Predictability of Weather and Climate: From Theory to Practice - From Days to Decades

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1. Introduction

A revolution in weather and climate forecasting is in progress, made possible as a result of theoretical advances in our understanding of the predictability of weather and climate, and by the extraordinary developments in supercomputer technology. Specifically, through ensemble prediction, weather and climate forecasting is set to enter a new era, addressing quantitatively weather and climate sensitive concerns in a range of commercial and humanitarian applications. This is possible because, through ensemble techniques, we can now tackle the problem of flow-dependent prediction of weather and climate risk. This paper gives some background to this revolution, with specific examples drawn from a range of timescales.

2. 20th vs 21st C Perspectives on Predictability

If something is said to be "predictable", then presumably it can, in principle, be predicted! The qualification "in principle" suggests that a measure of predictability should not depend, for example, on whether or not prediction models are in practice biased, or if weather measurements are in practice made with inaccurate instruments. This in turn suggests that predictability is somehow a more aesthetic subject of study than is prediction - consistent with the remark of the famous climatologist: "Predictability is to prediction as romance is to sex!" (Oscar Wilde who wrote, "The very essence of romance is uncertainty!", might well have approved!)

However, I wish to argue that predictability is no longer an ivory-tower pursuit, but an intrinsic part of operational weather and climate forecasting. By forecasting predictability, we predict weather and climate risk. I would claim that the full economic value of meteorological predictions will only be realised when quantitatively reliable flow-dependent predictions of weather and climate risk are achievable (Palmer, 2002). Ensemble prediction provides the means to achieve this goal.

Because of inevitable uncertainties in initial data and model equations (see below), weather and climate forecasting should fundamentally be thought of in terms of an equation where the basic prognostic quantity is a probability density $\rho(X,t)$, X being a weather variable and t being time. Essentially, $\rho(X,t)\, dV$ denotes the probability that at time t, the true value of X lies in some small volume dV of state space. For practical reasons we choose to solve these equations by ensemble techniques (see Buizza et al, 2003). The study of predictability is synonymous with the study of the prediction of $\rho(X,t)$, and users of weather forecasts will obtain much greater value from estimates of $\rho(X,t)$, than from best-forecast guidance of the weather (Smith, 2003).

Consider, the famous Lorenz (1963) model. In Fig 1 we show the well-known fact that the evolution of some isopleth of ρ(X,t) depends on starting conditions. This is a consequence of the fact that the underlying equations of motion

$$\dot{X} = F\left[X\right] \tag{1}$$

are nonlinear, so that the Jacobian dF/dX in the linearised equations

$$\frac{d\,\delta X}{dt} = \frac{dF}{dX}\delta X$$

depend at least linearly on the state X about which equation (1) is linearised. As such, the so-called tangent propagator

$$M(t,t_0) = \exp\int_{t_0}^{t} \frac{dF}{dX} dt'$$

depends on the nonlinear trajectory $X(t)$ about which the linearisation is performed, and the evolved perturbations

$$\delta X(t) = M(t,t_0)\,\delta X(t_0)$$

depend not only on $\delta X(t_0)$, but also on the region of phase phase through which the nonlinear trajectories pass.

It is of interest to note in passing that the formal solution of the Liouville equation for $\rho(X,t)$ (Ehrendorfer, 2003) can be written using the tangent propagator (for all time in the future, not just the time for which the tangent-linear approximation is valid). Specifically

$$\rho(X,t) \ = \ \rho(X',t_0)/\det M(t,t_0) \qquad (2)$$

where X' corresponds to the initial state which, under the action of equation (1), evolves into the state X at time t. Fig 1 shows solutions to equation (2) using a Monte-Carlo (ie ensemble) approach.

To illustrate the 21st Century pragmatist approach to predictability, I want to reinterpret Fig 1 by introducing Charlie, a builder by profession, and a golfing colleague of mine! Charlie, like many members of my golf club, takes great pleasure in telling me when (he thinks) the weather forecast has gone wrong. This is mostly done in good humour, but on one particular occasion, Charlie was in a black mood. “I have only four words to say to you”, he announced, “How do I sue?”. I looked puzzled. He continued. “They forecast a night-time minimum temperature of 5 degrees. I laid three thousand square yards of concrete, and it’s all ruined. There was a frost. I repeat - how do I sue?” Before I had time to realise that this might be a golden opportunity to explain probability forecasting to a captive member of the public, Charlie was off, no doubt telling others what a useless bunch these weather forecasters are!

