

Latitudinal Profiles of Seasonal Rainfall-Enso Association along the Coast of Central and South America, Using Contingency Tables

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Abstract

The Influence of the ENSO events over the west coast of Central and South America (22°N - 45S) precipitation was investigated using Pearson's association index and a generalized logit models. Data consisted on a couple of indices representing the ocean-atmosphere interaction along the Equatorial Pacific and 5x5 degrees gridded locations over the pacific coast of Central and South America, each represented by a rainfall monthly time series starting since 1900. We used a seasonal ocean-atmosphere ENSO index as predictor for the seasonal rainfall, to fit logit models to estimate the probability of classifying any seasonal observation into terciles (warm, neutral and cool) and associate with terciles in the response variable (dry, neutral, wet). We analyzed three way contingency tables, in which the third category corresponds to the lagged classification of the predictor. Results generally confirm preceding studies on influence of El Niño Southern Oscillation over the west coast of Southern America, i.e., warm/cool events are generally associated with wet/dry situations along the west coast, but it also gives further insight by providing estimates for the probability that a warm/cool ENSO event induces dry/wet seasons and vice versa along the coast of South America for each season.

Key Words: El Niño, rainfall, contingency tables, prediction

1. Introduction

Interest in useful climate predictions for various regions of the Americas had developed substantially over the past two decades given its enhanced recognized socio-economical as well geological impacts (Katz and Murphy 1997; Viles and Goudie 2003). Over recent decades, efforts have increased toward improving forecast techniques for seasonal climate (Goddard et al. 2001). This interest will extend now and for the next 10-15 years, on making useful climate predictions for various regions of the Americas (see IASCLIP project prospectus for example at <http://www.eol.ucar.edu/projects/iasclip/>). It is expected this will be done by coupled numerical (dynamical) models, or using any predictor field like sea surface temperature (SST) as input to statistical models of regional climates. Latin American countries gradually understand the need of cooperative efforts towards climate predictions. Actually, there are regularly Regional Climate Outlook Forums in different places like Central America and the West Coast of South America (e.g Donoso and Ramirez 2001).

The use of dynamical-numerical and mathematical-statistical models to represent the Ocean-Atmosphere interactions has become a major issue during the last few years, as tools for climate prediction with lead times of a month to a year in advance. These two

kinds of approaches are normally used as downscaling methodologies (Amador and Alfaro 2009). The dynamical-numerical models are generally preferred for predictive applications because they are based on physical equations of system behavior. (Barnston et al. 1999) Unfortunately, certain variables with high societal impact, such as rainfall, cannot be readily predicted by these models. Other variables, such as sea surface temperature (SST), can also be predicted successfully with these numerical methods. In view of the wealth of statistical information on the relationships between rainfall, atmospheric pressure, SST, plus a number of other quantitative variables, a feasible approach for predicting the occurrence of El Niño/La Niña events (Trenberth 1997), seems to be to use appropriate statistical models of those relationships, to empirically extend the numerical forecast of SST to other related atmospheric and-or oceanographic variables such as SLP, outgoing long wave radiation (OLR), rainfall or even SST from other oceans (Enfield 1996, Enfield et al. 2005, Folland et al. 2001).

At present we have some deterministic prediction ability. For example, we know from statistical analysis, that ENSO is related to these "warm/cold events" and that they are also associated with climate anomalies around the globe (e.g. teleconnections), (Ropelewski and Halpert 1987, Enfield and Cid-Serrano 2005, 2010), allowing us to make qualitative statements about expected climate effects, given a warming (or cooling) event of the SST (Montecinos et al. 2000, Montecinos and Aceituno 2003, Aceituno 1998, Enfield and Cid-Serrano 2005, 2006). But this it is not nearly good enough; economic and social sectors (agriculture, fisheries, health, etc.) need more concrete information (Katz and Murphy 1997). A farmer needs specifically to know a given year will be "dry" or a "wet" year to plan their crops and fishermen need to know if warm or cold event it is about to happen affecting the fisheries. With predictive models (numerical and numerical-statistical) we would be able to give them probabilistic outlooks, e.g., odds of occurrence of a given event, based on the marginal probability distribution of a number of "predictive" processes (Enfield and Cid-Serrano 2006).

Many of these investigations have been undertaken through the study of ocean-atmosphere indices, such as the Southern Oscillation Index (SOI) (Enfield 1989, and Enfield and Mayer 1997), that measures the difference in atmospheric pressure between Tahiti and Darwin, the El Niño indexes based on sea surface temperature (SST) in the equatorial Pacific, or the Atlantic warm pool (Wang et al. 2006, 2007, 2009). One of the frustrating problems with such schemes, however, has been the subjective nature of predictor identification, both in terms of variable selection and the identification of suitable (geographic) predictor domains.

Although most of the literature focus on the use time series modeling and/or spatial fields for predicting the time of arrival and the strength of an event. In the first case it is done by fitting continuous univariate or multivariate ARMA (Box et al. 2008) models in time domain, Fourier-derived methods for the frequency domain, as well as neural networks (Goddard et al. 2001). In the second case it is generally done mainly by using multivariate techniques such as principal components or derivations thereof (see Zwiers and Von Storch, 2004). Common practice, however, have shown that in most cases the primary interest is not to obtain such an exact value, but to simply determine, well ahead of time, the occurrence of an El Niño/La Niña event. In other words, the primary interest seems always to be whether or not a given year, will or will not be an El Niño (La Niña) year. Considering such a binary alternative, seems appropriate to focus our attention into the categorical aspects of the events, rather than in determining the exact amount of the SST or SLP anomalies for a given period.

