NUMERICAL APPROACH TO SEASONAL FORECASTING

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1. INTRODUCTION

The numerical weather predictions models (NWPs) are outstanding tools to make short term weather predictions (a few days), but they unfortunately loose all ability beyond 5 to 10 days. In other words, it is impossible to predict the day to day weather for the next season. For example, an attempt to forecast the exact day of the first fall frost early in summer would generally fail. Section 2 will present some of our seasonal data over Canada to further illustrate the non deterministic nature of seasonal predictions.

Although NWPs do not have skill on seasonal day to day weather, many studies (Zwiers 1996; Kumar et al., 1996) have shown that they do have some predictive ability on seasonal time scale for some variable e.g. temperature. This predictive skill comes from the lower boundary forcing anomalies that varies slowly in time. The best known of these anomalous forcing is the El Niño-southern oscillation (ENSO). The predictive skill coming from such forcing varies for regions to regions over the globe; it is generally higher in the tropics than in mid latitudes. There are many places in mid latitudes where the climate noise (synoptic storms activity) is so high that the signal induced by ENSO or other possible similar phenomenon is lost in the chaos. For these places, ENSO cannot help to make viable season forecast.

Even though some part of Canada have a good potential predictability for temperature (Shabbar and Khandekar, 1995), it is not obvious that the NWPs will be able to make use of it. To find out over which part of Canada and the rest of the world NWPs can make useful seasonal forecasts, the Historical Forecast Project (HFP) has been conducted. This project is a joint effort of McGill University and the following Canadian Government research and development groups: the Canadian Centre for Climate modelling and analyses (CCCma), the Canadian Meteorological Centre (CMC) and Recherche en Prévision Numérique (RPN). Two different NWP models have been run for 26 past years. Results from the HFP will be presented in section 3.

2. NO DAY TO DAY SEASONAL FORECASTS

Figure 1 shows a time series of the 1000 to 500 hPa geopotential thickness (DZ). This variable can be seen as the surface temperature: the thicker the layer between 1000 and 500 hPa the warmer the atmosphere and on the same token the warmer the surface. DZ is used at CMC for our routine operational seasonal forecast as we will see later (equation 7).

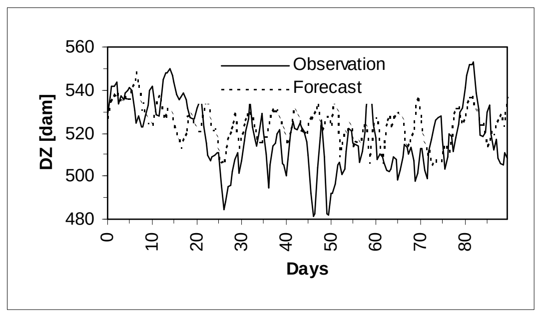

Fig. 1. DZ time series for winter 1993 (December 1993, January - February 1994) over Montréal.

The solid line on figure 1 shows the analysed (observed) DZ at every 12 hours for winter 1993 over Montréal. One can see that there is a lot of variation in DZ (temperature) with time which is typical of eastern Canada winters. The dashed line shows one of our model forecast for the same variable and for the same period. Figure 2 shows a zoom of figure 1 on days 0 to 20. One can see that the forecast is fairly close to the observation up to about 5 days. After that time the phase is lost: observed warm periods are forecasted as cold periods and vice versa.

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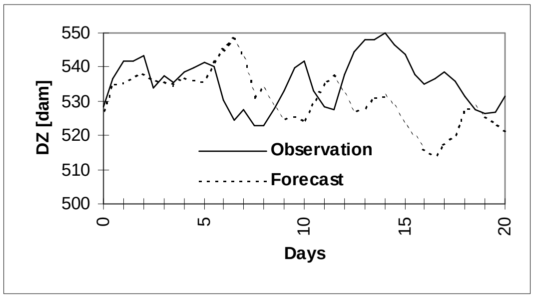

Fig. 2. Like figure 1 but zoomed in time between day 0 and day 20.

If one relies on such a forecast to find out the day of the season on which the temperature will reach a certain threshold, in average the skill will be non-existent past 5 to 10 days. All NWPs in the world would lead to similar conclusions (Anderson and van den Dool, 1994). For some situations, a particular forecast could be good for a longer period of time depending on the particular weather pattern or due to pure chance, but in average the results shown in figure 1 are typical for any mid latitude region.

