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Developments in dynamical seasonal forecasting relevant to agricultural management

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ABSTRACT: Recent developments in dynamical seasonal forecasting of potential relevance to agricultural management are discussed. These developments emphasize the importance of using a fully probabilistic approach at all stages of the forecasting process, from the dynamical ocean–atmosphere models used to predict climate variability at seasonal and interannual time scales, through the models used to downscale the global output to finer scales, to the end-user forecast models. The final goal is to create an end-to-end multi-scale (both in space and time) integrated prediction system that provides skilful, useful predictions of variables with socio-economic interest. Multi-model ensemble predictions made with the leading European global coupled climate models as part of the DEMETER (Development of a European Multi-model Ensemble system for seasonal to inTERannual prediction) project are used as an example to illustrate the potential of producing useful probabilistic predictions of seasonal climate fluctuations and of applying them to crop yield forecasting.

KEY WORDS: Seasonal forecasting · Ensemble forecast · Multi-model · Forecast quality · End-to-end approach

1. INTRODUCTION

The variability of weather at different time scales, such as daily, monthly, seasonal and beyond, is one of the factors that determine the growth of field-grown crops. The key weather parameters for crop prediction are rainfall, temperature and solar radiation, secondary parameters being humidity and wind speed. Crop predictions require forecasts of these variables several weeks or even months ahead to enable informed management decisions. However, weather is chaotic and therefore detailed day-to-day weather forecasting is effectively impossible >~2 wk ahead. In spite of that, seasonal climate forecasts are able to provide an insight into future climate evolution, because on timescales of seasons and longer, variability in the oceans can lead to significant fluctuations in weather statistics (Neelin et al. 1998). An example of a climatic phenomenon in which ocean dynamics play an essential role is the El Niño-Southern Oscillation (ENSO; Trenberth et al. 1998), which is predictable on a seasonal timescale.

Seasonal forecasts can be formulated using mathematical models of the climate system. Such dynamical seasonal forecasts are an extension of the numerical methods used to predict the weather a few days ahead. Dynamical models represent the climate system by a set of computer-solved equations, to predict its evolution several months in advance. As mentioned above, the ocean plays an important role at these time scales. Thus, fully coupled ocean-land-atmosphere models are required in order to predict seasonal climate by dynamical means (Stockdale et al. 1998). In addition to dynamical predictions, empirical seasonal forecasts (Moura & Hastenrath 2004) can also be used in an attempt to find statistical links between current observations and general weather conditions some time in the future. However, in this contribution only dynamical methods will be considered.

Palmer et al. (2004), Hagedorn et al. (2005) and Saha et al. (2006), among many others, show and describe results on the seasonal forecasting problem from the meteorological point of view. The present study offers an overview of recent improvements and future devel-

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opments in seasonal forecasting that are relevant for agricultural management. Results from the EU-funded DEMETER (Development of a European Multi-model Ensemble system for seasonal to inTERannual prediction) project are used to illustrate the potential to produce useful, reliable probabilistic predictions of seasonal climate fluctuations and their application to crop yield forecasting.

The paper is organized as follows. Section 2 introduces the concept of ensemble predictions that deal with both initial condition and climate model uncertainties. Section 3 discusses the multi-model ensemble approach as a pragmatic solution to the problem of forecast uncertainty. Section 4 outlines a strategy to assess the usefulness of seasonal forecast information for end users. Section 5 then offers a brief summary and describes future developments in the field.

2. PREDICTABILITY AND ENSEMBLE PREDICTION

Assessment of the extent to which climate is predictable may be linked to the applications for which the forecasts are being used. For instance, a plausible definition of predictability could be: a variable x is predictable if the forecast probability distribution function (PDF) of x differs sufficiently from the climatological PDF of the same variable to influence relevant decision makers in making better decisions than without forecast information. The prediction of PDFs is intrinsic to systems with uncertainty, as is the case for the climate system.