Figure 1. Finite time ensembles of the Lorenz (1963) system

With this encounter in mind, consider again Fig 1, representing an imaginary world whose weather was determined by the Lorenz equations. Let's suppose that all states on the left hand lobe of the attractor were "frosty" states, and all states on the right hand lobe of the attractor were "frost-free" states. In this imaginary world, Charlie is planning to lay a large amount concrete tomorrow. Should he? On the basis of the ensemble forecasts in Fig 1a he clearly should not - all members of the ensemble predict frosty weather. On the basis of the ensemble forecasts in Fig 1c he also should not - in this case it is almost impossible to predict whether it will be frosty or not. Since the cost of buying and laying concrete is significant, it is not worth going ahead when the risk of frost is so large. How about the situation shown in Fig 1b? If we took the patronising but not uncommon view that Charlie, like most of the general public, would only be confused by a probability forecast, then we might decide to collapse the ensemble forecast into an (ensemble-mean) "consensus" prediction. The best-guess consensus forecast indicates that frost will not occur. But if we tell him that frost will not occur, and it does, then we know Charlie will be enraged.

Alternatively we could tell Charlie not to lay concrete if there is even the slightest risk of frost. But Charlie will not thank us for that either, since on plenty of occasions where it would have been perfectly acceptable to lay concrete, our forecast would have prevented him. He cannot wait forever to lay concrete since he has fixed costs, and if he doesn't complete this job, he may miss out on other jobs. We can formalise this somewhat. Suppose Charlie's fixed costs are C, and suppose that by laying concrete when a ground frost occurs he loses L. Then a logical decision strategy will be to lay concrete when the ensemble-based estimate of the probability of frost is less than C/L. As meteorologists we do not know Charlie's C/L. So the best we can do is provide him with a probability forecast, and allow him to decide whether or not to lay concrete.

Clearly the probability forecast will only be of value to Charlie if he saves money using these ensemble forecasts. This notion of "potential economic value" (Murphy, 1977) is conceptually quite different to the notion of skill (in the meteorological sense of the word), since value cannot be assessed by analysing meteorological variables alone - value depends also on the user's economic parameters. Richardson (2000) discussed the value of the ECMWF Ensemble Prediction System.

The fact that value does not depend solely on meteorology means that we cannot use meteorological skill scores alone if we want to assess whether forecast system A is more valuable than forecast system B. This is relevant to the question of whether it would be better to utilise computer resources to increase ensemble size or increase model resolution. As discussed in Palmer (2002), the answer to this question depends on C/L. For small C/L more value may accrue from an increase in ensemble size (since decisions depend on relatively small probability thresholds), whilst for larger C/L more value may accrue from the better representation of weather provided by a higher-resolution model.

3. Why are forecasts uncertain?

Essentially, there are three reasons why forecasts are uncertain: uncertainty in initial state, uncertainty in the model itself, and uncertainty in external parameters. Consider the last of these first. For example, the rate of increase in carbon dioxide over the coming decades is clearly an important parameter in determining how climate is likely to have changed at the end of the century. But this rate of change depends, for example, on which nations sign up to agreements such as the Kyoto protocol. This is not something that can be determined by a physical climate model. On the other hand, since some countries might cite forecast uncertainty as a reason for not signing up to Kyoto, uncertainty in such external parameters are not independent of model uncertainties! However, we leave this third component of uncertainty aside; for predictions on timescales of days to seasons, perhaps the only significant "uncertainty of the third kind" is associated with volcanoes, and the associated release of aerosol into the atmosphere.

In the remainder of this section, we will focus on the first two of these uncertainties, bearing in mind that none is independent of the others.

3.1. Initial Uncertainty

There is a general formalism from which we can, in principle, estimate initial uncertainty. In operational weather prediction, the analysed state Xa of the atmosphere is found by minimising the cost function

$$J(X)=\tfrac{1}{2}(X-X_b)^T\ B^{-1}(X-X_b)+\tfrac{1}{2}(HX-Y)^T\ O^{-1}(HX-Y) \qquad (3)$$

where X_b is the background state, B and O are covariance matrices for the pdfs of background error and observation error, respectively, H is the so-called observation operator, and Y denotes the vector of available observations. The Hessian

$$\nabla\nabla J = B^{-1} + H^T O^{-1} H \equiv A^{-1}$$

of J defines the inverse analysis error covariance matrix.

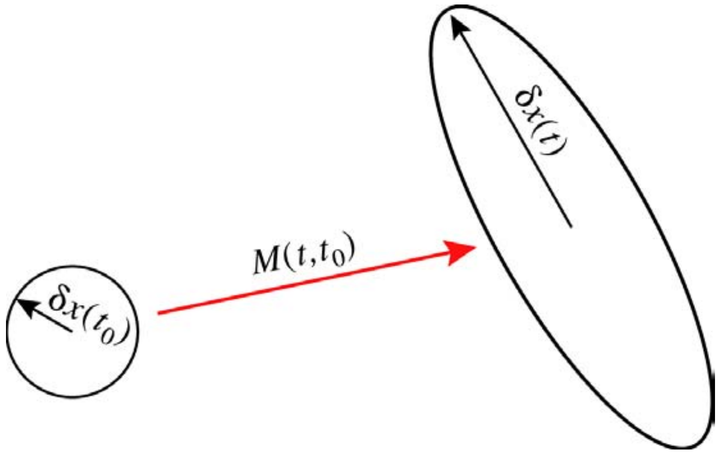

Figure 2: Isopleth of probability that the region enclosed by the isopleth contains truth, and associated singular dominant singular vector at initial and final time.

