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Seasonal Forecasting for Climate Hazards: Prospects and Responses

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Abstract. One of the most promising developments for early warning of climate hazards is seasonal climate forecasting. Already forecasts are operational in many parts of the tropics and sub-tropics, particularly for droughts and floods associated with ENSO events. Prospects for further development of seasonal forecasting for a range of climatic hazards are reviewed, illustrated with case studies in Africa, Australia, the U.S.A. and Europe. A critical evaluation of the utility of seasonal forecasts centres on vulnerability, communication channels, and effective responses. In contrast to short-term prediction, seasonal forecasts raise new issues of preparedness and the use of information.

Key words: climate hazards, seasonal forecasting, agriculture, water resources, Africa, Europe, Australia, U.S.A.

1. Introduction

Throughout history humans have been vulnerable to fluctuations in the climate system. In recent years the impact of inter-annual to multi-decadal climate variability has been apparent. For example, the El Niño-Southern Oscillation (ENSO), the largest mode of inter-annual variability in the climate system, may also be regarded as the largest climate hazard of our time. One phase of this phenomenon (El Niño) has been associated with worldwide climate anomalies (Rasmusson and Carpenter, 1982), including decreased rainfall over Indonesia and increased rainfall in East Africa. It is not easy to forget the smog in Indonesia, nor the reports of East African flooding, in the Autumn of 1997; 1997/8 will be remembered as the year of the largest El Niño event of the last century.

Accurate prediction of the state of the weather is difficult after 6 days and almost impossible after 10–14 days (Folland and Woodcock, 1986; Murphy and Palmer, 1986; Pierce *et al.*, 1997; Washington and Downing, 1999), due to non-linearity within the climate system and the growth of numerical forecasting model errors

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over time. However, a recent advancement in the form of seasonal forecasting provides a basis for earlier warning of climate hazards. There is mounting evidence that seasonal forecasts can be successfully made for many parts of the world with a lead times of up to several months (e.g., Ward and Folland, 1991; Folland *et al.*, 1991; Hastenrath *et al.*, 1995; Shabbar and Barnston, 1999).

This paper outlines how seasonal forecasting may increase the warning time for climatic hazards and asks how this information may be used most effectively to minimise risk. Greatest emphasis will be placed on drought and flood hazards in Africa, with corresponding examples from Europe, the U.S.A. and Australia. The next section discusses the paradigm of seasonal forecasting and how seasonal forecasts are developed. Section 3 outlines some existing seasonal forecasting schemes, while Section 4 reviews developments in approaches that directly link to climatic impacts. Section 5 explores the importance of an interactive, multidisciplinary approach to hazard management and early warning schemes; an area that is often ignored. It is not sufficient merely to develop a forecast; research is also needed into how that information can most effectively be distributed and utilised to reduce vulnerability to climate hazards. Therefore, both prospects for seasonal forecasting development and possible responses to such forecasts are reviewed.

2. Seasonal Forecasting Methodology

Seasonal forecasting is the outcome of a shift from deterministic predictions (e.g., 0.2 mm of rain will fall in Guernsey tomorrow) to probabilistic forecasting schemes. Here the emphasis is on forecasting the probability that a particular climate variable will be significantly above or below a mean state over a time-averaged period (usually ranging from a month to a season) (e.g., there is a 20% probability that in three months time monthly mean temperature in Central England will be higher than normal).

The current scientific approach behind seasonal forecasting relies on the fact that lower-boundary forcing, which gives rise to atmospheric perturbations, evolves more slowly than the atmospheric perturbations themselves and that the response of the atmosphere to this forcing is detectable. At the simplest level, Stockdale *et al.* (1998) provide an analogy between the atmosphere and an unbiased coin which, when tossed, may fall into one mode or the other with equal probability. The lower boundary forcing may bias the coin into one particular mode. The type of boundary forcing believed to be most important for long-term predictability is oceanic, and is normally monitored in the form of sea surface temperature anomalies (SSTAs) (Carson, 1998).

The paradigm that the ocean and atmosphere work together as a coupled system was outlined in the 1960s (Bjerknes, 1966, 1969). Under this paradigm the ocean and atmosphere exchange heat (both sensible and latent), mass (i.e., moisture through evaporation and precipitation) and momentum. For example, anomalously warm sea surface temperatures (SSTs) may drive atmospheric convection, which,

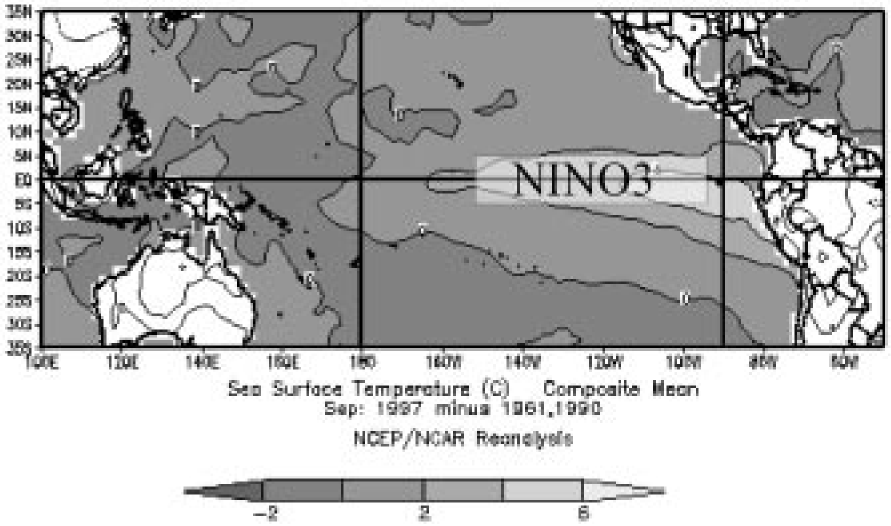

Figure 1. The Niño 3 region and Eastern Tropical Pacific SST anomalies for September 1997, plotted using NCEP data. (Image provided by the NOAA-CIRES Climate Diagnostics Centre, Bounder Colorado from their web site at http://www.cdc.noaa.gov/.)

in turn, influences low level convergence and divergence at locations remote from the anomalous SSTs. Feedbacks on the ocean result from wind stress and mass inputs (e.g., rainfall) which change the salinity content of the ocean. Together the ocean and atmosphere act as a coupled system in redistributing the energy received at the earth's surface.

Approaches to seasonal forecasting can broadly be divided into two categories, empirical/statistical techniques and numerical/dynamical modelling, of which the former have historically been more widely developed (see also Palmer and Anderson, 1994; Carson, 1998; Washington and Downing, 1999).

The first step in the development of empirical seasonal forecasts is statistical analysis of the global mean atmospheric response to different large-scale modes of oceanic variability, e.g., ENSO and associated teleconnections. It may then be possible to predict how the atmosphere will respond to certain oceanic situations, based on monitoring of the ocean and a knowledge of how the atmosphere has responded in the past to similar SSTAs, with a variety of lag times. For example, seasonal prediction of climate anomalies resulting from ENSO events are usually based on analysing how and where climate has changed in the past during El Niño and La Niña years and monitoring of SSTs in the Eastern Tropical Pacific Niño 3 region (Figure 1).