There are only few cases in which such an approach has been attempted, although it seems to be an obvious need. Mason and Mimmack (2002) compared different statistical techniques, including logit models, for predicting ENSO, but did not investigate the strength of the method for associating ENSO events and their worldwide climatic impacts. Along with these ideas, Enfield et al. (1989) used contingency tables to establish the relationships between extreme events in the Atlantic ocean and dipole configurations of the tropical Atlantic SST, using the areas north (NA) and south (SA) of the ITCZ for a 136-year period, recording the occurrence frequencies for which these indexes fall into their respective quartile extremes ranges, and then compared them against what the expected frequencies would be by chance. This analysis concluded that such dipole configurations are due only to chance, the two classifications being stochastically independent. Other examples of the use of contingency tables in climate related applications, are found in previous work of this research team with application to different socioeconomic sectors like energy and sugar cane production; Atlantic hurricane occurrences, summer temperature prediction in California are shown in Alfaro (2007); Moreno and Alfaro (2007), Alfaro et al. (2005) and Alfaro et al. (2004).

To model the ocean-atmosphere interaction in a discrete perspective, implies a different approach vis-à-vis the traditional models based on a time domain approach (Box et al. 2008), in which only continuous time series are modeled according to their auto-correlative structure, in the simpler case, or using cross-covariance arrays in the case of multivariate analyses. For such reasons, we need to develop or/and adapt current statistical methodology, particularly that related to the analysis multidimensional contingency tables for climate purposes Alfaro et al. (2003). We propose that the problem could be approached using generalized linear models (GLM) and discrete-valued time series.

The main purpose of this short study, is therefore to introduce rather simply the methodology associated with the analysis of contingency tables, into the study of the relationships between some of the variables most commonly used to evaluate the ocean-atmosphere interaction, such as the Southern oscillation index (SOI) or equatorial SST-related time series indices (e.g., NIÑO-3 or NIÑO-3.4) and the distribution of rainfall along the west coast of South America, using data from the 22.5°N southward to 45°S. We expect to confirm most of the well-known relationships between cool and warm events associated with ENSO and the rainfall regimes along the west coast of South America, such as those described by Rutilant and Fuenzalida (1991), as well give further insight by establishing the usefulness and practical need of this analysis tool.

2. Data and Methods

In lieu of such categorical alternative, a logical methodological approach to the problem is, instead of determining the exact magnitude of the sea surface temperature (SST) or the sea level pressure (SLP) anomalies for a given period, associated with an event, to translate the data into frequencies corresponding to a given discrete classification of the data, of which the simplest could be a binary classification of the type El Niño/La Niña. This binary approach includes, however, those periods which could be classified as transition years (neither El Niño nor La Niña or vice versa) so that we must consider three classes or categories in which any given period (month, trimester or year) could be classified. Using generalized linear models (Agresti, 2004), we can estimate the odds of

classifying a single event in each of the three predefined categories of the classification, based on the marginal probability distribution of a number of “predictive” processes.

To construct the contingency tables to evaluate the relationship between rainfall and the warm/neutral/cool events, we consider extended monthly time series from 1901 through 2008, for the Southern Oscillation Index (SOI) and equatorial SST represented by the series Niño 3.4 (N34), monthly mean SST along the equator between 5N and 5S and between 170W and 120W (Smith and Reynolds 2004, Smith et al. 2008, 2010). We summarize the two series in an index that considers therefore both the atmospheric and oceanic contributions of the coupled phenomenon. For this reason we work throughout this paper with a Niño-Southern Oscillation index (NSO), corresponding to the standardized difference $NSO = N34 - SOI$. The relationships between ENSO events and the NSO index is clear, since during the warm (cold) phase of ENSO, SST has positive (negative) anomalies and SOI has negative (positive) anomalies, so that the NSO has its maximum (minima) for El Niño (La Niña) events. As such, the NSO index has the advantage of summarizing in a straightforward manner the information given by both indices. To further validate the use of the index NSO, hereafter called simply the N index, we compared it with Wolter’s MEI (Wolter 1987, Wolter et al. 2011). Figure 1, shows that there is a close relationship between both. In fact, the cross correlation functions (CCF) and periodogram for both of them show no significant differences.