Fig 2 shows, schematically, an isopleth of this covariance matrix, and its evolution under the action of the tangent propagator *M* at forecast time. The vector pointing along the major axis of this forecast isopleth corresponds to the leading eigenvector of the forecast error covariance matrix. Its pre-image at initial time corresponds to the leading singular vector of *M*, determined with respect to unit norm in the metric given by A. The singular vectors of M correspond to the eigenvectors of M^TM in the generalised eigenvector equation

$$M^T M\ \delta x(t_0) = -\lambda A^{-1}\delta x(t_0)$$

By sampling the initial pdf with respect to the leading singular vectors we have an efficient sampling of the forecast pdf - we do not waste computer resources integrating directions which are likely to have little growth during the period where predictability is significant.

Singular vector sampling also provides a conservative methodology for generating initial perturbations for an ensemble prediction system. For example, estimates of *A* in operational data assimilation systems almost certainly underestimate the true uncertainty in the initial state. To take one example, estimates of *B* at ECMWF do not take account of model error.

3.2. Model Uncertainty

There is no known equation, such as equation (3), for estimating the underlying uncertainty in the model equations, and in parametrisation tendency in particular.

Parametrisation is a procedure to approximate the effects of sub-grid scale motions on the resolved scales. If there was a clear scale separation between these sub-grid motions and the resolved scales (as there is, for example, when considering the effect of Brownian motion on macroscale fluid behaviour), then one could be reasonably confident that parametrisations could be developed with acceptable accuracy. However, there is no such scale separation in the atmosphere; indeed the energy spectra of atmospheric motion shallows (from a -3 slope to a -5/3 slope) as the truncation limit of weather and climate models is approached.

As such, the parametrised tendency can at best be thought of as representing the expectation value of some underlying probability distribution of sub-grid tendencies. Suppose we knew the form of this underlying distribution and sampled it stochastically. If subgrid perturbations have the ability to cascade upscale, then stochastic sampling of sub-grid tendencies would affect the simulation of the variance of large-scale motion. Moreover, if the dynamics of such large-scale motions were governed by non-gaussian distributions (eg Corti et al, 1999), then the finite variance of sub-grid tendencies could lead to a change in the mean state of these large-scale motions.

Let us write, schematically, the equations of motion of our climate or weather prediction model as

$$\dot{X} = F[X] + \langle P \rangle + P'$$

where <P> denotes the conventional parametrisation term, represented as an expectation value, and P′ denotes some stochastic drawing from the probability distribution associated with P-<P>. As discussed in Buizza et al (1999), and Palmer (2001), a simple choice for P′ is P′=ε<P> (denoted "P" in the caption in Fig 4) where ε is a non-dimensional stochastic parameter with mean zero. Buizza et al (1999) showed that probabilistic skill scores for the medium-range EPS were improved using this stochastic parametrisation scheme. This physical basis for such a multiplicative form of stochastic parametrisation is that stochastic model perturbations are likely to be largest when the parametrisation tendencies themselves are largest, eg associated with intense convective activity, when the individual convective cells have some organised mesoscale structure, and therefore where the parametrisation concept breaks down. Alternative parametrisations P′=εF (denoted as "D") and P′=ε(<P>-F) (denoted as "PD") have also been tested. The effect of these parametrisations on the climatology of the ECMWF coupled model are shown in Fig 3.

An alternative more pragmatic approach to the representation of model uncertainty is given by the multi-model ensemble. In this, the ensemble utilises parametrisation schemes <P>$_i$ and possibly also different numerical representations F_i , developed quasi-independently by institute *i*. From a theoretical perspective, there are two fundamental differences between the stochastic physics and the multi-model approach to the representation of model uncertainty. Firstly, each representation <P>$_i$ in the multi-model approach is itself a quasi-independent estimate of the expectation of the sub-grid tendency - the ensemble of such <P>$_i$ does not therefore constitute a random sampling of the underlying pdf. In theory therefore, the multi-model approach may be too conservative a methodology for representing model uncertainty. Secondly, the multi-model approach cannot simulate the possible rectification associated with stochastic forcing on non-gaussian pdfs. On the other hand, the <P>$_i$ are relatively sophisticated in their representations of sub-grid processes, whilst the multiplicative representation of stochastic uncertainty as discussed above is rather crude and ad hoc. The multi-model approach has been shown to be beneficial in seasonal forecast studies (Palmer et al 2003), as discussed below.

