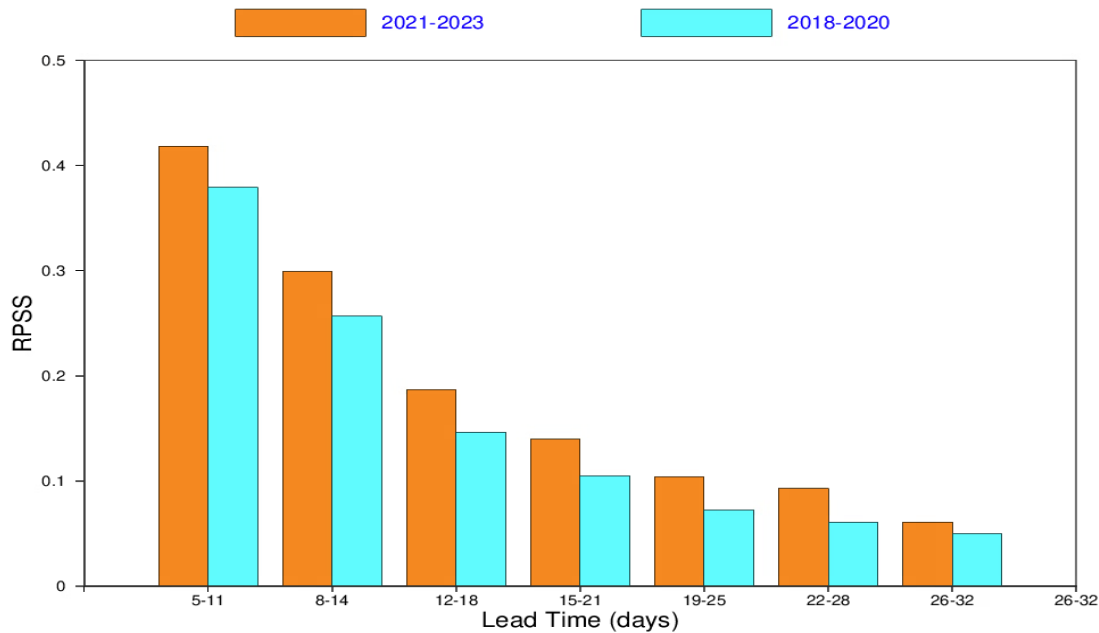


Figure 3: MJO forecast skill measured as the lead time (y-axis) when the MJO bivariate correlation between the ensemble mean re-forecasts of MJO index (Wheeler and Hendon, 2003) and re-analysis (ERA5) reaches 0.5. The forecast skill has been computed over the common re-forecast period November to March 1999-2010. Cyan bars (dark blue bars) indicate the performances of the operational models used in 2023 (2015).

#### 4. Sources of predictability

The S2S database has provided an important resource to better understand predictability in S2S models. To encourage its use, several sub-projects were organized around research topics: MJO, stratosphere, land, ocean, ensemble generation and aerosols. The outcomes of these activities are summarised below and reported in more detail at: <https://community.wmo.int/en/news/wwrpwcrp-subseasonal-seasonal-prediction-project-s2s-phase-2-final-report>.



*Figure 4: Ranked probability skill score (RPSS) of weekly mean 2-meter air temperature anomalies from the S2S multi-model ensemble 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 2021-2023 (2018-2020).*

#### 4.1 MJO and teleconnections

As shown in Figure 3, S2S models have skill in predicting the evolution of the MJO 2 to 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 or 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 skilful 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, 2020b; Stan et al. 2022). Reproducing the magnitude of the extratropical response to the MJO remains 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.

### 4.2 Stratosphere

An important source of subseasonal predictability is the stratospheric polar vortex, especially for 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 to 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 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).

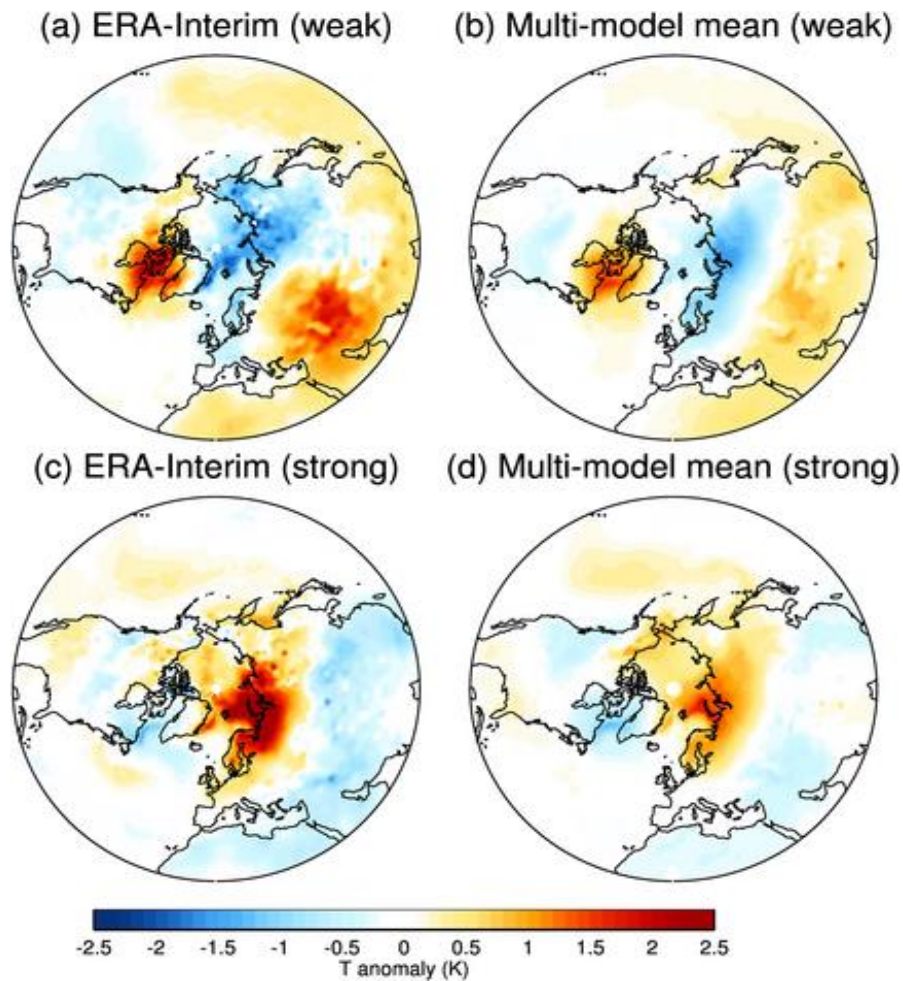


Figure 5: Composite of 2-m temperature anomalies (K) for weeks 3-4 for (top) weak vortex states and (bottom) strong vortex states. (b, d) The ensemble mean for forecasts initialized during weak/strong vortex states. (a, c) The equivalent anomalies for ERA-Interim where each date present in the multi-model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

