Development of a decadal climate prediction system

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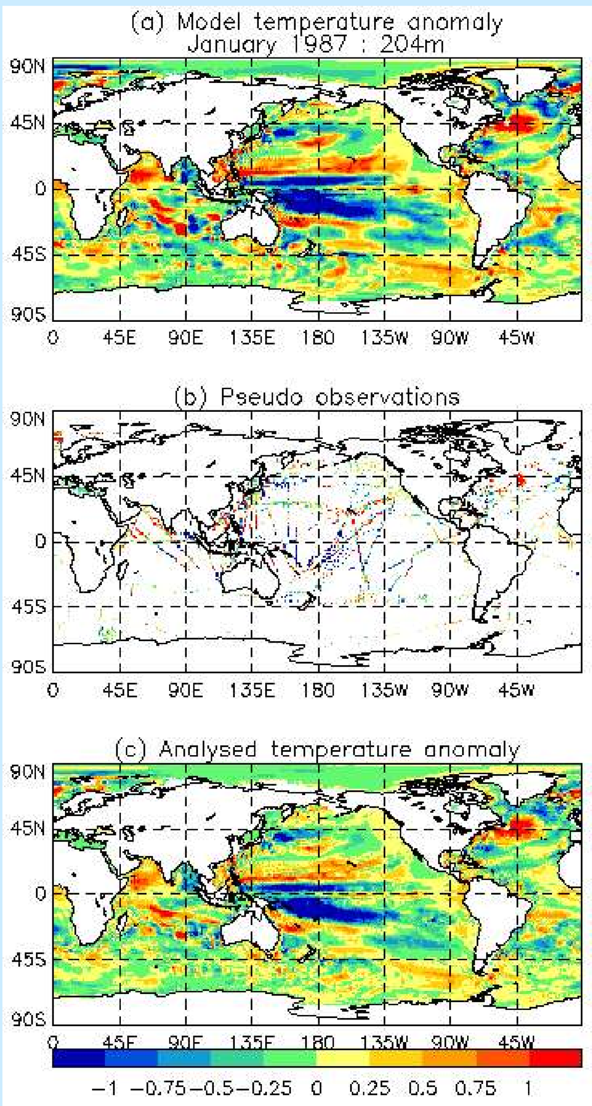

Figure 1: Reconstruction (c) of model temperature anomalies (a) at 204m by optimal interpolation of ‘ pseudo observations’ (b) sampled at typical real world observation density.

(1) Subsurface ocean analysis

• The ability to predict climate variability on annual to decadal timescales would be important both to pre-empt criticism of greenhouse gas emissions policy in the event of a run of cold years, and to enable vulnerable sectors of industry and commerce to take account of climate change in future planning.

• There is mounting evidence that low frequency climate variability is, at least partially, forced by the ocean. Accurate initialisation of the state of the ocean is therefore likely to be a key ingredient of a decadal climate prediction system using coupled climate models. To this end a new three-dimensional optimally-interpolated dataset of monthly mean ocean temperature and salinity anomalies has been developed.

• Optimal interpolation creates an analysis at any required location by combining the available observations with weights which depend on their spatial (and temporal) anomaly covariances. This is illustrated in figure 1 (c) which shows the analysed temperature anomaly obtained by optimal interpolation of ‘ pseudo observations’ (b) which were generated by sampling a monthly mean subsurface temperature field (a) from the control run of the Hadley Centre coupled global climate model (HadCM3) at locations typical of real ocean observations. In this case the anomaly covariances are well known (from HadCM3) and, although the observations are sparse, the analysis is a good representation of the truth.

• In reality, subsurface ocean observations are too sparse to provide reliable covariances. Instead, we base our optimal interpolation on covariances from HadCM3. Recognising that these will contain errors, especially at large distances, we restrict their use to objectively defined local regions.

• Example analyses are presented in figures 2 and 3. As a test of the analysis procedure, figure 2 demonstrates that analysed sea surface temperature (SST) anomalies (c) created by optimal interpolation of buoy data (b) are in reasonably good agreement with analyses which include satellite data (a). Figure 3 demonstrates that the analyses are able to capture important oceanic dynamical signals, such as the eastward propagation of subsurface temperature anomalies in the equatorial Pacific which contribute to the generation of El Niños and La Niñas.

• Since observations of salinity are particularly sparse, we employ multivariate optimal interpolation of temperature and salinity observations to generate the temperature and salinity analyses. This takes advantage of any correlation between temperature and salinity anomalies to generate salinity analyses from temperature observations, resulting in much better salinity analyses than would be obtained from optimal interpolation of salinity observations alone.