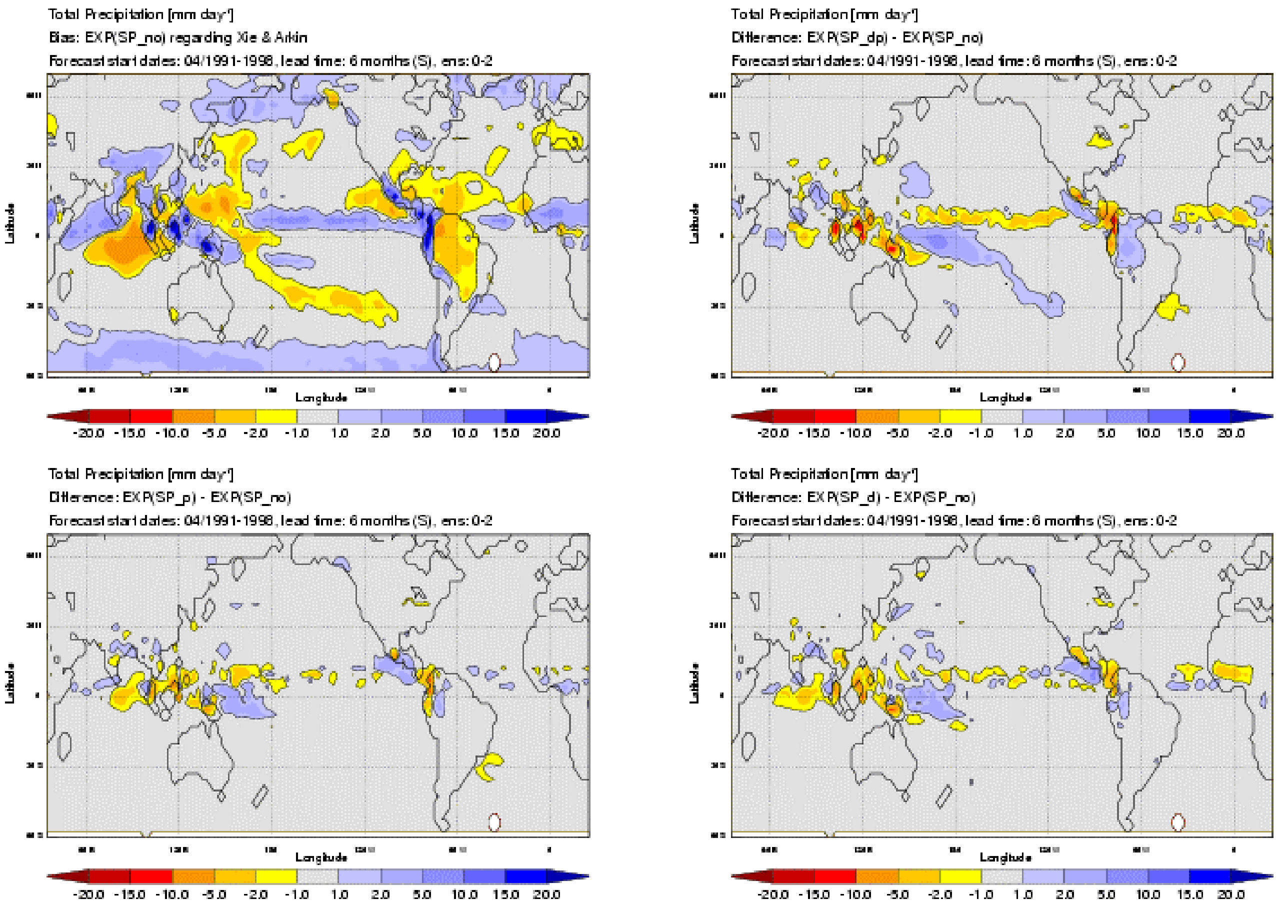

Figure 3. Systematic error in precipitation (top left) and impact of stochastic physics in the ECMWF coupled model, PD top right, P bottom left and D bottom right. Based on an ensemble of six month integrations over multiple start dates (R. Hagedorn, personal communication).

4. Ensemble Forecasts: Some Examples

4.1. Medium Range

The ECMWF EPS comprises 51 forecasts at TL255L40 resolution, and uses both singular vector initial perturbations and stochastic physics.

In late December 1999, two intense storms, subsequently named Lothar and Martin, ran across continental Europe leaving behind a trail of destruction and misery, with over 100 fatalities, over 400 million trees blown down, and over 3 million people without electricity and water. Fig 4a shows the EPS stamp maps (based on a TL255 model) for Lothar, at initialisation time on December 24 and for forecast time 6z on December 26. This storm was exceptionally unpredictable, and even at 42 hours lead time, there is considerable spread in the ensemble. The best-guidance deterministic forecast only predicts a weak trough in surface pressure. A number of members of the EPS support this forecast, however a minority of forecasts also show an intense vortex over France. In this sense, the ensemble was able to predict the risk of a severe event, even though it was impossible to give a precise deterministic forecast.