Predictions of climate system evolution on seasonal timescales suffer mainly from 2 sources of uncertainty: initial condition and model uncertainty. To address the first source of uncertainty, forecast models are run many times from slightly different initial conditions, consistent with the error introduced to estimate the best possible initial-condition. The resulting ensemble of forecasts can be used to produce a forecast PDF of the target variable. However, for seasonal ensemble prediction it is essential to take into account not only initial condition uncertainty, but also uncertainty in the model equations themselves. Uncertainty in model equations arises mainly because the process of parameterization, the way in which sub-gridscale motions are represented in weather and climate models, is not a precisely defined procedure (Palmer et al. 2005). At present, there is no underlying theoretical formalism from which a PDF of model uncertainty can be estimated. A more pragmatic approach relies on the fact that global climate models have been developed somewhat independently at different climate institutes. An ensemble comprising such quasi-independent models is referred to as a multi-model ensemble (Barnston et al. 2003, Palmer et al. 2004).

Other ways to represent model uncertainty are e.g. the stochastic physics (Palmer 2001) or the perturbed-parameter approaches (Murphy et al. 2004). The relative merits of these methods will be evaluated in the EU-funded project ENSEMBLES (www.ensembles-eu.org). ENSEMBLES will carry out predictions of climate variability and assess the human impact on climate, taking into account that these predictions are inherently probabilistic because of the uncertainties in the initial conditions, the representation of key processes within models and in climatic external forcing factors. The project will, for the first time, develop a common ensemble climate forecast system for use across a range of time (seasonal, decadal and longer) and spatial scales (global, regional, and local).

3. MULTI-MODEL SEASONAL PREDICTION

Until other methods are thoroughly assessed, the multi-model approach seems to be the most adequate to produce reliable probabilistic climate forecasts. The advantages of the multi-model approach have been illustrated in, among other research efforts, the DEMETER project. A thorough description of the DEMETER coupled models, the DEMETER hindcast integrations, the archival structure, and the common diagnostics package used to evaluate the hindcasts can be found in Palmer et al. (2004) and at www.ecmwf.int/research/demeter/index.html. Briefly, the DEMETER system comprises 7 global coupled ocean–atmosphere models. Uncertainties in the initial state were represented through an ensemble of 9 different ocean initial conditions. Atmospheric and land-surface initial conditions are taken directly from the ERA-40 (ERA: European Centre for Medium-Range Weather Forecasts [ECMWF] Re-analysis) atmospheric re-analysis (Uppala et al. 2005). The performance of the DEMETER system has been evaluated from a comprehensive set of predictions for past cases, or hindcasts, over a substantial part of the ERA-40 period (1958–2001). However, only hindcasts for the period 1980–2001 will be discussed in this paper, as this is the period for which all 7 coupled models participating in the project have generated hindcasts. Each year, four 9-member 6 mo long ensemble hindcasts were performed with each model, starting on the first day of February, May, August, and November at 00:00 h GMT.

Given that biases in the simulations made with the state-of-the-art dynamical models used in seasonal forecasting (Palmer et al. 2004, Saha et al. 2006) are non-negligible, bias correction of the systematic error in the mean is carried out on the DEMETER ensemble simulations. Anomalies for the prediction and the reference values are calculated as the difference between the value for a given season and the corresponding climatology. The anomalies have been computed using 1 yr out cross-validation, i.e. new model and reference climatologies have been estimated every season by removing the target year.