#### 4.3 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-meter air temperature at week 3 and week 4 lead time.

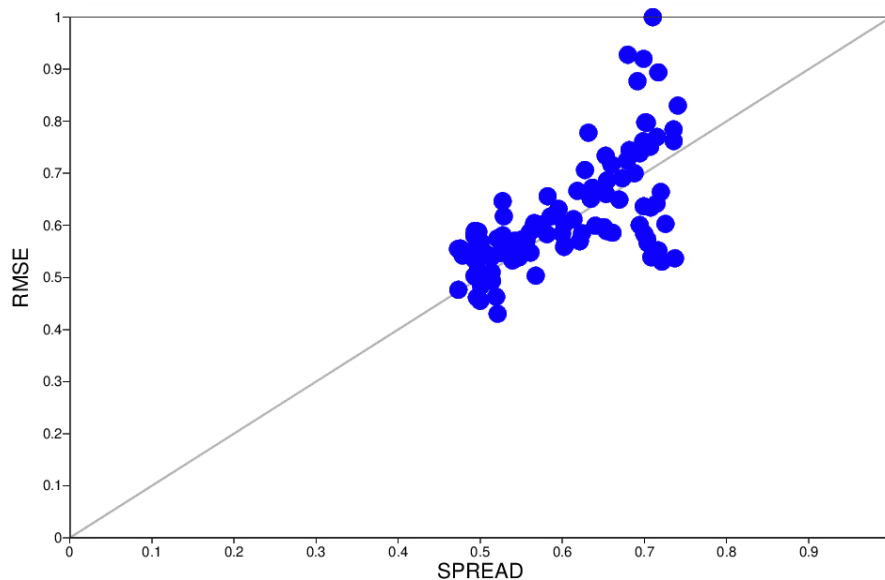
### 4.4 Ocean

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 (Amaya et al. 2022).

### 4.5 Ensemble generation

Numerical prediction on subseasonal timescales 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 Takya (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 2 separate sub-sets 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.



*Figure 6: Scatter plot 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 to March) 2017-2018.*

#### 4.6 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).

#### 4.7 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; Bueler et al. 2021; Osman et al. 2023) weather regimes. Charlton Perez et al. (2018) and Domeisen et al (2020) investigated the influence of the stratosphere on European weather regimes.

#### 4.8 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).

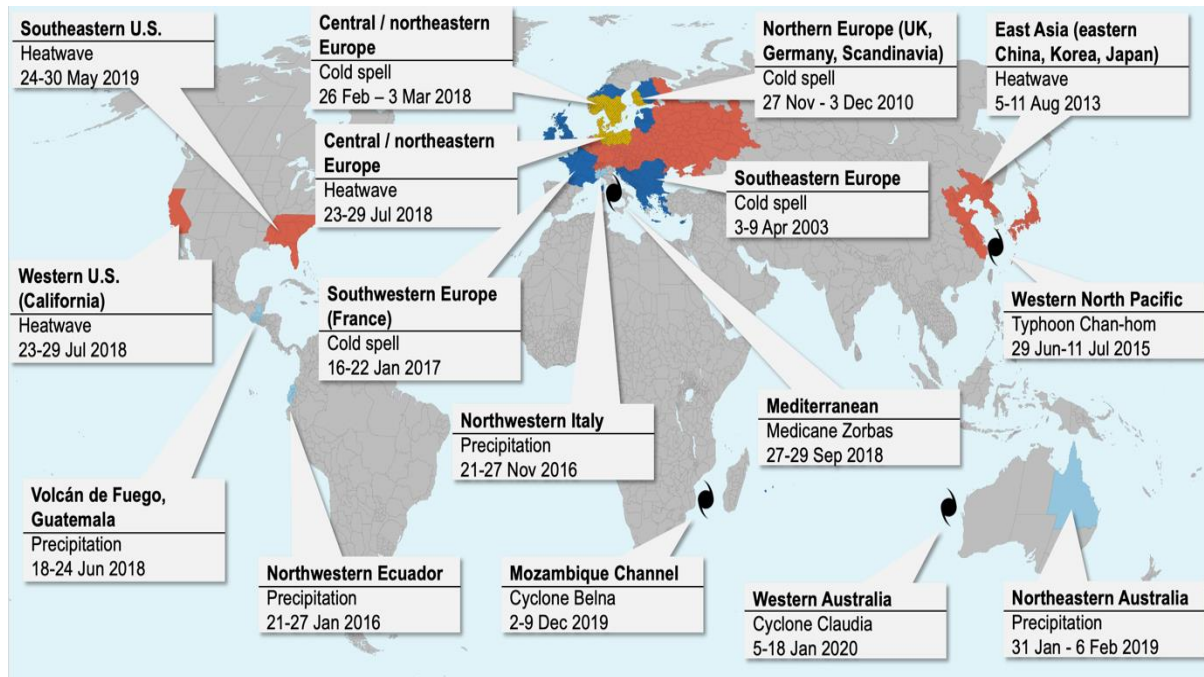
### **5 Prediction of extremes**

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: heatwaves, 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 Figure 8. Recent research has shown the potential for subseasonal prediction of heatwaves (e.g. Tian et al. 2017; Wulff and Domeisen, 2019; Vitart and Robertson, 2018; Pyrina and Domeisen, 2022; Lin et al. 2022), cold waves (e.g. Kautz et al., 2019; Karpechko et al. 2018), extreme precipitation events (e.g. Munoz et al. 2019; Wang et al., 2022), tropical cyclones (Lee et al. 2020) and atmospheric rivers (DeFlorio et al., 2019).



a)



b)