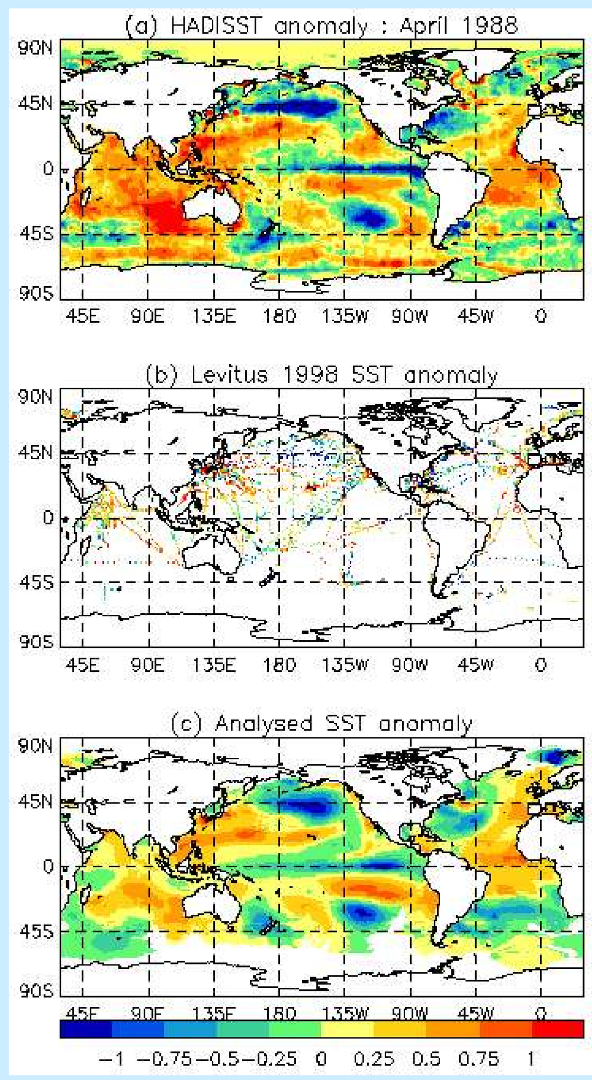

Figure 2: Reconstruction (c) of SST by optimal interpolation of surface buoy data from the Levitus 1998 dataset (b). HadISST (a) is an analysis of all SST observations, including satellite data, and may be regarded as close to the truth.

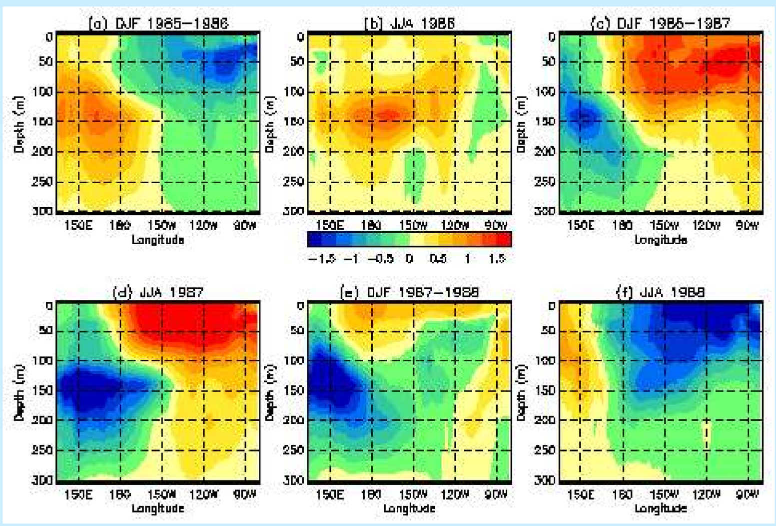

Figure 3: Time series of analysed temperature anomalies on a longitude-depth cross section of the equatorial Pacific. The eastward propagation of subsurface anomalies leading to the El Niño of 1986-87 and the following La Niña can clearly be seen.

Summary

• A decadal climate prediction system (DePreSys) based on the Hadley Centre coupled global climate model, HadCM3, has been developed.

• In order to initialise the ocean component a new dataset of monthly mean optimally interpolated ocean temperature and salinity anomalies has been created (panel (1)).

• Climate drift during forecasts is avoided by assimilating observed anomalies added to the model climate, rather than observed values (panel (2)).

• The skill of the system has been assessed in a set of 60 hindcasts initialised from 1979 to 1993.

• Compared with state-of-the-art seasonal forecasting models, DePreSys performs well on seasonal timescales (panel (3)).