One of the main results of the experiment is that the DEMETER multi-model forecast system provides, on average, more skilful seasonal forecasts than is possible using a single-model ensemble system. One example of the multi-model superiority is given in Fig. 1, showing predictions of sea surface temperature anomalies initialized on November 1 over the period 1980–2001. Given the relevance of the ENSO phenomenon in seasonal forecasting, the sea surface temperature has been averaged over the east and central tropical Pacific for Months 2 to 4 (December to February) of the integration. Fig. 1a is based on hindcasts performed with the ECMWF model only. Whilst there is obvious skill in predicting interannual variations (the correlation between the ensemble mean and the ERA-40 reference is 0.96), this single-model ensemble system does not reproduce the statistical properties of the reference because in some cases the verification lies outside the range of the ensemble of predictions. Fig. 1b is for the full DEMETER multi-model ensemble system, consisting of 7 coupled models, i.e. 63 members. Every model has received the same weight in the process of constructing the multi-model ensemble, an approach that will be used in the rest of this paper. The possibility of giving different weights to each single model will be discussed in Section 5. In Fig. 1b the verification lies within the range of the ensemble for every hindcast. This is one example among many (e.g. Barnston et al. 2003, Hagedorn et al. 2005) demonstrating that the multi-model ensemble is intrinsically more useful and skilful than sets of forecasts produced with any single (e.g. national) model (Doblas-Reyes et al. 2005).

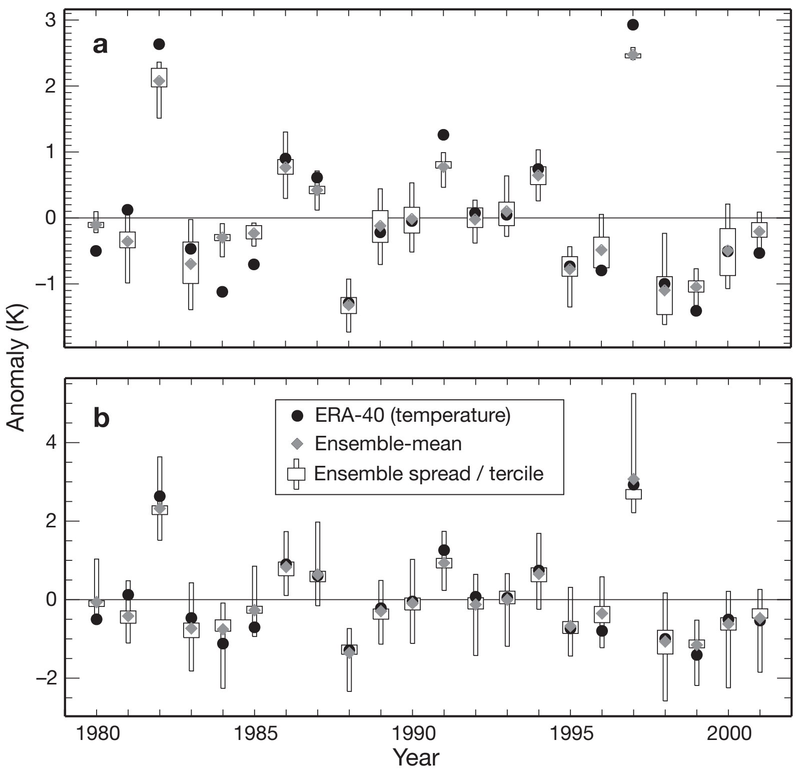

Fig. 1. Ensemble seasonal predictions of sea surface temperature anomalies (K) averaged over the east-central tropical Pacific (Niño3 region: 5° N–5° S, 150°–90° W) for the period 1980–2001. Hindcasts were started on November 1 and the values shown correspond to the 1 mo lead seasonal averages for December, January and February. (a) ECMWF single-model experiment carried out within the DEMETER project. The reference anomaly often lies outside the forecast range. (b) DEMETER multi-model ensemble, with 7 models and 63 ensemble members. The reference anomaly almost always lies within the ensemble. The probabilistic skill of the DEMETER multi-model ensemble is greater than for the single-model ensemble