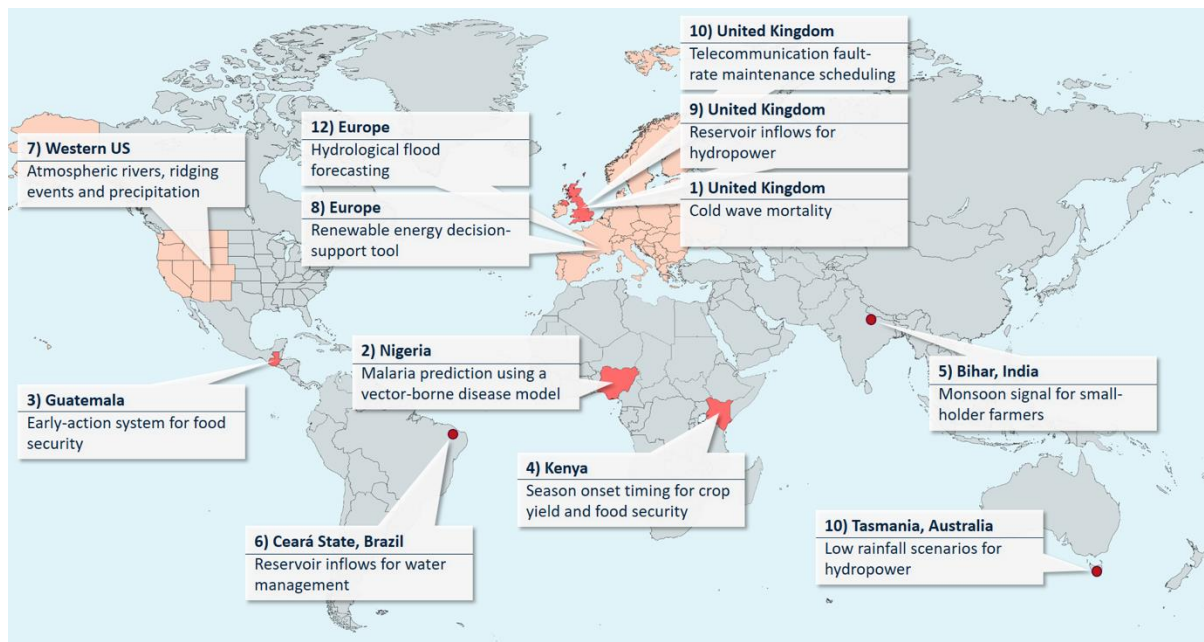
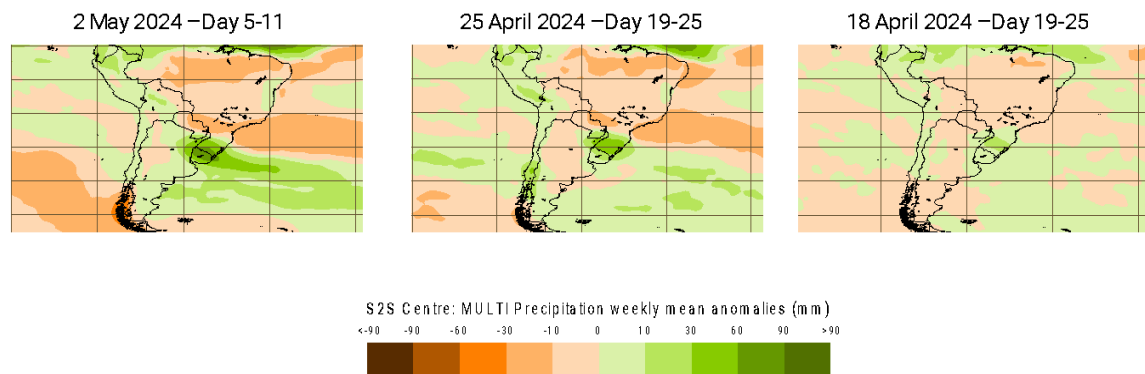


Figure 7: (a) Location of the extreme event case studies with predictability on subseasonal timescales documented in Domeisen et al. (2022). (b) Location of sectoral case studies with related subseasonal application and/or product in White et al. (2022) (from S2S Newsletters 18 and 19, <http://www.s2sprediction.net/static/newsletter>).

## South Brazil Flooding 6-13 May 2024



*Figure 8: Weekly mean precipitation prediction anomalies from the S2S multi-model ensemble combination (from the WMO Lead Centre for Sub-seasonal prediction Multi-Model Ensemble website” <https://charts.ecmwf.int/wmo/>) at different lead times and verifying on 6-13 May 2024.*

### **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 operationalisation (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 2020-2022, removing the 3-week delay. Co-development 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 semi-structured 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 Centres (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 Figure 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 studies (Fig. 7b) and in the special issue on “Subseasonal to decadal predictions in support of climate services” (Osman et al., 2023).

### **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 organized an AI/ML prize challenge (Vitart, 2022) in 2022 in collaboration with the Swiss Data Science Center (SDSC) and ECMWF. The three winners of this competition used ML methods for post-processing S2S models and produced more skilful predictions of temperature and precipitation than the benchmark which was 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 post-processing 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 post-processing methods.

