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Review

On the assessment of the value of the seasonal forecast information

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ABSTRACT: Seasonal climate forecasts are now routinely produced at many operational and research centres. With the availability of the emerging technology of seasonal climate predictions for managing risks, however, it has proven difficult to quantify the value of seasonal climate forecasts in various applications. The definition of the value in the context of the use of the Seasonal Forecast Information (SFI) is the net benefit a user (or society) incurs as a result of change in management practices in response to the availability of the SFI.

A review of the difficulties associated with the value assessment of the SFI is presented. The paper includes a broad overview of pathways how the SFI is used by the various users and applications. The discussion then summarizes difficulties associated with isolating the benefits of the use of the SFI leading to the current paradigm where the value assessments from the use of the SFI are hard to quantify. Copyright © 2009 Royal Meteorological Society

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1. Introduction

Seasonal climate forecasts have been routinely generated at various operational and research centres for at least a decade. Assessments of the economic value of the use of seasonal forecast information in decision making, however, have been hard to come by. For example, a position paper from the World Climate Research Programme (WCRP) Workshop on Seasonal Prediction held in 2007 states that 'No authoritative statement regarding the value [of seasonal forecasts] is currently possible, either within specific contexts or generically, in which sufficient cases are available to provide a stable estimate' (http://www.clivar.org/organization/wgsip/spw/spw_position.php). Some other examples reflecting similar sentiments include: 'Yet, as indicated earlier, it remains unclear that maximum value is being extracted from the current skill levels of the [seasonal] predictions' (Trocolli *et al*., 2008); 'In fact, there is accumulating evidence that significant segments of United States agriculture, particularly low end users, are not using much if any of the currently available climate forecasts' (Garbrecht and Schneider, 2007); 'The results of the application of the new technology have been mixed, not only in terms of effectiveness, that is, how much SCF [Seasonal Climate Forecast] has been used successfully to deflect losses, but also in terms of equity, that is, how SCF use has actually benefited those in need' (Lemos and Dilling, 2007).

Why is the process of assessing the economic and societal value so difficult? In an attempt to highlight various problems associated with the value assessment of the use of the seasonal forecast information, paradigms for how seasonal forecasts can be used by different communities are summarized. A discussion of potential difficulties in the use of seasonal forecasts and their value assessment then follows. It has been pointed out earlier, and reiterated here, that a prerequisite for a seasonal forecast system to have a value is that its use should lead to subsequent changes in key management decisions, thereby altering outcomes that are different than those based on business as usual scenarios that have evolved from the use of climatological information (Murphy, 1993; Stern and Easterling, 1999; Hammer, 2000; Hansen *et al*., 2006; Bert *et al*., 2006). Furthermore, value assessments incurring from the use of seasonal forecasts are different from the assessments of the economic impact that results because of favourable (or adverse) climate conditions (e.g. Chagnon, 1999) as the former involves a deliberate decision making process on the part of the user involving the use of Seasonal Forecast Information (SFI) while the latter is a natural outcome of climate conditions influencing a set course of actions developed over years. The fact that climate variability influences different aspects of society is a necessary but not sufficient condition that the uses of SFI would also lead to benefits because the use of the SFI in decision making depends on a host of other factors.

Use, and the subsequent value of, seasonal forecasts can accrue in various ways. For example, value from

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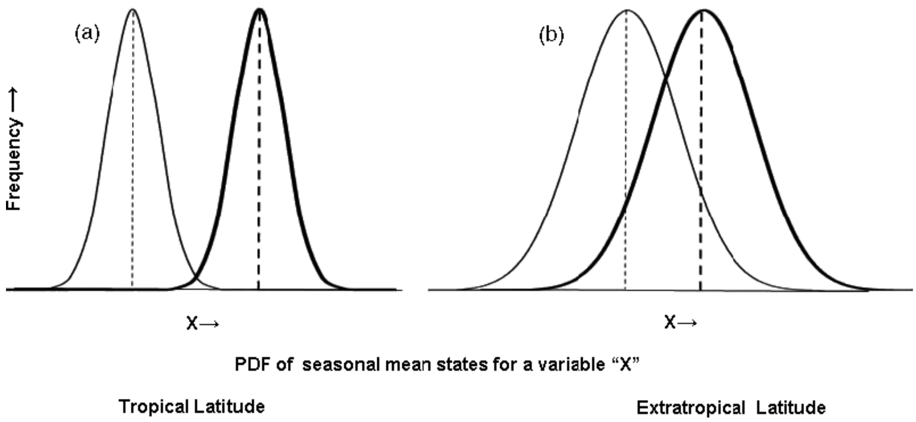