The single-model hindcasts showed in Fig. 1 consist of 9-member ensembles, an ensemble size much smaller than the 63-member multi-model ensemble. A question arising from this is whether the multi-model superiority over the single-model ensemble is only due to the larger ensemble size. Hagedorn et al. (2005) discussed in detail the rationale behind the multi-model concept and demonstrated that the superiority is not only caused by the increased ensemble size. To illustrate to what extent the multi-model can be better than a single model, a set of 54-member ensemble hindcasts were carried out over the period 1987–1999 with the ECMWF coupled model. Fig. 2 shows a comparison between this single-model set of hindcasts and the multi-model with the same (54 members) ensemble size. The 54-member multi-model ensemble was constructed by randomly choosing 54 members out of the 63 available. The multi-model scores were computed for the common period (1987–1999). The Brier skill score (BSS, Jolliffe & Stephenson 2003), a probabilistic measure of forecast skill, is used as the metric. The BSS is based on the Brier score (BS) that, for a given event (such as ‘the value is above the climatological normal value’), measures the distance between the accumulated PDF of the forecast and of the observation or reference. The reference PDF takes the value of 1 if the event occurs and zero otherwise; thus, the larger the BS of a forecast system, the lower its skill, because the distance between both PDFs will be large also. To obtain the BSS, the BS is