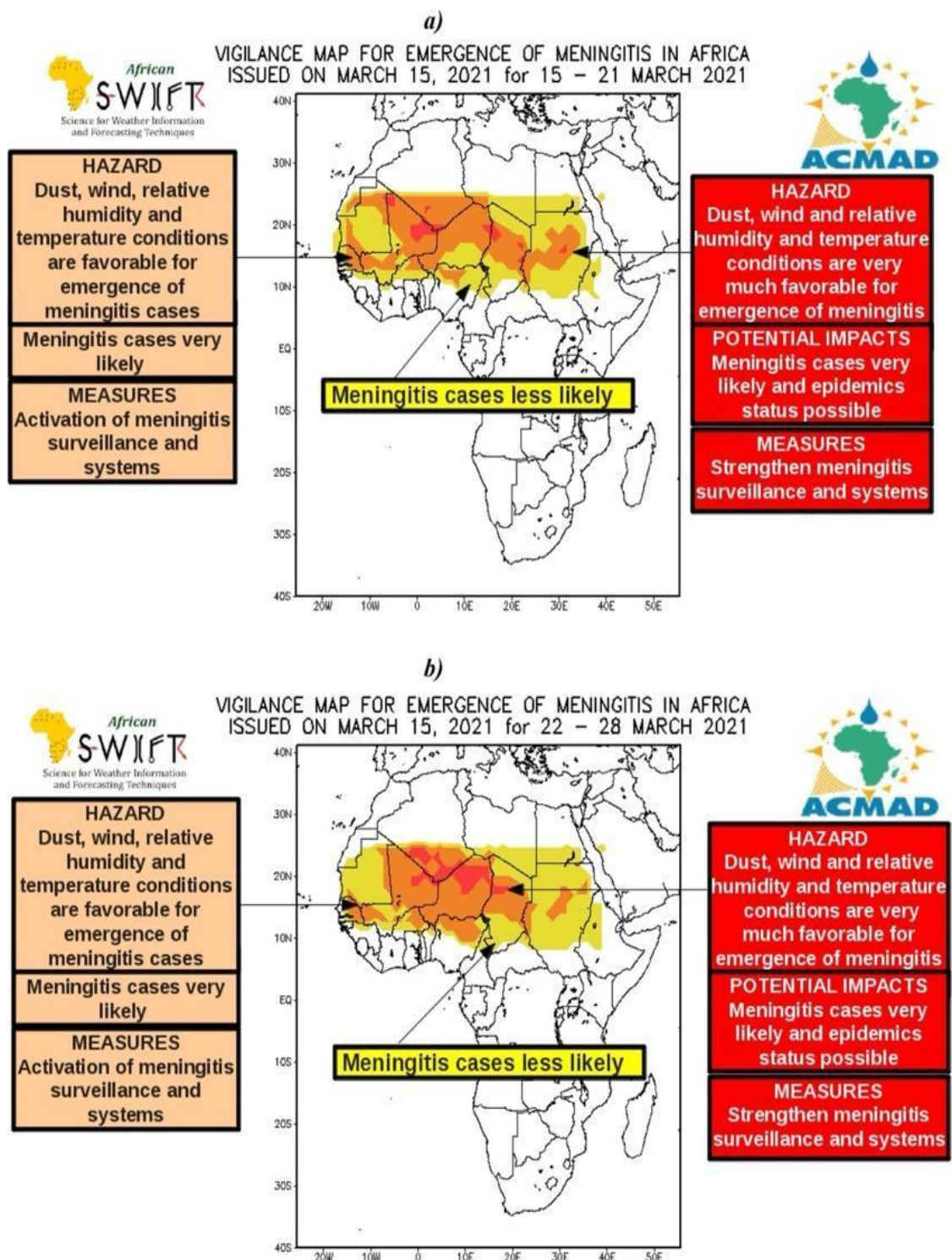


Figure 9: Vigilance map of meningitis cases over Africa produced on 15 March 2021 and valid for (a) week from 15th to 21st March 2021 and (b) week from 22nd to 28th March 2021. The vigilance map is computed based on temperature, relative humidity and surface dust concentrations forecast from ECMWF model.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



## **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, USA; the S2S/S2D conferences in Boulder in 2018 (Merryfield et al, 2020); S2S Summit at Reading University, UK 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 analysing 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 co-developing the curricula. These outreach activities, organized with the help of the International Coordination Office (ICO) for the S2S Project, which was hosted by Korea Meteorological Administration (KMA) and the 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 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 multi-model products (including verification products following established WMO standards) from a subset of the S2S data providers. Near real-time multi-model charts are already available from <https://charts.ecmwf.int/wmo/charts>. The S2S database will continue to be maintained and updated for at least 5 additional years. A major

## The WWRP/WCRP S2S project and its achievements

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 towards open data, several S2S data providers have agreed to reduce this delay to 48 hours.

In 2024, WWRP launched the Subseasonal Applications for Agriculture and Environment project (SAGE) 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 modelling to improve forecast skill. Within WCRP, subseasonal activities will be promoted particularly in connection to longer timescales, within the Working Group on Subseasonal to Interdecadal Prediction (WGSIP), which is part of the Earth System Modelling and Observations (ESMO) core project, and in the other WCRP core projects, including Atmospheric Processes And their Role in Climate (APARC), Global Energy and Water Exchanges (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 towards more skilful 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 QBO, and Domeisen et al., 2020a for MJO, QBO, and El-Niño Southern Oscillation (ENSO) teleconnections through the stratosphere), might also contribute to the too weak signal to noise ratio in mid-latitudes 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

## The WWRP/WCRP S2S project and its achievements

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](http://www.s2sprediction.net) up to at least the end of 2025.

## Acknowledgements

We are grateful to WWRP and WCRP for their guidance and strong support during the S2S project, KMA and APCC for hosting the S2S International project Office, and managing the S2S website, publishing newsletters and supporting the organization of events and the countries who contributed to the S2S trust fund (United Kingdom, Australia, Germany, Canada). We are indebted to Manuel Fuentes, Richard Mladek, Hu Xing, Jing Yuan, and their colleagues for setting up and managing the S2S archives at ECMWF, CMA and IRI. The S2S archive would not have been possible without support from the S2S partnership: the three archive centres and the 13 data providers. We also wish to acknowledge the S2S members who contributed to Phase 1 of the S2S Project: Harry Hendon, Duane Waliser, June-Yi Lee, Richard Graham, Alberto Arribas and Hyun-Kyun Kim and Willem Landman.

## Availability Statement

The data sets 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>).

**References:**

Amaya, D. J., M. G. Jacox, J. Dias, M. A. Alexander, K. B. Karneuskas, J. D. Scott, and M. Gehne, 2022: Subseasonal-to-seasonal forecast skill in the California Current System and its connection to coastal Kelvin waves. *Journal of Geophysical Research: Oceans*, 127, e2021JC017892. <https://doi.org/10.1029/2021JC017892>

Anstey J. A., N. Butchart, K. Hamilton, S. M. Osprey, 2022: The SPARC Quasi-Biennial Oscillation Initiative. *Q. J. R. Meteorol. Soc.*, 148(744), 1455-1458. <https://doi.org/10.1002/qj.3820>

Benson, D. O. and P. A. Dirmeyer, 2021: Characterizing the Relationship between Temperature and Soil Moisture Extremes and Their Role in the Exacerbation of Heat Waves over the Contiguous United States. *J. Clim.*, 34, 2175–2187, <https://doi.org/10.1175/JCLI-D-20-0440.1>.