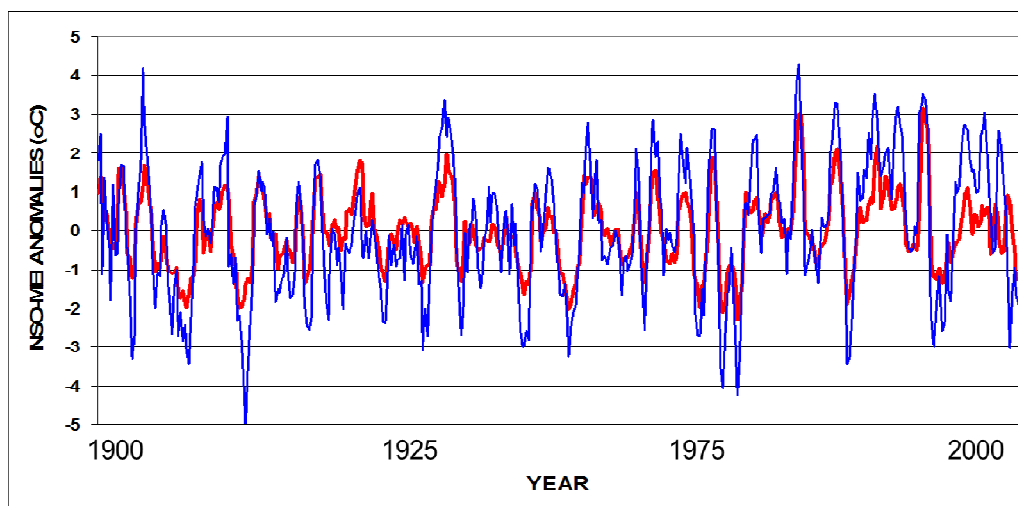


Figure 1. NSO (blue) and MEI (red) extended series.

The N time series is then summarized into seasons taking the average of three months DJF, MAM, JJA and SON, as a way to reduce the noise and the autocorrelation of contiguous observations. All the analyses were then performed independently for each season.

Monthly rainfall (R) data were obtained from the National Centers for Environmental Prediction (NCEP) of the National Oceanic and Atmospheric Administration (NOAA), and correspond to the anomalies of worldwide rainfall measures over a $5^{\circ} \times 5^{\circ}$ latitude-longitude grid from 1901 to 2008 (Chen et al. , 2002). From the database we selected the 14 grid points located along the west coast of Central and South America from 25° N to 45° S. Rainfall data were also summarized into seasons as indicated above.

2.1 Contingency Tables.

Consider the variables N, e.g. NSO and R, e.g. rainfall. For the purpose of this study, initially, we define a two-way (R×N) contingency table of order 3×3. The column and row marginals of the table are divided into three classes, each of them defined by the corresponding tercile of their distribution. Data points in the upper tercile of R corresponds then to wet periods and those in the first tercile to dry periods. For N, the first tercile defines the cool events for SST (La Niña) and the third defines the warm events (El Niño). The cell (i,j) corresponds then to the i-th tercile of the NSO and the j-th tercile of the response R.

For the statistical analysis of the contingency tables we first used Pearson's coefficient as a measure of association r . Since we are dealing with ordered classifications, it varies from -1 through $+1$ from negative to positive association.

$$r = \frac{\sum \sum n_{ij} (r_i - \bar{r})(c_j - \bar{c})}{\sqrt{\sum \sum n_{ij} (r_i - \bar{r})^2 \sum \sum n_{ij} (c_j - \bar{c})^2}} \quad (1)$$

where, n_{ij} represents the frequency observed in the j-th column and the i-th row, r_i and c_j represents the scores of the i-th row and the j-th column respectively.

A second approach for the analysis corresponds to the use of generalized linear models, which is a common statistical methodology to study how the cell counts are related to the levels of the categorical variables (see e.g. Agresti 2004), analyzing the association and interaction patterns between the variables. Logit models constitute in fact a special class of these log-linear models, for which one of variables is considered a response to one or more predictors (non symmetrical contingency table). The generalized logit model constitutes a special case for which the response is multinomial for variables categorized into ordinal classes.

There are two forms of a logit models for an I×J contingency table, where for a sample of n subjects, the cell probabilities are π_{ij} with expected frequencies being $\mu_{ij} = n\pi_{i+}\pi_{+j}$ the independence model is

$$\log \mu_{ij} = \lambda + \lambda_i^N + \lambda_j^R.$$

for a row effect λ_i^N and a column effects λ_j^R described. A second model, representing complete dependency between categories, corresponds to the saturated model,

$$\log \mu_{ij} = \lambda + \lambda_i^N + \lambda_j^R + \lambda_{ij}^{NR}.$$

here, the parameter λ_{ij}^{NR} , corresponds to the deviations from independence and represents the interaction between both categorical variables (for further details, see Agresti, 2004).

2.2 Three way tables.

There exist a good chance that there exists some lead time in the relationship (causality) between the predictor variable N and the response R, in fact, transfer function models (Box et al., 2008) indicate at least a one period lag between the input and the response variables. To include such chances into the model, we consider a third variable N1, corresponding to the predictor variable N, but lagged one period. We can define now a three-way contingency table of order 3×3×3. Using the terciles approach, we divide the marginals into three classes, each of them defined by the corresponding tercile of the distribution of the variables R and N and N1.

A three way table includes three variables with different forms of independence, starting from the fact that the variables are mutually independent if the i,j,k probability π_{ijk} is such that

$\pi_{ijk} = \pi_{i++}\pi_{+j+}\pi_{++k}$, which corresponds to the product of the margins of the table. For expected frequencies μ_{ijk} , the following models can be defined

Model Type I. Mutual independency, all variables are independent of each other. The loglinear form is

$$\log \mu_{ijk} = \lambda + \lambda_i^R + \lambda_j^N + \lambda_k^{N1}.$$

Model Type II. Joint independency, the response variable R is jointly independent of N and N1, with loglinear form

$$\log \mu_{ijk} = \lambda + \lambda_i^R + \lambda_j^N + \lambda_k^{N1} + \lambda_{ij}^{NN1},$$

meaning that R is independent of a variable composed of the JxK levels of N and N1.

