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1. INTRODUCTION

Since 1995, the Canadian Meteorological Centre (CMC) produces operational seasonal forecasts using dynamical and empirical models. These forecasts are "deterministic" in their nature. The seasonal temperature anomaly at any one location is forecast as being above normal or near normal or below normal. This approach does not take directly into account the confidence associated to the individual forecast. It is difficult to the users to make efficient use of this type of forecast partly because of that fact (Nicholls, 1999). In making use of the ensemble technique, we proposed a simple method to associate a probability of occurrence to each possible category. This method is called "probabilistic". The probability of occurrence is simply calculated using the number of model integrations that forecast each one of the 3 categories.

According to Nicholls (1999), another important factor that prevents the large use of long-range forecast is that their economic value has not been demonstrated. As shown in Derome et al. (2001), Kharin and Zwiers (2001) and Kharin et al. (2001), the CMC seasonal forecast system has some skill, although modest, for the prediction of surface air temperature anomaly in Canada. However, the relationship between skill and economic value is complex and reliance on skill alone may give a misleading impression of forecast value (Richardson, 2000). In this paper, adopting a simple decision model proposed by Katz and Murphy (1987), we study the relative economic value of the CMC seasonal forecasts.

In section 2, the data set used in the study is described. The deterministic and probabilistic approaches used at CMC are presented in section 3. The Katz and Murphy decision model is summarised in section 4. The results obtained with CMC seasonal historical forecasts during the 1969 to 1994 period are presented in section 5. Finally, some conclusions are drawn in section 6.

2. HISTORICAL FORECASTING PROJECT DATA

In order to assess the skill of CMC seasonal forecast system, all seasonal forecasts over the years 1969 to 1994 were generated in hindcast mode (Historical Forecasting Project or HFP). As described in Derome et al. (2001), this project is a joint effort between McGill University, the Canadian Centre for Climate modelling

and analyses (CCCma), CMC and Recherche en Prévision Numérique (RPN). The models used are the CCCma second generation General Circulation Model (McFarlane et al., 1992) and the RPN Global Spectral model (Ritchie, 1991). The forecast seasons are December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON). The HFP set-up is similar to the CMC operational one. The models use as input, amongst other things, sea surface temperature (SST) anomalies, sea ice extent (ICE), snow coverage, winds, temperatures, humidity and pressure. The global SST anomaly of the month prior to the start of the models runs is persisted through the 3 month forecast period. The details of the treatment of the surface boundary fields can be found in Derome et al. (2001).

Each model is integrated throughout the season (three months) in an ensemble of six members. These six runs for each of the two models are initialised with analysed atmospheric conditions that are lagged by six hours. This leads to twelve seasonal forecasts per seasons, or a twelve member ensemble.

3. DESCRIPTION OF THE DETERMINISTIC AND PROBABILISTIC METHODS

The current CMC operational seasonal products are based on a deterministic approach. The surface air temperature anomaly forecast is done using the 500-1000 hPa thickness (DZ) anomaly extracted from the twelve member ensemble. The DZ fields of the model runs are output every 12 hour and averaged over the season. The two ensembles of six forecasts are averaged separately for both models. Then a hybridisation of the two DZ forecasts is done using a Best Linear Unbiased Estimator (BLUE) method (Derome et al., 2001). This method has been shown to give better or equivalent results than a normalised average of the two model outputs for every season. The hybridised thickness anomaly field (DZ_h) is then related to the surface temperature anomalies using linear regression analysis.

The precipitation forecast is simply the ensemble average of the seasonal precipitation amount anomaly (PCPN). However, the anomaly field is normalised to take into account the individual models standard deviations. This is necessary to ensure that the variance of the forecasts is close to the observed inter-annual

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variance. The anomaly is calculated using as a climate the average of the HFP runs.

The temperature and precipitation anomalies are then compared to the model climatology in order to produce a three category forecast (“below”, “near” and “above normal”). The threshold values to be different from normal are ± 0.43 times the model inter-annual standard deviations. 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 on average.

The probabilistic forecasts are made by counting the number of members in each category divided by the ensemble size as a probability of occurrence. The predicted fields are the direct model output Surface Air Temperature (SAT) anomaly and PCPN.

