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Potential applications of subseasonal-to-seasonal (S2S) predictions

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Abstract

While seasonal outlooks have been operational for many years, until recently the extended-range timescale - referred to as ‘subseasonal-to-seasonal’ (S2S) - has received little attention. S2S prediction fills the gap between short-range weather prediction and long-range seasonal outlooks. Decisions in a range of sectors are made in this extended-range lead time, therefore there is a strong demand for this new generation of forecasts. International efforts are underway to identify key sources of predictability, improve forecast skill and operationalise aspects of S2S forecasts, however challenges remain in advancing this new frontier. If S2S predictions are to be utilised effectively, it is important that along with science advances, we learn how to develop, communicate and apply these forecasts appropriately. In this study, we present the emerging operational S2S forecasts to the wider weather and climate applications community by undertaking the first comprehensive review of sectoral applications of S2S predictions, including public health, disaster preparedness, water management, energy and agriculture. We explore the value of applications-relevant S2S predictions, and highlight the opportunities and challenges facing their uptake. We show how social sciences can be integrated with S2S development - from communication to decision-making and valuation of forecasts - to enhance the benefits of ‘climate services’ approaches for extended-range forecasting. While S2S forecasting is at a relatively early stage of development, we conclude that it presents a significant new window of opportunity that can be explored for application-ready capabilities that could allow many sectors the opportunity to systematically plan on a new time horizon.

1 Introduction

There is growing interest across the applications community in understanding and using a new generation of extended-range weather predictions that are currently in development by meteorological centres around the world. While long-range monthly and seasonal outlooks have been operational in some regions for many years (and are the subject of increasing research initiatives to explore and advance their application) the extended-range timescale, which sits between the medium- to long-range forecasting timescales (i.e. beyond 10 days and up to 30 days), has received minimal attention until recently. This extended-range timescale has in recent years become referred to as the 'subseasonal-to-seasonal' (or 'S2S') forecasting range, and is generally regarded as bridging the gap between weather forecasts and monthly or seasonal outlooks (Figure 1a) (Vitart, 2014a; Robertson *et al.*, 2014; Kirtman *et al.*, 2014)[1]. This timescale has long been seen as a 'predictability desert' (Vitart *et al.*, 2012) as it is notoriously difficult to provide skilful predictions on subseasonal or monthly timescales (Hudson *et al.*, 2011), however recent advances have spurred an increasing interest in S2S prediction (Shapiro *et al.*, 2010; Brunet *et al.*, 2010). At least ten international weather centres now have some capability for issuing experimental or operational S2S forecasts, including the European Centre for Medium-Range Weather Forecasting (ECMWF), the National Oceanic and Atmospheric Administration (NOAA), the China Meteorological Administration (CMA) and the UK Met Office (UKMO) (Vitart, 2014a). While S2S forecasting is still in development, the potential availability of these

[1] Medium-, extended- and long-range definitions based on WMO meteorological forecasting ranges: http://www.wmo.int/pages/prog/www/DPS/GDPS-Supplement5-AppI-4.html.

forecasts provides a significant 'window of opportunity' whereby S2S predictions can start to be explored for both operational forecasting and application-focused capabilities to complement existing forecast services.

The ongoing World Meteorological Organization (WMO) World Weather Research Programme (WWRP)-World Climate Research Programme (WCRP) Sub-seasonal to Seasonal Prediction Project (Vitart *et al.*, 2012; Vitart, 2014a; Robertson *et al.*, 2014) (http://s2sprediction.net/) is aimed at improving forecast skill and understanding of the S2S timescale and promoting its uptake. This is the first collaboration between the WWRP and the WCRP, and contributes to the WMO Global Framework for Climate Services (GFCS) which aims to help society cope with extreme events through better forecast accuracy on longer lead times. A key output of this collaborative project is a data repository of near real-time S2S forecasts and hindcasts (Vitart *et al.*, 2016) produced by several operational meteorological institutions (http://apps.ecmwf.int/datasets/data/s2s and http://s2s.cma.cn), providing valuable repositories against which the potential skill of multiple model predictions on the S2S timescale can be evaluated, and their usability for societal applications assessed for the first time. This effort closely aligns with other WMO initiatives, such as the THORPEX Interactive Grand Global Ensemble (TIGGE) project, the HIWeather project that has identified connections to S2S timescales through the forecasting of weather-related hazards, and ongoing efforts through the WMO Lead Center for Long-Range Forecast Multi-Model Ensemble (LC-LRFMME) project to extend into the S2S timescale.

The expansion into S2S forecasting has been triggered by a combination of growing demand from the applications community and progress in identifying and simulating key sources of S2S predictability (Vitart, 2014a). Although there are efforts underway to operationalise aspects of S2S forecasts (Robertson *et al.*, 2014), the S2S timescale is a developing frontier for forecasting science. S2S forecasting represents a potential opportunity for a range of applications, potentially enabling many sectors to systematically react and plan. However, to date there has not been a coordinated effort to examine the potential of application-relevant forecasts on the S2S timescale and a demonstration of how these forecasts can be employed to maximise societal benefit.

This paper reviews the advances since Brunet *et al.* (2010) first promoted the WWRP-WCRP weather-climate collaboration to jointly tackle the development of S2S prediction science. Focusing on potential user applications, we draw on recent advancements to demonstrate the status and prospects of S2S prediction, highlighting how they can be utilised and where the key challenges remain.

2 Forecasting on the S2S timescale

Accurate climate prediction requires a good representation of weather phenomena as well as the underlying physical laws that apply to all prediction timescales (Bauer *et al.*, 2015). While short- to medium-range weather forecasting is based on initial atmospheric conditions, for seasonal prediction the initial conditions of the coupled land-ocean system are more important, with the rapidly varying components of the atmosphere often less well predicted and initialised. The S2S timescale falls in between these time ranges and is influenced by both initial conditions of the atmosphere and the more slowly evolving boundary conditions such as sea surface temperatures (SST), soil moisture and sea-ice components. It is these different time and space scales of the atmosphere, land and ocean - and the ability to predict them - which makes S2S forecasting a major challenge (e.g. Chen *et al.*, 2010; Doblas-Reyes *et al.*, 2013; Vitart, 2014a).

