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# Challenges for integrating seasonal climate forecasts in user applications

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This review discusses the challenges for integrating seasonal climate forecast information in user applications within the design of a simplified end-to-end forecasting system framework. Seasonal climate forecasts are operationally produced at various climate prediction centers around the world. However, these forecasts are rarely objectively integrated in application models to help the end user decision-making process, in spite of recent advances demonstrated through pilot projects in health, agricultural and water resources applications. An example of crop yield forecast produced as part of the EUROBRISA multi-institutional initiative is presented for illustrating some of the challenges. The challenges for moving toward a more objective use of seasonal climate forecasts to help support decision making involve more efficient interaction among climate scientists, system scientists and decision makers, with the end user driving the skill assessment of the entire end-to-end forecasting system through real world forecast applications.

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**Current Opinion in Environmental Sustainability** 2010, **2**:1–9

This review comes from the Open issue
Edited by Rik Leemans and Anand Patwardhan

Received 1 July 2010; Accepted 16 September 2010

1877-3435/$ – see front matter


**DOI** 10.1016/j.cosust.2010.09.002

## Introduction

Seasonal climate forecasts are forecasts of the expected climate conditions for the next three to six months. These forecasts can be of great utility for a number of climate sensitive sectors (e.g. agriculture, health and water resources) [1–6,7••,8–10,11••]. The explanation for the feasibility of seasonal climate forecasting is given in Box 1. The current approaches used for producing seasonal climate forecasts include the use of physically based dynamical global climate models [12,13,14••], regional climate models [15–18], empirically based statistical models [19,20], or a combination of dynamical and empirical models [21]. All these four approaches produce probabilistic forecasts for expressing the existing uncertainties in the forecasting process. For example, for addressing forecast uncertainty due to the lack of precise information about the initial state of atmospheric conditions when starting the forecast model, physically based dynamical seasonal forecasts are produced using slightly different initial conditions, generating an ensemble (i.e. a group) of forecasts [22]. For addressing uncertainties in model formulation the multi-model ensemble approach is used [14••,23••]. Empirical forecasts are based on statistical models built using past observations. For example, one can build a simple statistical model that relates past equatorial Pacific sea surface temperature observations and past rainfall observations over South America. Given a new observation of Pacific and Atlantic sea surface temperature one can use the derived statistical relationship to produce rainfall forecasts for South America [21].

The main climate variables of interest for societal applications are atmospheric temperature, rainfall and humidity [33]. Even though climate is not the unique driver for these applications, the existence of relationships between climate variables and crop yield [34,35], food security [36–39], disaster management [40,41], disease incidence [42••,43–45] and disease risk [46] provides support and motivates scientists to explore the potential for the use of seasonal climate forecast information for planning activities in several societal, economical and environmental sectors [1]. In other words, user needs promote an interdisciplinary test bed for designing end-to-end forecasting systems [29,42••] investigating the utility of climate forecast information for real life applications. For this purpose seasonal climate forecasts need to be tailored to feed application models such as crop models, disease models and hydrological models, or to feed user-specific decision processes [47••,48]. In this paper the focus is on feeding application models. Although Brazil [49,50] and Australia took the lead in using seasonal forecast information for agricultural and natural ecosystems applications around the nineties [51], the use of physically based dynamical model seasonal forecasts in societal applications is relatively novel, and was extensively promoted by efforts in EU projects like DEMETER (www.ecmwf.int/research/demeter), ENSEMBLES (ensembles-eu.metoffice.com) and AMMA (www.amma-international.org), by the National Oceanic and Atmospheric Administration (NOAA), by the International Research Institute for Climate and Society (IRI, portal.iri.columbia.edu) and EUROBRISA (eurobrisa.cptec.inpe.br): A EURO-Brazilian Initiative for Improving South American Seasonal forecasts [52].