4. A COST-LOSS DECISION MODEL

Following work from Katz and Murphy (1987), Richardson (2000) applied a simple decision model to medium range forecasts to show the value of an ensemble forecast system. The decision model was also used by Palmer et al. (2000) and Graham et al. (2000) on a series of seasonal forecasts made by several forecast models. We simply applied the Richardson approach to CMC historical seasonal forecasts to study their economic value.

The decision model is based on Table 1 where the cost and loss for different outcomes are displayed. The model is based on the fact that a user of the forecast can take an action (at a cost C) to prevent a part L_1 of the loss L he/she will suffer if an event occurs. The events considered here are temperature or precipitation being below, near or above the normal on the seasonal time scale. As mentioned previously, the threshold values chosen for being above, near or below normal are 0.43 times the standard deviations of the fields.

Table 1: Cost and loss for different outcomes

		Occurs	
		No	Yes
Take action	No	0	L
	Yes	C	C + L - L ₁

From Table 1, we can calculate the expected expense of using only climatological information. With climatological information, the user’s only choice is always act or never act. He/she will always act if the

cost of always taking action is less than the cost of doing nothing and suffer the loss when the event occurs. Otherwise, he/she will never act. The expected expense of using climatological information is then

$$E_{c \text{ lim ate}} = \min \{ C + O \cdot (L - L_1), O \cdot L \} \quad (1)$$

where O is the climatological frequency of the event, C is the cost of the action, L is the lost if no action is taken and finally L_1 is the lost saved by the action.

Similarly, we can calculate the expected expense of using a perfect model (always act at the right time),

$$E_{\text{perfect}} = O \cdot (C + L - L_1) \quad (2)$$

The models performance are then verified using a 2x2 contingency table (Table 2) for every binary event (“below”, “near” and “above normal”). For grid points over Canada, 1 is added to the grid element of the contingency table for each observed event according to the fact that the event was forecast (see “d” in Table 2, called hits) or not (“b” in Table 2, called misses). The cases where the event was predicted but did not occur (called false alarms) are collected in “c” while the correct rejections are represented by “a” in Table 2.

Table 2: Contingency table of model performance

		Observed		
		No	yes	
Forecast	No	a	b	a + b
	Yes	c	d	c + d
		a + c = 1 - O	b + d = O	a + b + c + d = 1

From Table 2, the hit rate H and the false alarm rate F of the forecast system are

$$H = \frac{\text{number of correct forecasts}}{\text{total number of observed events}} = \frac{d}{b + d}$$

and

$$F = \frac{\text{number of forecasts not observed}}{\text{number of non - observed events}} = \frac{c}{a + c}$$

The hit rate and the false alarm rate are then use to calculate the expected expense of using CMC seasonal forecasts:

$$E_{\text{forecast}} = b \cdot L + c \cdot C + d \cdot (C + L - L_1) = F \cdot (1 - O) \cdot C - H \cdot O \cdot (L_1 - C) + O \cdot L \quad (3)$$

The relative economic value is then defined as the reduction in expense of using the CMC forecasts versus the climatology over the reduction in expense of using a perfect model versus the climatology. Then,

$$V = \frac{E_{climatology} - E_{forecast}}{E_{climatology} - E_{perfect}} \quad (4)$$

Using the equations 1, 2 and 3, the relative value becomes,

$$V = \frac{\min\{\alpha, O\} - F \cdot \alpha \cdot (1 - O) + H \cdot O \cdot (1 - \alpha)}{\min\{\alpha, O\} - O \cdot \alpha} \quad (5)$$

where $\alpha = C / L$, is the cost of taking action expressed as a fraction of the potential loss protected by the action or the cost-loss ratio. Similarly, for the probabilistic system there are a hit rate and a false alarm rate for each probability threshold (i.e. 0%, 10%, ..., 50%, etc.). With the probabilistic system, an event is predicted if the forecast probability is greater or equal to the threshold otherwise it is not. Equation 5 is then used for every threshold to estimate the value of the probabilistic system.