Büeler, D., L. Ferranti, L. Magnusson, L., J. F. Quinting and C. M. Grams, 2021: Year-round subseasonal forecast skill for Atlantic–European weather regimes. *Q J R Meteorol Soc*, 147(741), 4283–4309. Available from: <https://doi.org/10.1002/qj.4178>

Buizza, R., 1997: Potential forecast skill of ensemble prediction and spread and skill distributions of the ECMWF ensemble prediction system. *Mon. Wea. Rev.*, 125, 99–119.

Butler, A., A. Charlton-Perez, D. I. Domeisen, C. Garfinkel, E. P. Gerber, P. Hitchcock and co-authors, 2019: Subseasonal predictability and the stratosphere. In A. W. Robertson and F. Vitart (Eds.), *Sub-seasonal to seasonal prediction: The gap between weather and climate forecasting* (pp. 223–241), Elsevier.

Charlton-Perez A. J., L. Ferranti L and R. W. Lee, 2018: The influence of the stratospheric state on North Atlantic weather regimes. *Q J R Meteorol Soc.* 2018; 144: 1140-1151. <https://doi.org/10.1002/qj.3280>



## The WWRP/WCRP S2S project and its achievements

Chen, L., and co-authors, 2023: FuXi-S2S: An accurate machine learning model for global subseasonal forecasts. <https://arxiv.org/abs/2312.09926v1>.

DeFlorio, M. J., D. E. Waliser, F. M. Ralph, B. Guan, A. Goodman, P. B. Gibson and co-authors, 2019: Experimental Subseasonal-to-Seasonal (S2S) Forecasting of Atmospheric Rivers Over the Western United States. *Journal of Geophysical Research: Atmospheres*, 124, 11242–11265. <https://doi.org/10.1029/2019JD031200>

DeMott, C., Á. G. Muñoz, C. D. Roberts, C. M. Spillman, and F. Vitart, 2021: The benefits of better ocean weather forecasting, *Eos*, 102, <https://doi.org/10.1029/2021EO210601>.

Dione, C., and co-authors, 2022: Improved subseasonal forecasts to support preparedness action for meningitis outbreak in Africa, *Climate Services*, 28,100326, ISSN 2405-8807, <https://doi.org/10.1016/j.cliser.2022.100326>.

Dirmeyer, P. A., G. Balsamo, E. M. Blyth, R. Morrison, and H. M. Cooper, 2021: Land-Atmosphere Interactions Exacerbated the Drought and Heatwave Over Northern Europe During Summer 2018. *AGU Adv.*, 2, e2020AV000283, <https://doi.org/10.1029/2020AV000283>.

Diro, G. T., and H. Lin, 2020: Subseasonal Forecast Skill of Snow Water Equivalent and Its Link with Temperature in Selected SubX Models. *Weather Forecast.*, 35, 273–284, <https://doi.org/10.1175/WAF-D-19-0074.1>.

Domeisen, D. I. and A. H. Butler, 2020: Stratospheric drivers of extreme events at the Earth's surface. *Communications Earth & Environment*, 1(1), 59

Domeisen, D. I. V., A. H. Butler, A. J. Charlton-Perez, B. Ayarzagüena, M. P. Baldwin, E. Dunn-Sigouin, and co-authors, 2020a: The role of the stratosphere in subseasonal to seasonal

## The WWRP/WCRP S2S project and its achievements

prediction: 1. Predictability of the stratosphere. *Journal of Geophysical Research: Atmospheres*, 125, e2019JD030920. <https://doi.org/10.1029/2019JD030920>

Domeisen, D. I., A. H. Butler, A. J. Charlton-Perez, B. Ayarzagüena, M. P. Baldwin, E. Dunn-Sigouin, and co-authors, 2020b: The role of the stratosphere in subseasonal to seasonal prediction: 2. Predictability arising from stratosphere-troposphere coupling. *Journal of Geophysical Research: Atmospheres*, 125, e2019JD030923. <https://doi.org/10.1029/2019JD030923>

Domeisen, D. I., C. M. Grams and L. Papritz, 2020: The role of North Atlantic–European weather regimes in the surface impact of sudden stratospheric warming events. *Weather and Climate Dynamics*, 1(2), 373–388.

Domeisen, D.I.V., and co-authors, 2022: Advances in the subseasonal prediction of extreme events: Relevant case studies across the globe. *Bull. Amer. Meteor. Soc.*, <https://doi.org/10.1175/BAMS-D-20-0221.1>

Epstein, E. S., 1969: A Scoring System for Probability Forecasts of Ranked Categories. *J. Appl. Meteor. Climatol.*, **8**, 985–987, [https://doi.org/10.1175/1520-0450\(1969\)008<0985:ASSFPF>2.0.CO;2](https://doi.org/10.1175/1520-0450(1969)008<0985:ASSFPF>2.0.CO;2).

Ferranti L, Magnusson L, Vitart F, Richardson DS, 2018: How far in advance can we predict changes in large-scale flow leading to severe cold conditions over Europe? *Q J R Meteorol Soc*; 144: 1788–1802. <https://doi.org/10.1002/qj.3341>

Ford, T. W., and C. F. Labosier, 2017: Meteorological conditions associated with the onset of flash drought in the Eastern United States. *Agric. For. Meteorol.*, 247, 414–423, <https://doi.org/10.1016/j.agrformet.2017.08.031>.

Garfinkel, C. I., W. Chen, Y. Li, C. Schwartz, P. Yadav, and D. Domeisen, 2022: The Winter North Pacific Teleconnection in Response to ENSO and the MJO in Operational Subseasonal

## The WWRP/WCRP S2S project and its achievements

Forecasting Models Is Too Weak. *J. Climate*, **35**, 8013–8030, <https://doi.org/10.1175/JCLI-D-22-0179.1>.

Garfinkel, C.I., Knight, J., Taguchi, M., Schwartz, C., Cohen, J., Chen, W., et al., 2024: Development of the signal-to-noise paradox in subseasonal forecasting models: When? Where? Why? *Q J R Meteorol Soc*, 150(764), 4417–4436. Available from: <https://doi.org/10.1002/qj.482>

Hewitt, C., S. Mason, and D. Walland, 2012: The Global Framework For Climate Services. *Nat. Climate Change*, 2, 831–832, <https://doi.org/10.1038/nclimate1745>.