As with seasonal forecasting, S2S predictive skill relies on more than just realistic initialisation conditions and SST, but also large-scale circulation modes in the climate system, such as El Niño-Southern Oscillation (ENSO), Madden-Julian Oscillation (MJO), Indian Ocean Dipole (IOD) and North Atlantic Oscillation (NAO), and their known influence on specific weather phenomena including extreme events. For example, White *et al.* (2013), using the POAMA model, showed that increased skill in predicting extreme heat during the winter months over northern Australia comes mainly from La Niña periods, whereas skill over eastern and south-eastern Australia comes from El Niño periods, highlighting the importance of the state of ENSO for regional S2S prediction. S2S forecasts are, however, more generally limited geographically, working best in the tropics due to higher-frequency climate modes such as the Madden-Julian Oscillation (MJO), which is the dominant mode of convective activity in the mid to high latitudes and offers an enhanced source of predictability (e.g. Vitart, 2014a). MJO predictability, in particular, has improved significantly over the last decade, with MJO teleconnections over the Northern and Southern Extratropics improving dramatically through better representation of the MJO in the ECMWF model (Vitart, 2014b). The vertical resolution of the ocean component of forecasting systems, particularly in the top ocean layer, has also been documented to have a significant impact on the prediction of MJO on S2S timescales through a stronger diurnal cycle of SST (Woolnough *et al.*, 2007). Increased model resolution is expected to improve the forecast skill by allowing more physical processes to be resolved (Vitart, 2014a). Initial soil moisture conditions have also been shown to particularly increase the accuracy of both precipitation and temperature predictions on the S2S timescale, especially for summer extreme temperatures, however the utilisation of sea-ice conditions is a largely untapped and unknown source of potential predictability (Doblas-Reyes *et al.*, 2013).

A number of persistent biases and errors, however, still exist in most climate simulations, such as tropical precipitation and low cloud cover (e.g. Randall *et al.*, 2007). Some of these biases arise solely from the errors in the models and some may arise from the systematic misrepresentation of the coupled atmosphere-ocean feedbacks, which may compound existing errors or generate new biases (Brunet *et al.*, 2010; Vitart, 2014a). The lack of vegetation components and stratospheric disturbances in current forecast models are other impediments to improving forecasts on S2S timescales (Brunet *et al.*, 2010; Doblas-Reyes *et al.*, 2013).

3 The information gap

3.1 Unlocking the potential of S2S forecasting

Operational forecasting centres routinely issue weather and climate information products, but there remains a gap between what various industries and sectors of society need and what forecasters can produce. While weather forecasts have been proven to be useful for short-term decision-making (Brunet *et al.*, 2010), short-range weather forecasting - where predictability mainly comes from initial atmospheric conditions - has fundamental physical limits (i.e. up to about 10 days) (e.g. Slingo and Palmer, 2011). In contrast, instead of forecasting the weather for a given day, longer lead time forecasts provide information about the likelihood of averaged weather, such as rainfall totals, typically over periods up to a season in length. Seasonal forecasts do not predict the weather at a set location or time, instead they tell us about the likelihood of shifts from the normal climatic conditions - or put another way, a shift in the underlying probability distribution - where predictability is driven primarily by slowly varying components of the Earth System, such SST.

Society is used to short- to medium-term weather forecasts, but is still less familiar with longer lead time forecasts. Providing a forecast for increased/decreased likelihoods is not adequate for the need for reliable, actionable information on the timing, location and scale of weather events. For example, seasonal forecasts of oncoming 'colder than average' winters or 'hotter than average' summers - often delivered through mainstream media outlets - are the first stage of communication that can lead to a misinterpretation of what longer lead time forecasts are. Users are often exposed to someone's interpretation of forecasts, and the terminology typically used, such as 'increased or decreased likelihood' and 'normal conditions', are relative to past climate and therefore implicitly require additional knowledge to understand.

Communications issues therefore surround S2S forecasts given their probabilistic nature, yet it is recognised that to be of value S2S predictions must realistically represent day-to-day weather fluctuations and statistics (Brunet *et al.*, 2010). S2S predictions have the potential to support decision-makers through the ongoing development of skilful forecasts of high-impact weather events (e.g. Vitart, 2014a). For example, this has been demonstrated by skilful predictions of phenomena such as tropical cyclones on lead times of up to 28 days (Figure 2), but it is yet to be determined if S2S forecasts can predict such events with sufficient skill and reliability for many applications. Despite this, inroads have been made with forecast skill on the S2S timescale and there lies a largely unexplored middle ground between what is required and what is possible.

Vitart (2014a) also notes that while many end-users have benefited by applying weather and climate forecasts in their decision-making, there is evidence to suggest that such information is underutilised across a wide range of economic sectors (e.g. Rayner *et al.*, 2005; O'Connor *et al.*, 2005; Morss *et al.*, 2008). Indeed, there needs to be a distinction between what is 'useful' and what is 'usable' information, reflecting the different ways that forecasters and users perceive scientific information (Lemos *et al.*, 2012). Forecasters may make the assumption that knowledge is useful when they conduct research without fully understanding potential users' decision-making processes and contexts; in contrast, users may not know how they might make use of S2S forecasts (or may have unrealistic expectations) of how it fits within their decision-making processes and thus choose to ignore it, despite its usefulness (Lemos *et al.*, 2012).

It has been shown that an interactive, co-production approach to science and decision-making between information producers and users positively affects the rate of information use (e.g. Lemos and Morehouse, 2005; Feldman and Ingram, 2009; Lemos *et al.*, 2012) as well as the effective communication of decision-relevant science. Prioritising collaboration between scientists and those who rely on climate and weather information to make policy and management decisions through a 'co-exploration' approach supports this co-production of usable information (Meadow *et al.*, 2015; Steynor *et al.*, 2015), especially when exploring decisions where needs or sensitivities are yet to be identified. This iterative process explores the limits of climate model data in a place-based context that recognises the complex nature of decision-making and goes beyond the simplistic dichotomy of 'climate services' and 'end-users' by incorporating multifocal learning across the decision-making space (e.g. Hurrell *et al.*, 2009).