By contrast Fig 4b shows 42 hour forecast stamp maps for a more recent storm (with 100 mile per hour gusts) which ran across the United Kingdom in October 2002 killing 9. By contrast, this storm was predicted both in the best-guidance forecast, and by most of the EPS members. Compared to Lothar, this storm was extremely predictable.

Ensemble forecasts can also be made for severe weather risk in the tropics. Fig 5 shows a 5-day ensemble forecast for Tropical Cyclone Rusa. The high-resolution forecast shows the best-guess cyclone track moving into the Yellow Sea. The ensemble indicated a significant risk of recurvature to the north. The analysed track did recurve, and crossed Korea, where 150 people were reported killed due to flooding and mud slides.

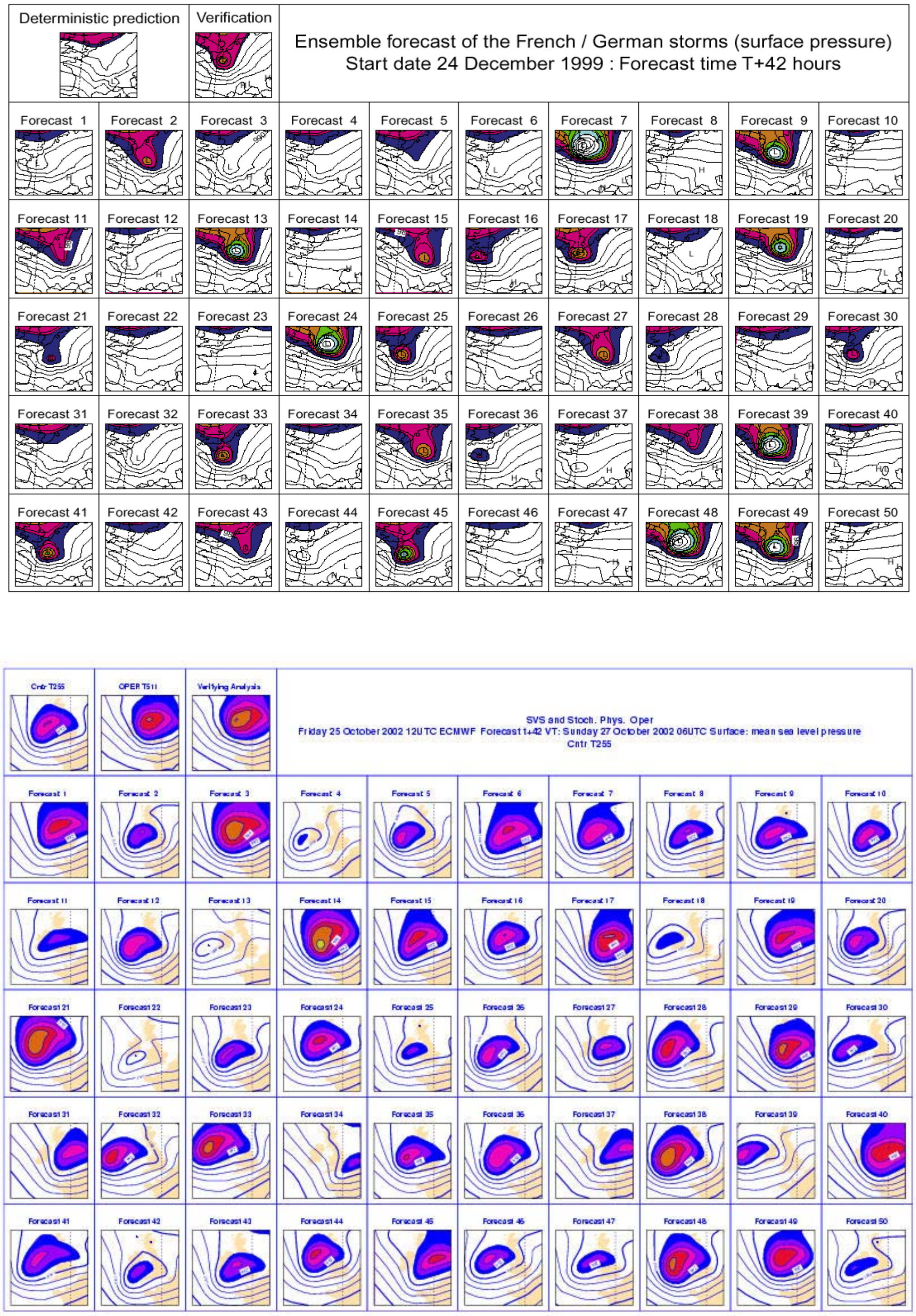

Figure 4. Ensemble prediction stamp maps for 42 hour forecasts of severe weather events. Top: Lothar, very unpredictable. Bottom storm of October 2002 rather predictable.

