Sub-Seasonal to Seasonal Prediction: linking weather and climate

1. Introduction

There is a growing interest in the scientific, operational and applications communities in developing forecasts that fill the gap between medium-range weather forecasts (up to 2 weeks) and long-range or seasonal ones (3–6 months). Ten years ago, only a couple of operational centres were producing forecasts at the sub-seasonal time range. Today, at least ten operational Centres, are issuing sub-seasonal to seasonal forecasts routinely.

To bridge the gap between medium-range weather forecasts and seasonal forecasts, WWRP and WCRP have recently launched a new initiative called the Sub-seasonal to Seasonal prediction project (S2S) whose main goal is to improve forecast skill and understanding of the sub-seasonal to seasonal timescale, and to promote its uptake by operational centres and exploitation by the applications communities (www.s2sprediction.net). Sub-seasonal to seasonal prediction is also central to several U.S. initiatives, such as the North-American Multi Model Ensemble (NMME) of seasonal forecasts funded by NOAA. There are also efforts in the U.S. to enhance collaboration between agencies (Navy, NOAA, NASA, NSF) for the development and implementation of an improved earth system prediction capability (ESPC) on time scales from a few days, to weeks, months, seasons and beyond. This interest in sub-seasonal prediction has been triggered by a growing demand from applications but also from progress in medium-range forecasting over the past decades and by progress in better simulating key sources of predictability for sub-seasonal to seasonal prediction, like the MJO and its teleconnections (e.g. Lin et al 2009, Vitart 2014).

Sub-seasonal forecasting is at a relatively early stage of development and represents a clear gap between the weather and climate communities. Many issues remain to be solved and coordination among forecast producers improved before the full potential of sub-seasonal prediction can be realised. There are glimpses of potential predictability well beyond the range of normal numerical weather prediction (NWP) (~10 days), but the range of processes involved is not yet fully understood. It is likely that predictive skill will be higher in certain windows of opportunity (e.g. as shown for Australia by Hudson et al. 2011), but exactly what these are or how to anticipate them is still unclear. The relevant science issues, ranging from sources of predictability, forecasting systems design, forecast quality assessment (verification) to the final integration of these forecasts in user application, that need to be addressed are reviewed in this article.

2. Relevant phenomenon for sub-seasonal to seasonal predictions and predictability

The sources of sub-seasonal predictability are associated with various phenomena and processes in the atmosphere, ocean and land, although they are not yet fully understood. The main ones are:

1) The Madden Julian Oscillation: The MJO is the dominant intraseasonal mode of organized convective activity in the tropics, and has considerable impact in the middle and high latitudes as

well; it is considered to be a major source of global predictability on the sub-seasonal time scale (e.g. *Waliser 2011*). Considerable efforts have been made on the prediction of the MJO. Several empirical and statistical models have been developed to predict the MJO (e.g. *Waliser et al. 1999; Lo and Hendon 2000; Wheeler and Weickmann 2001; Mo 2001; Jones et al. 2004; Maharaj and Wheeler 2005; Jiang et al. 2008*). The useful predictive skill of the MJO from these empirical models can reach a lead time of about 15–20 days. Regarding dynamical models, ensemble prediction systems (EPS) have shown remarkable improvements in MJO forecast skill in recent years. About 10 years ago, the actual forecast skill of the MJO by all the dynamical models was considerably lower than that of the empirical models (e.g. *Chen and Alpert 1990; Jones et al. 2000; Hendon et al. 2000*). In general these studies using dynamical models found some MJO skill only out to about 7–10 days. Recently, skilful MJO forecasts have been reported beyond 20 days (e.g. *Kang and Kim 2010; Rashid et al. 2010; Vitart and Molteni 2010; Wang et al. 2014*). This progress can be attributed to model improvement and better initial conditions, as well as the availability of historical reforecasts to calibrate the forecasts. However, limitations persist, and in particular the Maritime Continent is perceived to be a natural predictability barrier for the MJO; this is exacerbated in models by its poor physical understanding and by limitations in model representations of MJO - Maritime Continent interactions. Several modelling studies (e.g. Vitart and Molteni 2010, Weaver et al. 2011) have shown that numerical models have difficulties propagating the MJO across the Maritime Continent.