• There are encouraging signs of predictability on multi-annual timescales (panel (4)). The correlation between observed and predicted annual mean global near surface air temperature over land is almost 0.6 at a lead time of one year (figure 5). Furthermore, there are a number of regions for which the temperature over the next few years could be sufficiently predictable to be of use to industry and commerce (figures 8 & 9).

(2) Model initialisation

• Before making forecasts, the ocean component of HadCM3 is initialised by relaxing (with a 6 hour timescale) the temperature and salinity fields to the optimally interpolated dataset described in panel (1).

• In addition, the atmosphere component of HadCM3 is initialised by relaxing (with a 3 hour timescale) the horizontal winds, potential temperature and surface pressure to the ECMWF 15 year reanalysis of atmospheric observations (www.ecmwf.int/research/era/ERA-15).

• Models are not able to simulate the observed climate perfectly. This is liable to introduce a bias in the forecasts as the model drifts away from the observed state towards its preferred climate. In seasonal prediction it is standard practice to pre-calculate this bias over a large number of test cases and remove it from forecasts as an *a posteriori* empirical correction. We believe this strategy to be undesirable for decadal prediction, since generation of a set of test cases required to specify the time, space (and possibly flow) dependent bias accurately relative to the magnitude of the predictable signal being sought would require substantial computational resources. We therefore adopt an alternative approach in which the model is initialised with observed *anomalies* added to the *model climate,* rather than with observed *values.*

(3) Verification of seasonal forecasts

• In order to assess the skill of the decadal prediction system (DePreSys), a set of 60 hindcasts has been performed. Initial conditions were created as described in panel (2) for the period 1979 to 1993, from which 10-year forecasts were initiated from the 1st March, June, September and December in each year.

• During the forecasts anthropogenic forcing from greenhouse gases and sulphate aerosols was increased in line with observations. Aerosol from major volcanic eruptions occurring prior to initialisation was assumed to reduce exponentially with a timescale of one year, and solar variability was accounted for by repeating the previous 11-year solar cycle.

• Ensemble forecasts of 4 members were generated in order to sample the range of predictions consistent with observational uncertainty. Each ensemble member was initialised from consecutive days immediately preceding the forecast period.

• A system capable of predicting climate variability on inter-annual to decadal timescales would also be expected to perform reasonably well on seasonal timescales. This was verified by comparing forecasts of El Niño with state-of-the-art seasonal prediction systems from the European DEMETER project (table 1). DePreSys performs at least as well as most of the other systems, subject to the caveat that a totally clean comparison is not possible, since the DePreSys forecasts started on 1st March (cf 1st February for the DEMETER forecasts), and the forecast years are not the same (even for the different DEMETER models).

Model	Months 2-4	Months 4-6
ECMWF	0.95 (0.88)	0.79 (0.53)
GloSea	0.76 (0.87)	0.66 (0.73)
LODYC	0.84 (0.87)	0.61 (0.65)
MPI	0.65 (0.80)	0.44 (0.50)
CERFACS	0.90 (0.95)	0.58 (0.82)
INGV	0.89 (0.96)	0.72 (0.88)
Meteo-France	0.74 (0.89)	0.42 (0.71)
DePreSys	0.90 (0.94)	0.69 (0.79)

Table 1: Anomaly correlation of Niño3 (Niño4) SST for the Decadal Prediction System (DePreSys) developed in this study (March forecasts, 1979-1993) compared with seasonal forecasting models from the European DEMETER project (www.ecmwf.int/research/demeter).

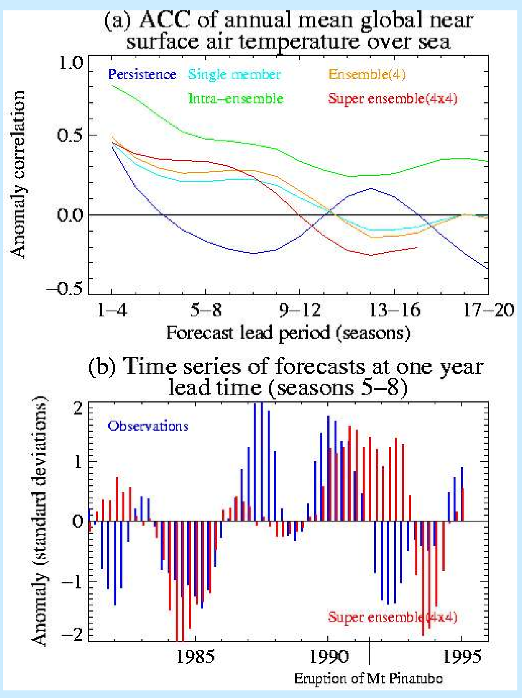

Figure 4: (a) Anomaly correlation coefficient (ACC) between forecast and observed annual mean global near surface air temperature over sea as a function of forecast lead time. See text for details of the different lines. (b) Time series of observations and forecasts at a forecast lead time of one year.