At the same time as understanding the 'information gap', there is a need to better understand user needs, including identify potential change agents and 'champions' who can communicate new information effectively, recognise competing stakeholder goals, and reception of user-centred information in innovative ways.

In support of understanding user needs, there is an additional need to increase awareness of the S2S timescale through better data visibility and accessibility. S2S data archives such as the North American Multimodel Ensemble (NMME; Kirtman *et al.*, 2014) and the new WWRP-WCRP S2S project repository are improving access to forecasts, as well as providing information about forecast uncertainty and quality (e.g. Slingo and Palmer, 2011). A lack of information about the accuracy of such forecasts precludes users from making effective use of them, whereas a more thorough understanding of forecast performance may help decision-makers determine how much and when to rely on them (Hartmann *et al.*, 2002). There may also be a lack of understanding and appreciation of the complexity of weather and climate processes and the yet-to-be quantified forecast skill on the S2S timescale (from the decision-makers' perspective) and of the numerous facets involved in decision-making (from the weather and climate scientists' point of view).

3.2 Putting the user first

S2S prediction is ultimately applied research with potentially significant value to society, and is an opportunity to create a scientific discipline characterised by co-design and co-production between the scientific and the application communities. Traditional applied research can be described by the linear (sequential) model of research and innovation where scientific discovery precedes innovation (i.e. the process in which the scientific findings are transferred into applications). A contrasting model is the 'user-centred' model of innovation (e.g. Lemos *et al.*, 2012), referred to as the 'climate services' concept, in order to meet the demand for customised climate-related tools, products and information (EU COM, 2015). This model puts an emphasis on the role played by users in the development and improvement of products and services, which can be used to illustrate the 'top-down' vs. 'bottom-up' debate[2].

Recent efforts in Europe, such as the EUPORIAS project (http://www.euporias.eu/) (e.g. Taylor *et al.*, 2015; Bruno Soares and Dessai, 2016), developed semi-operational prototypes of climate services to address the needs of specific users on seasonal to decadal timescales. By applying a similar user-centred climate services approach, the S2S research community could similarly increase the likelihood for successful development of S2S predictions. In doing so, the scientific community should focus on working with users to understand their decisions, including which ones are climate/weather-sensitive, and on what timescales; efforts to determine specifically what information might be of interest to users is then the next step after understanding the decisions (Ray and Webb, 2015). Decision-dependencies across a range of end-users could be determined through user-centred studies, including assessing which information, spatial and temporal scales and locations are most relevant to the seamless weather and climate services

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[2] There is an ongoing debate on the pros and cons of 'top-down' and 'bottom-up' approaches (e.g. Dessai and Hulme, 2004; Ray and Webb, 2015). The 'top-down' approach follows the sequence of first projecting future emissions of greenhouse gases, then developing climate scenarios, and thirdly studying impacts and adaptation options; in contrast, a 'bottom-up' approach starts from a given system and then studies vulnerabilities (i.e. the degree to which the system is susceptible to, and unable to cope with, adverse impacts of climate change). Most likely, the most successful approach for forecasting on longer lead times such as S2S needs to include a combination of both. For example, experience in the UK from a national 'top-down' probabilistic climate service demonstrated that although the probability-based climate information provided greater credibility, there was still a requirement to tailor the climate information generated so that stakeholders could use the information in decision-making (Tang and Dessai, 2012).

approach (e.g. Graham *et al.*, 2011; Vaughan and Dessai, 2014). However, the weather and climate community might engage with individual sectoral decision-makers in cases in which user studies have already matched the decision-maker with the forecast product. Scientists and users could co-develop tools and processes for fostering the joint development of S2S predictions, with stakeholder-based modelling (Voinov and Bousquet, 2010) or co-exploration/co-production processes (Lemos and Morehouse, 2005; Meadow *et al.*, 2015; Steynor *et al.*, 2015) involving the user-community not only as consumers, but as co-producers of climate information. Climate services need to move towards a demand-driven and science-informed approach and that boundary organisations will need to focus on use-inspired research (Lourenço *et al.*, 2015). Bringing partner boundary organisations into the process for co-production, co-exploration and communication of information, including translation of scientific products into usable formats, balances the trade-offs between salience, credibility and legitimacy and increases the potential overall uptake of climate information (McNie, 2007).

Collaboration and co-production across sectors and disciplines is key to narrowing the gap between S2S forecast information and application; a transformation is therefore needed in the way both industry and the weather and climate community conceptualise and communicate S2S predictions.

4 Potential sectoral applications of S2S predictions

The primary rationale for international efforts in pursuing a seamless weather-to-climate prediction process - which by default includes the S2S timescale - is that the resulting information influences decisions across predictive timescales, contributing to objectives such as protection of life and property, enhancement of socio-economic well-being, and sustainability of the environment (Brunet *et al.*, 2010). There is a range of efforts underway to operationalise aspects of S2S forecasts that may be used to demonstrate the potential value of applications-relevant S2S products, such as the NOAA Climate Prediction Center's operational outlooks and the Tropics Hazards and Benefits Outlook. However, S2S predictions provide new opportunities for 'user-centred' applications because many decisions fall into the interceding S2S timescale between the well established and utilised short- to medium-range weather forecasts on one side, and seasonal forecasts on the other. Where existing decision processes exist that already use information on these other time scales, there may be readiness to more easily uptake this new forecast information. S2S forecasts therefore provide a significant opportunity to provide actionable information on this relatively unexplored applications time horizon.

In the following section, we review some of the potential sectoral uses of S2S forecasts, highlighting key decisions that can be made on this timescale and their information requirements (Figure 1b).

4.1 Humanitarian sector

There is strong demand in the humanitarian sector for reliable longer-range forecasts (Braman *et al.*, 2012) - particularly of extreme events such as floods and droughts - and it is the S2S timescale where many risk reduction and disaster preparedness actions can be taken to mitigate impacts. S2S forecasts offer the opportunity for disaster risk reduction (DRR) managers to track the progress of the slowly evolving, large-scale climate modes that may have been predicted to shift in a preceding seasonal outlook, therefore supporting the transition from seasonal outlooks to weather forecasts to inform both disaster planning and systematic response (Tadesse *et al.*, 2016).