Model Type III. Conditional independency. N is independent of R conditioned on the level of N1.

$$\log \mu_{ijk} = \lambda + \lambda_i^R + \lambda_j^N + \lambda_k^{N1} + \lambda_{ij}^{NN1} + \lambda_{ij}^{RN1},$$

meaning that R and N are independent within each level of the third variable N1.

There still a fourth level of independence, corresponding to the homogeneous association, corresponding to the model

Model Type IV. Homogenous association.

$$\log \mu_{ijk} = \lambda + \lambda_i^R + \lambda_j^N + \lambda_k^{N1} + \lambda_{ij}^{NN1} + \lambda_{ij}^{RN} + \lambda_{ij}^{RN1},$$

meaning that the association (dependency) between any two variables is the same within the level of the third variable.

Finally, the saturated model,

Model Type V. Saturated model,

$$\log \mu_{ijk} = \lambda + \lambda_i^N + \lambda_j^R + \lambda_k^{N1} + \lambda_{ij}^{NR} + \lambda_{ij}^{NN1} + \lambda_{ij}^{N1R} + \lambda_{ij}^{NN1R}.$$

represents the complete dependency between the three variables.

2.3 Testing Hypothesis.

There are two main hypothesis that we are interested in to be tested. First, to determine if there exist a first order autocorrelation in the predictor N, and second, to determine the type of association, if there exist any, between the predictor (N) and the response (R).

Testing for autocorrelation. If we consider the model IV of homogenous association, the hypothesis to test is

$$H_0: \lambda_{ij}^{NN1} = 0$$

Testing for association with the predictor. If we do not reject this hypothesis, the model to consider is of Type III, which means to test two hypothesis

$$H_0: \lambda_{ij}^{RN} = 0$$

$$H_0: \lambda_{ij}^{RN1} = 0$$

The results of these testing, determine the type of association (model) we are dealing with.

2.4 Interpretation of response probabilities.

Table 1 shows the probabilities p_{ij} associated with a 3x3 contingency table, to be estimated through the logit model. In this table, the probability p_{ij} corresponds to the probability of any given trimester to be classified into the (i,j) cell of the contingency table. In the absence of any expectation for ENSO;

	RAINFALL TERCILES		
NSO TERCILES	R ₁	R ₂	R ₃
N ₁	p₁₁	p₁₂	p₁₃
N ₂	p₂₁	p₂₂	p₂₃
N ₃	p₃₁	p₃₂	p₃₃

Table 1. 3x3 Contingency table for the rainfall (R_j) as response and the N_i index as predictor. Rows and columns are the corresponds terciles of the series, p_{ij} is the probability that a given observation, being classified in the row i of the predictor, is classified into the column j of the response.

Table 1 shows the probabilities associated with more extreme climatic events, which can be interpreted as follows:

p₁₁ is the probability that the first tercile of NSO induces rainfall in the first tercile of the rainfall distribution, i.e., it measures the association of cool events and dry years.

p₁₃ is the probability that the first tercile of NSO induces rainfall in the third tercile of the rainfall distribution, i.e., it measures the association of cool events and wet years.

p₃₁ is the probability that the third tercile of NSO induces rainfall in the first tercile of the rainfall distribution, i.e., it measures the association of warm events and dry years.

p₃₃ is the probability that the third tercile of NSO induces rainfall in the third tercile of the rainfall distribution, i.e., it measures the association of warm events and wet years.

We will analyze the departure of these probabilities for 1/3, considered as a neutral probability or as produced by chance. The probabilities p_{21} , p_{22} , p_{23} , p_{12} and p_{32} are the probabilities for the central terciles.

Logit models were used to estimate the expected values for the cells of the contingency tables, when one of the classifications was used as causal and the other as dependent. In

3. Results

Figure 2, shows the Pearson association between the NSO index and rainfall variability for different seasons along latitudes from 24 °N degrees south to 45 °S. DJF shows negative association for the latitudes from 15 through, for three of the four seasons (excluding the southern hemisphere summer and winter, DJF and JJA).

Note that the seasons that typically generate more impact in Peru (from 7.5 through 17 °S), are DJF and MAM, which reflects the sensitivity in that region to remote and local SST anomalies during the rainy season.”