The relative value is usually plotted as function of the cost-loss ratio (cost-loss diagram). In Figure 1, an example of a cost-loss diagram is shown. The black solid line represents the deterministic value while the dashed lines indicate the value of the probabilistic system. For every probability threshold, there is a value curve. The thick dashed line is the envelope (maximum) of these curves. The Hanssen and Kuipers (1965) score (KS max) which corresponds to the maximum of the curves is also indicated for both systems.

The probabilistic system value varies greatly with the threshold for a given cost-loss ratio. The user can then choose the threshold to maximise the potential value as function of their cost-loss ratio value. This illustrates the benefits of probabilistic forecasts over deterministic forecasts (Palmer et al., 2000).

In the example presented in Figure 1, for cost-loss ratio less than 0.18, a user is better to always act. For cost-loss ratio between 0.2 and 0.8, the use of the forecasts maximises the value. For cost-loss ratio higher than 0.8, the user will benefit in never taking protective action. The peak occurs at the climatological frequency of the event (here 0.33) because the cost of either climatological options is the same. At this cost-loss ratio, the climatology does not help then the forecasts offer the greatest benefit (Richardson, 2000).

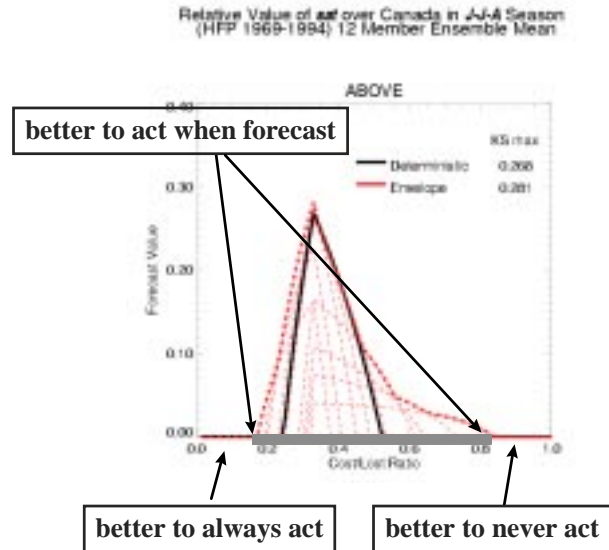


Figure 1: Example of cost-loss diagram where the relative economic value is plotted in function of the cost-loss ratio.

4. RESULTS

The relative economic value is then calculated as described in section 3 for the surface air temperature and precipitation anomaly forecasts made with the deterministic and the probabilistic systems. The forecasts are compared to Canadian surface station observations (see Vincent and Gullett, 1999 and Mekis and Hogg, 1999).

The economic values of the surface air temperature anomaly forecasts in Spring and Summer are presented in Figures 2 and 3 respectively. Only the values for the 2 extreme categories (below and above normal) are shown. For the near normal category, the value is usually clearly inferior to the one of the 2 extreme categories.

For temperatures in Spring, there is a peak at 0.25 for the above normal category forecast made by the probabilistic system (upper panel of Figure 2) at a cost-loss ratio of 0.33. This means that a user that makes decisions with the help of the probabilistic system will save 25% of what he/she will save if he/she knows perfectly the future state of the atmosphere. This is true for actions that cost 33% of the amount saved by these actions. For other cost-loss ratio, the value decreases sharply for the above normal category (higher panel of Figure 2) and more smoothly for the below normal category (lower panel of Figure 2). The forecast systems are useful for cost-loss ratios of 0.1 up to 0.7, while the value elsewhere is zero or negative. Then, it is

better to always act for cost-loss ratio less than 0.10 and to never act for cost-loss ratio higher than 0.7.

Figure 3 shows the value for surface air temperature anomaly forecasts during the 1969-1994 Summer seasons. This is the best results obtained by the probabilistic system for both categories. The value peak at 0.35 for the below category. There is a large range of cost-loss ratio for which the value is positive (0.15 to 0.8). The deterministic system has its higher value also in Summer but for the below category only. For the above normal category, the best season is Winter for the deterministic system (not shown). The worst season for both systems is the Fall season (not shown).