In this context, the Red Cross Climate Centre have adopted the 'Ready-Set-Go!' approach to decision-making for disaster management that utilises short- to long-range predictions (Goddard *et al.*, 2014). Seasonal forecasts can provide the 'Ready' monitoring information and early contingency planning such as volunteer training; subseasonal forecasts provide the 'Set' early warnings and alerting of volunteers; and short-range weather forecasts the 'Go!' activation stage, including evacuation and distribution of aid (Vitart *et al.*, 2014a). This concept highlights an increased/decreased likelihood of a particular event occurring over the forecast period, empowering DRR managers to adapt and react accordingly to instigate preparedness activities during the 'Set' phase as well as supporting the crucial shift to short-term actions in the 'Go!' phase.

Many of the disaster preparedness actions that can be taken based on increased risk of an extreme event require time to activate. Procurement of disaster response supplies can take several weeks (e.g. Boston Consulting Group, 2015) and is often the reason that actual response time to a disaster can lag well behind the event itself. While a short-term forecast allows for a head-start, a S2S forecast would allow for such response materials to be pre-purchased and prepositioned in the at-risk region in advance of the actual event, allowing for more immediate responses. Similarly, supplies needed for risk reduction actions, such as pesticides for mosquito fumigation, chlorine tablets for water purification, or sandbags to reinforce river banks, are subject to the same time constraints as the response materials. The prepositioning of emergency supplies has been shown to yield a return on investment of between 1.6 and 2.0 (Boston Consulting Group, 2015).

Continuing the ‘Ready-Set-Go!’ concept, there are a number of quick and resource-independent actions that can then be taken by vulnerable people a few days in advance of a potential disaster, including evacuation and preparing food or water to last through the emergency period. Such actions appear in heat wave early warning plans (e.g. Ebi *et al.*, 2003; Knowlton *et al.*, 2014) and cyclone preparedness plans (e.g. Roy *et al.*, 2015), which could be expanded to include ‘Ready’ actions within the S2S timescale. The Sendai Framework for Disaster Risk Reduction 2015-2030 (UNISDR, 2015) points to an opportunity to connect the joint weather and climate communities’ efforts surrounding S2S prediction to global DRR activities and planning, as well as utilising seamless forecasting and climate services approaches. Priority 4 of the Framework recommends investment in the development, maintenance and strengthening of people-centred, multi-hazard and multi-sectoral forecasting and early warning systems, developed through a participatory process and tailored to the needs of users.

Advances in S2S prediction - specifically if focused towards extreme events - could allow the humanitarian sector to systematically react before potential disasters, saving lives and livelihoods through a better informed early response.

4.2 Public health

Brunet *et al.* (2010) highlighted public health as one of the key potential domains of application of seamless weather-to-climate forecasts, where decisions cover a wide range of temporal scales that directly relate to positive health outcomes (e.g. expected disease outbreak patterns, available medical supplies, poverty indicators). Heat waves, for instance, are amongst the weather events that have the strongest societal impact with severe disruption of activities and significant loss of life. In the 2003 European heat wave, health authorities estimated that about 14,000 died in France alone (Vitart, 2005; Murray *et al.*, 2012). The prediction of the evolution of such an extreme event (including onset, persistence and decay) a few weeks in advance would be particularly useful (Vitart, 2014a). Case studies of subseasonal heat wave prediction are starting to demonstrate significant promise (e.g. Vitart, 2005; Hudson *et al.*, 2015), however, issues around the accuracy of forecasts - especially for predicting the timing, duration, location and severity of heat events (e.g. Perkins and Alexander, 2013) - as well as a lack of an internationally recognised definition, makes heat wave forecasting complex and difficult to tailor to individual users' needs.

The potential benefits of S2S applications are perhaps greatest in developing nations, especially in Africa where at least 30 climate-sensitive diseases pose a major threat to the lives and livelihoods of millions of people. More than 500 million Africans live in regions endemic with malaria that is highly correlated with the seasonal climate for example (Brunet *et al.*, 2010). Malaria forecasting on seasonal timescales has been well documented, including Morse *et al.* (2005) that show skilful one-month lead seasonal predictions using a malaria transmission model driven with output from seasonal predictions, and Thomson *et al.* (2006) and MacLeod *et al.* (2015) that demonstrate skilful malaria epidemic forecasts in Africa two months before the start of the season.

It is likely, however, that one of the major challenges with integrating S2S predictions into public health practices will be working with an initially less familiar (and perhaps less receptive) set of decision-makers than some other sectors. The necessary infrastructure (e.g. near real-time hospital patient data) may be in place in some regions to develop an operational weather-related hospital admissions forecast, but not in others. In developing country contexts, logistical access to forecasts and data has its own additional challenges and may be reliant on humanitarian disaster-related activities.

4.3 Energy

Weather-related risk is a primary driver for energy pricing, production and usage. Because formal decision-making processes already exist within the energy generation sector, it may be easier to develop successful relationships with this sector than many other sectors with less formal practices (Brunet *et al.*, 2010). For instance, it is routine practice for the wind energy sector to utilise short-range weather forecasts (Barthelmie *et al.*, 2008; Foley *et al.*, 2012) and, to a lesser degree, seasonal outlooks (Roulston *et al.*, 2003). Taylor and Buizza (2003), for example, show that energy demand scenarios based on ensemble predictions are more accurate than those produced using traditional weather forecasts up to 10 days in advance, therefore S2S forecasts could be used to support these activities by hedging for anticipated energy peaks and other weather-related energy trading opportunities and risks.

In recent years, wind power has experienced rapid growth, contributing close to 5% of global electricity production (Pryor and Barthelmie, 2010). One of the biggest challenges facing the wind power industry is intermittency, where energy grid operators must match production to demand at all times, irrespective of whether wind energy is produced or not (Albadi and El-Saadany, 2010). S2S wind speed forecasts could help address the challenge of intermittency by enabling transmission service operators to plan operations further ahead and increase grid efficiency (Pinson, 2013), although at present only mean wind values (zonal and meridional) are available on the S2S timescale. However, as S2S forecasts become more skilful and more complete, grid operators may further optimise the pricing system by using forecasts relevant to supply (e.g. wind speed for wind power, precipitation and temperature for hydropower operations) as well as demand (especially temperature) to inform switching on and off longer-start fuel sources like nuclear. This challenge of balancing a fluctuating wind energy resource with more stable energy sources will only grow as more wind power capacity is installed.