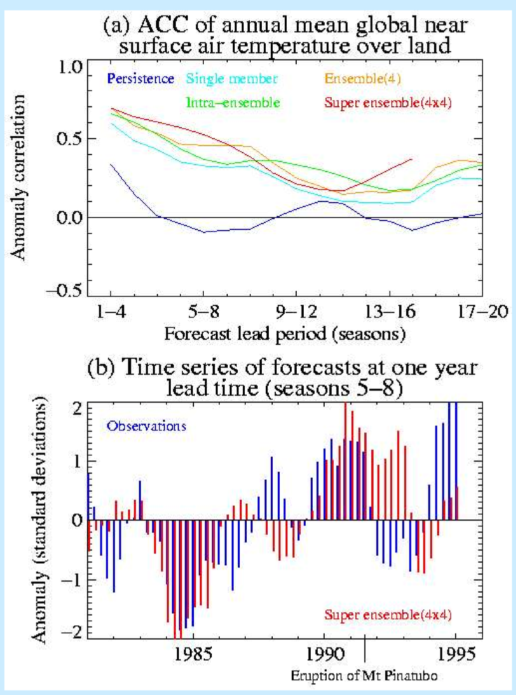

Figure 5: As figure 4 but for annual mean global near surface air temperature over land.

(4) Multi-annual forecasts

• Figure 4(a) shows the anomaly correlation coefficient (ACC) between forecast and observed annual mean near surface (1.5m) air temperature over sea as a function of forecast lead time averaged over all 60 hindcasts. The green curve (labelled intra-ensemble) is the average ACC between individual ensemble members. The difference between the actual skill of single member forecasts (light blue curve) and the intra-ensemble skill gives some indication of the potential for improving skill by increasing the density of observations and eliminating modelling errors. The single member forecasts are significantly more skillful than forecasts obtained by persisting the initial anomalies (dark blue curve). The potential for improvement by ensemble forecasting can be seen by comparing the 4 member ensemble mean (orange curve) with the single member. In order to assess the possible impact of additional ensemble members we create a ‘ super ensemble’ (red curve) by averaging 4 seasonally-lagged 4 member ensemble forecasts. For example, the super ensemble forecast for the annual mean from March 1980 would be an average of the ensemble forecasts from March 1980 (seasons1-4), December 1979 (seasons 2-5), September 1979 (seasons 3-6) and June 1979 (seasons 4-7). The 4x4 member super ensemble is significantly more skillful than either the single member or the 4 member ensemble forecasts at medium lead periods (e.g. 5-8 seasons), indicating a need for larger ensemble sizes. Figure 4(b) shows the time series of observations and super ensemble forecasts at a lead time of one year. The sign of the anomalies are forecast reasonably well, except for the cooling following the eruption of Mount Pinatubo in 1991 which would only be predictable if the eruption could be forecast.

• Surprisingly the global air temperature appears to be more predictable over land (figure 5) than over sea (figure 4). Further investigation is required to uncover the reason for this.

• In order to identify the sources of the predictability exhibited in figures 4 & 5, figure 6 shows a map of the ACC of annual mean near surface air temperature at a lead time of one year for 15x15 degree boxes (regridded to 5x5 degrees). As expected, the tropical Pacific appears to be an important source of predictability, and it is encouraging that the correct sign of annual mean Niño3 anomalies is usually predictable a year in advance (figure 7). On these timescales, regions of the Indian ocean, the central North Atlantic and the Kuroshio current also appear to be predictable, and could therefore be sources of oceanically forced climate variability.

• Many sectors of industry and commerce affected by climate variability require regional forecasts of the next few years. To identify potentially predictable regions, figure 8 shows a map of the ACC of 4-year mean near surface air temperature at zero lead time for 15x15 degree boxes (regridded to 5x5 degrees). On these timescales there are encouraging signs of predictability over many regions, including east Asia, north-east Africa, western USA and parts of western Europe (figure 9).