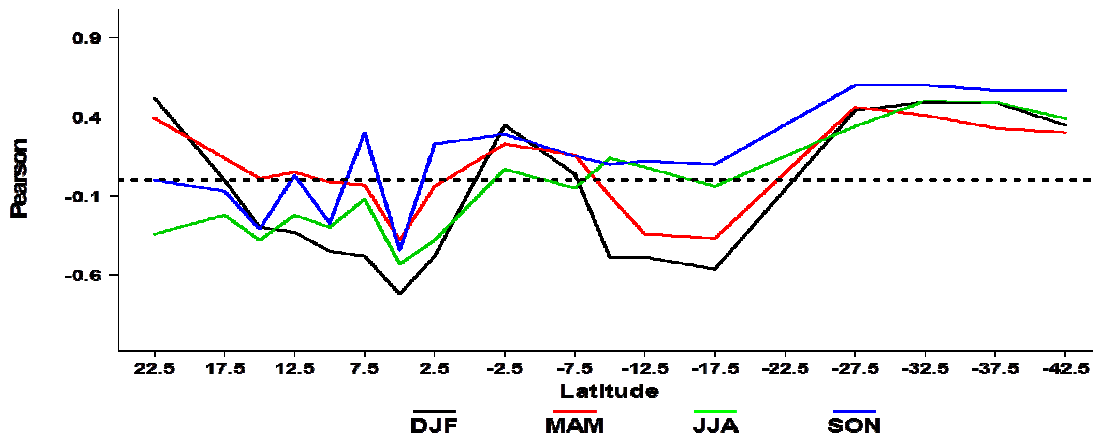


Figure 2. Pearson correlation between NOS and rainfall.

3.1 Logit Models.

In the following we will analyze the results of the response to logit models, in which we associate the events (cool, neutral, warm) with the rainfall response (dry, neutral, wet). The association between warm/cool events and the dry/wet phases will be emphasized. Therefore we will investigate mostly the direct relationships, Cool-Dry, Cool-Wet, Warm-Dry, Warm-Wet, respectively and their corresponding probabilities P11, P13, P31 and P33, i.e., the corners of the contingency tables (see Table 1).

We will first investigate the yearly average response before moving into the seasonal analysis. According with Figure 4, the relationship El Niño = more rain and La Niña = less rain (Warm-Wet and Cool-Dry, respectively P33 and P11) are particularly intense and meaningful from 15 degrees south to southern Chile, as well as north of 6 degrees. Instead the other relation, Cool-Wet and Warm-Dry is particularly intense between 6 and 15 degrees.

Also note the lack of amplitude of the Cool-Wet and Warm-Dry associations. Typically dry or wet situations over most of Chile, Ecuador and northern Peru are associated with cool or warm events in ENSO phenomena related variability. In the case of the Chilean desert, discrimination between noise and rainfall is particularly difficult given the poor rainfall there, it is well known that rainfall only occur episodically.

The relationships found makes sense for Ecuador, northern Peru and Chile but not (in a simplistic way) for central-southern Peru (6°S-15°S). However, between Chimbote and Tacna El Niño does not typically produce rain along the coast. In fact, Enfield (1981) shows that El Niño destabilizes the planetary boundary layer and weakens the inversion, which in turn means and less cloudiness and *garua* (drizzle)..

The correlations found over central Chile for the four seasons are therefore related with Warm-Wet and Cool-Dry association. As thought rainfall along Central Chile is related to El Niño episodes, whereas lack of rainfall is associated to La Nina events. Because the summer season, generally the dry season, presented lower relationship for the Pearson association coefficient along Central Chile (for yearly averages) (it is even showing slight negative values), it is not possible to conclude something for an association between outstanding summer season (particularly dry or particularly wet) and cool or warm

characteristics in the ENSO index. The analysis of these particularities can only be given by an investigation of each season association, which will be shown in the following.

In what follows we present the analysis by season, are shown in Figures 3 to 10 and correspond respectively to DJF, MAM, JJA and SON.

DJF.

Results for the austral summer (boreal winter) in Figure 3, shows the response of rainfall to cool events (La Niña), with no regular behavior. Figure 4, shows the response of rainfall to warm events (El Niño). This figures are of particular interest, since they show the change of sign in the association, depending upon the latitude. The association dry/cool is high for central and southern Chile, Ecuador and Costa Rica whereas the wet/cool association

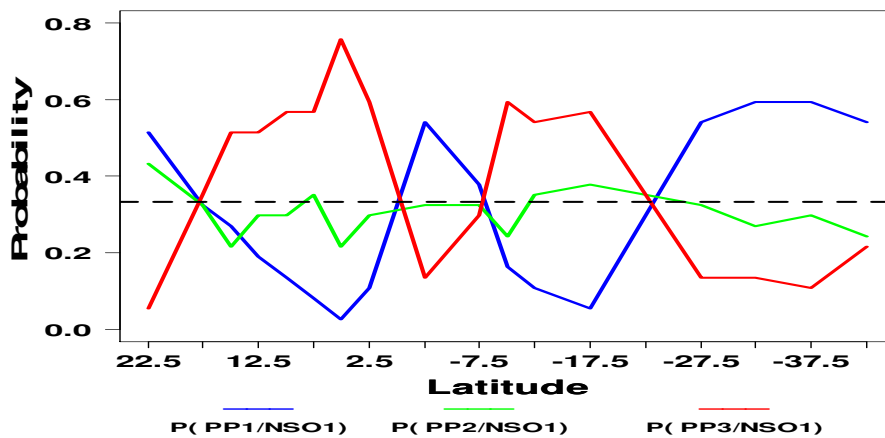


Figure 3. Profiles of rainfall response to cool events for DJF.

association is noticeable and particularly interesting for Panama and Colombia; southern Peru and central and northern Chile. Interestingly, when conditioning on the warm events, the association is the opposite. Notice that second tercile, corresponding to normal rainfall, it is not affected by the cool or warm events.