Hersbach H, B. Bell, P. Berrisford and co-authors, 2020: The ERA5 global reanalysis. *Q J R Meteorol Soc*, 146, 1999–2049. <https://doi.org/10.1002/qj.3803>

Hirsch, A. L., and Coauthors, 2019: Amplification of Australian Heatwaves via Local Land-Atmosphere Coupling. *J. Geophys. Res. Atmospheres*, 124, 13625–13647, <https://doi.org/10.1029/2019JD030665>.

Hitchcock, P., A. Butler, A. Charlton-Perez, C. I. Garfinkel, T. Stockdale, J. Anstey, and co-authors, 2022: Stratospheric Nudging And Predictable Surface Impacts (SNAPSI): a protocol for investigating the role of stratospheric polar vortex disturbances in subseasonal to seasonal forecasts. *Geoscientific Model Development*, 15(13), 5073-5092.

Jie, W., F. Vitart, T. Wu, and X. Liu, 2017: Simulations of the Asian summer monsoon in the subseasonal to seasonal prediction project (S2S) database. *Q. J. R. Meteorol. Soc.*, 143: 2282-2295. <https://doi.org/10.1002/qj.3085>

Karpechko, A. Y., A. Charlton-Perez, M. Balmaseda, N. Tyrrell and F. Vitart, 2018: Predicting sudden stratospheric warming 2018 and its climate impacts with a multimodel ensemble. *Geophysical Research Letters*, 45, 13,538–13,546. <https://doi.org/10.1029/2018GL081091>

## The WWRP/WCRP S2S project and its achievements

Kautz, L-A, I. Polichtchouk, T. Birner, H. Garny and J. G. Pinto, 2020: Enhanced extended-range predictability of the 2018 late-winter Eurasian cold spell due to the stratosphere. *Q.J.R. Meteorol Soc.*, 146, 1040–1055. <https://doi.org/10.1002/qj.3724>

Kent, C., A. Scaife, A. and N. Dunstone, 2023: What potential for improving sub-seasonal predictions of the winter NAO? *Atmospheric Science Letters*, 24(4), e1146. <https://doi.org/10.1002/asl.1146>

Kim, H., Ham, Y.G., Joo, Y.S. et al., 2021: Deep learning for bias correction of MJO prediction. *Nat Commun*, 12, 3087. <https://doi.org/10.1038/s41467-021-23406-3>

Kirtman, B. P., and Coauthors, 2014: The North American Multimodel Ensemble: Phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction. *Bull. Amer. Meteor. Soc.*, 95, 585–601, doi:10.1175/BAMS-D-12-00050.1.

Kumar, A., M. Chen and W. Wang, 2011: An analysis of prediction skill of monthly mean climate variability. *Clim. Dyn.* 37, 1119–1131. <https://doi.org/10.1007/s00382-010-0901-4>

Lawrence, Z. D., and co-authors, 2022: Quantifying stratospheric biases and identifying their potential sources in subseasonal forecast systems, *Weather Clim. Dynam.*, 3, 977–1001, <https://doi.org/10.5194/wcd-3-977-2022>.

Lee C.-Y., S. J. Camargo, F. Vitart, A. H. Sobel, J. Camp, S. Wang., M. K. Tippett, and Q. Yang, 2020: Subseasonal predictions of tropical cyclone intensity and occurrence in the S2S dataset. *Wea. Forecasting*, 35, 921-938, <https://doi.org/10.1175/WAF-D-19-0217.1>

Lim, Y., S.-W. Son, and D. Kim, 2018: MJO prediction skill of the subseasonal-to-seasonal prediction model. *J. Climate*, 31, 4075–4094, <https://doi.org/10.1175/JCLI-D-17-0545.1>.

Lin, H., R. Mo, and F. Vitart, 2022: The 2021 western North American heatwave and its subseasonal predictions. *Geophysical Research Letters*, 49, <https://doi.org/10.1029/2021GL097036>

Mariotti, A., and Coauthors, 2020: Windows of Opportunity for Skillful Forecasts. Subseasonal to Seasonal and Beyond. *Bull. Amer. Meteor. Soc.*, **101**, E608–E625, <https://doi.org/10.1175/BAMS-D-18-0326.1>.

Merryfield, W. J., J. Baehr, L. Batté, E. J. Becker, and co-authors, 2020: Current and emerging developments in subseasonal to decadal prediction. *Bull. Amer. Meteor. Soc.*, **101**(6), E869–E896.

Miralles, D. G., P. Gentile, S. I. Seneviratne, and A. J. Teuling, 2019: Land–atmospheric feedbacks during droughts and heatwaves: state of the science and current challenges. *Ann. N. Y. Acad. Sci.*, **1436**, 19–35, <https://doi.org/10.1111/nyas.13912>.

Molteni, F., Brookshaw, 2023: A. Early- and late-winter ENSO teleconnections to the Euro-Atlantic region in state-of-the-art seasonal forecasting systems. *Clim Dyn* **61**, 2673–2692. <https://doi.org/10.1007/s00382-023-06698-7>

Muñoz, Á. G., and Coauthors, 2019: NextGen: A next-generation system for calibrating, ensembling and verifying regional seasonal and subseasonal forecasts. 2019 Fall Meeting, San Francisco, CA, Amer. Geophys. Union, Abstract A23U-3024, <https://agu.confex.com/agu/fm19/meetingapp.cgi/Paper/581954>

Murphy, J. M., 1988: The impact of ensemble forecasts on predictability. *Quart. J. Roy. Meteor. Soc.*, **114**, 463–493.

Nebel, D. M., C. I. Garfinkel, J. Cohen, D. I. Domeisen, J. Rao and C. Schwartz, 2024: The predictability of the downward versus non-downward propagation of sudden stratospheric warmings in S2S hindcasts. *Geophysical Research Letters*, **51**(16), e2024GL110529.

Osman, M., D. I. Domeisen, A. W. Robertson and A. Weisheimer, 2023: Subseasonal to decadal predictions in support of climate services. *Climate Services*, **30**, 100397.