A wide variety of statistical techniques have been used to identify lagged statistical associations between SST indices and climate variables. A basic starting point is simple correlation analysis between predictand and predictor variables. However, seasonal forecasting models cannot be developed using this technique alone. Multiple regression (e.g., Ward and Folland, 1991; Colman *et al.*, 1996), linear (e.g., Colman *et al.*, 1996) or quadratic discriminant analysis (e.g., Mason, 1998), canonical correlation analysis (CCA) (e.g., Thiaw and Barnston, 1999), or neural networks (e.g., Hastenrath *et al.*, 1995; Greischar and Hastenrath, 1996) are all statistical techniques that may be used for this purpose. The main differences between these methods are that multiple regression gives the probability of only one outcome, whereas discriminant analysis produces a probability forecast that the predictand climate variable, e.g., temperature, will fall into each of a number of categories, e.g., five (termed quints) representing much below average, below average, average, above average and much above average. Both these techniques investigate the relationship between several predictor variables and one predictand (e.g., temperature at one location in southern Africa). CCA can be used to forecast more than one predictand. For example, several time-series of temperature or rainfall can be related to the global SST field in a way that maximises the correlation between the two sets of time-series. All these methods are based on the basic principle of minimising least-squares between predicted and observed variables. Neural networks (NNs), on the other hand, are potentially more powerful and sophisticated modelling techniques which are capable of modelling extremely complex functions. They operate by learning from examples. Given a representative data set, NNs invoke training algorithms to automate data structure. Characteristics of NNs that are suited to the seasonal forecasting problem include their ability to deal with non-linear relationships and large data dimensionality. The results of using different techniques are compared in Ward and Folland (1991), who have compared the use of multiple regression and linear discriminant analysis in forecasting north Nordeste Brazil wet season (February or March to May) rainfall, and Hastenrath *et al.* (1995), who have compared neural networking, multiple regression and linear discriminant analysis in the forecasting of DJF precipitation in the eastern part of southern Africa.

Before an empirical forecast model can be used to forecast in real-time the method must be developed and tested or ‘validated’ on independent time-periods with pre-existing data, termed ‘hindcasts’. The data can be separated into two continuous discrete segments of time, e.g., 1900–1945 and 1946–1990, or subdivided by keeping alternate years in each data set (termed ‘jack-knifing’), or validated by omitting one year at a time in the data-set, testing the scheme on this particular year, and repeating this analysis for all years. Jack-knifing is not preferable because inter-annual persistence or autocorrelation in many time-series (e.g., SST) may mean that the time-periods cannot be considered truly independent (Hastenrath, 1995).

Numerical modelling schemes employ a fundamentally different approach to seasonal prediction. General circulation models (GCMs) are used to mathematically model the ocean and atmosphere, with each system divided into a series of grid-boxes. Basic equations of mass, momentum and energy (e.g., see Peixoto and

Oort, 1992) are then solved for many different variables at each grid-box as the GCMs are integrated forward through time.

Two types of models can be used in seasonal prediction. Either SST persistence is assumed (as in the case of the purely empirical forecast models outlined above) and observed SSTs are used to force an atmosphere-only model over a few months, or a fully-coupled ocean-atmosphere model can be used to mathematically model both atmospheric and oceanic processes, and their interaction, thereby allowing SSTs to evolve. In reality, the sensitivity of the atmosphere to respond to the lower boundary forcing (e.g., SSTs) often depends on the initial state of the atmosphere. (In empirical seasonal forecasting this may be partially overcome by incorporating atmospheric variables into the forecast model.) Models are run several times for each forecast, each commencing from a slightly different set of initial conditions. These runs are collectively termed ‘an ensemble’. The atmospheric variance that is common to each ensemble member (the average result, if the standard deviation between each ensemble member and the mean is low) is likely to have been driven by the lower boundary forcing. The proportion of the atmospheric variance that is different in each ensemble member is likely to have arisen due to internal, random or ‘chaotic’ variability in the atmospheric system. The key to determining where seasonal forecasting can be successfully applied is therefore the degree to which the atmospheric variability is externally forced by lower boundary conditions in a way that is detectable, compared to internal, seemingly random, variability, which is dependent on the initial state of the atmosphere (Rowell, 1998). This ratio of SST forcing to internal atmospheric variability is greatest in the tropics (Rowell, 1998) where the dynamics governing the atmosphere tend to be more linear.

Numerical model forecasts are currently being developed by several research groups such as the U.K. Meteorological Office (UKMO) (Harrison *et al.*, 1997; Graham *et al.*, 1997; Evans *et al.*, 1998), the European Centre for Medium Range Weather Forecasting (ECMWF) (Stockdale *et al.*, 1998), and in the United States (NCEP (National Centres for Environmental Prediction)/NOAA (National Oceanic and Atmospheric Administration)) (Barnston *et al.*, 1998). The ECMWF model uses a fully coupled ocean-atmosphere model to run about 30 individual forecasts each month, integrated forward for six months from the initial conditions. Climate variations can then be assessed on a probability basis from the resulting ensemble. The onset of the 1997/98 El Niño event was successfully portrayed in this model (Stockdale *et al.*, 1998).

Although operational empirical forecasts have so far experienced more success than those using numerical modelling methods, they are usually derived by applying linear statistics to a non-linear system and assume, rather than prove, causality. Application of empirical seasonal forecasts without an understanding of the underlying physical mechanisms is risky. These mechanisms can be better understood using controlled dynamical model experiments (e.g., Rodwell *et al.*, 1999). The skill of numerical model forecasts currently rests on the ability of the model to replicate the observed climate of the area to which the forecast is being applied, the sensitivity of the region of interest to SST forcing and the model resolution. The majority of coupled models still require a heat flux correction at the ocean-atmosphere interface due to the tendency for drift in the atmospheric temperature. However, there is much scope for the ability of numerical model forecasts to improve, as computing power and the amount of high quality observed data rapidly increase. Therefore, most operational seasonal forecasts are currently based on the empirical approach, while numerical models are seen by many to hold the greatest hope for future improvement (Stockdale *et al.*, 1998; Washington and Downing, 1999). However, the empirical and numerical approaches are also complementary; it is possible to forecast SSTAs using dynamical models, e.g., Zebiak and Cane (1987) (foregoing the assumption of SST persistence) and use empirical methods to predict the atmospheric response to these SSTAs.

3. Current Seasonal Forecasting Schemes

This section reviews a selection of seasonal forecasting schemes. Many more can be found in NOAA's Experimental Long-lead Forecast Bulletin (website: http://nic.fb4.noaa.gov/products/predictions/experimental/bulletin/ (up to 1997) or http://grads.iges.org/ellfb/ (1998 onwards)).