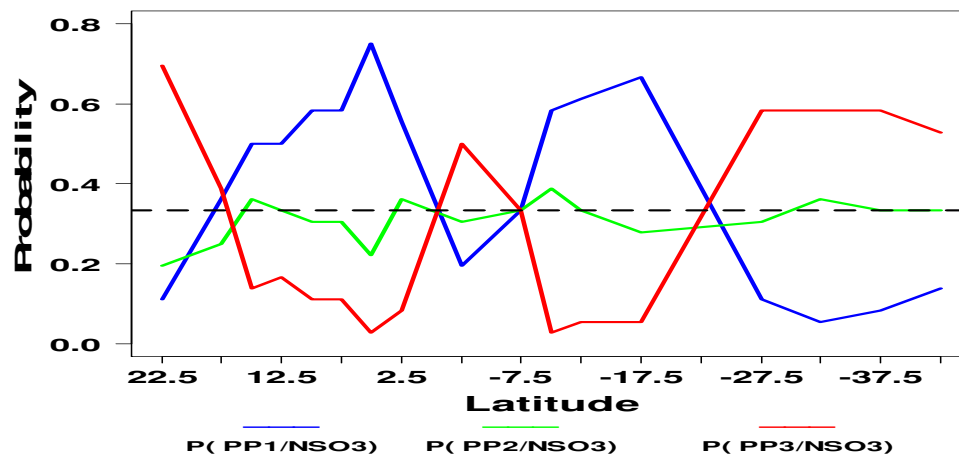


Figure 4. Profiles of rainfall response to warm events for DJF.

MAM.

Results for the austral fall in Figures 5 and 6, show the latitudinal profiles of response of rainfall to cool and warm events respectively for the austral fall (boreal spring). The wet response to cool events is significant only in northern Ecuador and southern Peru, while a dry response is significant only for Gulf of Panama and Central and southern Chile.

When conditioning on warm events (Figure 6), we find almost exactly the opposite, with the association wet/warm dominating (i.e. abnormal wetter fall) in northern Ecuador and southern Peru, while the dry/warm association (i.e. abnormal dryer fall) dominates only in Costa Rica and Central and southern Chile

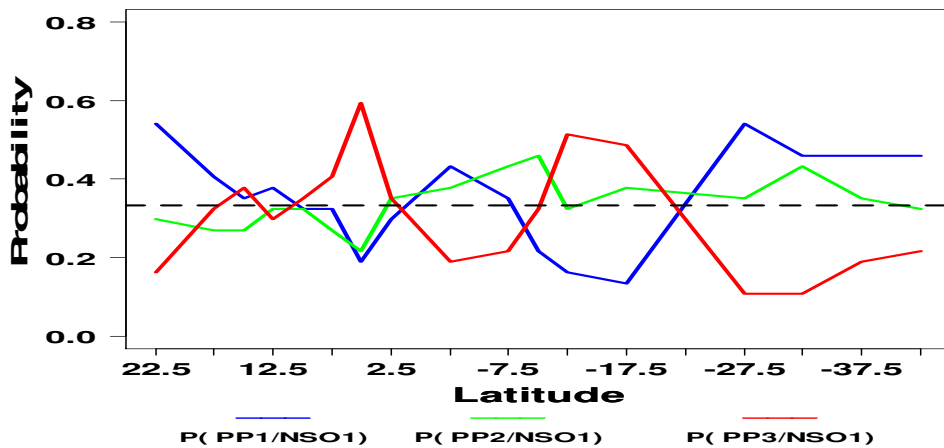


Figure 5. Profiles of rainfall response to cool events for MAM.

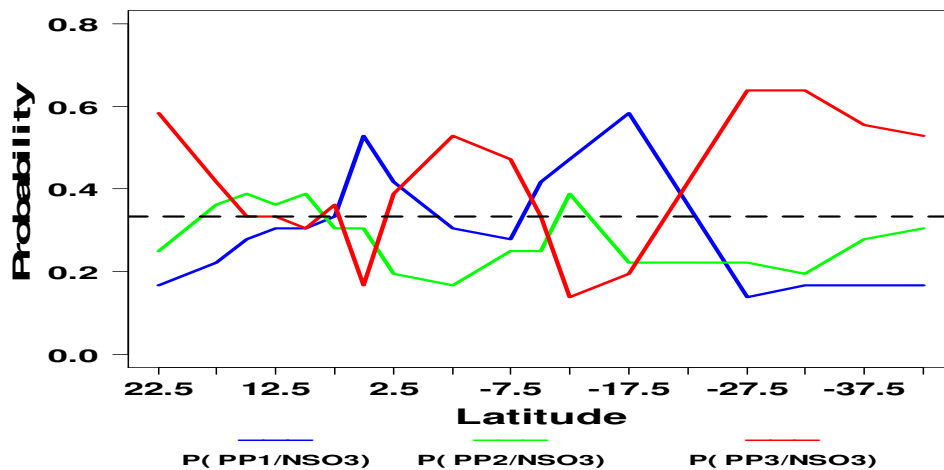


Figure 6. Profiles of rainfall response to warm events for MAM.

JJA.