For the precipitation forecasts, the economic value for each season is very low (not shown). The maximum of positive value is found in Fall and in Spring (close to 0.09) for the below normal category. There is no positive value in all season for cost-loss ratio lower than 0.2 and higher than 0.45. The probabilistic system is slightly better than the deterministic one.

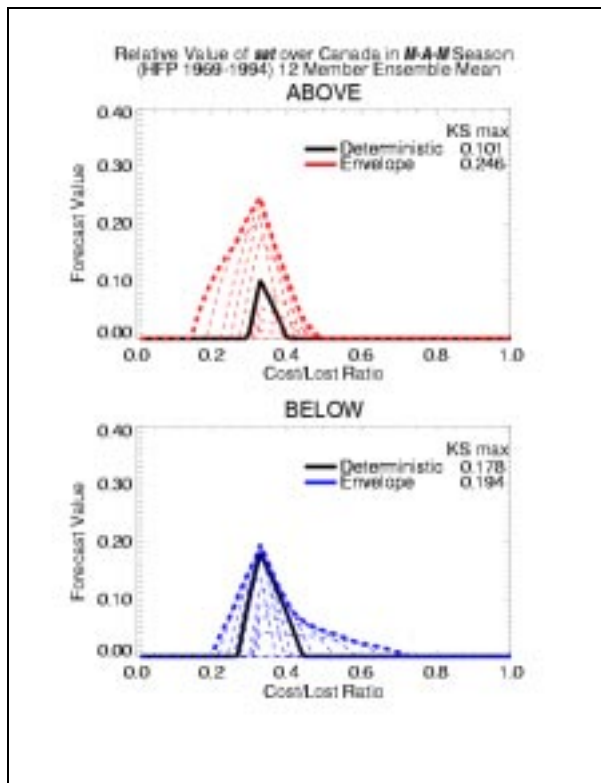


Figure 2: Relative economic value of CMC system in predicting surface air temperature during Spring (March-April-May) in function of the cost-loss ratio. The value was determined over the period 1969-1994. The black line represents the deterministic system while the dashed lines show the probabilistic system results.

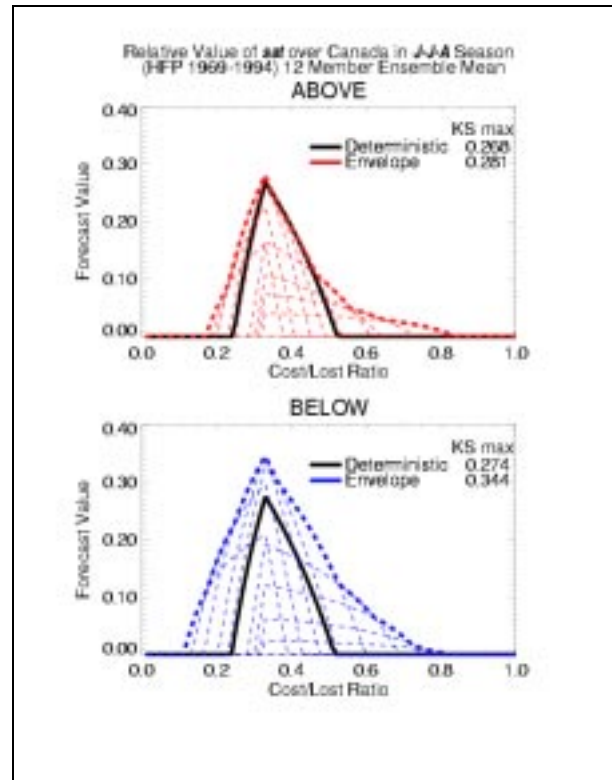


Figure 3: Idem as Figure 2 but for the Summer forecasts.

5. CONCLUSIONS

- There is economic value in using the temperature forecast anomaly in every season (probabilistic and deterministic).
- Relative value is maximum (0.35) for a cost-loss ratio of 33.3% in Summer temperature probabilistic forecasts (below normal) and in Winter deterministic forecasts (above normal).
- Probabilistic forecasts convey more information in allowing the user to choose his/her own threshold to maximise the value.
- There is little or no value for seasonal precipitation anomaly forecasts in Canada with the current system.

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