Osman, M., Beerli, R., D. Büeler and C. M. Grams, 2023: Multi-model assessment of subseasonal predictive skill for year-round Atlantic–European weather regimes. *Q. J. R. Meteorol. Soc.*, 149(755), 2386–2408. Available from: <https://doi.org/10.1002/qj.4512>

Palmer, T. N., and Coauthors, 2004: Development of a European Multimodel Ensemble system for Seasonal-to-Interannual Prediction (DEMETER). *Bull. Amer. Meteor. Soc.*, **85**, 853–872, <https://doi.org/10.1175/BAMS-85-6-853>.

Pyrina, M. and Domeisen, D.I.V., 2022: Sub-seasonal predictability of onset, duration, and intensity of European heat extremes. *Q. J. R. Meteorol. Soc.*, 149(750), 84–101. <https://doi.org/10.1002/qj.4394>

Qin J, L. Zhou L, B. Li and Z. Meng, 2022: Prediction of the Central Indian Ocean Mode in S2S Models. *Front. Mar. Sci.*, 9, 9:880469. doi: 10.3389/fmars.2022.880469

Quinting, J. F and F. Vitart, 2019: Representation of synoptic-scale Rossby wave packets and blocking in the S2S prediction project database. *Geophysical Research Letters*, 46, 1070-1078. <https://doi.org/10.1029/2018GL81381>

Risanto, C. B., H. I. Chang, T. M. Luong, and co-authors, 2024: Retrospective subseasonal forecasts of extreme precipitation events in the Arabian Peninsula using convective-permitting modeling. *Clim Dyn* **62**, 2877–2906. <https://doi.org/10.1007/s00382-022-06336-8>

Robertson, A.W. and F. Vitart (Eds), 2019: Subseasonal to seasonal forecasting: The gap between weather and climate forecasting (pp. 1–585). Amsterdam: Elsevier.

Robertson, A. W., N. Vigaud, J. Yuan, and M. K. Tippett, 2020: Toward Identifying Subseasonal Forecasts of Opportunity Using North American Weather Regimes. *Mon. Wea. Rev.*, 148, 1861–1875, <https://doi.org/10.1175/MWR-D-19-0285.1>

## The WWRP/WCRP S2S project and its achievements

Scaife, A.A., Smith, D. A signal-to-noise paradox in climate science. *npj Clim Atmos Sci* **1**, 28 (2018). <https://doi.org/10.1038/s41612-018-0038-4>

Scaife, A. A., M. P. Baldwin, A. H. Butler, A. J. Charlton-Perez, D. I. Domeisen, C. I. Garfinkel, and co-authors, 2022: Long-range prediction and the stratosphere. *Atmospheric chemistry and physics*, 22(4), 2601-2623.

Schumacher, D. L., J. Keune, C. C. van Heerwaarden, J. V.-G. de Arellano, A. J. Teuling, and D. G. Miralles, 2019: Amplification of mega-heatwaves through heat torrents fuelled by upwind drought. *Nat. Geosci.*, 12, 712–717, <https://doi.org/10.1038/s41561-019-0431-6>.

Schwartz, C., C. I. Garfinkel, P. Yadav, W. Chen, and D. I. Domeisen, 2022: Stationary wave biases and their effect on upward troposphere–stratosphere coupling in subseasonal prediction models. *Weather and Climate Dynamics*, 3(2), 679-692.

Seo, E., Lee, M.I., Jeong, J.H. and co-authors, 2019: Impact of soil moisture initialization on boreal summer subseasonal forecasts: mid-latitude surface air temperature and heat wave events. *Clim Dyn* **52**, 1695–1709. <https://doi.org/10.1007/s00382-018-4221-4>

Skinner, D.T., A. J. Matthews and D. P. Stevens, 2022: North Atlantic Oscillation response to the Madden–Julian Oscillation in a coupled climate model. *Weather*, 77: 201-205. <https://doi.org/10.1002/wea.4215>

Stan, C., C. Zheng, E. K. Chang, D. I. Domeisen, C. I. Garfinkel, A. M. Jenney H. Kim, Y. Lim, H. Lin, A. Robertson, A., C. Schwartz, F. Vitart, J. Wang and P. Yadav, 2022: Advances in the prediction of MJO-Teleconnections in the S2S forecast systems, *Bull. Amer. Meteor. Soc.*, 103, E1426–E1447. <https://journals.ametsoc.org/view/journals/bams/aop/BAMS-D-21-0130.1/BAMS-D-21-0130.1.xml>

Spaeth, J., P. Rupp, M. Osman, C. M. Grams and T. Birner, 2024: Flow-dependence of ensemble spread of subseasonal forecasts explored via North Atlantic-European weather

regimes. *Geophysical Research Letters*, 51, e2024GL109733. <https://doi.org/10.1029/2024GL109733>

Swinbank, R. and Coauthors, 2016: The TIGGE Project and its Achievements. *Bull. Amer. Meteor. Soc.*, 97, 46-67, <https://doi.org/10.1175/BAMS-D-13-00191.1>

Takaya, Y., K.K. Komatsu, N. G. Ganeshi, and co-authors, 2024: A sub-monthly timescale causality between snow cover and surface air temperature in the Northern Hemisphere inferred by Liang–Kleeman information flow analysis. *Clim Dyn* **62**, 2735–2753 (2024). <https://doi.org/10.1007/s00382-024-07112-6>

Tian, D., E. F. Wood and X. Yuan, 2017: CFSv2-based subseasonal precipitation and temperature forecast skill over the contiguous United States. *Hydrology and Earth System Sciences*, 21(3), 1477-1490.

Tompkins, A. M., and Coauthors, 2017: The Climate-System Historical Forecast Project: Providing open access to seasonal forecast ensembles from centers around the globe. *Bull. Amer. Meteor. Soc.*, 98, 2293–2301, <https://doi.org/10.1175/BAMS-D-16-0209.1>

van Straaten, C., K. Whan, D. Coumou, B. van den Hurk, and M. Schmeits, 2022: Using Explainable Machine Learning Forecasts to Discover Subseasonal Drivers of High Summer Temperatures in Western and Central Europe. *Mon. Wea. Rev.*, **150**, 1115–1134, <https://doi.org/10.1175/MWR-D-21-0201.1>.

Vigaud, N., A. W. Robertson, and M. K. Tippett, 2017: Multimodel Ensembling of Subseasonal Precipitation Forecasts over North America. *Mon. Wea. Rev.*, 145, 3913–3928, <https://doi.org/10.1175/MWR-D-17-0092.1> .