Related to this, S2S forecasts could be used to manage distribution and transmission infrastructure and maintenance scheduling. For example, specialist maintenance vessels are scheduled several weeks in advance for offshore wind farm maintenance and installation. Work is halted and money lost when high wind and waves prevent operations. Currently the decision to leave port is informed by current wave height and trend over previous hours, but a reliable S2S forecast of an optimal operational window could potentially save money and minimise risks.

4.4 Water management

Most international operational forecast centres issue flood forecasting and warning services based on short-range rainfall forecasts. At the other end of the forecasting timescale, many meteorological/hydrological centres have been issuing probabilistic seasonal streamflow forecasts as part of climate outlook services for many years; i.e. 3-month outlooks of total flow volumes rather than flood forecasts (e.g. Wood and Lettenmaier (2006) in the U.S.; Robertson and Wang (2012) in Australia) or have documented needs for S2S forecasts in short-term water management decisions (e.g. Raff *et al.*, 2013). Seasonal streamflow forecasts are contingent on climate information for short-term planning (e.g. water allocation) and setting up contingency measures during extreme years. However, the water allocated based on seasonal forecasts issued at the beginning of the season requires revision using updated (i.e. subseasonal) forecasts throughout the season (Sankarasubramanian *et al.*, 2009).

There have been some efforts to forecast streamflow on longer-range timescales, with Bennett *et al.* (2014) finding positive forecast skill for higher streamflows in the 1-month lead time in southeast Australia, Sankarasubramanian *et al.* (2009) modelling seasonal and subseasonal water allocation in the Philippines, and Werner *et al.* (2005) for operational streamflow forecasting in the U.S. Similarly, whilst specific flood predictions cannot be made on S2S lead times (i.e. they reflect risks but are not intended for predicting the timing, frequency, severity or extent of flood), S2S forecasts could be employed to highlight an increased chance of flooding where total streamflow volume has already been predicted to be high for a given season (White *et al.*, 2015). African hydrological centres, for example, would benefit from S2S forecasts of the onset and subseasonal evolution of the rainy season, whilst S2S forecasts of the frequency of daily rainfall amount could be relevant to rain-dependent agricultural applications and flood prediction in the tropics (Robertson *et al.*, 2014).

S2S forecasting therefore provides a significant opportunity to bring together the flood warning and streamflow forecasting communities in a seamless hydrological forecasting service, extending flood forecasting to longer lead times through the integration with rainfall-runoff hydrological models (White *et al.*, 2015), and improving water resource allocation and management decision-making on timescales less than a season.

4.5 Agriculture

The agriculture sector is one of the most advanced user groups in terms of using weather forecasts and outlooks to support operational decisions on the timing of irrigation, spraying and harvesting (e.g. Meinke and Stone, 2005; Harrison *et al.*, 2007 and references therein). Clements *et al.* (2013) show the S2S timeframe to be highly relevant in agriculture, noting studies that evaluated the use of meteorological information in agriculture for crop management, irrigation decisions, product marketing, input use (e.g. fertilizers), and commodity pricing. Using a similar approach to the 'Ready-Set-Go!' concept, by extending downward from the seasonal scale, a seasonal forecast of rainfall totals might inform strategic decisions regarding crop-planting choices, whereas S2S forecasts of rainfall extremes or heat waves could help irrigation scheduling and pesticide/fertilizer application (Vitart, 2014a). S2S forecasts could be used as dynamic updates to an existing cropping calendar, such as for the estimation of crop yields (Vitart, 2014a) to help alleviate global food security issues (CGIAR, 2009). Regional mechanisms such as the strong intraseasonal oscillation, which is a major cause of monsoon breaks within the Indian monsoon season, could add valuable information for irrigation scheduling.

The experienced user-base within the agriculture sector is very familiar with the need to express seasonal forecasts in terms of daily weather characteristics, such as dry spells during critical growth periods (e.g. Verbist *et al.*, 2010), and presents perhaps one of the best opportunities to bridge the gap between the weather and climate forecasting timescales. As weather impacts are just one of many stressors shaping users' decisions in the agriculture sector, to successfully integrate S2S forecasts into existing decision-making practices, highly participatory, context-specific dialogues, aided by modelling approaches bringing together producers and users of knowledge across disciplines, are needed (Meinke *et al.*, 2009).

4.6 Emerging sectors

There are many other sectors that could potentially benefit from skilful S2S forecasts but which have not yet been explored in detail. For example, S2S forecasts could be used to augment the existing use of seasonal environmental management forecasts, such as providing additional decision support information for marine fisheries and aquaculture (e.g. Spillman and Hobday, 2014), and wildfire risk management (Owen *et al.*, 2012). Similarly, S2S forecast applications that target the retail sector could be used for advanced stock orders where the timing of seasonal changes is important, or support preparedness ahead of extreme weather events such as heat waves (e.g. Hudson *et al.*, 2015), tropical cyclones/hurricanes (e.g. Vitart *et al.*, 2010), and snow (e.g. Cohen, 2003).

In a broader sense, the value of weather forecasts needs to be better understood and quantified. It has, however, proven difficult to isolate the benefits and assess the economic value of longer lead time forecasts in applications (Kumar, 2010). The financial derivatives markets and insurance industry understand the concept of weather-related risk and the application of forecasts (e.g. through hedging strategies, weather-based decision rules, loss scenarios) perhaps better than any sector (e.g. Zeng, 2000; Jewson and Caballero, 2003), which the weather and climate community can benefit from. For the potential benefits of S2S predictions to be fully realised, there needs to be a focus on economic impacts and benefits, understanding the asymmetry of the cost loss and benefit matrix, a measure of sensitivity of the impact of particular weather phenomena, and an understanding of how they could influence decision-making across sectors.