Figure 1. Schematics illustrating the fundamental concept of seasonal prediction. For both left and right panels, two Probability Density Functions (PDF) for seasonal mean states are shown. The PDF with the thicker black line is for the target forecast season, while the PDF with the thinner black line is the climatological (or reference) PDF. The separation between the PDFs is directly related with level of predictability, and expected value of prediction skill. For the tropical latitudes, and for different sea surface temperature states (for example, related to ENSO), PDFs of seasonal means are well separated (a), and predictability is high. For the extratropical latitudes (b), there is considerable overlap between PDFs, and predictability is low. The essence of seasonal prediction is estimating the forecast PDF for the target season, and various empirical or dynamical (or a combination thereof) prediction methods are used. The verifying observation for an *individual* target season, however, could be anywhere on the PDF, and in essence, limits prediction skill.

the use of seasonal forecasts can be judged in terms of economic benefits. The value could also be judged in terms of non-economic measures such as applications of seasonal forecasts for enhancing food security and saving lives. In this note, however, the focus is on the assessment of the economic value derived from the use of the SFI as a consequence of its use in the decision making process. To illustrate the concepts involved, the extensive literature on the use of seasonal forecasts for agricultural management is drawn on heavily (for example, Hammer *et al*., 2000; Hansen, 2005; Meinke and Stone, 2005).

The scope and purpose of this note is to bring issues related to the use and value assessment of seasonal forecasts on par with other aspects of the prediction enterprise; encourage a discussion that is grounded in realism and moves beyond merely theorizing about potential benefits and the value of the SFI; highlight various paradigms for how seasonal forecasts might be used and what the data needs are; communicating needs and expectations about forecasts that user communities have and how such needs measure up against the current state of seasonal predictions. The paper is not intended to provide a comprehensive survey of published literature on applications and value assessments of the SFI. The paper also does not touch on social and institutional nuances related to the application of seasonal forecasts that sit between the forecast and its applications (Lusenso *et al*., 2003; Vogel and O'Brien, 2006), for example, need for intermediaries between the forecast producers and users; communication issues related to probabilistic forecast information; loading dock *versus* end-to-end approaches of linking seasonal forecasts with end users (Cash *et al*., 2006; Garbrecht and Schneider, 2007) capacity building, and the role of various governmental and NGOs (Glantz, 1985; Pulwarty and Redmond, 1997).

2. Possible users and applications of seasonal predictions and data requirements

2.1. A brief review of seasonal forecasting

The aim of the seasonal forecast is to specify the probability density function (PDF) of seasonal means for the target forecast season. This PDF is compared with the corresponding climatological (or a reference) PDF, and relative differences between the two PDFs form the basis of seasonal climate predictions (Figure 1) (Kumar and Hoerling, 1995). The degree of change in the forecast PDF, relative to the climatological PDF, determines the expected skill (e.g. hit and false alarm rate) and predictability of seasonal means. The analysis of seasonal predictability has conclusively shown that while PDF of seasonal mean for different sea surface temperature (SST) states (for example, neutral and El Niño) are well separated in the tropical latitudes, in the extratropics there is considerable overlap (Figure 1) (Trenberth *et al*., 1998; Kumar *et al*., 2007).

For the target forecast season, a change in the PDF may be dictated by the past, present or future expectations for the state of known predictors, e.g. El Niño-Southern Oscillation (ENSO) SST, or could be a direct outcome of the ensemble of realizations based on dynamical models (see van den Dool, 2007; Trocolli *et al*., 2008 for a review of various seasonal prediction methodologies). Changes in the PDF from the climatology are then translated into different approaches for communicating the seasonal forecast information. Various commonly used methods are: sub-dividing the climatological PDF into discrete categories (e.g. terciles) and specifying forecast probabilities for each category; providing the PDF in terms of Probability of Exceedence (POE) diagrams (Barnston *et al*., 2000).