Although we cannot hope to forecast daily weather throughout the season, we can forecast the seasonal averages with some success over some region of the globe. This is due to the fact that averaging a variable results in filtering out some of the unpredictable climate noise. If there is a signal induced by ENSO or other phenomenon, it will better show in the seasonal average than it would in daily weather. One has to keep in mind that some unpredictable climate noise will always contribute, to some degree, to the seasonal average. So, there will always be some part of the seasonal average that we won't be able to predict. This is the major limitation of the seasonal forecast. To further clarify this important point, let's write the forecast error of model i "E_i" as the difference between the forecast seasonal mean M_i and the observed seasonal mean M_o:

$$E_i = M_i - M_o \qquad (1)$$

Like we have seen above, the observed seasonal mean is composed of a predictable signal S_o and an unpredictable climate noise N_o :

$$M_o = S_o + N_o \qquad (2)$$

The seasonal mean M_i is also composed of a predictable part or signal S_i and some noise N_i:

$$M_i = S_i + N_i \qquad (3)$$

By replacing (2) and (3) in (1) we can write the model error as ,

$$E_i = S_i + N_i - S_o - N_o \qquad (4)$$

Let's suppose that the model gives a perfect forecast of the signal, so that S_i cancels S_o in (4). In this case the absolute forecast error is :

$$/E_i/ \leq /N_i/ + /N_o/ \qquad (5)$$

By nature N_o and N_i are random quantities so, in general, they do not cancel each other. This is why we put the absolute operator on N_i and N_o in (5). The main effect of the model noise is to increase the forecast error. A large part of the model noise can be removed by using an ensemble technique. Since the noise of individual forecast are randomly distributed they will tend to average out to 0 as the ensemble size increases. So, what's left of the forecast error by using an ensemble technique is at least equal to N_o:

$$/E/ = /N_o/ \qquad (6)$$

The error will always depend of the atmospheric climate noise on which we have no control and have no hope to forecast. Also since the models are not perfect, the actual error will be larger or equal to (6).

3. HISTORICAL FORECASTING PROJECT (HFP) SETUP AND RESULTS

In order to assess the skill of CMC seasonal forecast, all seasons in years 1969 to 1994 were forecasted. The HFP set-up is the same as the CMC operational set-up. The models use as input, among other things, sea surface temperature (SST), sea ice extent (ICE), snow coverage, winds, temperature, humidity and pressure. All these fields are global. The SST and ICE data are taken from the GISST2.2 data set (Parker et al., 1995). The SST anomaly of the month prior the start of the integrations is persisted through the 3 months forecasts. The ICE is initialised with a 30 year climatology. The snow line is specified from weekly satellite observations (from NCEP). In the SEF model, the snow anomaly of the 10 days prior to the starting time is persisted during the first month of the run and it is reverted climatology afterwards.

The GCM model was initialised with the observed snow line and then used a prognostic scheme.

Each model is integrated throughout the season in an ensemble of 6 in order to filter their climate noise as explained in section 2. These 6 integrations differ in their starting time that is lagged by 6 hours (different initial atmospheric conditions). This leads to 12 seasonal forecasts per seasons. The CMC issues forecast for 2 variables: the surface air temperature anomalies and the seasonal accumulated precipitation anomalies.

The surface air temperature anomaly forecast is done using the 500-1000hPa thickness (DZ) anomaly. The DZ variable of the model runs are output every 12 hours and averaged over the season. The 2 ensembles of 6 forecasts are averaged separately for both models. Then a hybridisation of the 2 DZ forecasts is done using the BLUE method (Derome et al., 1999). This method has shown to give better or equivalent results than a normalised average of the 2 model outputs for every season. It is currently used at CMC operations (since Spring 1999). The hybridised thickness anomaly field (DZ_a) is then related to the surface temperature anomalies T_a by the following “perfect prog” technique :

$$T_a = b\, DZ_a. \qquad (7)$$

The coefficient b in (7) was derived at Canadian stations from analysed DZ (NCEP reanalysis, Kalnay et al., 1996) and observed T (Vincent, 1998; Vincent and Gullett, 1999) for years 1969 to 1994. There is a different b for every selected stations and seasons. The values of b range from about 0.3 to 0.5 [°C/dam]. The temperature forecast is then compared to the model climatology in order to produce a 3 category forecast (below normal, normal and above normal temperature). The threshold to be different from normal is ±0.43 times the model inter-annual standard deviation. By design all categories have the same probability (1/3) to occur, so that a random forecast would be correct one third of the time in average. Using a contingency table, the Percent Correct (number of correct forecasts divide by the total number of forecasts multiply by 100) was calculated to verify the categorical forecast.