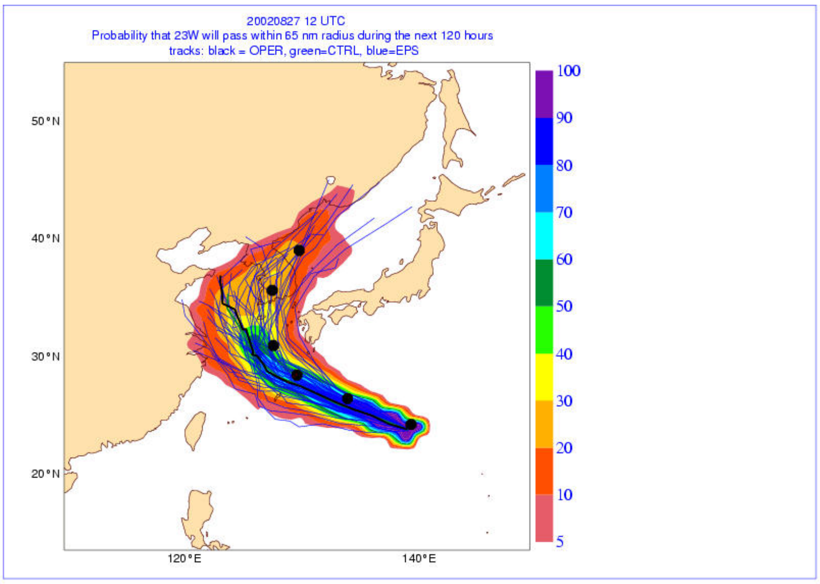

Figure 5. 5-day ensemble prediction for typhoon Rusa.

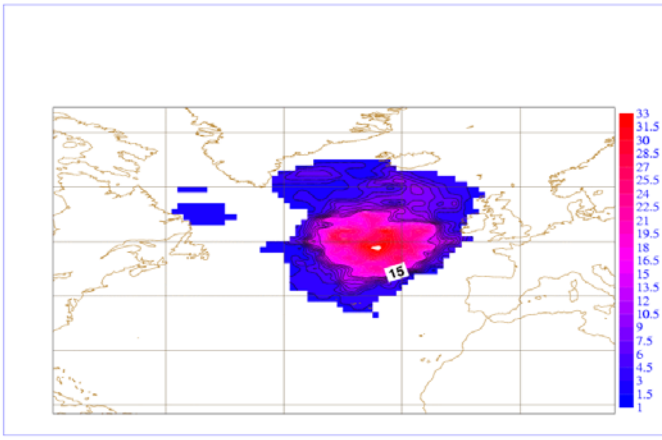

Figure 6. Example of joint probability forecast, that wave swell exceeds 4m and wave period lies between 14 and 17 seconds (O. Saetra, personal communication)

As discussed above, the utility of ensemble forecasts depends on the ability of the ensemble to relate directly to specific user risk. Fig 6 shows a product which can be readily produced from the EPS, as the forecast model is coupled to a global ocean wave model. Specifically, Fig 6 shows the probability that wave swell exceeds 4m and the swell period lies between 14 and 17s. The relevance of this is that such conditions can excite resonance in certain ocean-going container vessels.

The utility of such forecasts depends on the reliability of the associated probabilities. These forecasts are, in fact, remarkably reliable (O. Saetra, personal communication 2002). Consistent with this, these forecasts indicate significant potential economic value.

4.2. Seasonal Prediction

Representing model uncertainty is a key element in predicting climate risk on seasonal and longer timescales.

The ability of multi-model ensembles to produce more reliable forecasts of seasonal climate risk over single-model ensembles, has been addressed by the PROVOST (Prediction of Climate Variations on Seasonal to Interannual Timescales) project funded by the European Union IVth Framework Environment Programme; a similar "sister" project DSP (Dynamical Seasonal Prediction) was undertaken in the United States (Palmer and Shukla, 2000).

As part of the PROVOST project, 3 different atmospheric general circulation models (including one model at two different resolutions) were integrated over 4 month timescales with prescribed observed sea surface temperatures (SSTs). Each model was run in ensemble mode, based on nine different initial conditions from each start date; results were stored in a common archive in identical format. One of the key results from PROVOST and DSP, is that despite identical SSTs, ensembles showed considerable model-to-model variability in the estimates both of the SST-forced seasonal-mean signal, and the seasonal-mean "noise" generated by internal dynamics (Straus and Shukla, 2000).

As a result, single-model ensemble estimates of the response to observed SSTs were generally not reliable. Within the PROVOST project, such ensembles were treated as potential forecasts (assuming, in some sense, oracle knowledge of the ocean), and scored using probability-forecast skill scores (Doblas-Reyes et al 2000, Graham et al 2000, Palmer et al 2000). A key result from such an analysis was that probability scores based on the full multi-model ensemble overall scored better than any of the individual model ensembles.