**Box 1 Why is it possible to forecast the climate on the seasonal time scale**

Given the chaotic nature of the climate system one might question the feasibility of forecasting climate conditions months in advance. Seasonal climate forecasting is feasible because atmospheric variability on the seasonal time-scale is modulated by slowly varying boundary conditions [24,25]. The El Niño Southern Oscillation (ENSO) phenomenon, characterized by anomalous heating or cooling of the equatorial Pacific Ocean depending on its phase, is the most evident example of such modulation. The maintenance of anomalous surface temperature conditions in the equatorial Pacific for a few months during ENSO generates global scale atmospheric circulation patterns [26] able to produce anomalous climate conditions in remote regions (e.g. South and North America, Africa, Indonesia and Australia). This climate modulation promoted by slowly varying boundary (sea surface) conditions is not noticeable in day-to-day weather conditions but in seasonal averages (e.g. three-month mean) becomes evident [27]. Seasonal climate forecasting science takes advantage of the observed state of global boundary conditions (e.g. sea surface temperature (SST), snow cover and soil moisture) to make climate predictions for the next three to six months. This science has progressed considerably in the last decade but the tropics remain the region where seasonal forecasts are most successful [12,14••,21,23••,28–32].

The aim of the review is to discuss the challenges [53] for integrating seasonal climate forecast information in user applications within the design of an end-to-end forecasting system [29,42••]. The main focus of the paper is on the process of producing forecast information relevant to user applications rather than using forecast information in the decision-making process. As this is a relatively new field of inter-disciplinary research the review will cover the period 2005–2010, although previously published literature fundamental for supporting the bases for seasonal climate forecasting is also included. A practical example of crop yield prediction is used to illustrate some of the discussed challenges. These forecasts are potentially useful for farmers, government agencies, banks and insurance companies. The review is concluded with the authors' views on how to improve the way seasonal forecast information can be objectively integrated into real life application to support decision making.

## Simplified framework for an end-to-end forecasting system

Figure 1 shows a simplified framework for an end-to-end forecasting system. At the top end of this framework climate science is in charge of producing climate forecasts through knowledge of climate processes, which will feed the so-called systems science, placed at the center of the framework. Systems science investigates impacts of climate on natural and human systems through knowledge about physical and socio-economic impacts. Systems science is capable of analyzing climate risk in conjunction with non-climate related risks, and also performing vulnerability assessments. Finally at the bottom end of the framework, decision making is performed on the basis of forecast information jointly produced by climate and systems sciences. Such a framework allows usefulness/utility assessment of climate forecast information through the use of application models predicting variables of societal interest. This assessment is distinct from the traditional climate forecast assessment generally performed in climate science, which directly compares observed climate with forecast climate produced by climate models. By assessing the output at the bottom end of this framework the complete end-to-end forecasting system is indirectly assessed.

## Challenges of an end-to-end forecasting system

The link between each component of the proposed framework represents a challenge for the system success in terms of forecast information production relevant for user applications. The success of integrating seasonal climate forecasts in user applications will therefore only be achieved if the entire chain of challenges is thoroughly resolved. The first challenge appears within climate science and represents the production of climate forecast information of relevant variables for user applications [54–58] one to six months in advance. This challenge is resolved with the aid of physically based global climate models [12,14••], empirically based climate models [19,20] or a combination of both [21]. However, these models generally produce forecast information at coarse spatial resolution (of the order of 100–200 km).

As application models usually require climate forecast information at much refined spatial and time resolution [59], there is therefore the need for downscaling the forecasts produced by climate models to the desirable level of details required in application models [60]. Such refinement of forecast information represents the second challenge that is placed in the interface between climate and systems science. This challenge can be resolved using: physically based regional climate models that are able to transform course resolution forecasts produced by global climate models into forecasts at smaller spatial scales [15–18], statistical downscaling techniques [61–64] that relate the observed climate at a number of locations or regions with climate forecasts produced by climate models, creating statistical relationships for producing local scale forecasts, and time disaggregation procedures, know as weather generation [65–67,68••], that transform monthly climate forecasts into daily forecasts, preserving for example the statistical properties of the monthly mean forecast and daily observations (e.g. daily rainfall intensity and frequency) for the location to where the forecast in being timely disaggregated. However these approaches inevitably promote the propagation of systematic biases [69] from global to the regional spatial scale and consequently to the local scale where application models usually operate.