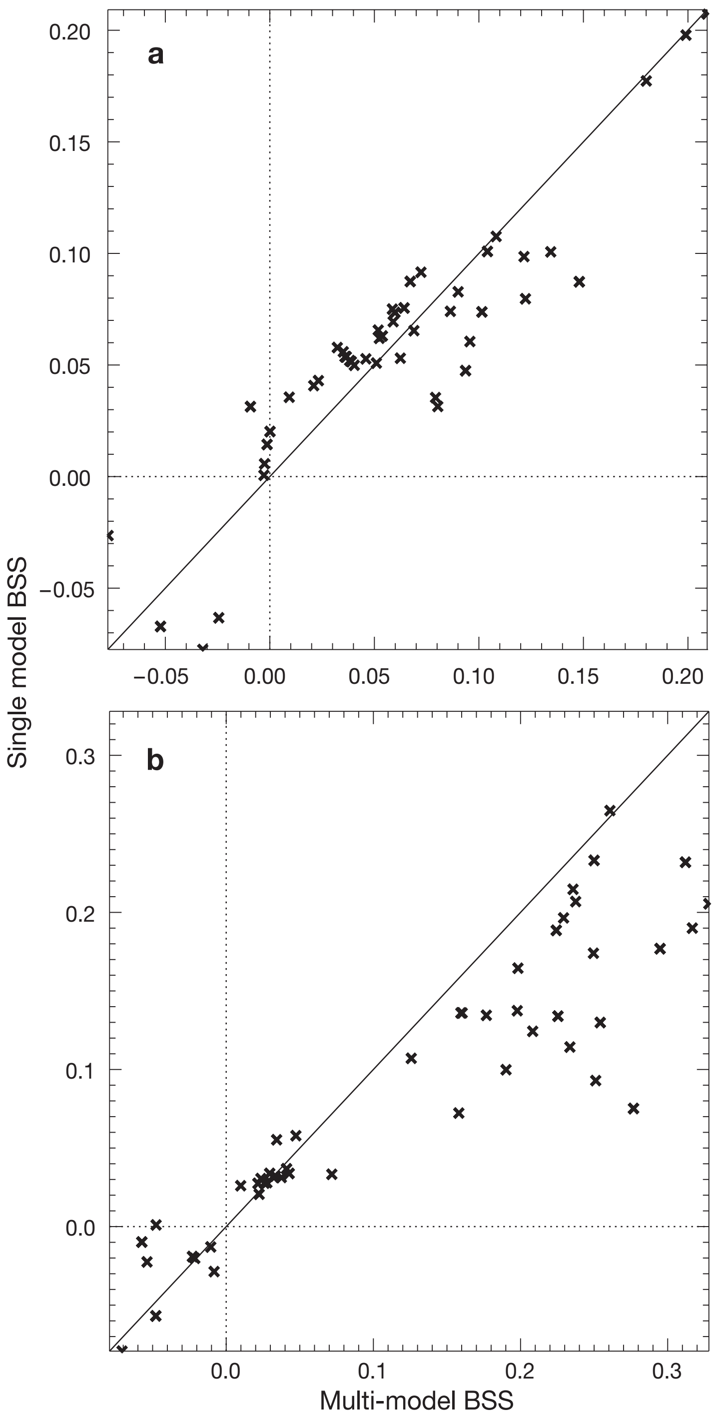

Fig. 2. Scatter plots of multi-model (6 models, 54 ensemble members) vs. single-model (54 ensemble members) Brier skill score (BSS) for seasonal predictions of (a) 2 m temperature and (b) sea-level pressure, collected over 8 regions (Northern extra-tropics, tropics, southern extra-tropics, North America, Europe, West Africa, East Africa and Southern Africa), 2 lead times (1 mo and 3 mo) and 4 events (anomalies above and below zero, above the upper tercile and below the lower tercile). Hindcasts were started on May 1. Climatological terciles were computed with the count method, using 1 yr out cross-validation

normalized by a measure of no skill that is usually the BS obtained using the climatological frequency of the event as forecast probability, BS_c. The BSS can then be written as $BSS = 1 - BS/BS_c$. If the BSS is >0 (<0), the corresponding forecast system has a better (worse) forecast quality than a climatological probability forecast, with an upper limit of 1.

For 2 m temperature, the DEMETER multi-model shows higher BSS than the single model for the majority of predictions. This means that, for most regions, events and lead times for which the forecast system is skilful enough, the multi-model offers the best option as a forecast system. In the case of sea-level pressure (Fig 2b), the better performance of the multi-model is more obvious, the BSS threshold for which the multi-model always outperforms the single model being 0.1. This figure illustrates that, although in some cases (depending on the variable, lead time, etc) the single-model ensemble can be more skilful than a multi-model with the same ensemble size, the overall effect when all the different options are taken into account is a better performance of the multi-model. Unfortunately, this feature is not as clearly evidenced in predictions of precipitation (not shown) due mainly to the low skill typically obtained for this variable.

Seasonal forecasts have shown to be skilful for variables and regions highly relevant for agricultural production (e.g. Challinor et al. 2005). Fig. 3 offers several illustrative examples from the DEMETER multi-model system with 1 mo lead seasonal predictions averaged for Australian winter 2 m temperature (Fig. 3a) and precipitation (Fig. 3b), which are useful for the management of cereal yield, and Ukrainian spring 2 m temperature (Fig. 3c), relevant to winter wheat yield. These hindcasts are skilful in predicting interannual variations of seasonal averages, as indicated by the correlations between the reference and the ensemble mean of 0.64, 0.79 and 0.66 for the 3 time series mentioned above (correlations statistically significant at the $p < 0.05$ level). The skill of probability forecasts of several events is also high (not shown), emphasizing the usefulness of the multi-model ensemble.

Agricultural regions are not the only ones that can benefit from multi-model ensemble predictions. River flow management is an essential component of economies in certain developing countries and could also benefit from incorporating seasonal forecast information in their knowledge construction process (Hartmann et al. 2002, Verdin et al. 2005). Fig. 3d displays the 1 mo lead winter (December to February) precipitation averaged over the Amazon catchment area. As for the other time series in Fig. 3, the precipitation over the Amazon area is highly predictable with a statistically significant (at $p < 0.05$ level) correlation between the ensemble mean and the reference of 0.77.