Initial seasonal forecasting efforts were concentrated on semi-arid, sub-tropical areas where there is a strong signal to noise ratio and high coefficient of variation in predictand time-series. Thus many forecasting schemes have been developed for regions such as the North East of Brazil (e.g., Ward and Folland, 1991; Colman and Davey, 1999; Greischar and Hastenrath, 1999) and parts of Africa (mainly the Sahel and Guinea Coast, East Africa and southern Africa). The latter will be discussed here, since drought-stricken African regions, with low rainfall totals and often unstable political systems are home to some of the most vulnerable communities in the world. Hence the early warning of low rainfall totals to help prepare for, and mitigate the effects of, the food crises which so often result (e.g., 1983/84) must be a priority for the seasonal forecasting of climate hazards (see also Hulme *et al.*, 1992a; Hulme *et al.*, 1992b; Washington and Downing, 1999 for reviews of seasonal forecasting of African rainfall).

Experimental seasonal forecasts for the Sahel have been developed by the UKMO since 1986 and, since 1992 these have also included the Sudan and Guinea Coast (Colman *et al.*, 1996). Multiple linear regression and multiple linear discriminant analysis (LDA) models have been used to produce a forecast of JAS rainfall (issued in May) from March to April SST variability which is subsequently updated with May and June SSTs (issued in July). Of particular importance for explaining the variance in Sahel rainfall is the difference between Northern and Southern Hemisphere Atlantic SSTs (Folland *et al.*, 1991), as this is thought to determine the extent to which the Inter-Tropical Convergence Zone (ITCZ) moves inland during the West African monsoon. Additional influences include ENSO (which influences higher frequency variability) and local SST anomalies in the Southern Tropical

Atlantic (Colman *et al.*, 1996; Ward, 1998; Ward *et al.*, 1999). Similar conclusions have been reached by Thiaw and Barnston (1999a,b), who have developed a CCA forecast for the same season's rainfall to develop four month lead and one month lead forecasts (using SST predictors, up to February and May, respectively). The skill of such forecasts may be determined by comparing the correlation between forecast and observed rainfall over the 'validation' period. This can then be compared to a forecast based only on persistence. For example UKMO forecasts of Sahel rainfall for 1901–1945 using a training period of 1946–1992 gave a correlation coefficient between predicted and observed rainfall of $r = 0.51$, compared with a value of $r = 0.10$ for a forecast based on persistence only (Colman *et al.*, 1996). Between 1986 and 1995 the UKMO Sahel rainfall forecasts were accurate within one quint using LDA (i.e., one of five rainfall categories), apart from 1988 and 1994, where actual rainfall conditions were wetter than predicted (Colman *et al.*, 1996).

In East Africa, Mutai *et al.* (1998) have found promising seasonal forecast skill for the OND 'Short' Rains using multiple regression techniques and predictors based on eigenvectors of global SST. Forecasting skill for predicting the 'Short' Rains has also been demonstrated using neural networks (Greischar and Hastenrath, 1996). However, perhaps the most exciting development in East African seasonal forecasting has been the addition of dynamical modelling methods since 1997 by the UKMO. Their dynamical one month lead forecast in 1997 predicted above-average rainfall for parts of East Africa (Graham *et al.*, 1997) with relatively high confidence; verification of this forecast in 1998, using a combination of satellite and rain-gauge derived data, showed that these regions had received about 170% of average rainfall during the forecast period (Evans *et al.*, 1998).

Extended-range predictions for South Africa are available from the South African Weather Bureau (SAWB) through its Long-term Operational Group Information Centre (LOGIC) and Research Group for Seasonal Climate Studies (RGSCS). The RGSCS Advisory Bulletin includes seasonal outlooks (categorical temperature and precipitation forecasts for one to four months ahead) as well as global SST forecasts.

The RGSCS advisory bulletin and associated products are closely related to the findings of the Southern African Regional Climate Outlook Forum (SARCOF). Regional Climate Outlook Fora (initiated by the NOAA Office of Global Programs (OGP)) are one of the mechanisms through which CLIPS (The Climate Information and Prediction Services) brings together representatives of national and regional meteorological services and the user community in order to construct a consensus forecast for the region each year (Harrison, 2000); southern Africa was chosen as a pilot project. As well as promoting a dialogue between the international climate science community and forecast users and developing a consensus method for production of forecasts, SARCOF also aims to address gaps in training and technical capabilities (NOAA/USDC, 1999).

The SARCOF process first operated prior to the 1997/98 wet season in southern Africa. The process consists of an annual program of three meetings, with the first meeting held in September prior to the onset of the wet season. Within a workshop format, technical and discussion sessions are held on global and regional climate dynamics, forecast methodologies and seasonal forecast presentations. A consensus forecast is achieved through discussions among the participating climate community, dividing the region into different homogeneous forecast zones based on the predictions provided by each of the forecast groups. For each zone rainfall forecasts for the coming season are expressed as probabilities of occurrence of rainfall in three tercile classes, average, below average, and above average rainfall. This probabilistic product is then distributed to users.

A mid-season correction meeting follows, in December, in which an assessment of the early season forecast is made. This assists in the update of Forum forecasts for the remaining main wet season period, again through a process of consensus. Finally a post season meeting is held in April or May in which an extensive validation of the Forum product is conducted and the process debated within the context of user feedback. This allows the process aims and methods to be related directly to the requirements of a range of users. An important component of the process is the capacity building exercises in which training on climate science and seasonal forecasting methodologies is provided by international and national experts through technical sessions at the Forum meetings.

Although initially experimental, the SARCOF process is continuing each year and has been adopted world-wide as a model for seasonal forecasting, and in that sense can be seen as a success. Regional Climate Outlook Fora are currently operating for other regions including South and Central America, other parts of Africa and South-east Asia (Harrison, 2000). Products from a number of RCOFs can be obtained from (http://www.cpc.ncep.noaa.gov/products/african_desk/rain_guidance/).

A comparable service providing operational seasonal forecasts has been available from the Australian Bureau of Meteorology throughout the 1990s (http://www.bom.gov.au/silo/products/Sclimate.html). Early Seasonal Climate Outlooks used the Southern Oscillation Index (SOI) to produce the seasonal rainfall forecasts; however since 1998 there has been a switch to using SST predictors from the Indian and Pacific Ocean instead. This switch was prompted by experimental work carried out by the Bureau of Meteorology Research Centre (BMRC) (Drosdowsky and Chambers, 1998; Drosdowsky, 2000). Since January 2000, the rainfall outlook has been supplemented by similar forecasts for seasonal average maximum and minimum temperatures.

The forecast system uses linear discriminant analysis (LDA) to estimate the probability of seasonal rainfall (or temperatures) being in one of three categories (terces). The forecasts use the time series of the first two eigenvectors of SSTAs, taken one or three months prior to the season to be forecast, as the main predictors.

These eigenvectors are currently calculated using the UKMO GISST1.1 data set and are updated using real-time SSTA analyses.

The Seasonal Climate Outlook contains a number of different forecast products. There are maps showing the probability or chance of rainfall (or temperatures) being in one of the three terces in the next three months. These are complemented by tables showing the chance of conditions being in each terce and also showing the probability of exceeding given rainfall amounts on a district by district basis throughout Australia. Additional information from a GCM forecast of Niño3 temperatures is used to assess the state of the ENSO system over the forthcoming season. ENSO variability is also considered using graphs to show historical analogues of the SOI which most closely resemble the recent movement of the SOI. Rainfall maps for these years are provided as analogues to the forecast climatic conditions. Accuracy is about 70 to 80% at present in skilful areas; however in the least skilful areas the outlooks perform no better than random chance or guessing.