2) Soil moisture: Memory in soil moisture can last several weeks which can influence the atmosphere through changes in evaporation and surface energy budget and can affect the forecast of air temperature and precipitation in certain areas during certain times of the year on intraseasonal time scales as demonstrated by the GLACE experiment (Koster et al, 2010). The GLACE experimental protocol consists in running a first series of model integrations where the land has been properly initialized and a second series of integrations where the land initial conditions have been randomized. Three different studies have focused respectively on the United States, Europe and the global domain as documented in Koster et al. (2009), van den Hurk et al. (2012), Koster et al. (2010), respectively. The three studies showed the added value from realistic initialization of the soil moisture, measured in terms of predictability gain of 2m temperature and precipitation on US and Europe (Figure 15) with forecasts lead-time ranging from 16 to 60 days ahead. Continental US has generally higher potential predictability and this is also mirrored in the actual predictability results. It is remarkable that for temperature at 2m also over Europe the predictability gain obtained from better soil moisture initial conditions, extends significantly beyond the ranges typically considered in NWP (and up to 16-30 days ahead), and capable of detecting also extreme events such as summer 2003 (e.g. Weisheimer et al. 2011)

3) Snow cover and sea ice: The radiative and thermal properties of extensive snow cover anomalies have the potential to modulate local and remote climate over monthly to seasonal time scales (e.g. Yang et al. 2001; Sobolowski et al., 2010; Lin and Wu 2011). Sea ice cover could also

provide a source of memory that is not present at the lower latitudes. This may enable some predictive skill at longer time scales in polar and mid latitudes (*Holland et al. 2011*). The degree to which sea ice anomalies influence the atmosphere locally and remotely in the mid-latitudes is not yet fully understood. Modelling results do suggest, however, that sea ice anomalies can influence the atmosphere, especially in the sea ice margin zones of the Labrador Sea and Greenland-Icelandic-Norwegian seas (*Deser et al. 2007*). Progress in sub-seasonal to seasonal polar prediction hinges on significant improvements to the polar observing system, the way (coupled) models are initialized and the way key polar processes such as stable boundary layers and sea ice are represented in numerical models. A further challenge is the representation of initial and model uncertainty in the polar regions which might require modifications to the techniques which have been successfully used in the lower latitudes. Observational data is particularly limited in polar regions, leading to a large reliance on satellite observations. While satellite observations provide a useful characterization of some atmosphere and sea ice conditions, they provide little information on the underlying ocean. Issues with observational data sparseness, incompleteness, and bias are a critical challenge in terms of adequately initializing coupled model forecasts. Furthermore, satellite data are usually not sufficient when it comes to improving models at the processes level.

4) Stratosphere-troposphere interaction: Changes in the polar vortex and the Northern Annular Mode/Arctic Oscillation (NAM/AO) are often seen to come from the stratosphere, with the anomalous tropospheric flow lasting up to about two months (*Baldwin et al., 2003)*. Perturbation experiments also reproduce negative NAO/AO in response to weakened stratospheric winds on both seasonal and longer timescales (for example, *Boville 1984, Norton et al. 2003, Scaife et al. 2005, Scaife and Knight 2008*). *Jung et al. (2010)* found that relaxation of the extra-tropical stratosphere to the observed state leads to forecast error reduction in the high latitude and European troposphere, but that the tropical stratosphere has no such impact. They caution the interpretation of these results, however, as the troposphere strongly influences the NH stratosphere and other studies suggest a role for the tropical QBO on the extra-tropical surface climate (*Boer and Hamilton 2008, Marshall and Scaife 2010*).