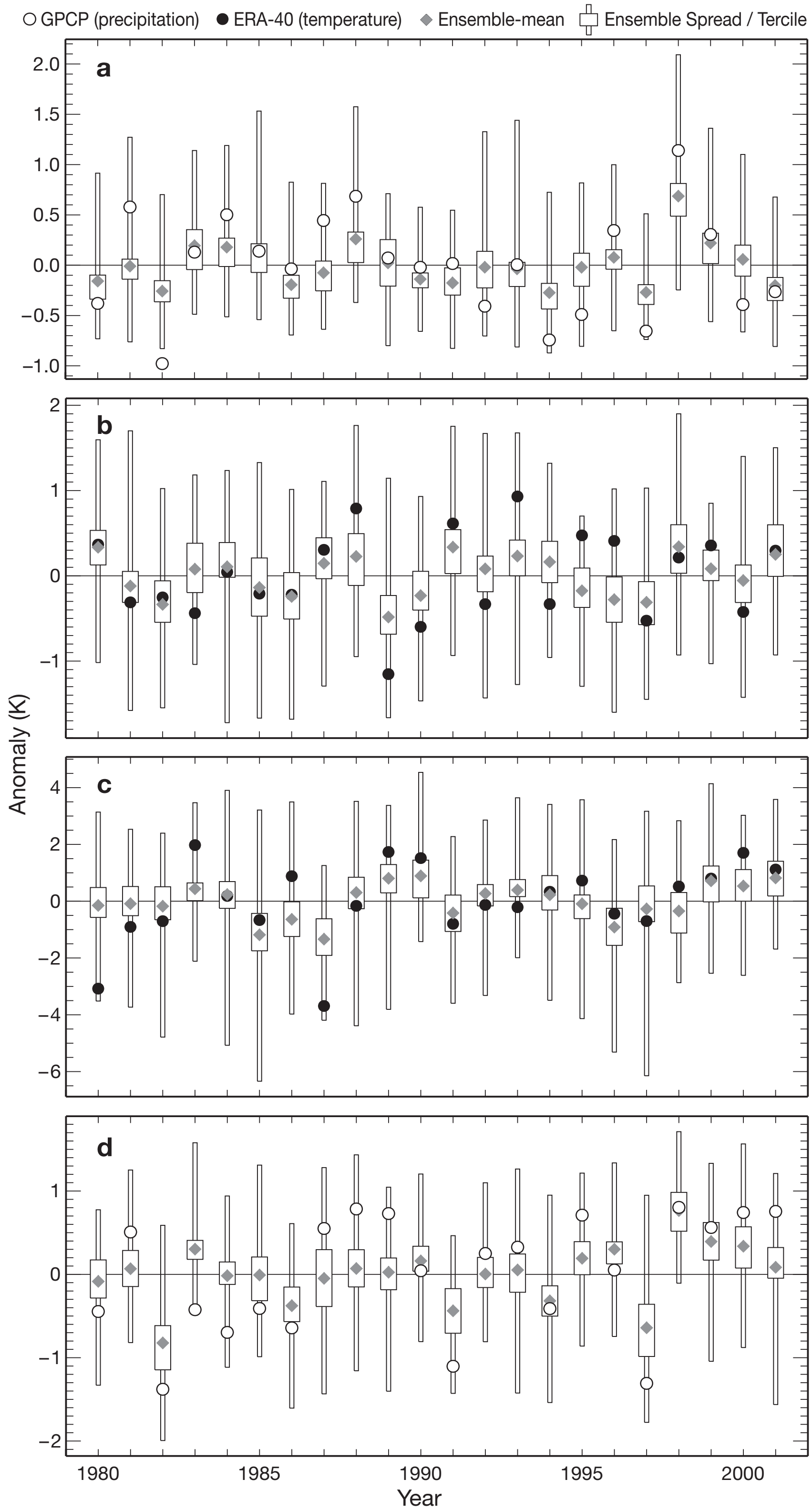

Fig. 3. Ensemble seasonal predictions of (a) precipitation (mm d^{-1}) and (b) 2 m temperature anomalies (K) over Australia (25°–40° S, 142.5°–152.5° E), (c) 2 m temperature anomalies (K) over Ukraine (45°–52.5° N, 22.5°–40° E), and (d) precipitation (mm d^{-1}) averaged over the Amazon basin for the period 1980–2001 for the DEMETER multi-model. The 63-member ensemble (7 models) hindcasts were started on May 1 for (a) and (b), in February for plot (c) and in November for plot (d). Values shown correspond to the 1 mo lead seasonal averages. The reference anomaly is nearly always inside the forecast range. Temperature is verified against ERA-40 and precipitation against Global Precipitation Climatology Project (GPCP) data