Outside of the tropics the prospects for seasonal forecasting have generally been considered weaker, due to the lower SST signal to internal atmospheric noise ratio and the importance of non-linear dynamics (Palmer and Anderson, 1994; Rowell, 1998). However, seasonal forecasts for the U.S.A. have been successfully developed. For example, Barnston *et al.* (1998) describe a two-tiered coupled modelling system for forecasting surface temperature, 700 mb geopotential heights and, with considerably lower skill, precipitation. Their system initially uses the Geophysical Fluid Dynamics Laboratory (GFDL) ocean model to forecast forthcoming SST anomalies These SSTA predictions are then used as the lower boundary conditions for forcing eighteen ensemble member integrations of the NCEP medium range atmospheric GCM to produce the final temperature and precipitation forecasts. Moderate predictive skill has been found in the boreal winter during ENSO extremes (when tropical Pacific SSTs are greater than one standard deviation from the mean) (Barnston *et al.*, 1998). Statistical forecasts have also been developed for Canada, using CCA (Shabbar and Barnston, 1999), and the U.S.A. (Unger, 1999), using multiple linear regression.

Attempts have also been made in the U.S.A. to integrate climate forecasts from forecast development to applications in the community through the International Research Institute for climate prediction (IRI). This is a recent initiative which is a cooperative agreement between NOAA/Office of Global Programs and Columbia University/Lamont-Doherty Earth Observatory which looks at development and delivery of forecast products for a range of climate applications world-wide. There are three groups within the IRI, a modelling/prediction research group to improve forecasts, an experimental climate forecast group which is responsible for routine production of all experimental forecast, and a training program responsible for the utilisation of these forecasts at a regional level (see http://iri.ldeo.columbia.edu/).

Of final interest in this section are attempts to extend seasonal forecasting schemes into Europe. Attempts to predict July and August anomalies of Central England temperatures have been made using linear regression with the time-series of the leading eigenvector of January and February North Atlantic SST as the predictor (Colman and Davey, 1996; Colman, 1997; Colman and Davey, 1997; Colman, 1998). Johansson *et al.* (1998) have also attempted to develop a prediction scheme for surface temperature over Europe using a form of CCA analysis, with SST data, 700 mb geopotential heights and surface air temperature in eighteen countries across Europe. They found a combination of 700 mb geopotential height and surface air temperature gave the most skillful forecast for the JFM winter season, which extended to a time lead of three months. They suggest that the level of skill is similar to that which can be obtained in North America but that the origin of skill is the North Atlantic Oscillation (NAO), rather than ENSO.

4. Direct Forecasts of Climatic Impacts

Section 3 provided examples of seasonal forecasts for temperature and precipitation using both empirical and model climate forecasts. Temperature and precipitation forecasts can also be indirectly applied to other forewarning schemes for various hazards such as droughts, floods and their associated impacts. This section illustrates how seasonal forecasts can be applied directly to climatic impacts with respect to selected regions of Africa and case studies from Australia and the U.S.A., before outlining the possibility for direct application of seasonal forecasting to climate and related hazards in Europe.

Drought and floods that affect crop yields are especially important in African regions, with a high dependence upon agriculture. One approach to seasonal forecasting is to predict crop yields from ‘upstream’ variables such as SSTAs, rather than first temperature or precipitation. Potentially important variables in determining crop yields, other than temperature and precipitation, could be used, e.g., humidity, solar radiation and potential evapotranspiration. Such a direct crop forecast would also bypass some of the communication and interpretation hurdles between forecast developer and recipient.

Cane *et al.* (1994) suggest that over 60% of maize yield variability in Zimbabwe could be explained by Pacific SSTs. They suggest that accurate forecasts of maize yield could be made up to a year in advance using model predictions of ENSO SST variability. Such studies (e.g., Nicholls, 1985) rely on the availability of accurate historical time-series of maize yields, which also include effects of prices, land reform and other socio-economic factors. Furthermore, recent historical yields should no longer be used for seasonal forecasting in southern Africa since the historical yields themselves have been largely influenced by seasonal forecasts of the 1997–1998 El Niño. The Environmental Change Institute and School of Geography and the Environment in Oxford have developed a direct seasonal forecasting method for maize yield potential in Zimbabwe and South Africa, using an agroclimatological model forced with observed climate data from 1961–1994 to create a time-series that is predicted from SSTAs and sea-level pressure anomalies (Martin, 1998; Martin *et al.*, 2000).

Table I. Aug.-Sep.-Oct. predictors included in the seasonal maize WRSI jack-knife forecast for South Africa and Zimbabwe (after Martin, 1998).

South Africa	Zimbabwe
Difference between Pacific and Indian Ocean (SLP)	East Pacific (SLP)
North Atlantic (SST)	
South-west Indian Ocean (SLP)	
Pressure difference between Tahiti and Darwin (SOI)	

The agroclimatological model calculates a water stress index based on planting date, plant available soil water, rainfall, temperature, wind speed, sunshine, vapour pressure and cloud cover. Monthly values are summed over the season to produce a Water Requirement Satisfaction Index (WRSI). This index captures the agroclimatology of maize; it compares well with FAO (Food and Agriculture Organisation of the United Nations) crop yield data (correlation coefficient of 0.61 for South Africa and 0.63 for Zimbabwe for 1961–1994, with significance greater than the 0.005 level (Martin *et al.*, 2000)).

A linear regression model has been developed for predicting maize WRSI at a May harvest using the OND Southern Oscillation Index (SOI) as the predictor for South Africa, and OND Niño3 SSTs as the predictor for Zimbabwe, at a four month lead time. For South Africa the correlation between predicted maize WRSI (using the climate regression model) and the actual WRSI (from the agroclimatological model) training data set was $r = 0.67$, and the correlation between forecast and validation data, $r = 0.69$, but the model performance for Zimbabwe was less promising (Martin *et al.*, 2000). Regression models for predicting South African and Zimbabwean maize WRSI were also developed at a six month lead time using the predictors listed in Table I (Martin, 1998). These predictors were selected from significant correlations of WRSI with both between SST and sea-level pressure. The variance in each maize time-series explained by the regression model is shown in Table II while the relationship between forecast and modelled WRSI for South Africa for the validation period is illustrated in Figure 2. It should be noted that the use of alternate years for the training and validation data may overestimate the model skill since the two time periods are not truly independent, as discussed in Section 2.

More recently South African maize WRSI has been predicted from the NCEP re-analysis data with a lead time of three months or more. Correlation coefficients between WRSI for a particular season and preceding Oct.–Jan. 700 mb zonal wind and Nov.–Jan. 850 mb specific humidity are shown in Figure 3. These, and a number of other different variables in the NCEP data set, suggests that there may room for further improvement in such forecasts.