5) Ocean conditions: Anomalies in SST lead to changes in air-sea heat flux and convection which affect atmospheric circulation. The tropical intraseasonal variability (ISV) forecast skill is found to be improved when a coupled model is used (e.g. *Woolnough et al. 2007; Fu et al. 2007*). The time scale of sub-seasonal prediction is such that the influence of initial conditions on the predictability is on the wane while the contribution from slowly evolving oceanic conditions may be on the rise. For this intermediate range, realistic representation of ocean-atmosphere coupling can be important for at least two reasons. It is possible that as the contribution of atmospheric initial conditions on the prediction skill goes down, the relative contribution of including a realistic ocean-atmosphere coupling on prediction skill increases. However, the potential contribution of realistic ocean-atmosphere coupling on prediction skill relative to initial conditions, and how this contribution changes with lead time, has not been quantified. The answer to this question primarily depends on the role of ocean-atmosphere coupling in constraining the atmospheric variability. It is also conceivable that correct representation of ocean-atmosphere coupling may be important for some specific phenomena, e.g. prediction of intensity and tracks of hurricanes, Madden Julian Oscillation etc., while it may not be of importance for atmospheric variability in high latitudes.

6) Tropics-Extratropics Teleconnections: There is great potential gain in sub-seasonal forecast skill in mid-latitudes if the model can capture the atmospheric teleconnections associated with MJO. However, many scientific questions remain to be answered. For example, what is the relative importance of tropical convection in generating teleconnections in comparison to other dynamical processes such as interactions with synoptic-scale eddies? What are the processes involved in the initiation of tropical convection by Rossby wave-trains propagating from the extratropics into the tropics? There has not been a systematic assessment of how the current models perform in simulating global teleconnections on the sub-seasonal time scale, especially for those related to tropical-extratropical interactions. How the models differ and what determines a model's ability to capture the teleconnections are also unclear.

3. Extreme events

Extremes are an area of clear common interests to the climate and user communities, spanning both climate attribution and real-time early warning. There have been several predictability studies on the 2010 Russian heat wave (*Matsueda 2011; Dole et al. 2011*) and the 2010 Pakistan floods (*Webster et al. 2011; Lau and Kim 2011*). It was suggested that the 2010 Russian heat wave was predictable up to 9 days in advance (*Matsueda 2011*), and the Pakistan rainfall was predictable out to 6–8 days (*Webster et al. 2011*). Both of the extreme events were related to an extraordinary strong and prolonged extratropical atmospheric blocking event, and excitation of a large-scale atmospheric Rossby wavetrain spanning western Russia, Kazakhstan, and north western China/Tibetan Plateau region. A connection with the monsoonal intraseasonal oscillation was also found (*Lau and Kim 2011*). The extremely warm March 2012 over US is a good example of how conditional information on different time scales enters into the prediction problem. Dole et al (2014) showed that probability for extreme warmth evolved dynamically as different phenomena became predictable across time scales from climate (PDO and ENSO) to MJO and weather, necessitating a seamless approach.

The predictability of extreme events at the sub-seasonal time scale often originates from the modulation of extreme events by the large scale circulation (e.g. Marshall et al. 2013; White et al. 2013). For instance, White et al (2013) showed that the increased skill of the POAMA sub-seasonal to seasonal coupled model prediction system to predict extreme heat in the winter months over northern Australia comes mainly from La Nina periods and over eastern and south-eastern Australia from El Nino periods, highlighting the impact of ENSO events for sub-seasonal forecasts. Identifying such windows of forecast opportunity requires a reforecast set that spans a sufficiently long period, particularly when associated with low frequency variability such as ENSO. Numerous studies have also shown the impact of the MJO on the probability of extreme events, like tropical cyclones (TCs). The modulation of TC numbers by the phase of the MJO has been quoted to be as high as 4:1 in some locations (e.g., Hall et al. 2001; Maloney and Hartmann 2000a). Statistical and dynamical models have been developed to predict the genesis or occurrence of TCs at the intraseasonal time range (Leroy et al. 2004; Frank and Roundy 2006; Leroy and Wheeler 2008, Vitart et al. 2010).