The analysis of the austral winter (boreal summer), Figures 7 and 8, show the latitudinal profiles of response of rainfall to cool and warm events respectively. Figure 7 shows a particularly high value wet/cool association for central Chile. This association is not evident in any other latitude, whereas the wet/cool association is high from Gulf of Panama through Ecuador. Conditioning on warm events (Figure 8) shows high values of the association wet/warm association for central and southern Chile (30°-45°). There

exists also a less significant wet/warm association for Gulf of Panama through northern Ecuador and northern Mesoamerica.

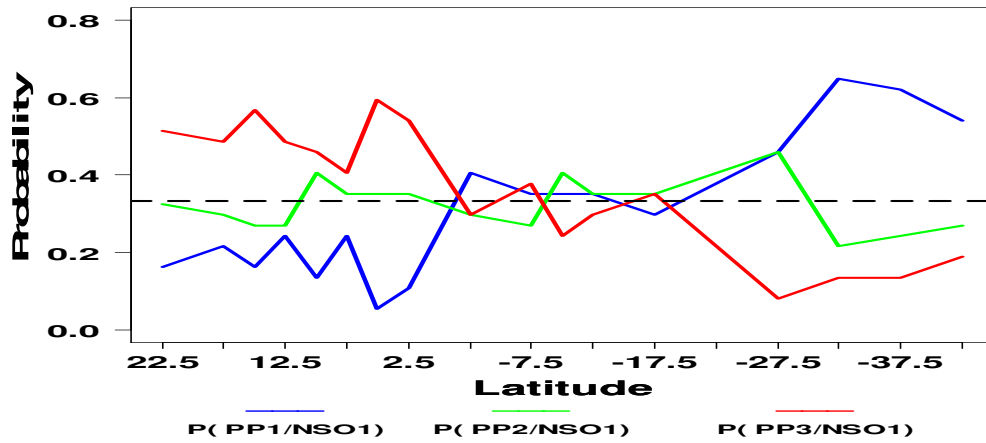


Figure 7. Profiles of rainfall response to cool events for JJA.

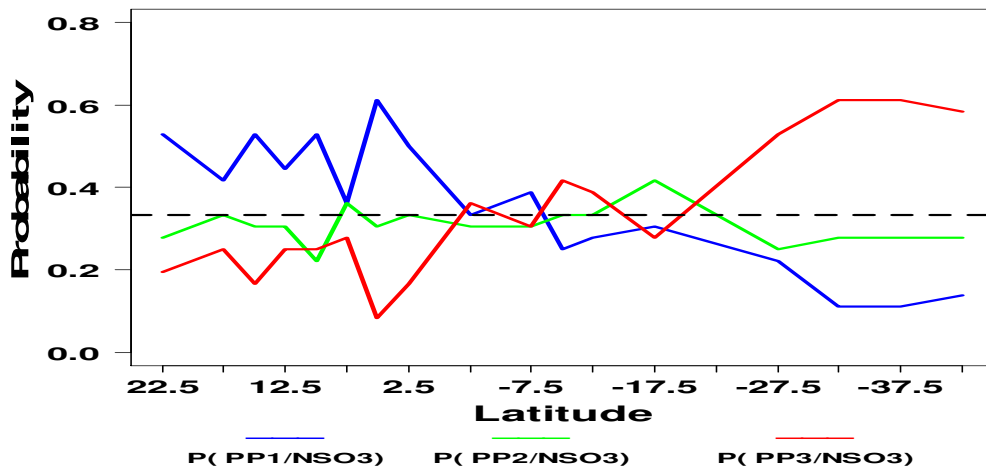


Figure 8. Profiles of rainfall response to warm events for MAM.

SON.

This season corresponds to the austral spring (boreal autumn). Figures 9 and 10, show the latitudinal profiles for the west coast. From the analysis presented here, (Figure 9) it can be inferred that the austral spring discriminates clearly the effects of the cool phase of ENSO in the zone of central and southern Chile, with irregular results for the rest of the West Coast, except for single points in northern Ecuador, Colombia and Panama. Figure 10, shows the association of rainfall with the warm phase of ENSO. The wet/warm association appears stronger for central and northern Chile, and southern Ecuador and Colombia. A less significant dry/warm association can be observed only for northern Ecuador.

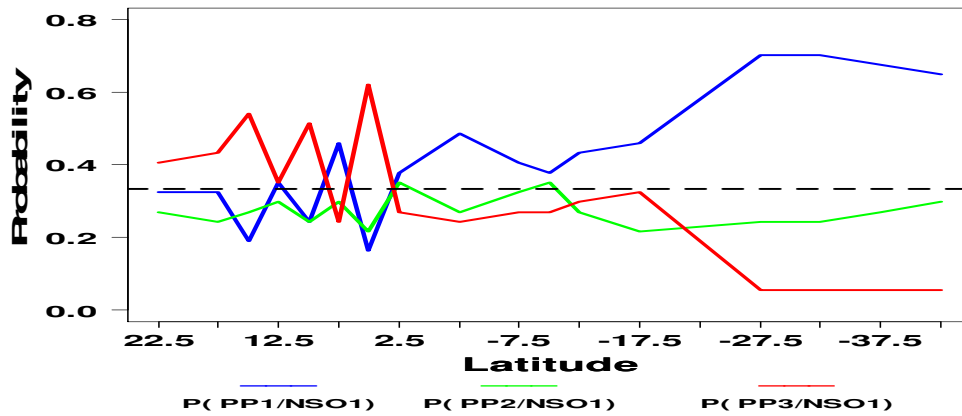


Figure 9. Profiles of rainfall response to cool events for SON.