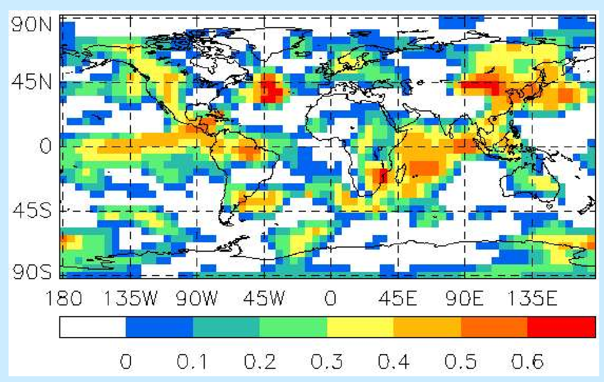

Figure 6: Anomaly correlation of annual mean near surface air temperature at a forecast lead time of one year (seasons 5-8) for 15x15 degree boxes (regridded to 5x5 degrees).

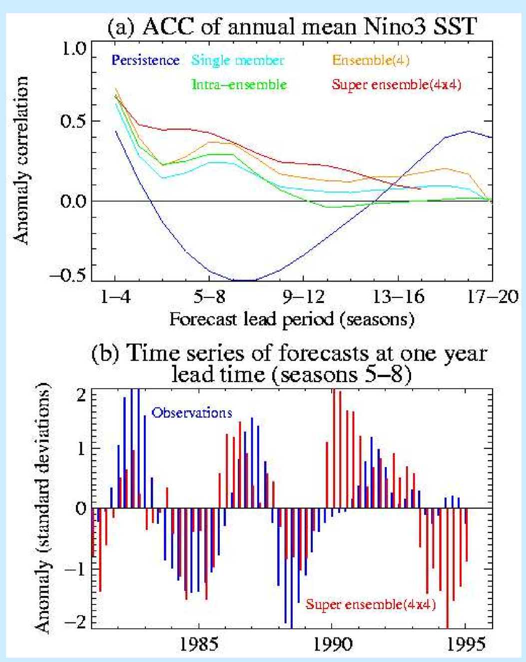

Figure 7: As figure 4 but for annual mean Niño3 SST.

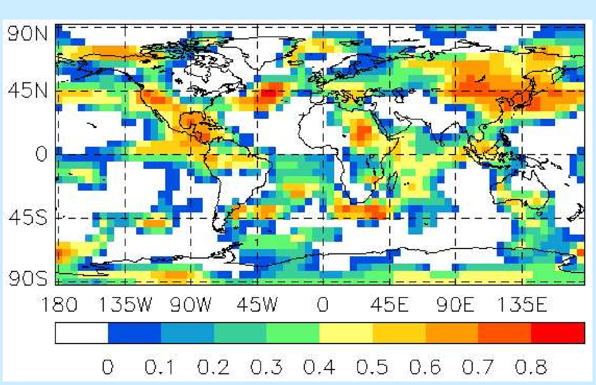

Figure 8: As Figure 6, but for 4-year mean near surface air temperature at zero forecast lead time (seasons 1-16).

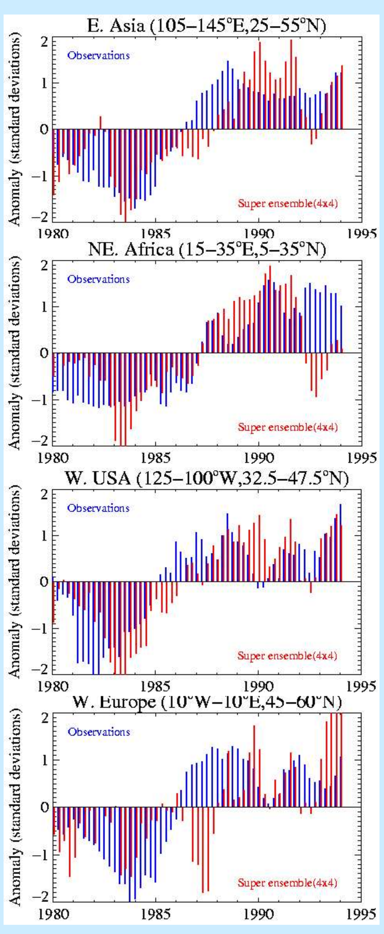

Figure 9: Time series of observed and forecast 4-year mean near surface air temperature over land at zero lead time (seasons 1-16) for selected regions.

(5) Future work

• Further analysis is required in order to assess the predictability of other climate variables, including precipitation and extreme events, and to present results in a probabilistic framework.

• The gap between the actual skill and the theoretical skill diagnosed from the intra-ensemble correlation (figure 4(a)) suggests that improving the model and its initialisation would give more accurate forecasts. Efforts to improve the model are ongoing and methods for improving initialisation, by achieving more balanced initial conditions and including additional observations (such as altimeter data), will be explored.

• The ensemble technique used so far accounts for the influence of uncertainties in the initial conditions but not for modelling uncertainties. The possibility of generating ensembles which account for modelling uncertainties, through perturbations to the model physics, will be investigated.