5 Challenges and opportunities of the S2S timescale

After three decades of research into seasonal climate predictability and the development of dynamical prediction systems (Kirtman *et al.*, 2014), there is substantial evidence that dynamic S2S prediction offers a significant opportunity to be useful to the applications community (Pegion and Sardeshmukh, 2011; Kirtman *et al.*, 2014). However, we find many challenges to the successful application of S2S predictions summarised in Table 1).

The potential utility of longer lead time forecasts by the applications community - including both S2S and seasonal - is based on end-user decision support (e.g. Morse *et al.*, 2005). To achieve this, an improved understanding of how perceptions, willingness and ability to use information changes across predictive timescales including S2S, and understanding how a piece of information goes from being useful to usable (Lemos *et al.*, 2012) is required, such as Bruno Soares and Dessai (2016) that provide examples of barriers and enablers to the uptake and use of long-range seasonal forecasts in Europe. The current lack of 'success stories' of S2S predictions (e.g. case studies that focus on a high-impact weather events or other successful uses) though needs to be addressed to support promotion of S2S forecasts and their integration into applications, which in turn would help raise awareness of the S2S prediction timescale and its potential uses.

The fundamental limits to skill of longer lead time predictions need to be identified to manage expectations of potential users. Brunet *et al.* (2010) suggests a practical first step is to determine where the greatest potential for use of S2S forecasts exists, and where the largest social benefit can be realised. Here, the social sciences (e.g. Demuth *et al.*, 2007) can contribute by identifying effective mechanisms for generating and communicating decision-relevant information, assessing the integration, use and value of this information in decision-making, transferring knowledge and experiences to other users (Brunet *et al.*, 2010) and understanding the context into which the information can be usable (Ray and Webb, 2015). A similar approach could advance the understanding of potential stakeholders, uses and research needs in the S2S timescale, potentially avoiding the applications community having unrealistic expectations of about S2S predictions, as well as the forecasting community understanding end-users' limitations on what information can be useful.

Raising awareness of both the S2S predictive timescale and the availability of such data provides a unique opportunity for a participatory approach across the weather and climate communities to develop decision-relevant information for a range of sectoral applications. The WWRP-WCRP S2S project's database of S2S forecasts co-hosted by ECMWF and the CMA (delayed behind real time by three weeks but including hindcasts), is a significant resource that will allow model output to be more widely assessed to identify when and where there is skill, better understand the underlying processes and model weaknesses, and develop applications that can support decision-making.

To address the science challenges of understanding and improving the predictive skill of S2S forecasts, identifying sources of predictability (including locations and times of skill), teleconnections to known climate modes, and quantifying the limitations and uncertainties of S2S forecasting are all areas of active research. Important modelling design issues remain, including initialisation techniques, initial conditions (e.g. soil moisture, sea-ice), model resolution and ensemble size, ocean-atmosphere coupling, post-processing and downscaling, and coordination between forecast producers all need to be improved before the full potential of S2S prediction can be realised (Vitart, 2014a). To address these issues, improved quantitative information regarding uncertainty in forecasts and probabilistic measures of forecast quality in their verification (e.g. Palmer *et al.*, 2004; DeWitt, 2005; Doblas-Reyes *et al.*, 2005; Slingo and Palmer, 2011) needs to be included with S2S forecasts. There is also a growing recognition that a multimodel ensemble strategy is a viable approach for resolving some of the forecast uncertainty (e.g. Doblas-Reyes *et al.*, 2005; Palmer *et al.*, 2008; Kirtman *et al.*, 2014), which will present additional data management and communication issues.

6 Conclusions

Since Brunet *et al.* (2010) recommended that the weather and climate communities collaborate to jointly tackle the challenge of providing skilful and useable S2S forecasts, many advancements have been made. Through initiatives and data repositories such as the WWRP-WCRP S2S project and the NMME, we are now in a position to explore some of the potential sectoral applications of S2S forecasts in earnest. However, their integration into decision-making is neither easy nor straightforward (Lemos *et al.*, 2012). For instance, although the ability to forecast the specific details of high-impact events within the S2S timescale is not yet possible (and perhaps may not be for some time), there exists a growing repository of untapped predictive information that presents tangible and realistic opportunities that can be explored by the applications community for socio-economic benefits.

Forecasts on the S2S timescale need to be tailored to specific users' needs and communicated in a way that allows the applications community to be able to make informed decisions. To achieve this, decision-makers and forecasters need to collaborate to determine essential S2S forecast attributes, including determining appropriate thresholds and their usefulness in decision-making, as well as their economic value (Hartmann *et al.*, 2002). Part of this involves the inclusion of realistic and unbiased messages on forecast skill (or lack thereof), potential usefulness and quantified uncertainties to manage expectations, as well as the continued integration of S2S as a key component in the concepts of seamless prediction and co-production.

There are three broad categories that require attention, each of which present their own set of challenges and opportunities: 1) identifying where and when the skill of the S2S forecasts lie and how they could be improved, 2) quantifying and addressing systematic model deficiencies, errors and uncertainties, and 3) communicating and delivering forecasts in collaboration with the applications community such that they have value in a societal decision-making context. A great return on investment in both science and model development may be expected if S2S forecasts can be successfully connected to societal applications (Vitart, 2014a); the goal over the next 5-10 years is therefore to generate useful, usable and actionable S2S forecast information and services for (and with) the applications community that can be integrated with existing risk management and decision-making practices across sectors and timescales.

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Tables

Table 1 Categorised challenges and opportunities related to applications of S2S forecasts.

