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Rainfall forecast in Uruguay and southern Brazil using canonical correlation analysis

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Abstract

In Diaz and Studzinski (1994) a relationship between sea surface temperature (SST) anomalies in Pacific and Atlantic Ocean and rainfall anomalies in Uruguay and Southern Brazil is found for the seasons November-February and October-December. Using canonical correlation analysis (CCA) statistical models are built having Pacific and Atlantic Ocean SST as predictor fields and precipitation as predictands, for the period 1982 to 1986 or 1987. Six different models were considered. The local and global forecast skills were determined and simulation experiments were performed. The simulation results are classified in terciles , the three forecast categories are: above, normal and below normal. It was found that , in general, the season October-December, using Pacific Ocean SST as predictor was more consistent, having a better "global skill". All the models produced good results for the wetter years. A preliminary review of all the analysis shows that the predictability in the region differs for different periods of the year.

1. Introduction

Several canonical correlation analysis (CCA) models were used in Diaz and Studzinski (1994) to make diagnostic analysis about the relationship between sea surface temperature (SST) and rainfall in Uruguay and Southern Brazil (UY-RS). In order to make an assessment of the capability of these models to make forecasts two kinds of studies are pursued here: 1) determine the local and global forecast skill of some of those models (it is known that the ability of models to produce estimates of the predictand field for the training period (i.e., the hindcast skill) is expected to be higher than the forecast skill, see Davis, 1976),.and 2) make some simulation experiments for years not belonging to the training period.

2. Methodology

The input data for performing CCA are described in Diaz and Studzinski, 1994: SST (from either Atlantic or Pacific Ocean, or both) as predictors and precipitation from 40 stations in UY-RS as predictands. The considered seasons are November-February and October-December for precipitation and the same (simultaneous) for SST. The training period covered by both data fields is 1946-1979 (or 1980). It must be pointed out that, when making "predictions" for years not belonging to the training period, observed SST will be used so the experiment will be a simulation. However, those SST could be instead the output of a model, like Zebiak-Cane model. In that case, a real forecast would be performed. Taking this into account, the words 'forecast' and 'prediction' will be used in the text.

The prediction of rainfall anomalies for the 40 stations of UY-RS and for any year are produced by using the corresponding SST data following the procedure outlined in Barnett and Preisendorfer, 1987, or Preisendorfer, 1988.

To estimate the forecast skill of the model the cross-validation approach is used. This consists essentially of removing the data for both predictor and predictand for one year (for example, 1946), then building the model for the remaining years and making a prediction for the removed year . This is done for all the years of the training period (withdrawing one year at a time and making the prediction for it). It is worth to note that this implies building as many models as years in the training period (i.e. 34 or 35 in this case). Thus, a prediction for all the stations for each year from 1946 to 1980 is obtained which will be compared to the observed rainfall as it will be explained. Whenever there is a possibility of confusion these predictions will be referred to as "cross-predictions" to distinguish them from hindcast or real predictions.

It should be clear that these predictions are obtained in a more similar way to a real forecast than to a hindcast because each removed year is not included at all in building the model used to predict it. However, it is possible that there is a strong one-year lag autocorrelation in the predictand field which may have an undesired influence in the cross-validation predictions. To avoid this possibility, the cross-validation may be performed removing three years at a time (instead of one) and making a prediction for the middle-year . In this study both kinds of cross-validation were used in all the cases to compare the forecast skills, although a Montecarlo test performed on each station gave as a result that, in average for the different seasons, 90 % of them did not have a significant one-year lag autocorrelation.

After the cross-validation predictions have been obtained the procedure to assess the forecast skill of the model goes on as follows (Barnett and Preisendorfer, 1987).

Suppose that the season November-February is considered. In this case the training period is 1946-1979 and comprises 34 years. For each station the vector Zo containing the 34 observed precipitations sorted in ascending order and the vector Zp containing the 34 cross-predicted precipitations (also sorted in ascending order) are considered and each one is separated into three equally divided classes (terciles); below, normal and above categories (B,N,A) according to its own distribution.(Note: for the cases of 34 years the lengths of terciles (B, N and A) were 11, 12 and 11 respectively and for the case of 35 years, they were 12, 11 and 12.)

Then each of the 34 years is checked to see whether the observed and predicted terciles were coincident; in an affirmative case, the forecast for that year is considered correct. Let Nc be the total number of correct forecasts. According to this, the 'local skill' for the station is defined as the percent of correct forecasts. That is,

$$SL = 100^*(Nc/nt)$$

The significance of the local skill can be determined by comparing it with chance, i.e., with the case of someone who, for each of the 34 years, makes a random guess (B, N or A). More strictly speaking, one answers to the question: what is the probability of correctly guessing bychance Nc or more forecasts? The answer is given by the binomial distribution with nt independent tries and with a 1/3 probability of success in each try. For the cases of 34 and 35 years, the 90%, 95% and 99% levels of significance are attained with values of Nc of 15, 16 and 18 respectively, which correspond to values of SL of 44%, 47% and 53% (for 34 tries) and 43%, 46% and 51% (for 35 tries). Notice that the expected value (by chance) is 33% (i.e., 11 or 12 correct guesses).

After a significance level has been selected (95% in this study) the number of significant stations Ns is used to define the 'global skill' of the model for UY-RS, i.e.,

$$SG = 100^*(Ns/nst)$$

where nst is the number of stations in all the region (40 in this case). Also, the significance of SG can be calculated; all the cases were significant at a level of 95%.