A complete specification of the seasonal mean PDF notwithstanding, the realized observed outcome of a seasonal mean could be anywhere on the forecast PDF, and if the forecasts are reliable, then over a large sample of forecast-observation pairs, the PDF of the observed seasonal means replicate the forecast PDF. The probabilistic nature of seasonal forecasts, and the limited number of instances over which such forecasts are used to alter decisions, however, poses inherent problems for assessing the value of the SFI.

Based on the content of the SFI required for its use in decision making, the SFI can be broadly divided into two categories: A macro view of the seasonal forecast where forecast use only depends on the seasonal mean information, and a micro view where detailed information about possible weather histories within the season are also required. From a decision making context (and corresponding applications) the users of seasonal forecast information could be broadly categorized into four different classes.

2.2. Forecast use for resource allocation

Seasonal climate variability has considerable influence on societal issues, and substantial resources are required for mitigation purposes. Examples include droughts, floods (Hamlet *et al*., 2002) and food security (Hammer *et al*., 2000); disease outbreaks (Thompson *et al*., 2006), and wildland fires (Roads *et al*., 2005). In the absence of any forewarning of near future climate conditions, mitigation options tend to be reactive in nature. Although all seasonal climate variably cannot be predicted, over certain parts of the globe the predictable part (for example, associated with the ENSO) has the potential for developing proactive mitigation strategies that could be used either to lessen the adverse impact of climate variability or to enhance the benefits from favourable climate conditions. Thus, based on the availability of the SFI, mitigation strategies and allocation of resources could be put in action prior to the target season. In general, the required SFI is at the macro level of shift in the PDF of the seasonal mean.

Positive value (i.e. benefits) from the use of seasonal forecast information accrues if a proactive resource allocation management decision is taken, and leads to a reduction in overall cost of mitigation that would have been incurred in a reactive mode when no SFI was used. These benefits are not only in terms of cost effectiveness of increased resource allocations prior to when adverse climate conditions happened (e.g. allocating wildland fire fighting resources in anticipation of a dry season at a cheaper cost) but also in terms of reducing the resource allocation when favourable climate conditions are predicted (e.g. allocating less resources if predicted seasonal conditions indicate less risk for wildland fire).

2.3. Forecast use for managing commodity output

Another class of applications that has the potential to benefit from the use of seasonal forecast information is maximizing output of agricultural commodities; livestock management; optimizing reservoir management and distribution of water consumption among different competing demands including hydroelectric generation, irrigation and ecological management. Applications in this category often rely upon detailed and comprehensive integrated decision systems, which in turn also require detailed weather histories within the season (Stone and Meinke, 2005). Therefore, these applications of the SFI require data at a micro level.

A specific example is the use of seasonal forecast information for agricultural crop management and optimizing crop yields. A user can generate probabilistic crop yield curves based on alternative weather histories that are consistent with the seasonal forecast (Hansen, 2005; Cantelaube and Terres, 2005). The user can also evaluate various 'what. . .if' scenarios by altering actions; assess economic costs of different actions; evaluate risks for various 'what. . .if' scenarios and choose a set of preferred actions that will optimize the commodity output in terms of its yield, associated risks and costs incurred (although some decisions may lead to increased commodity yield, they may also be associated with increased management costs, and an increased risk for the loss that, depending on the risk tolerance of a user, may be deemed unsuitable). A set of decisions which a user may have the freedom to vary, and which may also be sensitive to the availability of the SFI, include planting density, variety planted, nitrogen application and timing, planting and harvesting time; pest control management and crop rotation.

2.4. Forecast use for inventory management

Another possible use of seasonal forecast information is inventory management, for example in the retail business. One specific example is that if the winter-time seasonal temperature is below normal, it is likely to result in an increased sale of winter garments. With the availability of seasonal forecast information, retailers may be in a position to use this information in their long term planning of inventories and minimize losses due to either unsold inventories or maximize gains when anticipated demand does occur. The seasonal forecast information required for this category is likely to be on the macro scale.