Recently, the skill of the ECMWF monthly forecasting system for predicting tropical storm modulation of TC activity has been demonstrated, prompting a comparison of the skill and reliability of the statistical and dynamical models (Vitart et al. 2010).

Heat waves and cold waves are amongst the weather events which have the strongest societal impact. This is particularly true for the heat waves during the warm season and the cold waves during the cold seasons. For instance, the 2003 summer heat wave over Europe was particularly intense. Its overall impact on society has been exceptional, with severe disruption of activities and heavy loss of life in many European countries. Health authorities estimated that, because of the soaring temperatures, about 14,000 died in France alone, and thousands more casualties were reported in other countries. The prediction of the evolution of such an extreme event (onset, maintenance, decay) a few weeks in advance would be particularly useful. Blocking diagnosis and the use of daily circulation regimes in forecasts and observations can be used to understand sub-seasonal to seasonal predictability of weather extremes in mid-latitudes through tropical-extratropical teleconnections, as well as flow dependent predictability. Prediction systems with demonstrated skill can also help diagnose causes with implications for climate change attribution of extreme events.

4. Design of forecast systems

4.1 Initialization

The approach for medium-range forecasting has been to use the most accurate initial conditions as possible for the atmosphere and to largely ignore the more slowly varying ocean conditions. For seasonal prediction, the initial conditions of the coupled system are important, particularly the upper ocean, and the rapidly varying components of the atmosphere are often less well predicted and initialised. The solution for the sub-seasonal timescale probably lies somewhere in-between. Forecasts in this timescale are influenced by initial conditions of both the fast (i.e. atmosphere) and slow (i.e. ocean,land and cryosphere) components of the coupled system. A major challenge for data assimilation and initialisation of sub-seasonal forecasts is addressing these different time and space scales of the atmosphere and ocean, and trying to exploit information from both the fast and slow components.

The most common approach is to analyse and initialise the atmosphere and ocean components separately. Quite sophisticated schemes are generally used to analyse the atmospheric state, such as 4d-var or EnKF. Ocean analysis techniques tend to be less sophisticated but EnKF and 4d-var techniques are being developed. However, it is not clear that uncoupled initialisation is optimal and coupled data assimilation is often mentioned as an objective, such that observed information in one component is used to correct fields in the other coupled components. Research and development for coupled data assimilation is still in relative infancy. There are no operational fully coupled data assimilation systems in existence, although weakly coupled schemes (e.g. assimilation into each component of the coupled model separately, but evolving the background states using the coupled model) are being developed or, in the case of NCEP, already implemented. Coupled assimilation should include land surface conditions and sea-ice, and thus provide a balanced initial state for the whole coupled system.

Initial conditions are required not only for real-time forecasts, but also back in time (reanalyses e.g. ERA-Interim) for initialising the reforecasts needed for calibrating the real-time forecasts. This raises a number of issues:

- What observations of the coupled atmosphere-land–ocean system are needed for capturing details of the initial conditions for successful sub-seasonal predictions? For example, how important are correct stratospheric initial conditions?
- How important is it to have consistency between the initial conditions of the reforecasts and real-time forecasts?
- There are differences between reanalyses used to initialise reforecasts. How accurate are these reanalyses in describing sub-seasonal variability in the real-world? Are some reanalyses better than others?