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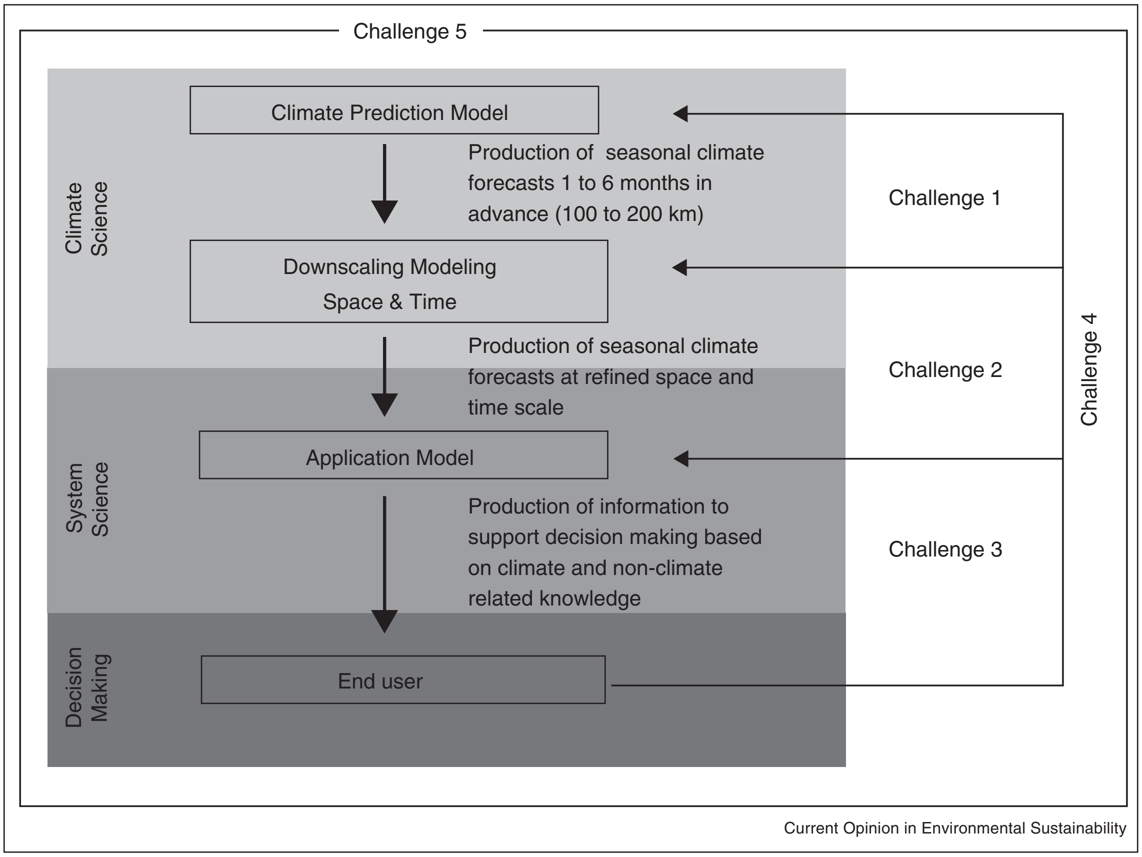
**Figure 1**




A simplified framework for an end-to-end forecasting system.

After climate forecast information is tailored at the desirable spatial and temporal scales for use in application models there is also the need for developing procedures for interfacing climate forecast information into application models [59]. This interfacing process concludes the second challenge. The third challenge of the chain appears within systems science and represents the production of information to help support decision making through the use of application models based on both climate and non-climate related knowledge. Application models are process-based [35,46,70–72] or empirical [43••,73–76]. The recent literature contains examples of the use of application models producing relevant information for decision making in agriculture [34,35,77–80], health [43••,45,46,73,74,76,81] and water resources [16,50,59,61,82–84]. At the bottom end of the framework is the end user who will receive the produced information (e.g. crop yield forecast, river flow forecast, and disease risk forecast) and combine with other non-climate related information to make decisions. This process usually involves planning and decision tools commonly used in climate risk management [59,70, 85••,86,87••,88,89]. Depending on how well in advance this information is available for the user it will be possible to make strategic plans that can be updated/revisited in the future when new forecast information becomes available. An effective communication between climate and system scientists with decision makers is a fundamental ingredient for successfully resolving the third challenge [47••,90,91••,92••,93]. End users need to be trained for assimilating the information produced by climate and system scientists to maximize the utility of the forecasts in their decisions. For example, application models can produce probabilistic forecast information based on ensemble of climate model forecasts, and end users need to be prepared for using this information [92••,94].