Table II. Percent variance in South African and Zimbabwean maize WRSI explained by the 16/17 year jack-knife regression forecasts (after Martin, 1998)

	South Africa	Zimbabwe
Training period (alternate years commencing 1961/62)	84%	39%
Validation period (alternate years commencing 1962/63)	72%	62%

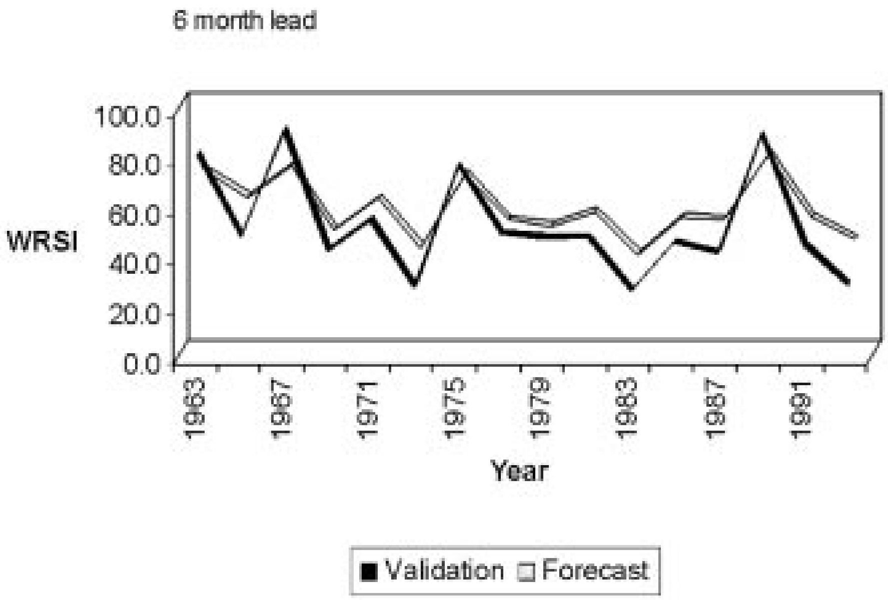

Figure 2. Comparison of actual (from the agroclimatological model) and forecast maize water-stress (WRSI) for South Africa for the validation data set using multiple regression, the jack-knife technique, and a six month lead time (after Martin, 1998).

In Australia ‘The Aussie Grass Project’ (http://www.dnr.qld.gov.au/longpdk/agrass/index.html) was set up, initially in Queensland, to help promote sustainable management practices using up-to-date forecast information on seasonal climate variability. The first stage, completed in 1996, involved running a pasture growth model (GRASP) on a 5 km grid for Queensland, calibrated to take account of the range of soil, pasture and climate types over the region. Since 1997 attempts have been made to operationalise these assessments and forecasts of pasture conditions for other parts of Australia, e.g., in the Northern Territories and Kimberley region.

Seasonal forecasting of Atlantic hurricane activity has been attempted at Colorado State University since 1983 (Landsea *et al.*, 1994). The schemes have focused on probabilistic predictions, e.g., forecasting the number of hurricanes that are likely to occur over a particular hurricane season, compared to an average period. The different hurricane variables currently forecast are listed in Table III (Gray

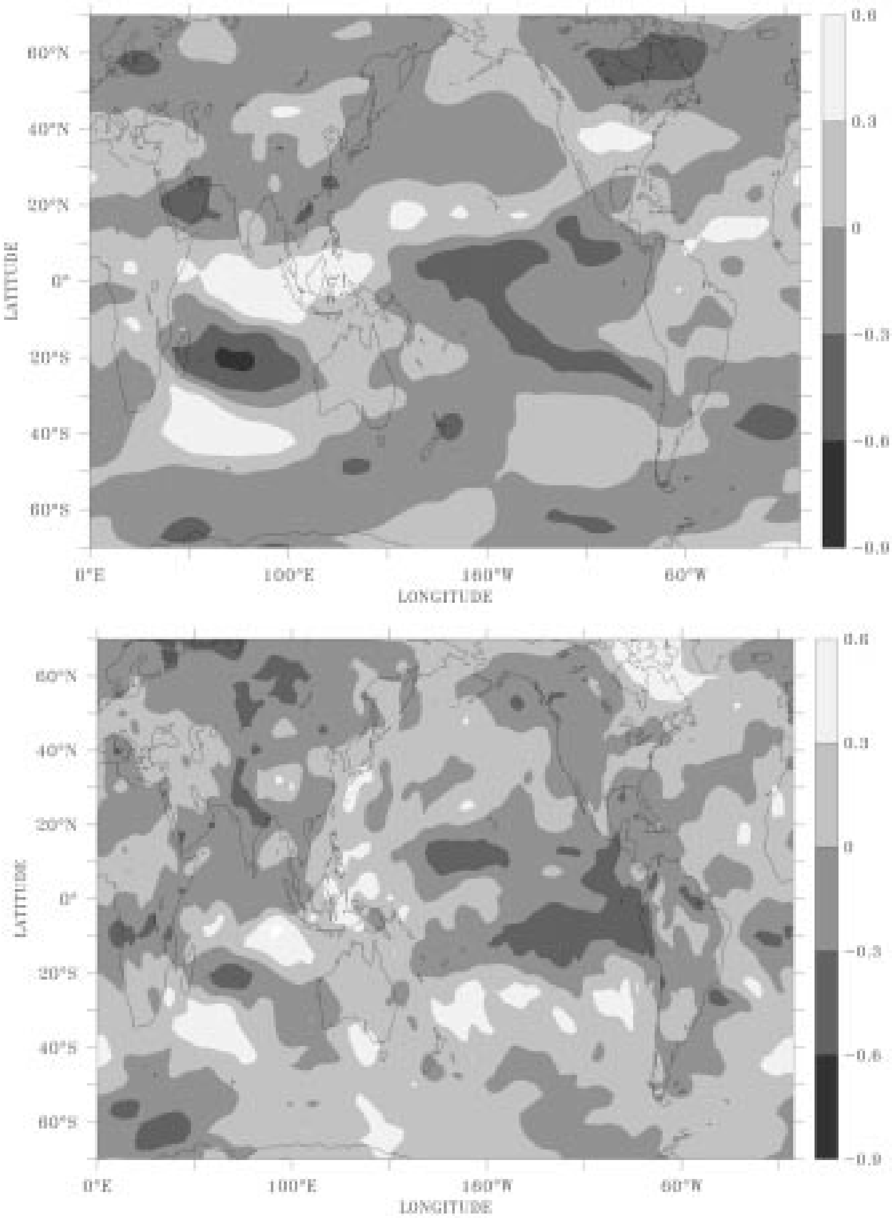

Figure 3. Correlations between 1962–1994 South Africa maize water-stress/yield and (a) NCEP Oct.–Jan. 700 mb zonal-wind, (b) NCEP Nov.–Jan. 850 mb specific humidity. Correlations greater than $r = 0.34$ are significant at the 0.05 level. (Image produced using data from the NOAA-CIRES Climate Diagnostics Centre, Bounder Colorado from their web site at http://www.cdc.noaa.gov/.)

Table III. Hurricane variables currently predicted, and actual and predicted values for the 1995 Atlanta Hurricane season (after Gray *et al.*, 1995a,b; Gray *et al.*, 1998a,b).