4.2 Perturbations

The representation of uncertainty in initial conditions has been approached by using random sampling, singular vectors, breeding schemes or lagged averaging. The representation of uncertainty in model formulation has been approached by using multi-model, stochastic physics or perturbed parameters ensembles (although the latter has only been used in climate change and multi-annual forecast experiments). Some studies (a.g. Weisheimer et al, 2014) have shown that stochastic physics has a positive impact on the representation of the MJO in sub-seasonal forecasts. Lee et al (2009) have also shown that sub-seasonal MJO forecasts produced by a multi-model ensemble were more skilful than the MJO forecasts produced by each model separately. The impact of stochastic physics or multi-model ensemble on other sub-seasonal skill scores in the Extratropics as well as in the Tropics need to be investigated.

The optimal ways of sampling uncertainty in the initial conditions needs to be explored. So far very few studies have tried to address this issue for sub-seasonal to seasonal prediction. Waliser et al (2014) have shown that all the current operational models display a spread in predicting the MJO that is too small relative to the RMS error. It is not clear if, for instance, the singular vectors used in some operational centres to perturb the initial conditions are appropriate for sub-seasonal forecasting. It is also not clear if the lagged-ensemble approach produces better sub-seasonal to seasonal forecasts than a “burst” ensemble. Hudson et al. (2013) showed significant improvements to the reliability and skill of sub-seasonal forecasts through the implementation of a breeding scheme compared to using a lagged-ensemble approach. Maybe, the focus should be on perturbing the slow modes of the coupled system, e.g. the MJO and annular mode. Some seasonal forecasting systems perturb the ocean, but maybe stochastic parameterisation should be extended to the ocean and land surface models to account for uncertainty in model formulation. Maybe the community should aim to produce coupled ocean-atmosphere perturbations.

4.3 Resolution

Current operational sub-seasonal to seasonal forecasting system display very different horizontal and vertical resolutions. Increased model resolution is expected to improve the forecast skill by allowing more physical processes to be resolved. Although the previous statement is derived mainly from work using atmosphere-only models, it is applicable to coupled models. For example, resolution plays an important role with respect to tropical/extra-tropical teleconnections (Toniazzo and Scaife, 2006) and the response of surface and boundary layer fluxes to sea surface temperatures. However, coupled models may need to get down to the Rossby radius of deformation (a few 10s of km) in the ocean in order for the atmosphere to respond to ocean variability (Minobe et al., 2008). The impact of resolution may depend on the phenomenon considered. For instance, higher resolution is known to have a positive impact on the representation of tropical cyclones.However, some studies suggest that increasing horizontal resolution had little impact on the representation and prediction of the MJO (e.g Vitart 2014), whereas other studies suggest that the MJO was sensitive to an increase in vertical resolution (Inness et al. 2001).

4.4. Systematic errors

Despite decades of effort devoted to model development, a number of persistent biases still exist in the CGCMs in e.g. tropical precipitation, low cloud cover (e.g. Randall et al. 2007) used in climate simulations and sub-seasonal and seasonal prediction. Some of these biases will arise solely from the errors in the component models and some may arise from misrepresentation of the coupling processes themselves. Furthermore the coupled feedbacks between the atmosphere and ocean may compound existing errors in individual components or generate new biases. A number of authors (e.g. Jakob 2003, Phillips et al. 2004) propose the use of initialized forecasts as a way to diagnose the development of systematic errors in models, both through the analysis of the very short range error growth using data assimilation increments, and through analysis of the time dependent growth of the initial error over the first few days of the forecast. To date much of this work has focused on atmospheric model development, making use of the regularly initialized operational forecasts, to provide a large database of the initial model error development. The increase in operational seasonal and sub-seasonal forecasting using coupled systems allows to extend such an approach for coupled models and allows the impact of the coupling on the error development to be assessed.

The identification of systematic errors requires a sufficiently large database of initialized forecasts to distinguish between random errors and systematic errors. Furthermore if error is flow dependent then sufficient examples of this flow state are required. Such analysis for sub-seasonal to seasonal forecasts relies heavily on the reforecast dataset which needs to be long enough with an ensemble size large enough to allow the estimation of systematic errors and also flow dependent errors. Such study also request the re-forecasts to share the same design as the real-time forecasts with initial conditions as consistent as possible with the real-time initial conditions.