The fourth challenge is to stimulate feedback provision by the end user to system and climate scientists for improving the forecasting process [48]. Such feedback is of great importance for tailoring forecast information adequately to facilitate decision making. Finally, the fifth and fundamental challenge for the success of an end-to-end forecasting system able to effectively integrate seasonal climate forecasts in users applications is to design and implement the whole system. In the authors opinion



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this is the most difficult challenge involving inter-disciplinary work among climate scientists, system scientists and decision makers. Others might argue that the greatest challenge is to make sure that the forecasts benefit the people who need them most, rather than the ones who are already economically advantaged [95–97].

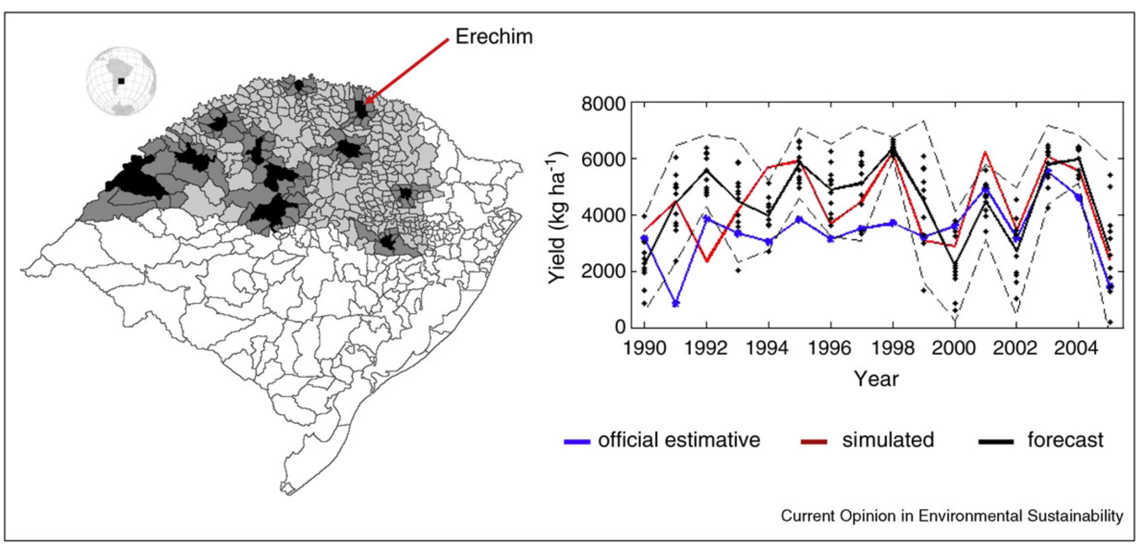
## Example of crop yield prediction

Agriculture is an economic activity that strongly depends on climate and weather information. In this section we briefly report how the first three challenges of Figure 1 have been addressed in EUROBRISA for producing maize crop yield forecasts for Rio Grande do Sul State (RS), a region in south Brazil where seasonal climate forecasts have skill and consequently promising useful value. Brazil is the third main maize producer in the entire world after USA and China, and RS State is the second greatest producer in Brazil (Brazilian Institute of Geography and Statistics; www.sidra.ibge.gov.br). Intraseasonal variability of maize yields is high, mainly due to irregular rainfall during the cropping seasons. Therefore, it is important to predict the expected yield during the crop season to support decision making.