Variable	Early June forecast	Actual values	Average over 1950–1994 period
No. of named storms	12	19	9.3
No. of named storm days	65	121	46.2
No. of hurricanes	8	11	5.7
No. of hurricane days	35	62	23
No. of intense storms	3	5	2.1
No. of intense storm days	6	11.5	4.5
Net tropical cyclone activity (as % of average over 1950-1994)	140%	237%	100%
Hurricane destruction potential	–	–	–
Maximum potential destruction	–	–	–

et al., 1998a,b). The Atlantic hurricane season lasts from June to November, but with only 6% of hurricane activity (where hurricane activity is defined as one-minute average winds of 18–33 m/s) occurring before August 1st on average (Landsea, 1993; Landsea *et al.*, 1994). Forecasts (developed using data post-1950) are therefore issued in early August, early June, early April and early December of the previous year (Gray *et al.*, 1998b). Important predictors include the state of the Quasi-biennial Oscillation (QBO), ENSO, African rainfall over the Western Sahel and Guinea coast, Atlantic SSTs, the North African temperature and pressure gradient anomalies across the Sahel, and sea-level pressure and 200 mb zonal wind anomalies in the Caribbean basin (see Gray, 1990; Landsea *et al.*, 1994; Jones and Thorncroft, 1998; and Gray *et al.*, 1998b). The June forecast is thought to encompass about 50–70% of the hurricane variability in the hurricane season (Landsea *et al.*, 1994). The 1995 season forecast was particularly successful when significantly above average hurricane activity was forecast (Table III) (Gray *et al.*, 1995a). Although the forecast still underestimated the amount of activity that actually occurred, this proved to be a record year for hurricane activity in the Atlantic (Gray *et al.*, 1995b). Similar attempts are being made to forecast tropical cyclone activity from November to May around Northern Australia based on the October value of the SOI (Nicholls, 1998).

Is there potential for further seasonal forecast development in Europe? Scepticism has been expressed by some authors due to the smaller SST signal identified in the mid-latitude atmosphere than in the tropics (Palmer and Anderson, 1994). However, a large-scale atmospheric influence on the climate of Europe has been identified in the form of the NAO, and experimental seasonal forecasts outlined above (e.g., Colman, 1997 and Johansson *et al.*, 1998) would suggest otherwise.

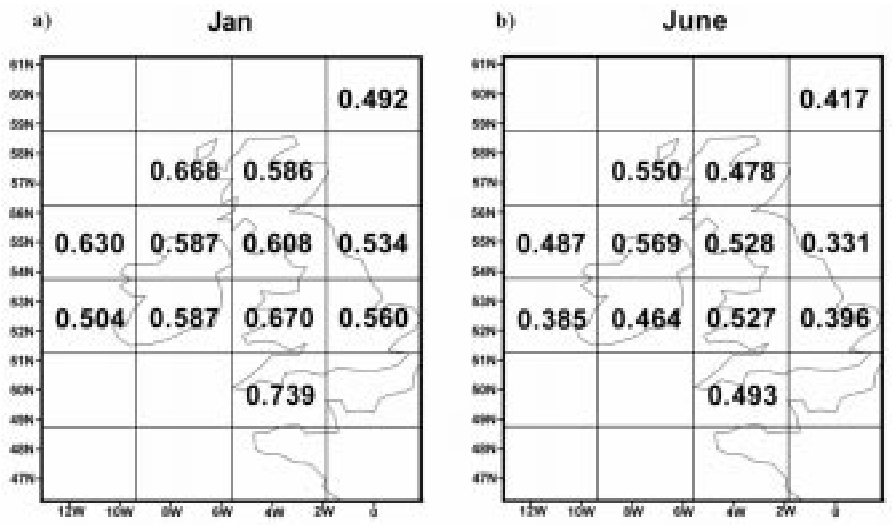

Figure 4. Variance (R^2) in (a) January and (b) June gridded U.K. and Ireland precipitation explained by 1–3 indices of concurrent North Atlantic SLP using a simple stepwise linear regression model (as outlines in Murphy and Washington, 2000).

Murphy and Washington (2001) have shown that three indices of the North Atlantic sea-level pressure field can be used to explain 49–74% of the concurrent variance in U.K. and Ireland precipitation in January and 33–55% in June (Figure 4). For twelve grid-box time-series of U.K. and Ireland precipitation for each month of the year, it was found that over 40% of U.K. and Ireland precipitation variance could be explained 80% of the time. The key to developing seasonal forecast schemes for Europe may therefore lie in determining what drives the dominant modes of SLP variability over the North Atlantic, which involves investigating the ocean-atmosphere relationship in the Atlantic. Additionally, the ECMWF coupled GCM (Stockdale *et al.*, 1998) and the UKMO unified model show tentative suggestions of links between ENSO and predictability over Europe (Carson, 1998).

There are several potential uses of seasonal forecasts in Europe. Intensively managed arable farms use high inputs of nitrogen, pesticides and irrigation water, if needed. Winter wheat dominates the cereal area in northern Europe. Despite high inputs, yield often fails to meet quality standards for internal markets, EU intervention or export. Recent research has shown that quality is affected by climate (Kettewell *et al.*, 1999). Hagberg falling number (an indicator of bread-making quality) over the period 1972–1997 has a strong correlation with the January to February NAO index and with the January to February SST index. Quality may be improved with the use of seasonal climate forecasts. Indeed, a forecast model of wheat quality has been developed which predicts quality at harvest with reasonable skill two months before harvest, using average past weather data (Smith and Gooding, 1999); integration of this approach with seasonal forecasts should improve this level of skill. Better targeting would increase fertiliser efficiency and reduce risks of nitrate leaching (Olesen *et al.*, 1997; Goodlass *et al.*, 1997).

Too much water is often as great a problem as too little, as the Autumn 1997 floods in East Africa or the 1998 flooding in Europe exemplify. Attempts to forecast anomalous river discharges include a probability forecasting scheme of the annual discharge of the Murray River, Australia, using an index of Eastern Equatorial Pacific SSTs (Simpson *et al.*, 1993a,b). The SSTs were predicted using the Zebiak and Cane (1987) model of ENSO. From this the probability of annual discharge falling into a particular category could then be determined. Likewise, Hastenrath *et al.* (1998) have attempted to forecast February to March discharge of the Caroni River in Venezuela using multiple linear regression and the previous July to August Southern Oscillation and river discharge as predictors. Attempts are being made to extend such approaches to African and Europe utilising some of the extensive databases available (e.g., the FRIEND archive (Oberlin and Desbos, 1997)) and also to feed climatological predictors directly into hydrological numerical models. Shorthouse and Arnell (1997) have demonstrated that a significant relationship exists between the large-scale North Atlantic SLP field and European river flows and Wilby (2000) has produced an empirical forecast of selected summer (particularly August) river flows from the preceding winter NAO index.

5. Integrating Seasonal Forecasts and Responses

'*Utility of forecasts can be increased by systematic efforts to bring scientific outputs and users' needs together*' (Stern and Easterling, 1999, p. 3). As this National Academy of Sciences review reports, to achieve success in using seasonal forecasts we need to understand the nature of seasonal forecast information, how information is transferred to the appropriate users and the range of effective responses. This section discusses impediments in the presentation and distribution of seasonal forecasts. A comparison of reliability and utility indicates where forecasts could have the greatest impact on coping with climatic hazards. Addressing the weaker links in the end-to-end dissemination process will provide a means for improving forecast applications.