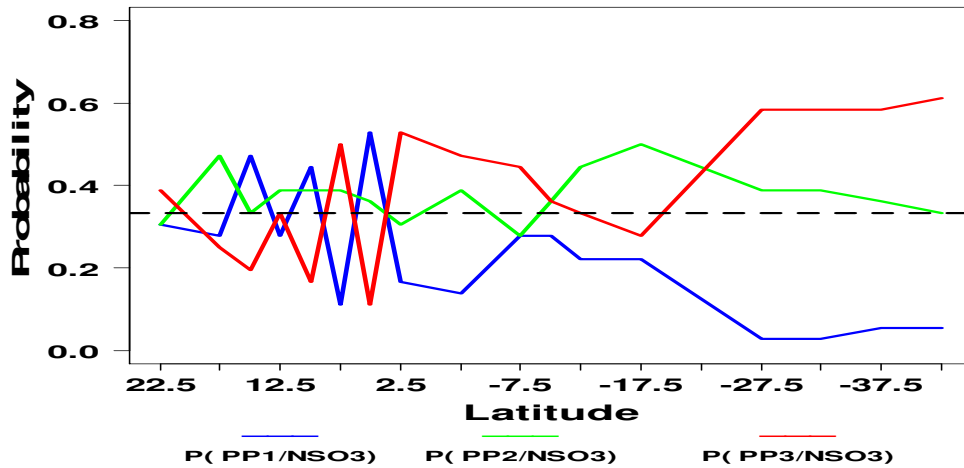


Figure 10. Profiles of rainfall response to warm events for SON.

4. Conclusions an Discusion

Although drier situations are associated with cool events (upper than 1/3), and if a cool event take place there's significant probabilities that a dry situation may takes place in most of Central Chile, the analysis performed here not preclude a warm/dry association at particular latitudes. Elsewhere, from Ecuador to most of Peru (1 to 10S), wetter/drier than normal winters are associated particularly to cool/warm events in ENSO. Instead for most of southern Peru and northern Chile the Warm-Wet and Cool-Dry association as for central Chile, although less strong, dominates.

Based in the analysis of the last 110 years, considering the probabilities of association as given by a particular logit model between warm/cool events in an ENSO index, and dry and wet situations, as given by monthly rainfall data over most of the western side of Central and South America, from Gulf of Panama to southern Chile, discretized into seasonal values. Although the data is based in a 5x5 degrees grid, which makes difficult to identify a specific region, rather working in a synoptic scale, it has the advantage of a long time span, which provide us with better quality contingency tables, since a specific requirement for the use of the models, is that the expected frequency for each cell should be large enough, to avoid low frequency (below five) cells, given its logarithmic

calculation. The analysis of the profiles, at any given latitude can provide us with further insights of the different forms of association between the amount of rainfall (categorized) and the different phases of ENSO. As it is clearly seen in the previous figures, this association changes in sign, when shifting from a cool to a warm phase of ENSO.

Although most criticisms, for this type of analysis, focus in the fact that there is an obvious loss of information, since we locate a continuous variable into only few classes, it needs to be noticed that this loss of information allows to center the analysis on the occurrence of the events, in a way which make more evident the specific categories of the event in which we are interested. In a first stage, this means that we are not really interested into how strong a strong event is going to be but in whether we are going to have an event or not. Such information cannot be lost using the categorization procedure, but to be emphasized instead. Only in the second stage of this study in progress, we will be focusing in the intensity of the events, try to determine how strong (or weak) an event will be if occurs.

Although the probabilities of the corners (P11, P13, P31, P33), respectively Cool-Dry, Cool-Wet, Warm-Dry and Warm-Wet of the table, seem to be more interesting and having a more straightforward interpretation, there is some interest in the center row and column, since they represent the fact that we do not have any basis to expect any extreme condition (warm or cool event), which then correspond to a probability close to 1/3.

However, the results herein presented are viewed as a preliminary study on cause effect relationships, by introducing the logit models. We did not, for example, discriminate association between strong, moderate and weak events to rainfall statistics, neither had we studied a particular event impact as for example Curtis et al. (2001) for the 1997-98 event. It will be necessary to extend this research to higher density estimations for rainfall along west coast.

We must, as well, concentrate the research to some particular time scales. For example, in this study we neither separate the different modes that participate in ENSO, say interannual from the decadal time scales (Zhou and Lau, 2001), nor we separate ENSO from non-ENSO variability (Mestas-Nunez and Enfield, 2001). All these modes can be focused on the type of relationship found here and will need a different study, particularly the effect of the decadal time scales, or even lower frequencies, like global warming effect in rainfall. Finally we might also to extend our results to rainfall prediction given precedent season variability (see Montecinos et al., 2000). Coming years will be fruitful in this regard given the practical benefit this kind of models may have for agriculture, epidemiology, and generally the economy associated with climate.

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