The first challenge of Figure 1 was resolved with monthly mean rainfall forecasts produced by the European Centre for Medium-range Weather Forecast (ECMWF) seasonal climate forecast model (known as System 3) [13,28,98,99]. Maize in RS is sown from September to October and harvested from January to the beginning of March. In order to produce a forecast for the end of the crop season ECMWF monthly mean rainfall forecasts issued in the beginning of September for the following six months (i.e. zero to five month lead forecasts, from September up to February of the following year) were used in this study. Rainfall forecasts for the closest climate model grid point to the main maize producer region in RS (shaded area on map of Figure 2) were used in the study. Before proceeding to the second challenge, monthly ECMWF rainfall forecasts were calibrated (bias corrected) by removing the long-term mean model climatology of retrospective forecasts for the period 1981–2005 and adding the observed [100] monthly mean climatology for the same period.

The second challenge of Figure 1 was addressed with the use of a non-homogeneous hidden Markov model (NHMM, portal.iri.columbia.edu/portal/server.pt?open=512&objID=697&PageID=7575&cached=true&mode=2&userID=2) that integrates weather classification with a stochastic weather model. This model was used for disaggregating bias corrected ECMWF monthly mean rainfall forecasts into daily sequences of rainfall a location named Erechim (27.6°S, 52.3°W). The weather generator estimates the occurrence of rainfall based on a first-order Markov chain and the rainfall amount based on a gamma distribution fit to 16 years of daily observed rainfall (i.e. daily climatological distribution) in Erechim. The NHMM has previously been applied to disaggregating seasonal rainfall predictions [101], and to disaggregate rainfall data in space and time as input to a maize simulation model [66].

Figure 2




Map of main maize yield producer region in Rio Grande do Sul State (RS), in southern Brazil (left). Maize grain yield forecasts for February produced in the previous September (i.e. five months in advance) for Erechim (27.6°S, 52.3°W), which is located in the main maize producer region in RS, for the period 1990–2005. Grain maize yield simulated by GLAM using the observed daily rainfall (red line). Ensemble mean grain yield (i.e. the mean of the eleven dots shown in the figures for each year) using disaggregated daily rainfall forecasts (black line). The dashed lines indicate the 95% forecast interval given by the ensemble mean plus or minus 1.96 times the ensemble standard deviation. Official grain maize yield estimated by the Brazilian Institute of Geography and Statistics (blue line).



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The disaggregated daily rainfall forecasts were then used as input data to a process-based crop model — GLAM (General Large Area Model, [102]) to predict maize (*Zea mays* L.) crop yield in Erechim. This crop model has previously been used to simulate groundnut in India [103,104] and wheat in China [105]. As part of the third challenge in Figure 1 the crop model was calibrated for simulating maize based on a comprehensive soil and crop phenology database observed in RS [106,107] and also adjusted to assimilate a total of 11 ensemble member daily rainfall forecasts produced with the weather generation procedure described above. GLAM requires daily rainfall, maximum and minimum temperature and surface incident solar radiation. Temperature and solar radiation were assumed being monthly daily climatology conditioned on wet and dry conditions observed in Erechim.

As an example of information to support decision making within the third challenge, Figure 2 shows maize grain yield forecasts for February produced in the previous September (i.e. five months in advance) for Erechim, which is located in the main maize producer region in RS, for the period 1990–2005. The red line shows grain maize yield simulated by GLAM using the observed daily rainfall, which represents the potential yield that could be produced given the observed climate conditions. As highlighted in [42••], in the absence of observed data for verifying forecasts produced by application models a feasible alternative is to use the application model fed with observed climate to produce the reference verification data — the so-called tear-2 verification procedure. The black line is the ensemble mean grain yield (i.e. the mean of the eleven dots shown in the figures for each year) using disaggregated daily rainfall forecasts. The dashed lines indicate the 95% forecast interval given by the ensemble mean plus or minus 1.96 times the ensemble standard deviation. The blue line is the official yield estimate by the Brazilian Institute of Geography and Statistics. A generally good agreement is observed between the simulate yield (red line), the official yield estimate (blue line) and the forecast yield (black line) for the last six years. For most of these years the observed yield is within the 95% forecast interval, indicating good reliability of grain yield forecasts. The better agreement between forecast, simulated and official yield estimates in the later forecast period compared to those in earlier forecast period is likely to be related to quality improvements in both observed rainfall and yield estimates in latter part of the period. This kind of information provided to end users (e.g. a consortium of farmers, banks, and insurance companies) together with a real-time grain yield forecast for the next growing season can potentially be used as an additional source of information to support their decision making process for mitigating possible losses. The forecast yield information could for example benefit farmers by planting a different crop, commodity future traders on defining prices for selling maize in the food market, banks in making decisions on loans for planting in particular years and insurance companies deciding whether or not to issue policies.