Preparation and presentation of seasonal forecast information is the first stage in addressing how applications can be maximized (as shown in Figure 5). The scale and manner in which information is presented is crucial. Spatial and temporal resolution, forecast skill and probabilistic formats all contribute to impediments in the use of forecasts.

The temporal generality that characterizes seasonal forecast information may not be specific enough for some stakeholders. Water managers may be able to use the forecasts effectively without knowing the timing and distribution of rain throughout the season. Farmers, on the other hand, may require more accurate forecasts, for example of the seasonal distribution and onset of the rains. If the time lag between the development and receipt of seasonal forecasts could be de-

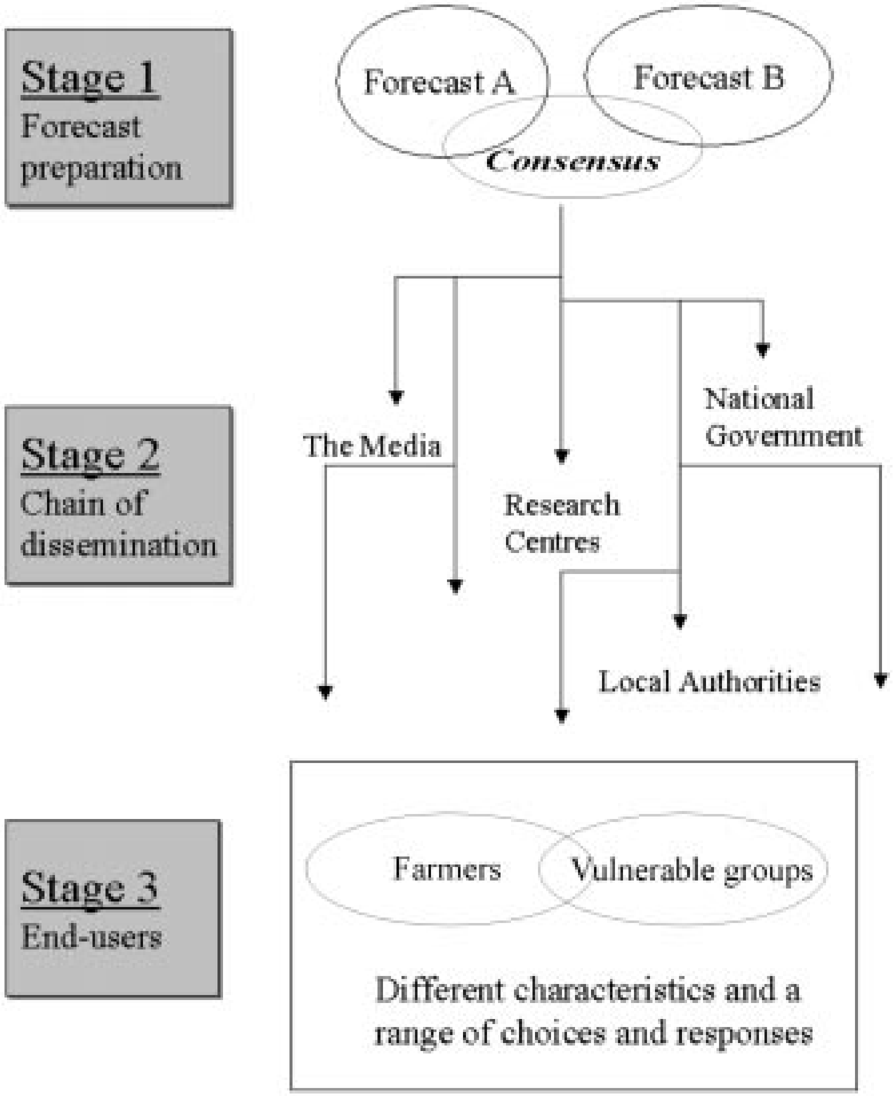

Figure 5. Seasonal forecast applications; the production, dissemination and end-users (after Washington and Downing, 1999).

creased, the information could have increased utility. By providing information when needed, decisions such as the type and timing of which crop to plant could be altered to reflect the predicted climate. Timing is also imperative to aid agencies, which require about four months to deliver food to an area (e.g., after a famine early warning system confirms need for aid (Farmer, 1997)).

The spatial generality of the forecast has similar consequences to the temporal concern. A smallholder farmer that relies on a regional forecast could be heavily penalized by following the seasonal forecast. Impact models may suffer problems from down-scaling of coarse resolution output; forecasts tend to be issued for large areas that consist of a myriad of microclimates that may not be reflected in the forecast. Delivering a general forecast to local users could thus prove more harmful than no forecast at all. Considerations like this must be assessed before assuming that forecasts can be of use to everyone.

A response-orientated approach could report response options for different sectors. These should not be prescriptions; responsibility for action must be retained by the users and not by the agency supplying the forecasts. The information needs to be communicated in a way that allows it to become the property of the user. Risk is an inherent part of decision making; seasonal forecasting must be portrayed in this context. Although the information may be of limited utility until forecast skill and timing can be improved, it is important that users are given the opportunity to understand the information. This allows individuals to decide for themselves whether to take the risk of using the forecast information to improve their management plans.

The limited skill of forecasts cannot be overlooked. It is particularly helpful to communicate information on the accuracy of past predictive models. The comprehensiveness of the forecast, coupled with an understanding of its specificity and probabilistic nature can help individuals to evaluate the most effective response. If forecasts are utilised and they prove to be incorrect, it is important that the users realise what the skill was so they know how much confidence to attach to the forecast. This should be combined with attempts to improve verifications methods so that figures can be put to the validity of forecasts (Harrison, 2000). More work needs to be done, as it would aid the communication of probabilities by expanding on the tercile forecasts which do not always specify the skill for the region. Communicating the limited skill remains one of the largest challenges that the seasonal forecasting and early warning community must face in order to minimise the impacts of extreme natural events.

The chain of dissemination has great potential for adapting the forecasts (Figure 5 Stage 2). Each step can result in mis-interpretation of valuable information or the loss of specific information to the target users for which it was intended or the information can be tailored for specific clients. The way information is conveyed in a seasonal forecast is therefore of critical importance.

The source of the forecast can elicit various responses. Individual forecasts may be collated to provide a composite forecast, e.g., Outlook Fora (as mentioned in Section 3) where forecasters and users produce a consensus forecast for the region (Buizer *et al.*, 2000). In general, however, a wide variety of forecasts are issued, either directly from the World Meteorological Organisation and national meteorological centres, or indirectly via national governments, the media and through international organisations and early warning prediction centres (e.g., USAID-funded Famine Early Warning System (FEWS)).

The perception of seasonal forecasting at the national level may determine the amount, nature of, and speed with which information is communicated to end-users. Individual and community perceptions determine the nature of the localised acceptance and response. These responses are in turn determined by the apparent success of earlier warnings, as well as cultural norms, which include the use of environmental indicators, local traditions and risk attitudes that are strongly determined by the success of last years behaviour (Weber, 1994).