2.5. Forecast use in economic markets

Seasonal forecasts have obvious implications for influencing the financial markets. The SFI (that could be used by the commodity producer) could impact commodity prices. Seasonal forecast information also has influence on the trading of commodity futures such as agriculture and energy, weather derivatives, the insurance and reinsurance industry, hedging against the adverse impact of climate variability (Zeng, 2000). The dynamic nature of financial markets and reaction to the very SFI that is being used by the users has the potential to create negative feedback that may dampen the overall value of the forecast information over a broader economy. In addition, such feedback also hinders a prior value assessment of the use of the SFI.

3. Application based use paradigms of seasonal forecasts and value assessment

As discussed, different applications require different levels of granularity for the SFI, and further, also have different input data requirements. How the necessary information can be provided, how it can be used by users to alter decisions and change their business practices, how the subsequent value can be assessed together with potential difficulties associated with the entire process are now discussed.

3.1. Applications requiring use of high-frequency weather data within the season

3.1.1. Dynamical model paradigm

Seasonal prediction based on dynamical models follows the ensemble approach. The necessity for the ensemble approach is based on the recognition of the fact that the future seasonal mean states, starting from slightly different initial conditions, are not unique. The ensemble approach based on dynamical models, therefore, attempts to provide an adequate sampling of the PDF of seasonal means for the target forecast season (Figure 1). General circulation model (GCM) predictions also provide much more information than just the PDF of the seasonal means. For example, weather histories of all kind of weather variables on a daily (or shorter) timescale within the season are available, and this 'forecast' information, by using 'what...if' scenarios, can be used with appropriate application and decision models for optimizing returns (e.g. the commodity yield). The general framework for this process is outlined below.

For a target season, 'i', an ensemble of forecasts based on a dynamical model (or models in the case of multi-model ensembles), is made. For subsequent discussion the individual ensemble members are indicated by the index 'j'. For different weather variables, each forecast has a weather history $W_{ij}(t)$ within the season at time 't'. For each ensemble member's $W_{ij}(t)$ there is corresponding time-averaged seasonal mean value S_{ij} and collection of various S_{ij} is the PDF of seasonal means for the target season 'i'. This PDF can be compared with the climatological PDF of seasonal mean to assess changes in the PDF for the target forecast season under consideration. The mapping from $W_{ij}(t)$ to S_{ij} could be degenerate, i.e. for a given S_{ij}, in principle, distinct weather histories within the season are possible. The larger the ensemble size, the better the sampling of the seasonal mean PDF, and of weather histories within the season. Based on the availability of an ensemble of weather histories, the discussion below for the use of the SFI is within the application framework of enhancing commodity yields.

For different commodities there are corresponding application models, that, for given weather histories, provide an estimate for the commodity yield. Based on an ensemble of weather histories for the season 'i', a probability distribution for the commodity yields and an expected value for the commodity can be generated. By varying the alternatives for user driven actions such as outlined in Section 2.3, and taking the cost of different actions into account, the expected value of the commodity output can be optimized. The difference in the expected value of the optimized commodity yield with and without the use of the SFI, multiplied by the price of commodity *per* unit, then provides an estimate of the expected value of the seasonal forecast information for the target season. The above analysis only provides expected value of the change in the cash flow for a specific season 'i'. This information can then be integrated over all seasons, to establish the value of use of the SFI in the management of commodities. More details about dynamic model, and alternate approaches, are described in Mjelde and Cochran (1988), Hansen (2005), Rubas *et al.* (2006).

The steps outlined above present a conceptually elegant framework for assessing the economic value of seasonal forecasts that integrates detailed information contained in an ensemble of weather histories with the application and related decision making models. In practice, however, the approach is fraught with numerous difficulties discussed below.

The application and decision support models tend to be very complex. Such models are also very data intensive. For example, crop decision support systems may require daily histories of several meteorological variables together with variables associated with the component models (e.g. crop model, soil model). For the case of agriculture commodities the requirement on meteorological variables might include daily variations of minimum and maximum temperature, rainfall, solar radiation, humidity, surface wind and soil moisture. The development of application models, because of spatial heterogeneity, e.g. variations in soil type, or irrigated *versus* rain-fed agriculture, also requires site-specific calibration putting them beyond the technical expertise of small users (who then no longer benefit from the availability of the SFI). Further, upscaling the value assessment from the individual user level to sector level, and to a broader economy, is also not a trivial task. All these factors taken together hinder a comprehensive assessment of the potential value of the SFI.