4. TOWARDS AN INTEGRATED SEASONAL-TO-INTERANNUAL FORECAST SYSTEM

Seasonal forecasts are of value to a wide cross-section of society, for personal, commercial and humanitarian reasons (e.g. Thomson et al. 2000, Pielke & Carbone 2002). However, the application of seasonal forecast information is not an automatic task. Users of seasonal forecast information tend to formulate 3 main requirements that are difficult to achieve: (1) skilful and reliable predictions of climate variability dealing with the common uncertainties in climate prediction (Hartmann et al. 2002), which implies the use of a fully probabilistic approach such as the one based on the ensemble method, (2) the integration of forecasts with appropriate climate information (Verdin et al. 2005) obtained from historical records (local climatologies, long-term trends, etc.) to prepare the 'climate knowledge' that is actually used in decision making, and (3) the provision of forecasts with a specific spatial scale (Buizer et al. 2000), usually of a higher resolution than the dynamical coupled models currently in use, which implies downscaling the data using either dynamical or statistical/empirical methods[1].

Once seasonal forecast information has been used in an application, its beneficial impact needs to be verified (Hartmann et al. 2002, McIntosh et al. 2005). A general methodology for assessing the value of ensemble climate forecasts in end-user applications was discussed in Morse et al. (2005). In particular, if users have quantitative application models requiring weather information as input, as in the case of crop models, these models can be directly linked to the output of individual members of the forecast ensemble (Palmer 2002). The net result is a probability forecast, not of weather or climate, but of a variable directly relevant to the user, e.g. a forecast PDF of crop yield (Cantelaube & Terres 2005). The poten-

[1]Working document available at http://www.ecmwf.int/research/EU_projects/ENSEMBLES/documents/20050526_s2ddownscaling.pdf)

tial usefulness of the prediction system can then be judged by asking whether the forecast PDFs of crop yield are sufficiently different from climatological PDFs, and sufficiently reliable, for the agronomist to be able to make decisions or recommendations.

A key component of the DEMETER project was to demonstrate the value of seasonal predictions for applications in health and agriculture. To achieve this goal, the design of DEMETER was based on the concept of an 'end-to-end' system (Buizer et al. 2000), wherein users feed information back to the forecast producers who, in turn, communicate with the users to understand their needs. The end-to-end strategy requires that (1) the wide range of climate forecast products take into account the user requirements, (2) the users develop or adapt their models to maximize the benefit from the limited skill of current climate predictions, (3) the forecasts have statistical properties similar to those of the meteorological reference used to develop the end-user model, to reduce the need of further calibration of end-user forecasts, and (4) the forecast quality assessment process includes estimates of the actual forecast value obtained by a set of users, which requires the development of user-oriented verification strategies.

In order to quantitatively assess the benefits of this approach, taking into account at the same time the user requirements mentioned above, a collaborative strategy was chosen with a leading role played by the downscaling partners (Feddersen & Andersen 2005), as well as partners with experience in malaria (Morse et al. 2005, Thomson et al. 2006) and crop yield prediction (Cantelaube & Terres 2005, Challinor et al. 2005). For this latter case, whilst only a limited number of years have so far been studied, there is evidence of useful probabilistic skill over Europe. In particular, the multi-model ensemble forecasts have proven more skilful than forecasts made (using statistical/empirical techniques) by the European Commission's own crop yield forecasters.

Scientists wishing to assess the extent to which there is useful predictability for parts of the world of interest to them or for their specific user applications are strongly encouraged to retrieve the DEMETER data from the ECMWF public data server http://data.ecmwf.int. Most of the data, as well as the ERA-40 data used for validations, can be downloaded from this site in several formats on a common 2.5° grid.