The response to the 1997–1998 El Niño event in the Peruvian fishering sector highlights some of the complexities associated with equity and dissemination (Pfaff *et al.*, 1999). The common method for distributing information was via the internet in English. This immediately cut out a large percentage of the Spanish fishing communities. The danger is that the forecast unintentionally disadvantaged some groups against their competitors. Forecast distributors need to address the complex political issues of who gains and who loses.

Users needs have to be addressed (Stage 3). Australia is the best example of user-oriented initiatives (Hammer *et al.*, 2000). The Bureau of Meteorology (BoM) began issuing forecasts in 1989 (Orlove and Tosteson, 1999) and evolved to reflect user needs. Forecasts have taken the form of on-line resources, stand-alone software packages (such as Rainman, which allows users to analyse historical SOI and rainfall data to assess the probability of seasonal rainfall distribution), telephone and fax hotlines and education and training manuals and activities. Institutional links have promoted successful integration; strengthening institutional links is vital for ensuring success and user feedback. The opportunity for users to contribute to the development of the process needs to be integrated into the system so that it can aid the development of user-oriented products.

Still required is an understanding of the user-profile. A matrix of forecast predictability and use illustrates the level of forecast predictability skill users require (Table IV). There is a trade-off between the ability to predict seasonal climates and the extent to which such predictions might be used. The combination of forecast skill and potential utility provides some insight into the processes of forecast uptake in the end-to-end chain, which can highlight where further development ought to be concentrated. Reliability of the forecast needs to be seen as a long-term learning strategy rather than a short-term response to an individual forecast. This is critical because it affects perceptions of probability, how it is developed and acted on.

Clearly, where there is low predictability, high use is not likely. However, even with low predictability, there may be some users who will seek the information to make decisions that are sensitive to climatic variations (Cell L in Table IV). For example, the summer forecast in England is not altogether reliable, yet it is widely reported and if the subsequent signals confirm the forecast, they may be used to make some decisions. Water companies may also use the forecast by anticipating higher than normal demand and monitoring the likelihood of supply shortages, but taking more extreme measures only if it is the second year of a drought.

Table IV. The predictability and skill of the forecast versus the potential use for the forecast.

Predicability	Potential utility	
	Low	High
Low	X	L
Medium	**M-L**	**M-H**
High	**?**	**H**

L, low use; M, moderate use; H, high use; X, no use; ?, uncertain.

At the other end of the spectrum, where predictability and potential utility are high, high use (Cell H) indicates that users are sensitive to climate information, have organised effectively to promote and receive forecasts, and can make profitable decisions based on this information (Katz and Murphy, 1997). Australia falls into this category. Information is likely to be widely available, disseminated through multiple channels directly to the users and translated and tailored to suit their needs (for example, the Rainman product described above).

If predictability is high but use is not widespread then either there is a failure in the system (if potential utility is also high) or utility is low. It may be that users are not particularly sensitive to climate information (for example, a water company with a secure supply). If users could benefit from the forecasts but are not using it, then there must be some constraints in the system. Parts of Africa would fall into this category. Barriers could include political motives to regulate effective dissemination of information or there may be a limited understanding of what the information represents and what measures could be taken to use the information effectively.

In between these extremes, use depends on the balance between predictability and utility. The difference between low and high utility can vary between users (e.g., vulnerable smallholders vs. commercial farmers) and between scales of decision making (e.g., regional planning vs. community development). It is these areas that present the greatest challenge for applying seasonal forecasts.

Who are the vulnerable – in terms of climatic hazards – that could benefit from seasonal forecasts? The first answer is to recognize that vulnerability is embedded in many layers of decision making, from international markets to national politics to local resource management. It may be that seasonal forecasts will have the greatest benefits to reduce vulnerability through decisions at the regional and higher level. Early warning systems for drought and floods, for example, could incorporate forecasts into preparedness efforts, including targeting of vulnerable areas, prepositioning emergency relief supplies and hazard mitigation (such as small-scale irrigation and temporary floodplain evacuation).

Direct use of forecasts by vulnerable populations will depend on the end-to-end chain of dissemination and the profits of utility. In developing countries, the most dramatic use may be through the concerted effect on livelihood security. Vulnerability, or more generally livelihood security, is the concatenation of resource production, exchange entitlement and political economy of empowerment (see Sen, 1981; Downing, 1996). However, while famines can occur where there has been no significant decline in the available supply of food, no food must surely lead to famine (Tapscott, 1997). A seasonal forecast that aids food production may have limited effect where labour, credit, agrotechnology and health are the defining characteristics of vulnerability. However, the widespread use of seasonal forecasts could reduce a range of threats to security. Bringing to bear forecasts on vector-borne diseases, water shortages, risk of crop failure for investment, and market requirements and supplies could make a difference. By fitting the constraints and users' needs on to a matrix it becomes clear that forecasts of varying degrees of skill are utilised differently by different stakeholders. By formalizing the interaction of predictability and usage a framework to focus an integrated management regime is provided.

6. Summary and Conclusion

Seasonal forecasting has good prospects for application to early warning of drought and flood hazards. This is of economic value in Europe, and a matter life and death in the more vulnerable communities of Africa. It is a hazard early warning system that has taken a back seat in the 1990s, the International Decade for Natural Disaster Reduction (IDNDR). "Were it not for earthquakes, climate prediction could be called the last frontier in natural disaster early warning" (Dilley, 1997, p. 1).

This article has explained the methods of, and prospects for, further inclusion of this type of forecasting in the detection, monitoring and early warning of climate hazards. Prospects for further applications of seasonal forecasting to these hazards are particularly promising in tropical and sub-tropical regions, such as marginal areas of semi-arid Africa, where a number of seasonal rainfall forecasts are currently operational. The potential also exists to extend such forecasting schemes to Europe. The possibility of direct application of seasonal forecasting to crop yields and hydrological hazards has been emphasised, thereby bypassing one step in the complicated transfer of information from forecast developer to recipient user. Preliminary investigations into the former, in the form of direct application of seasonal forecasting to maize yields in Southern Africa and Zimbabwe using an agroclimatological model, have been illustrated.

Successful mitigation of the impacts of climate hazards cannot purely be concerned with seasonal forecast development. It requires an interactive approach between the physical and social sciences. Ultimately this must incorporate research into the types, and channels, of communication between forecast developer and recipient (a two-way process (Dilley, 1997)), how this transfer of information can be improved so that it is available at all levels, e.g., through education, and how best it should be acted upon. This requires an understanding of the 'user-profile', as discussed in Section 5.

Seasonal forecasting is an emerging skill. Forecast schemes are getting better in some regions, and more regions are being added to the list where forecasts could have significant utility. The methods are becoming more sophisticated, both in the forecast schemes and in the connection to users. However, there is still a long way to go. The potential for misinterpretation of forecasts and the dangers of wrong forecasts continue to be major issues. But imagine a world where seasonal forecasts are common knowledge – not perfect, but widely available and widely used. We would no longer be able to blame the weather for the impacts of a bad drought, where the drought had been predicted up to a year in advance. We would not have an excuse to tackle vulnerability where we fully expected storms to be severe and areas at-risk of floods.

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