GCMs are also known to have numerous biases, and an extensive effort is required to calibrate weather histories of various meteorological variables. Further, if the model biases are not removed it can render the expected value analysis quite ineffective. Dynamical prediction models are also being continually upgraded and remain in a state of flux requiring that value assessment also be continually re-evaluated.

While the computation of expected commodity yields and economic outcomes sounds elegant in theory, it only provides information about the potential economic value from the use of the SFI. On the other hand, there is only a handful of sample histories over which actual economic value from the use of forecasts is realized by the user. Economic assessment based on the actual cost incurred, together with actual outcome of weather histories leading to a realized outcome for the commodity yield, and returns based on the commodity price, can lead to a very different 'realized value' from the use of the SFI over a small sample. Therefore, an assessment of value based on the expected value analysis could be different from the analysis based on a limited number of cases (see Murphy, 1993; Msangi *et al.*, 2006; Thornton, 2006 for further discussion of the *ex ante* and the *ex post* assessment of the SFI). In a more social context, it is the weal and woe of economic returns over finite instances of event sequences that may determine the outcome, and test the resilience of individuals, managers, organizations and governments.

There are also many exogenous factors that are hard to assess and incorporate in the application and decision analysis. These could include consequences of unexpected outbreaks of plant disease; impact of forecast information on the commodity prices themselves (based on altered future expectations of the commodity output as perceived by the financial markets); random fluctuations in the financial markets impacting the cost of commodities as well as the cost of actions (Letson *et al.*, 2005). Each of these influences the input as well as the returns on a year-by-year basis and may not be easily incorporated in an *a priori* assessment the potential value of the use of the SFI.

In contrast to the static management system outlined above where a set of actions is chosen based on optimizing a commodity output prior to the start of the target season, in reality, management practices are a dynamic process where decisions may be continually updated based on evolving conditions and other exogenous factors. Such a dynamic decision making process also makes the assessment of the value of seasonal forecasts much harder.

Finally, given a set of forecast weather histories, an application model can be optimized in terms of commodity yield, but actually deciding which particular action to take among competing choices depends on the specific users and cannot be generalized, thus increasing difficulties in the upscaling of the information. Furthermore, for society as a whole, a beneficiary of the seasonal forecast information may also have a counterpart that suffers a loss for exactly the same reason. A comprehensive analysis of the use of seasonal forecasts, then requires value assessment at the user, sector and broader economic level and generally remains beyond the scope economic models used for the value assessment of the SFI (Mjelde *et al.*, 2000).

3.1.2. *Weather generator paradigm*

At many operational centres, seasonal forecast products are often presented as a shift in probabilities for different forecast categories, or as probability of exceedence (POE) diagrams that contain information about the full PDF of the seasonal means for the target season. Such final products are a combination of forecasts based on empirical and dynamical prediction systems. These forecasts can be coupled with statistical weather generator techniques, and possible weather histories that are consistent with the shift in the PDF of seasonal mean can also be derived (Pickering *et al.*, 1994; Hansen *et al.*, 2006; Moron *et al.*, 2008). Once weather histories are available, a procedure similar to that outlined in Section 3.1.1 for the value assessment of the application of the SFI based on dynamical models can be used. A possible advantage of the weather generator paradigm may be that weather histories have less biases as they are derived based on observations. On the negative side, at present the weather generator paradigm could only be applied for selected variables such as surface temperature and rainfall for which the majority of operational seasonal forecasts are currently available. Further, even if macro-scale seasonal forecasts for other variables (e.g. short-wave radiation and cloudiness) are provided, generation of corresponding weather histories may not even be possible because of the paucity of the observational data.

3.2. Applications requiring use of seasonal mean values

The other approach, following the macro view of the application of the SFI is the direct use of the change in the PDF of seasonal mean, or of corresponding POE information, or of the use of simple historic analogue years obtained based on the current and evolving climate conditions (Jones *et al.*, 2000; Meinke and Stone, 2005). Using historical analogue years one can also make use of weather histories based on the observations, and value assessment will then follow the approach outlined in Section 3.1.1. Alternatively, based on past experience, users can develop a set of rules that connect a set of forecasts (or the predictors used to make forecasts, e.g. the Southern Oscillation Index or the ENSO) to a set of discrete actions that are taken. For example, if El Niño conditions are expected, then, based on past experience, a user may stock up on food supplies, or may switch to more drought resistant varieties if drought conditions have been observed to occur more frequently, or may stock up on medicines if instances of adverse health conditions (e.g. a malarial outbreak), have been recorded in previous situations. To summarize, if the shift in the seasonal mean PDF is large, as is often the case for certain geographical locations in the tropical latitudes, or when forecast probabilities exceed certain pre-determined thresholds, the users of the SFI may use a set of heuristic rules developed based on past observations instead of relying on comprehensive application models.