In figures 3 to 6 (Summer, Winter, Spring and Fall respectively), the percent correct of the HFP surface air temperature anomaly forecasts on 50 km grid is presented. The values at 210 Canadian stations locations are shown. In theory, the PC has to be higher than 33% to be better than chance. But since there are only 26 years in the verifications it is easy to get score higher than 33% just by chance. With 26 trials a score has to be greater or equal to about 46% to be considered statistically better than the chance (according to the binomial distribution with a 10% confidence level). The areas where the PC is higher than 46% are shaded.

It could be see from figure 3 that there is good skill in Summer over the centre of Canada. The Winter skill cover most of the western and central parts of the country (figure 4). In Spring, the system have good scores in British Columbia, Yukon and Nunavut (not shown). In Fall, the skill is mainly found in Quebec and western Ontario (not shown).

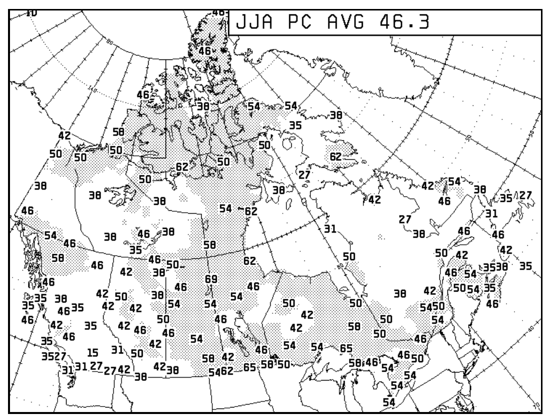

Fig.3. HFP Summer PC for T field during 1969-1994.

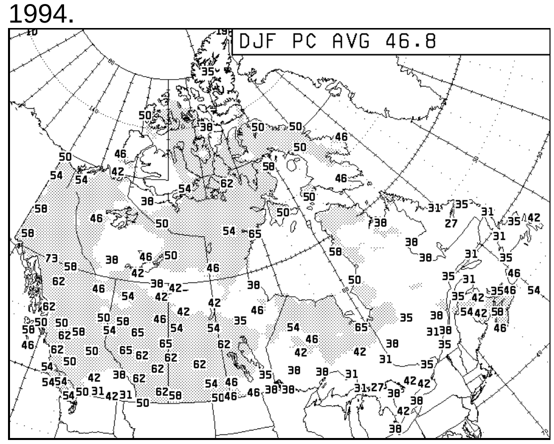

Fig.4. HFP Winter PC for T field during 1969-1994.

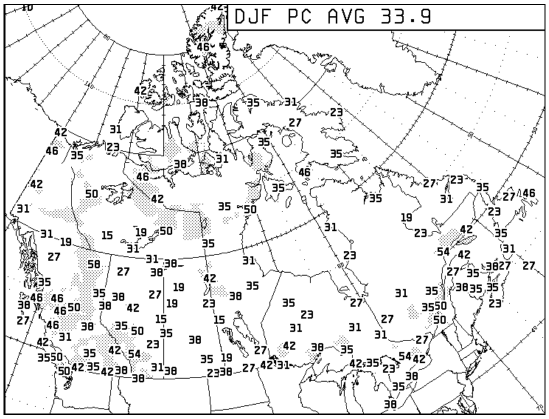

Fig.5. HFP Winter PC for PCP field during 1969-1994.

The precipitation forecast is made using a normalised average of the 2 model outputs. The categorical forecast fields were compared to the observations at more than 340 Canadian stations described by Mekis and Hogg (1999). The performance of the models in forecasting this variable is much lower than for the T forecast performance. The best results is found in Winter over British Columbia (figure 5) and in Spring over Yukon (not shown). Given the small scale nature of the precipitation field, it is very difficult to obtain accurate forecasting using coarse grid global models.

4. CONCLUDING REMARKS

The seasonal forecast is non deterministic in nature so one should not expect to get daily weather forecast one season in advance. This is due to the chaotic nature of the atmosphere. On the other hand, averaging a quantity like temperature over a season removes some of the climate noise that we cannot forecast. If there is a persistent forcing throughout the season, like ENSO, the associated anomaly may show through the remaining climate noise for some places in Canada. Only this part of the seasonal anomaly can be predicted by the models (other than the first 5 to 15 days of the season). The Historical Forecasting Project shows that CMC actual seasonal forecast set-up has large areas of statistically significant skill in Summer and in Winter for the surface air temperature anomaly field and generally marginal skill for the precipitation anomaly field.

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