## Conclusions

This review discussed the challenges for integrating seasonal climate forecast information in user applications in the context of a simplified framework for an end-to-end forecasting system. Research and developments during the last five years through a number of pilot projects (DEMETER, ENSEMBLES, AMMA, and EUROBRISA) indicate promising signs of the utility of integrating seasonal forecast information in user applications. The previous section presented an illustration of crop yield forecasting recently developed as part of EUROBRISA. Although seasonal climate forecasts are produced operationally at a number of centers around the world they are rarely integrated objectively (i.e. used as input variables for application models) in the process of producing user-oriented forecasts variables (e.g. crop yield forecasts) to help decision making. In the authors view the reasons for this lack of use are likely to be related to the challenges in interfacing forecast information from climate to systems science. Good communication is also advocated by some authors in support of good system science [108,109]. Deficiencies in communicating forecast uncertainty, which propagates from the global climate scale to the regional and local scales, are also causes for limited use of seasonal forecast in decision making [110–112]. To allow more efficient utility the current decision-making procedures need to be adapted for objectively assimilating seasonal climate forecast information (e.g. site or region-specific probabilistic forecasts in the form of probability density function). There is therefore the need to move toward more quantitative use of forecast information.

There is a clear need for additional inter-disciplinary research to facilitate more effective implementation of end-to-end forecasting systems able to objectively use seasonal forecast information in user-oriented applications. Supplementary pilot projects need to be designed and implemented to promote the integration of decision makers, forecast developers and providers through the development of forecast products relevant for end users. The involvement of users is these projects is fundamental for improving credibility in forecast applications [97,113–116]. These projects provide the opportunity to develop and validate end-to-end forecasting systems, which allow verification of forecasts through application models predicting variables of direct societal interest rather than climate variables produced by climate models. A well-designed combination of observed climate, weather and seasonal forecasts should be envisaged in these projects to allow the update of user-oriented forecast information for decision making at varying lead times from the target



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forecast month. The investigation on forecast skill transfer between spatial scales should also be prioritized because forecast skill has to be adequate for the needs of the end user (e.g. at the farm, river or neighborhood level).

In summary the implementation success of an end-to-end forecasting system for integrating seasonal climate forecast information in user applications will depend on thoroughly designing the system in a way that the end-user feeds information back to climate and system scientists for improving the system. The user is then in charge of driving the skill of the forecasting system, because the output of a user-specific application model when used as an ingredient for a decision-making process will define the real world forecast application skill. In more practical terms, the success of the system will also depend on the kind of required information, forecast target period, skill of seasonal climate forecast at the spatial and temporal scale of interest and status of application model development. The remaining outstanding challenge is effective communication and cooperation between climate scientists, system scientists and decision makers [90,91,92••]. The overall success of the system can be assessed by comparing the outcomes of what would have been produced without the availability of forecasts tailored for the particular application of interest [48,117].

## Acknowledgments

CASC acknowledges Fundação de Amparo a Pesquisa do Estado de São Paulo (FAPESP), Processes 2005/05210-7 and 2006/02497-6 for funding this research. The authors also thank the Leverhulme Trust for funding the EUROBRISA network project (F/00144/AT). The dynamical ensemble forecast data were kindly provided by ECMWF as part of the EUROBRISA license agreement. We also thank Andrew Challinor for making GLAM available for EUROBRISA research.

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