4.5 Ocean-atmosphere coupling

As some of the operational monthly prediction systems are uncoupled and some are coupled, the contribution of ocean-atmosphere coupling on monthly and sub-seasonal predictions, together with the role of ocean-atmospheric coupling on modifying atmospheric variability is an important question for the design of operational monthly prediction systems. An implicit assumption for weather predictions based on atmospheric models alone is that because of slow evolution of SSTs, the skill of persisting initial SST analysis remains high (Jung and Vitart 2006). Whether this holds for the monthly time scales, and how the skill of persistence of SST forecasts compares with predictions based on coupled models remains an open question (Kumar et al. 2011).

Several studies have documented the impact of ocean-atmosphere coupling on some specific phenomena, e.g., prediction of intensity and tracks of hurricanes, Madden Julian Oscillation etc.. The vertical resolution of the ocean model, particularly in the top ocean layer, has been documented to have a significant impact on the MJO through a stronger diurnal cycle of sea surface temperature (Woolnough et al, 2007). The frequency of ocean-atmosphere coupling may also have an impact on sub-seasonal to seasonal forecasts through a better representation of the sea surface temperature diurnal cycle.

5. Approaches to integrate sub-seasonal to seasonal forecasts into applications

Sub-seasonal to seasonal prediction represents a great opportunity to help societal decision makers through skilful forecasts of extreme weather risk for instance, although some important challenges remain to make sub-seasonal forecasts sufficiently reliable and skilful for some applications. A great return on investment in climate science and model development is to be expected if the science of sub-seasonal to seasonal prediction can be successfully connected to societal applications. Weather-related hazards, including slow onset and chronic events such as drought and extended periods of extreme cold or heat, trigger and account for a great proportion of disaster losses, even during years with other very large geophysical events (e.g., Haitian and Chilean earthquakes). While many end-users have benefited by applying weather and climate forecasts in their decision-making, there remains ample evidence to suggest that such information is underutilized across a wide range of economic sectors (e.g., Morss et al., 2008; Rayner et al., 2005; O'Connor et al., 2005; Pielke and Carbone, 2002; Hansen, 2002). This may be explained in part by the presence of 'gaps' in our forecasting capabilities, for example at the sub-seasonal scale of prediction, and by a lack of understanding and appreciation of the complex processes and numerous facets involved in decision making.

Weather and climate span a continuum of time scales, and forecast information with different lead times is relevant to different sorts of decisions and early-warning. Extending downward from the seasonal scale, a seasonal forecast might inform a crop-planting choice, while sub-monthly forecasts could help irrigation scheduling and pesticide/fertilizer application, by making the cropping calendar a function of the subseasonal-to-seasonal forecast, and thus dynamic in time. In situations where seasonal forecasts are already in use, sub-seasonal ones could be used as updates, such as for estimating end-of-season crop yields. Sub-seasonal forecasts may play an especially important role where initial conditions and intraseasonal oscillation yield strong sub-seasonal predictability, while seasonal predictability is weak, such as in the case of the Indian summer monsoon. Extending upward from application of NWP, which is much more mature, there is a potential opportunity to extend flood forecasting with rainfall-runoff hydraulic models to longer lead times. In the context of humanitarian aid and disaster preparedness, the Red Cross Climate Centre/IRI have proposed a "Ready-Set-Go" concept for making use of forecasts from weather to seasonal, in which seasonal forecasts are used to begin monitoring of sub-seasonal and short-range forecasts, update contingency plans, train volunteers, and enable early warning systems ("Ready"); sub-monthly forecasts are used to alert volunteers, warn communities ("Set'); and, weather forecasts are then used to activate volunteers, distribute instructions to communities, and evacuate if needed ("Go"). This paradigm could be useful in other sectors as well, as a means to frame the contribution of subseasonal forecasts to climate service development within GFCS.