Based on such results, the DEMETER project (Development of a European Multi-model Ensemble System for Seasonal to Interannual Prediction) was conceived, and successfully funded under the European Union Vth Framework Environment Programme. The principal aim of DEMETER was to advance the concept of multi-model ensemble prediction, by installing a number of state-of-the-art global coupled ocean-atmosphere models on a single supercomputer, and to produce a series of six-month ensemble hindcasts with common archiving and common diagnostic software. Such a strategy posed substantial technical problems, as well as more mundane but nevertheless important issues, (eg getting agreement amongst the modelling groups as to whether simulated precipitation should be archived as an amount accumulated since the beginning of an integration, or as a rate in mm/day).

A description of the DEMETER coupled models, the DEMETER hindcast integrations, the archival structure, and the common diagnostics package used to evalulate the hindcasts, is described in Palmer et al (2003). An example of the relative value of multi-model hindcasts over single model hindcasts is shown in Fig 7.

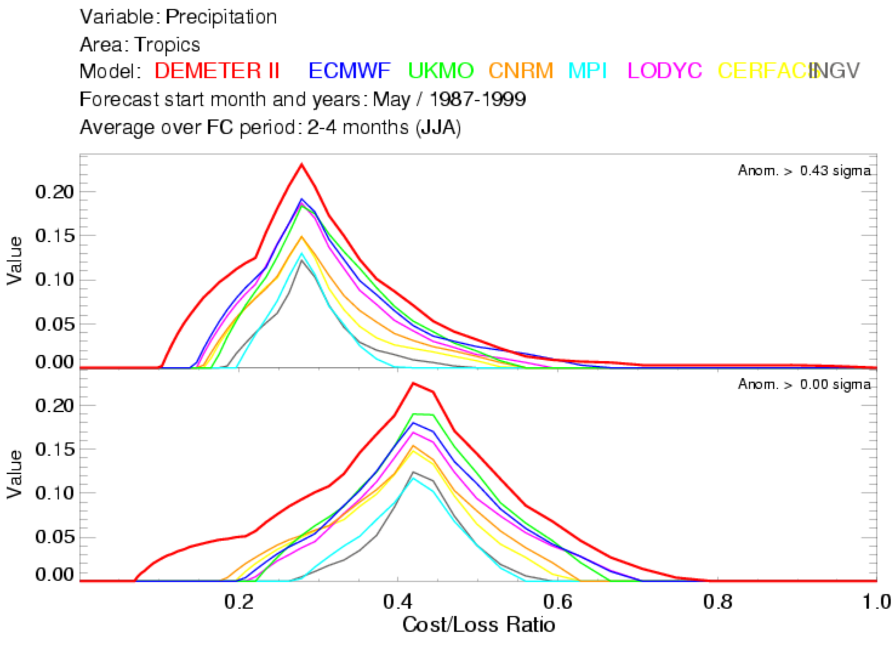

Figure 7. Value of multi-model DEMETER seasonal hindcasts, compared with individual model hindcasts based on precipitation in the tropics.

4.3. Climate Change

When extreme climate anomalies occur, it is natural to try to find some underlying cause, and in recent years, the public and media alike have sought explanations in man's possible impact on climate. The climate anomalies occurring in boreal summer 2002, including the widespread drought in the US and the floods in central and eastern Europe, are no exceptions. However, since flood and drought are part of the natural variability of climate, it is impossible to establish a direct linkage between any specific climate anomaly and anthropogenic forcing. On the other hand, it is meaningful to ask whether anthropogenic perturbations to climate can increase the risk of drought or flood.

In a recent paper, Palmer and R@is@nen (2002) used the ensemble technique to assess the impact of increasing levels of CO_2 on the changing risk of extreme seasonal rainfall over Europe in winter, and also for the Asian summer monsoon. Here this analysis is extended to study the changing risk of flood and drought in North America in both summer and winter, defined as the months June-August (JJA) and December-February (DJF) respectively. The analysis is performed on 80-year integrations from the CMIP2 (Second Coupled Model Intercomparison Project) multi-model ensemble of 19 global coupled ocean-atmosphere climate models (Meehl, 2000) as used in the recent IPCC third assessment report (IPCC, 2001). The first ('control') ensemble was run with a constant 20thC CO_2, the second ('greenhouse') ensemble was run with a transient compound increase in CO_2 of 1% /year. In the greenhouse ensemble, CO_2 doubling occurs around years 61-80. This simplified scenario overestimates the expected rate of CO_2 increase, but it excludes increases in other greenhouse gases like methane and nitrous oxide that are expected to accelerate climate change in the real world. As a result, the scenario is in the mid-range of the more detailed IPCC SRES emission scenarios in terms of global mean radiative forcing and temperature change.