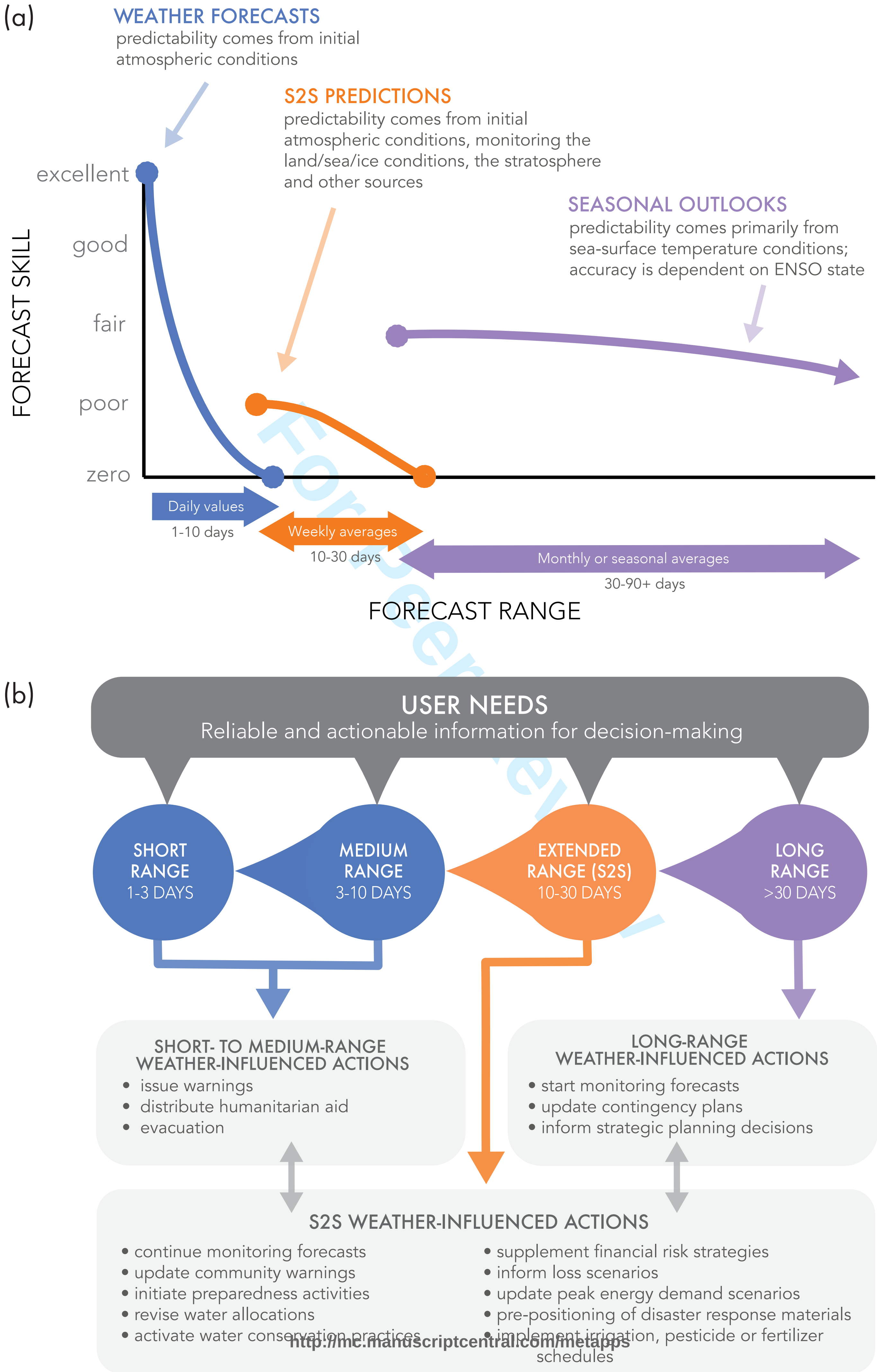
Category	**Challenges**	**Opportunities**
Systematic model deficiencies	Systematic misrepresentation of coupled atmosphere-ocean feedbacks, which may compound existing errors or generate new biases, and a number of persistent biases and errors remain in the climate models, as well as limited understanding of some aspects of the physical world	Continued investment in supercomputers, data collection (including long-term observations) and initiatives that support both the further development and uptake of S2S forecasts, such as the WMO WWRP-WCRP S2S project (Vitart *et al.*, 2012; Robertson *et al.*, 2014; Vitart *et al.*, 2016) and the WMO GFCS
Quantifying uncertainty	Inherent errors and uncertainties in probabilistic prediction systems due to predictability limits and deficiencies in models and initialisation (e.g. Slingo and Palmer, 2011)	Utilise the multimodel S2S datasets, such as the NMME (http://www.cpc.ncep.noaa.gov/products/NMME/data.html) and the S2S Project (http://apps.ecmwf.int/datasets/data/s2s) repositories, to quantifying forecast uncertainty in a practical and relatively simple way
Forecast verification	Verification is critical in the context of making S2S forecasts useful (and usable) for applications	Develop new seamless verification methods, such as time averaging windows that are equal to the forecast lead time (e.g. 1-week means used to