5. DISCUSSION AND CONCLUSIONS

Many other developments have also taken place recently, amongst them the relative benefits of the application of non-uniform weighting to the models contributing to the multi-model ensemble (Doblas-Reyes et al. 2005). In principle, non-uniform weighting is appropriate when the members of the ensemble are not highly correlated and have unequal forecast quality. Stephenson et al. (2005) addressed the calibration and combination of dynamical and statistical forecasts to maximize the content information, introducing the concept of 'forecast assimilation'.

As mentioned above, downscaling is a basic component of the end-to-end strategy for climate prediction (Palmer et al. 2004, Feddersen & Andersen 2005). However, the downscaling of seasonal-to-interannual ensemble forecasts is still in its infancy, although some valuable work has already been carried out (e.g. Misra et al. 2003, Misra & Kanamitsu 2004). Future work on this topic will have to take into account (1) the combined use of dynamical (regional models) and empirical/statistical methods because none of them has proven to be clearly superior to the rest, (2) the correction of the systematic errors of the global models using relatively short (15 to 30 yr) training samples to provide probabilistic predictions, (3) the availability of ensembles of forecasts (versus single deterministic predictions) produced by different models that verify the same date, which represents a limit to the feasibility of the computationally expensive dynamical downscaling methods, and (4) the generation of time series of surface variables with high time resolution (e.g. daily), which in some cases implies the need to couple empirical/statistical methods to weather generators. In addition, the traditional debate on the relative merits of empirical/statistical and dynamical downscaling (Schmidli et al. 2006) methods may have to face a different framework in seasonal ensemble forecasting. Empirical/statistical downscaling methods will also have to be considered as forms of calibration (Stephenson et al. 2005), because even regional climate models require calibration of their high-resolution simulations.

Climate is not only predicted at the seasonal time scale. There is a whole range of forecast systems, from medium-range weather, through monthly up to decadal and longer climate time scales, which are available with a varying updating frequency, as described in Rodwell & Doblas-Reyes (2006). Agricultural management can make use of all these systems in an integrated forecasting system, updating crop management decisions. For instance, managers might have access to seasonal forecasts once a month; this information can be merged with that provided by monthly forecasts available once a week to improve the first few weeks of the seasonal forecast information. Similarly, given that long-term decisions in agricultural systems are made at the interannual timescale, adaptation to ongoing climate change can be achieved by training the users to employ climate forecast information from seasonal-to-interannual predictions. The ENSEMBLES project will investigate these issues for different end-user systems.

The forecast quality of seasonal predictions is thoroughly assessed in both research experiments and operational systems. This information is made widely available to the users because knowledge about the skill of the forecasts is as important as the forecasts themselves. However, as mentioned above an end-to-end system necessitates a comprehensive forecast quality assessment that includes the end-user predictions, including a component of user-oriented verification. Some attempts in this direction are described in Morse et al. (2005) and Thomson et al. (2006), but important aspects still need to be addressed. For instance, end-user forecast variables such as crop yield include in a non-linear way the effect of several weather variables at the same time. Therefore, multivariate (e.g. both temperature and precipitation as a 2-dimensional variable) verification will be necessary to allow for an adequate interpretation of the end-user forecast quality assessment results.

In this paper, recent developments in seasonal forecasting of potential relevance for agricultural management have been discussed. These developments emphasize the importance of a fully probabilistic approach encompassing all the elements involved in the forecasting process, from the dynamical ocean–atmosphere models used to predict the climate in seasonal and interannual timescales, through the models used to downscale the global output to finer scales, to the end-user models. Regardless of the method used to represent initial condition and model uncertainty, the key point is that the climate forecast community is now capable of producing ensemble forecasts adequate to be used as extrinsic variables in application models in health, agriculture and hydrology, which in turn can produce useful probability forecasts for variables of a specific application. The final goal of these efforts is to develop an end-to-end multi-scale (both in space and time) integrated prediction system that will provide skilful predictions of variables with socio-economic interest.

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