Used at a macro level the SFI, coupled with heuristic rules, provides a simple pathway for the application of seasonal forecasts, and is probably the most widely used application paradigm of SFI currently in use (Meinke and Stone, 2005). An *a priori* value assessment of such forecasts can be made based on the cost-loss analysis if a historical set of real-time forecasts (or hindcasts) is available (Murphy, 1985; Wilks and Hamill, 1995; Palmer, 2002; Vizard *et al*., 2005). This approach for the use and value assessment for the SFI, although simpler than the use of weather histories and detailed application and decision models, still has many difficulties, including:

1. because of small sample history of real-time forecasts or hindcasts, accurate estimates for the distribution of forecast probabilities, together with forecast skill and their quality are hard to come by. This information is required to evaluate value of the use of the SFI following a cost-loss analysis approach;
2. for different applications the cost of various actions (and year-to-year variability because of their dependence on other financial market factors) may not be known. This also holds for the amount of loss under adverse climate conditions (Letson *et al*., 2005);
3. threshold probabilities that lead to optimal use of seasonal forecasts and economic value may not be known as they require a prior estimate of cost and loss, forecast probability distribution and its quality (e.g. hit and false alarm rate) (Mason, 2004);
4. forecast biases, e.g. cost-loss analysis based on reliable *versus* unreliable forecasts have severe effects on the value assessment (Vizard *et al*., 2005);
5. Once again, an *a priori* assessment of the value of the use of seasonal forecasts may be different from the assessment based on a time sequence of actual realizations, as any estimate when carried over a small sample of forecasts can be different from a value analysis based on hindcasts, and,
6. As for the case of weather histories, upscaling the value assessment from an individual user to a sector to broader economics remains a difficult task (Mjelde *et al*., 2000).

4. Summary

The above discussion outlines ways in which the SFI can be used for various applications, and factors that make assessment of the value of seasonal forecast an extremely difficult task. It is, therefore, understandable that faced with serious challenges value assessment of SFI have been slow to come and much progress has not been made. It should be emphasized once again that the seasonal forecasts only have value if their use leads to changes in key management decisions. Indeed, there are factors that are also responsible for the low use of seasonal forecasts in decision making to begin with, and if forecast information is not even used to alter decisions it does not have any intrinsic value that needs to be assessed. Some current impediments against the use of seasonal forecast information are discussed below.

Deviations of the PDF of the seasonal mean for the target season (or the anomalous probabilities for forecast categories) are generally not well separated from their climatological distribution (Figure 1). In the absence of a clear separation between two PDFs, the user may equally well rely on operating practices developed based on the use of climatological information. Small shifts for the seasonal mean PDF may not be because the science of seasonal prediction is in its infancy, but is likely because of low inherent predictability, particularly in extra-tropical latitudes.

A natural outcome of the low predictability regime is also the fact that the skill, or the quality of seasonal forecasts, tends to be low. Even worse, the skill of rainfall forecasts, a meteorological variable with the largest societal impact, is also much smaller compared to that for surface temperature (Vizard *et al*., 2005; Schneider and Garbrecht, 2003). Further, seasonal forecasts for other meteorological variables, although in principle available based on dynamical models, are not routinely produced.

Seasonal forecast information is also just one factor in the decision making process. There are other unknown, and possibly random, factors that have an equal or larger impact on decisions, and that might overshadow a willingness to use the SFI. Furthermore, it is likely that the impact of climate variability tends to be very asymmetric, i.e. losses under unfavourable climate conditions are much larger than the benefits under favourable conditions (Murphy, 1993; Harrison, 2005). This is particularly true for small-scale users, for example subsistence farmers. Asymmetric cost functions for the impact of climate variability also deters use of SFI, and encourages users to follow conservative (and already established) business practices.