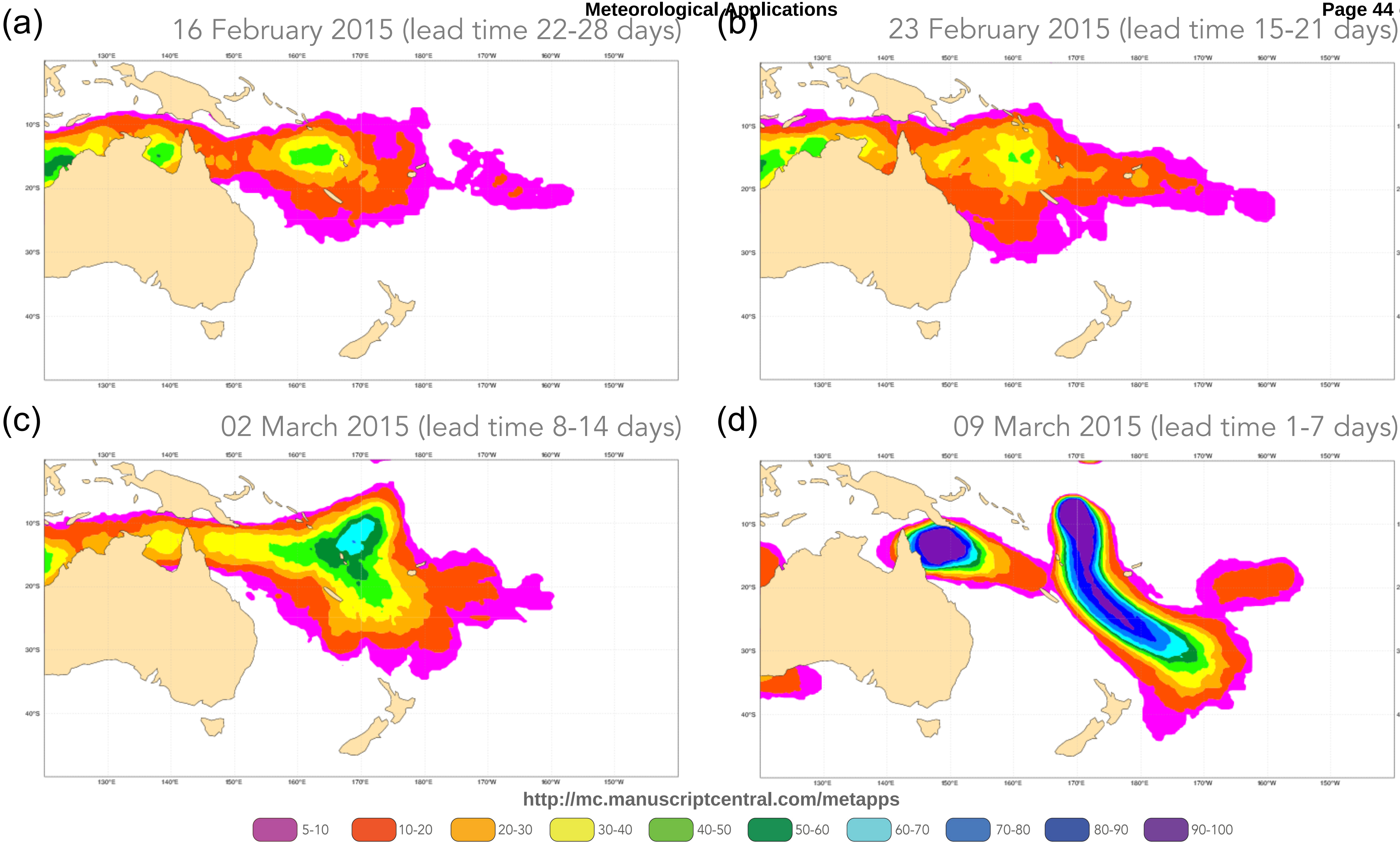
		verify forecasts at day 7; 2-week means for forecasts at day 14, and so forth) (Robertson *et al.*, 2014)
Awareness of S2S	Raising awareness of the ‘new’ S2S timescale, data availability, and its potential uses	Promote the NMME and S2S Project repositories, and possible integration of S2S forecasts into the Regional Climate Outlook Forums (RCOFs), which provide real-time regional seasonal outlook products in several parts of the world (https://www.wmo.int/pages/prog/wcp/wcasp/clips/outlooks/climate_forecasts.html)
Case studies	Few ‘success stories’ of S2S predictions to support promotion of S2S forecasts and their integration into applications	Increase the number of case studies using S2S hindcast repositories, demonstrating retrospective forecast skill
Integration with social sciences to ensure forecasts are useful and usable	Little current understanding and characterising of decision-making frameworks and processes at relevant spatial, temporal, and end-user scales	Collaborate with the social science communities to leverage existing knowledge on information creation, communication, use, and valuation of S2S predictions

Figure captions

Figure 1 (a) Qualitative estimate of forecast skill based on forecast range from short-range weather forecasts to long-range seasonal predictions, including potential sources of predictability. Relative skill is based on differing forecast averaging periods. (b) Schematic highlighting the relationship between the S2S 'extended-range' forecast range and other prediction timescales, with examples of actionable information that can enable decision-making across sectors. Actions are examples only and are not exclusive to a forecast range. Figure (a) adapted by Elisabeth Gawthrop from an original figure by Tony Barnston, both International Research Institute for Climate and Society; edited and reproduced with permission. Figure (b) based on Meehl *et al.* (2001), Hurrell *et al.* (2009) and Goddard *et al.* (2014). Definitions based on WMO meteorological forecasting ranges: http://www.wmo.int/pages/prog/www/DPS/GDPS-Supplement5-AppI-4.html.

Figure 2 Ensemble prediction of Tropical Cyclone Pam which made landfall in Vanuatu on 13 March 2015. Panels show weekly-averaged probability of a tropical cyclone strike within 300 km for (a) 22-28 days, (b) 15-21 days, (c) 8-14 days and (d) 1-7 days forecast lead time. Predictions made using the ECMWF Ensemble Prediction System (ENS).


(a)
WEATHER FORECASTS
predictability comes from initial atmospheric conditions
S2S PREDICTIONS
predictability comes from initial atmospheric conditions, monitoring the land/sea/ice conditions, the stratosphere and other sources
SEASONAL OUTLOOKS
predictability comes primarily from sea-surface temperature conditions; accuracy is dependent on ENSO state
FORECAST SKILL
excellent
good
fair
poor
zero
Daily values
1-10 days
Weekly averages
10-30 days
Monthly or seasonal averages
30-90+ days
FORECAST RANGE
(b)
USER NEEDS
Reliable and actionable information for decision-making
SHORT RANGE 1-3 DAYS
MEDIUM RANGE 3-10 DAYS
EXTENDED RANGE (S2S) 10-30 DAYS
LONG RANGE >30 DAYS
SHORT- TO MEDIUM-RANGE WEATHER-INFLUENCED ACTIONS
• issue warnings
• distribute humanitarian aid
• evacuation
LONG-RANGE WEATHER-INFLUENCED ACTIONS
• start monitoring forecasts
• update contingency plans
• inform strategic planning decisions
S2S WEATHER-INFLUENCED ACTIONS
• continue monitoring forecasts
• update community warnings
• initiate preparedness activities
• revise water allocations
• activate water conservation practices
• supplement financial risk strategies
• inform loss scenarios
• update peak energy demand scenarios
• pre-positioning of disaster response materials
• implement irrigation, pesticide or fertilizer schedules


(a)
16 February 2015 (lead time 22-28 days)
(b)
23 February 2015 (lead time 15-21 days)
(c)
02 March 2015 (lead time 8-14 days)
(d)
09 March 2015 (lead time 1-7 days)
5-10
10-20
20-30
30-40
40-50
50-60
60-70
70-80
80-90
90-100