Vigaud, N., M. K. Tippett, and A. W. Robertson, 2019: Deterministic Skill of Subseasonal Precipitation Forecasts for the East Africa-West Asia sector from September to May. *Journal*



## The WWRP/WCRP S2S project and its achievements

of Geophysical Research: Atmospheres, 124, 11887– 11896.

<https://doi.org/10.1029/2019JD030747>

Vigaud, N., A. Robertson, and M. K. Tippett, 2018: Predictability of Recurrent Weather Regimes over North America during Winter from Submonthly Reforecasts. *Mon. Wea. Rev.*, 146, 2559–2577, <https://doi.org/10.1175/MWR-D-18-0058.1>.

Vitart, F., and Coauthors, 2017: The Subseasonal to Seasonal (S2S) Prediction Project Database. *Bull. Amer. Meteor. Soc.*, **98**, 163–173, <https://doi.org/10.1175/BAMS-D-16-0017.1>

Vitart, F., 2017: Madden—Julian Oscillation prediction and teleconnections in the S2S database. *Q.J.R. Meteorol. Soc.*, 143: 2210-2220. <https://doi.org/10.1002/qj.3079>

Vitart, F., Robertson, A.W, 2018: The subseasonal to seasonal prediction project (S2S) and the prediction of extreme events. *npj Clim Atmos Sci* 1, 3. <https://doi.org/10.1038/s41612-018-0013-0>

Vitart, F. and Takaya, Y., 2021: Lagged ensembles in subseasonal predictions. *Q. J. R. Meteorol. Soc.*, 147(739), 3227–3242. Available from: <https://doi.org/10.1002/qj.4125>

Vitart, F., A.W. Robertson, and Coauthors, 2022a: Outcomes of the WMO Prize Challenge to Improve Subseasonal to Seasonal Predictions Using Artificial Intelligence. *Bull. Amer. Meteor. Soc.*, 103, E2878–E2886, <https://doi.org/10.1175/BAMS-D-22-0046.1>.

Vitart, F., M.A. Balmaseda, L. Ferranti and M. Fuentes, 2022b: The next extended-range configuration for IFS Cycle 48r1. *ECMWF Newsletter* 173 (Autumn 2022), 21-26. [https://www.ecmwf.int/sites/default/files/elibrary/102022/20502-newsletter-no-173-autumn-2022\\_0.pdf](https://www.ecmwf.int/sites/default/files/elibrary/102022/20502-newsletter-no-173-autumn-2022_0.pdf)

## The WWRP/WCRP S2S project and its achievements

White, C. J., and Coauthors, 2022: Advances in the Application and Utility of Subseasonal-to-Seasonal Predictions. *Bull. Amer. Meteor. Soc.*, **103**, E1448–E1472, <https://doi.org/10.1175/BAMS-D-20-0224.1>.

Xu, L., and P. Dirmeyer, 2013: Snow–Atmosphere Coupling Strength. Part II: Albedo Effect Versus Hydrological Effect. *J. Hydrometeorol.*, **14**, 404–418, <https://doi.org/10.1175/JHM-D-11-0103.1>.

Xue, Y., and Coauthors, 2021: Impact of Initialized Land Surface Temperature and Snowpack on Subseasonal to Seasonal Prediction Project, Phase I (LS4P-I): organization and experimental design. *Geosci. Model Dev.*, **14**, 4465–4494, <https://doi.org/10.5194/gmd-14-4465-2021>.

Wang, J., H. Kim, D. Kim, S. A. Henderson, C. Stan, and E. D. Maloney, 2020a: MJO teleconnections over PNA region in climate models. Part I: Performance- and process-based skill metrics. *Journal of Climate*, **33**, 1051–1067.

Wang, J., H. Kim, D. Kim, S. A. Henderson, C. Stan, and E. D. Maloney, 2020b: MJO teleconnections over PNA region in climate models. Part II: Impacts of MJO and basic state. *Journal of Climate*, **33**, 5081–5101.

Wang, X., S. Li, L. Liu, L. H. Bai, and G. Feng, 2022: The Performance of S2S Models on Predicting the 21.7 Extreme Rainfall Event in Henan China. *Atmosphere*, **13**, 1516. <https://doi.org/10.3390/atmos13091516>

White, C.J., and co-authors, 2017: Potential applications of subseasonal–to–seasonal (S2S) predictions. *Meteorological Applications*, **24**, 3, <https://doi.org/10.1002/met.1654>

White, C. J., and co-authors, 2022: Advances in the application and utility of subseasonal-to-seasonal predictions, *Bull. Amer. Meteor. Soc.*, **103**(6), E1448–E1472, <https://doi.org/10.1175/BAMS-D-20-0224.1>

## The WWRP/WCRP S2S project and its achievements

Wicker, W., I. Polichtchouk, and D. I. Domeisen, 2023: Increased vertical resolution in the stratosphere reveals role of gravity waves after sudden stratospheric warmings. *Weather and Climate Dynamics*, 4(1), 81-93.

Williams, N. C., A. A. Scaife and J. A. Screen, 2023: Underpredicted ENSO teleconnections in seasonal forecasts. *Geophysical Research Letters*, 50, e2022GL101689. <https://doi.org/10.1029/2022GL101689>

Woolnough, S.J., and coauthors, 2024: Celebrating 10 Years of the Subseasonal to Seasonal Prediction Project and Looking to the Future. *Bull. Amer. Meteor. Soc.*, 105, E521-E426, <https://doi.org/10.1175/BAMS-D-23-0323.1>

Wulff, C. O. and D. I. V. Domeisen, 2019: Higher subseasonal predictability of extreme hot European summer temperatures as compared to average summers. *Geophysical Research Letters*, 46, 11520–11529. <https://doi.org/10.1029/2019GL084314>

Zampieri, L., Goessling, H. F., & Jung, T. (2018). Bright prospects for Arctic sea ice prediction on subseasonal time scales. *Geophysical Research Letters*, 45(18), 9731-9738

Zhu, H., H. Chen, Y. Zhou, and X. Dong, 2019: Evaluation of the subseasonal forecast skill of surface soil moisture in the S2S database. *Atmospheric Ocean. Sci. Lett.*, 12, 467–474, <https://doi.org/10.1080/16742834.2019.1663123>.