For the current generation of seasonal forecasts, there is a recurrent issue of mismatch between the scales at which the SFI is provided and at which it needs to be used. Although techniques to downscale large spatial scale, time averaged forecasts are available (e.g. from dynamical or statistical downscaling techniques; weather generators) it is not clear what the corresponding scaling for the predictability is. While it is generally accepted that predictability increases with increasing temporal and spatial averaging as unpredictable random fluctuations tend to be smoothed out, a comprehensive understanding and quantification of spatial and temporal scale dependency of predictability has not been done. Given that, even if downscaling of seasonal forecasts is technically feasible, its use may not be as widely acceptable.

Another factor against the widespread use of seasonal forecast information is that development of generic approaches for use are generally not possible, and use of the forecasts has to be tailored for a specific sector, and for specific users within the same sector. Such contextualization of seasonal forecasts for specific sectors and users is an investment, which in the absence of information about the value of the SFI, may not be easily justifiable. Of course, this creates a vicious circle slowing the adoption of seasonal forecasts as an emerging technology.

To complicate matters further, skill estimates for forecasts for individual seasons are generally not available, although if the forecasts are reliable, and if the forecast PDF of seasonal means are unbiased, then they implicitly contain information about their success rate (Kumar, 2007). However, reliable forecasts, at present, are seldom achievable. Unreliable forecasts also adversely influence the inference about the probabilistic yield curves and could also lead to incorrect decisions (Vizard *et al*., 2005).

It has also been recognized that the use of the SFI is hindered because of various perception biases on the part of forecast producers, ways the information is disseminated, and on the part of users in their decision making process. A thorough discussion of such perception biases appears in Nicholls (1999).

The user community also faces a plethora of choices regarding availability of the SFI from government organizations, private enterprise, individual researchers and academic institutions. Often, this information could be ambiguous and contradictory leaving the user community confused and with an overload of information that needs to be sorted out prior to its inclusion in the decision making process (Hu *et al*., 2006).

Even though the value assessments of the use of the SFI have been hard to come by, there have been numerous reports of the economic benefits of the SFI (Meinke and Hochman, 2000; Hammer *et al*., 2001; Podesta *et al*., 2002; Hamlet *et al*., 2002). Most of these studies have been in the area of agricultural management at a local or the farm level, and have been in geographical areas with large predictable signals, e.g. Australia, and provide hopes for the application and acceptance of seasonal prediction technology. On the other hand, it remains unclear the extent to which the SFI is being incorporated in management decisions as an additional tool on a routine basis. One potential factor against the acceptance of seasonal prediction technology, or the open knowledge that this tool is being successfully applied, may be that, while on one hand small-scale users may not have the wherewithal to adopt this technology, on the other, large-scale users who may have adopted the technology, and have benefited, treat this as propriety information and may not want to advertise this fact. It is also conceivable that the adoption of the SFI as a management tool is progressing through a natural phase of adoption of new technologies in management practices and has not yet evolved to maturity (Matthews *et al*., 2008).

In terms of the increased application of the SFI, one of the biggest user requirements for the applicability of SFI, which has been repeated in many fora, is the need for improved skill and spatial specificity of the information (Pulwarty and Redmond, 1997; Johec *et al*., 2001; Greenfield and Fisher, 2003; Vizard *et al*., 2005; Ash *et al*., 2007; Garbrecht and Schneider, 2007). It remains an open question as to what level the skill of seasonal prediction could be improved and what is the gap between the skill that is currently realized and what is potentially predictable. As for more specificity, a general notion in predictability theory is that smaller spatial scales have lesser predictability. This is likely to be true unless a predictable part of seasonal variability has a large spatial dependence. In this case a large scale seasonal forecast, while averaging random noise, will also average out the predictable component. These, however, remain some unsolved questions.

Looking ahead, as discussed in detail by Hammer (2000), a pathway for increased application of the SFI, and its influence, and assessment, on the economic value for the users, will require 'the ability to connect a [seasonal] forecasting system to an analysis of decision-making in the target system.' Success of such efforts will require a dedicated collaboration between forecast producers, decision makers and managers, economists, and possibly intermediaries who can be effective in facilitating the connection between disparate entities and work cultures.

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