6. Forecast quality assessment

Forecast quality assessment (i.e. forecast verification) is a critical component of making forecasts useful to applications and seamless verification will be important for the sub-seasonal to seasonal time scale. For instance, the time windows for verifying short range forecasts is not the same as for seasonal forecasts, and a time averaging window equal to the forecast lead time could be a possible approach (Zhu et al, 2014). There is also a need to unify the verification methodology used for medium-range databases (TIGGE) and seasonal databases (CHFP, EUROSIP). In terms of science verification questions the S2S project will provide opportunities to address the following:

• What forecast quality attributes are important when verifying S2S forecasts and how they should be assessed?

• How should issues of short hindcast period availability and reduced number of ensemble members in hindcasts compared to real-time forecasts be dealt with when constructing probabilistic skill measures?

• How can the contributions of MJO and ENSO to S2S forecast skill be assessed (e.g. consider skill assessment conditioned on ENSO phases and try to identify opportunities for improved skill when MJO and ENSO are acting simultaneously)?

• How well do current S2S forecast systems predict active and break rainfall phases and wet/dry spells?

7. Conclusion

Recent publications (e.g. *Brunet et al. 2010; Hurrell et al. 2009; Shapiro et al. 2010; Shukla et al. 2010*) have stressed the importance of and need for collaboration between the weather and climate communities to better tackle shared critical issues, and most especially to advance sub-seasonal to seasonal prediction. Such an initiative would help bridge the gap between the numerical weather and short-term climate communities and be an important step towards a seamless weather/climate prediction system. Weather, climate, and Earth-system prediction services would greatly benefit from this joint effort. Based on this proposal and on the potential for improved forecast skill at the sub-seasonal to seasonal time range, a sub-seasonal prediction (S2S) research project has been established. Its main goal is to improve forecast skill and understanding on the sub-seasonal to seasonal timescale, and promote its uptake by operational centres and exploitation by the applications community (Vitart et al, 2012). To achieve many of these goals an extensive database is being established, containing sub-seasonal (up to 60 days) forecasts and reforecasts (sometimes known as hindcasts), modelled in part on the THORPEX Interactive Grand Global Ensemble (TIGGE) database for medium range forecasts (up to 15 days) and the Climate-System Historical Forecast project (CHFP) for seasonal forecasts. The research topics of the WWRP/WCRP Sub-seasonal to Seasonal Prediction project (S2S) are being organized around a set of five sub-projects (Madden-Julian Oscillation, Monsoons, Africa, Extremes and Verification), each intersected by the cross-cutting research and modeling issues, and applications and user needs discussed in the above. The draft science plans of each sub-project are available on line (http://www.s2sprediction.net/documents/reports), and it is hoped that these sub-projects will provide a vehicle for broad community research engagement in S2S. The database and these 5 sub-projects should help promote the use of sub-seasonal to seasonal forecasts in applications and also help answer some of the important scientific questions with have been mentioned in this article, like for instance:

- What is the importance of multi-model forecast for sub-seasonal to seasonal prediction
- What is the predictability of extreme events and how can we identify windows of opportunity for sub-seasonal to seasonal prediction?
- What is the best strategy for the initialization of the forecasting system, including ocean, land and cryosphere. What is the optimal way to perturb ensembles of sub-seasonal to seasonal forecasts
- What is the impact of horizontal and vertical resolution of atmosphere and ocean models on sub-seasonalt o seasonal forecasts
- What is the origin of the systematic errors which affect sub-seasonal to seasonal forecasts
- How are state-of-the-art models representing tropical-extra-tropical teleconnections?
- What forecast quality attributes are important when verifying S2S forecasts and how they should be assessed?
- What are current S2S forecasting capabilities for daily weather characteristics relevant to agriculture, water resource management and public health, such as heavy rainfall events, dry spells and monsoon onset/cessation dates?

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