For each model in the control ensemble, the maximum and minimum seasonal-mean rainfall are calculated (for DJF and JJA separately) at each grid point. These define model-specific '80-year flood and drought' events respectively. For each model, the greenhouse integration was analysed between years 61-80, to assess both the number N_f of times that DJF- and JJA-mean precipitation exceeded the corresponding 80-year maximum, and the number N_d times that the seasonal precipitation was less than the 80-year minimum. The values $20/\langle N_f \rangle$ and $20/\langle N_d \rangle$, where <..> denotes an ensemble mean, gives what we refer to as the expected return period of the 80-year drought and flood, in a doubled CO_2 atmosphere.

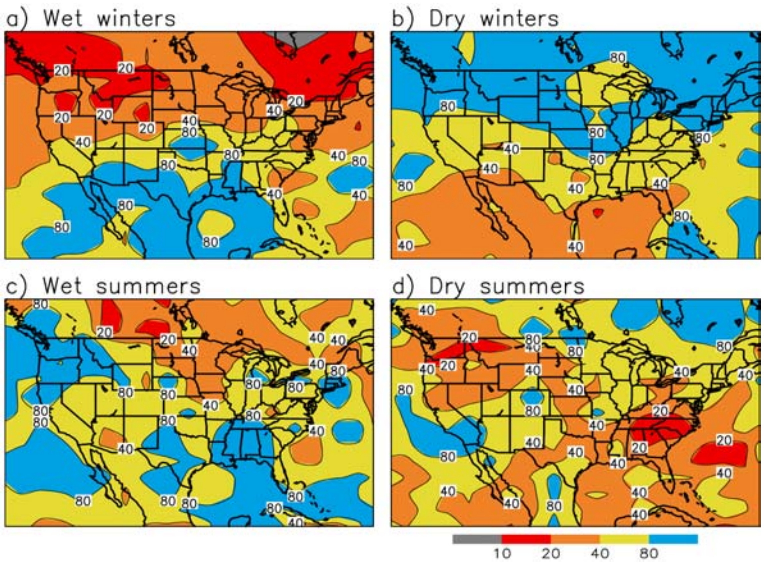

Figure 8 The expected return period in the CMIP2 multi-model greenhouse ensemble, of a seasonal mean rainfall event with 80-year return period in the CMIP2 control ensemble. a) flood events in winter. b) drought events in summer. c) flood events in summer, d) drought events in summer. Results evaluated around the time of CO_2 doubling (J.Räisänen, personal communication).

Fig 8 shows the expected return period for the 80-year flood and drought, over North America between years 61-80 of the greenhouse integrations. In winter, there is a clear decrease in the expected return period of flood from 80 to 40 years or less (20 years over parts of Canada), corresponding to an increase in the risk of flood by up to a factor of 4 (Fig 8). These values are associated with 'wetter' and more intense storm-track activity, and are consistent with the increased risk of flood found by Palmer and R@is@nen (2002) over Northern Europe in winter. In addition, there is an increased risk of drought over the southern United States and Mexico, by a factor of about 2 (Fig 8b). In summer, there is a decrease in the expected return period of 80-year drought in many parts, with expected return periods of less than 20-years in the eastern United States (Fig 8d). In general, there are extensive regions where the risk of drought has increased by a factor of 2. However, over some of the northern mid-west states, the impact of anthropogenic forcing is to increase both the risk of drought and flood, in approximately equal measure (Fig 8c,d). That is, greenhouse forcing has broadened the multi-model probability distribution of seasonal rainfall, rather than biased it in a specific direction. In part, this broadening results from the fact that the changes in long-term mean precipitation differ (even in sign) between different models. However, it is also associated with an increase in interannual precipitation variability in the models (R@is@nen, 2002).

A critical question concerns the reliability of these probabilistic results, especially as there will only be one occurrence of climate around the time of carbon dioxide doubling. This issue has been addressed by Allen and Ingram (2002) who stress the importance of assessing how well a particular climate model has been in modelling observed 20th Century climate change. However, in addition, multi-model ensembles can be validated in seasonal forecast mode. It is recommended that future generations of coupled models used in climate change prediction should also be validated in this way.

5. Conclusions

In the last few years, ensemble prediction has become an established procedure for daily seasonal and century-timescale prediction of weather and climate. This has been made possible because of dramatic advances in super-computer technology. Such ensemble prediction systems allow a quantitative estimate of flow-dependent forecast uncertainty, or, conversely, predictability. It has been argued that such estimates enhance enormously the value of weather and climate prediction.

The next step in this revolution is the linkage of output from individual members of weather and climate ensembles with quantitative application models. A prototypical example is the linkage of DEMETER seasonal ensemble hindcasts with state-of-the-art malaria prediction models, as discussed in Palmer, 2003.

In this way 'weather' will be relegated to a somewhat intermediate quantity in the environmental risk prediction systems of the future, where the final output will be some probability distribution function of specific user variables. The use will finally be in a position to make best use of weather and climate predictions for their specific decision needs.

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