3. Results

a. Forecast Skill Results

The cross-prediction and forecast skill analysis were performed for the seasons November-February and October-December considering as a predictor SST for Atlantic Ocean, Pacific Ocean and both oceans combined . In each case the cross-validation was performed in two ways: removing one year and removing three years. This gives 12 cases.

Six out of the twelve cases were selected to make simulation experiments for the period 1982-1987. The choice was based on different aspects: maximum value of SG, the desire of making comparisons among different predictors and the two approaches for cross-validation.

Table 1 shows some features and results for these 6 models.

Figs. 1a and 1b show the maps for the local skill (SL) for cases 1 and 6. The darkest, intermediate and lightest shadings correspond respectively to the 99%, 95% and 90% significance levels.

b. Simulation Results

Simulation experiments were performed for the period 1982-1986 for the season Oc-De and for 1982-1987 for No-Fe. There were two reasons which led to these choices: 1) the GOGA dataset ends in 1988, and 2) there was some missing data for some stations in Uruguay since 1981 . This latter fact may produce poorer results than expected.

Two different types of simulation experiments were performed. The first was a categorical approach (i.e.,'below, normal and above') and the second was based on averaging over significant stations. The experiments were performed for the 6 cases mentioned above.

For the selected case (for example, No-Fe Atl, Y=1), the prediction for each year (from 1982 to 1987) is carried out using the model built for the whole training period, 1946-1979. The prediction for the 40 stations is obtained but the results for only the 95%-level significant stations (referred to local skill) will be considered. Then one year of the forecast period is considered (e.g., 1982). For each station the vector Zp of cross-validated predictions is considered and it is checked to which tercile of Zp corresponds the prediction for 1982. The same is done for the observed value and vector Zo. In this way it is possible to determine in how many stations the forecast was correct (that is, the terciles were coincident) for that year and have a fair idea of how good (or bad) the forecast was for that case and and that year.

In Table 2 it is shown for each of the 6 models the percentage of coincident forecasts for each of the years of the testing period. It is worth noting that both A-N and A-B forecasts were considered equally incorrect.

For each case, the stations having a 95% significance level for the local skill were selected and the observed and forecast anomalies for the forecast period were averaged on those stations. The results for the forecast period are shown in Figs. 2a and 2b for cases 1 and 6.

Also, the trend is well obtained from the predictions with some exceptions. The bigger errors are obtained for 1985 (cases 6,5, 4 and 3) and 1983 (cases 3 and 4). The errors for 1982 are sometimes big (cases 1 to 4) but at least in this case the sign of the anomaly is correctly predicted. These results are in a fairly good agreement with those obtained for the categorical approach.

4. Conclusions

The simulations with the statistical models were performed for a very short period (1982 to 1986 or 1987) and there was also some missing data for some of the stations in Uruguay. Nevertheless, taking into account these limitations, some comments can be made.

In general, the categorical simulations gave better results for the 'wetter' cases.

For No-Fe, when all the 4 forecasts were coincident (that is, for most of the significant stations)they were correct. It should also be noted that in 1982 and 1986 in this season the SOI was in its negative phase and attained its most negative values.

The driest year for the period was not well predicted by any of the models.

The consideration of Nino 3 Index suggests that models which use Pacific Ocean as a predictor give better results for the cases of larger SST anomalies.

It is not yet well known under which conditions the models tend to give better or worse results and this is a crucial point to define before being able to produce reliable forecasts.

A preliminar review of all the analysis performed seems to show that the results for the season Oc-De are more consistent. This suggests that rainfall predictability in UY-RS may vary from seasons to seasons or months to months . So a probably useful line of work will be to perform several (lagged and non-lagged) analysis on a monthly basis to have a better insight of this predictability.

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Table 1. Global skill (SG) in percent for 6 selected models. Y represents the number of years removed in the cross-validation procedure and q' is the number of canonical modes retained to make the prediction in order to obtain maximum global skill.

Case	Season	Predictor	Y(cr-val)	q'	SG
1	No-Fe	Atl	1	2	52.5
2	No-Fe	Atl	3	1	50.0
3	No-Fe	Pac	1	1	32.5
4	No-Fe	Both	1	1	47.5
5	Oc-De	Pac	1	3	52.5
6	Oc_De	Pac	3	4	72.5

Table 2. Percentage of coincident forecasts for each of the years of the testing period (1982-1987). For 1987 there was some missing precipitation data in October.

Case	Year					
	82	83	84	85	86	87
No-Fe Atl1	100	56	25	32	75	62.5
No-Fe-Atl3	**100**	71	15	0	78	65
No-FePac1	90	0	67	0	75	67
No-FeBoth1	68	0	68	38	75	56
Oc-De Pac1	67	28	33	22	56	----
Oc-De Pac3	65	38	46	31	74	----

Figure Captions:

Fig. 1a. Local skill (SL) in percentage for case 1: (November-February, Atlantic SST as predictor, Y=1). Notice that the result expected by chance is 33 % .(The darkest, intermediate and lightest shadings correspond respectively to the 99%, 95% and 90% significance levels.)Fig. 1b The same as 1a except for case 6 (October-December, Pacific SST as predictor, Y=3).

Fig. 2a. Observed and predicted precipitations for case 1 (1982-1987). Fig. 2b. The same as 1a except for case 2 and 1982-1986.