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# Is ENSO associated with Precipitation Patterns in Lake Valencia Venezuela?

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## Abstract

The objetive of this investigation is to determine if there exists an effect between El Niño phenomenon and the rainfall in the Lake Valencia basin. The Standardized Precipitation Index (SPI), is used to measure the different intensities of precipitation in the area of study. We implemented a Gaussian hidden Markov model (GHMM) to describe the temporal evolution of each rainfall regime. Autoregressive models are implemented to describe the monthly evolution of the different states of the Southern Oscilation Index (SOI) and the Multivariate ENSO Index (MEI). Finally, the relationship between the Macroclimatic variables associated to the ENSO and the hydrometereological variables associated to Lake Valencia basin, were caculated using the Pearson correlation coefficient (r).

**Key words:** Lake Valencia, Hidden Markov model, Autoregressive with Markov Regime (AR-RM), Standardized Precipitation Index (SPI), Gaussian hidden Markov model (GHMM), Southern Oscillation Index (SOI) and Multivariate ENSO Index (MEI).

***Resumen***

*El objetivo de este trabajo es determinar si el fenómeno de El Niño influye o no en el régimen de precipitaciones de la cuenca del Lago de Valencia. Las precipitaciones en el área de estudio son estandarizadas por intensidades utilizando el índice SPI. Se implementa un modelo oculto de Markov Gaussiano para describir la evolución temporal del régimen pluviomérico. Modelos Autorregresivos con régimen de Markov son implementados para describir las distintas fases de los índices SOI y MEI. Finalmente, la relación entre las variables macroclimáticas asociadas al ENSO y las variables meteorológicas en la cuenca del Lago de Valencia es medida a través del cálculo del coeficiente de correlación de Pearson (r).*

***Palabras clave:*** *Lago de Valencia, Modelo Oculto de Markov, Autorregresivos con régimen de Markov (AR-RM), Standardized Precipitation Index (SPI), Modelo oculto de Markov Gaussiano (GHMM, siglas en inglés), Southern Oscillation index (SOI) y Multivariate ENSO Index (MEI).*

## 1. Introduction

The purpose of this work is to determine if there exists an effect of *El Niño-Southern Oscillation* (ENSO) with precipitation patterns in Lake Valencia, Venezuela. For this, we study the rainfall in the Lake Valencia basin and evolution of the different states of the Southern Oscilation index (SOI) and the Multivariate ENSO Index (MEI; Wolter and Timlin, 1993). The Standardized Precipitation Index (SPI), is used to measure the different intensities of rainfall data from a network of stations in Lake Valencia basin.

We fit Gaussian hidden Markov model (GHMM) to the SPI. This model provides a classification of meteorological regime (weather type). Such models are used to model rainfall, the basic idea consists of introducing an extra variable to describe the weather type, see Allard *et al.* (2015) and references. In fact, characterizing the intensities that could produce floods is of great interest in the study of lakes that

are located near to populations. In Lake Valencia, floods have been reported in its southern zone. These precipitations have caused disasters affecting the population and services, Arias *et al.* (2017).

The climatic phenomenon under study, ENSO, has two phases: the warm (El Niño) and the cold (La Niña). These phases occur alternatively with neutral conditions. The intensity of the phenomenon is usually measured using both the Multivariate ENSO index (MEI) and the Southern Oscillation Index (SOI). We propose to use an autorregressive process with Markov regime (AR-RM) to fit ENSO index and SOI index data. This modeling approach for this data type have been studied for example by Xuan (2004) and Cárdenas-Gallo *et al.* (2015). Finally, the relationship between the macroclimatic variables associated to the ENSO and the hydrometereological variables associated to the Lake Valencia basin were caculated using the Pearson correlation coefficient (r).

This article is organized in seven main parts. In Section 2, we describe the data used for this work as well as the preliminary treatments. Section 3 provides a model for the precipitation. We proceed with classic time series analysis. Section 4 is devoted to calculating the SPI and using a Gaussian Hidden Markov model for classifying the levels of intensity of the precipitations. The ENSO phases are modeled by an AR-RM process in Section 5. A SAEM-type algorithm is used to estimate the parameters of process AR-RM. In Section 6, we compare the rainfall regime and the ENSO phenomenon. We carry out the comparison by calculating the correlation between the two series. Finally, Section 7 is devoted to the conclusion.

## 2. Data description

Lake Valencia 2943 km$^2$ basin lies between the Aragua Valley and Carabobo state at an elevation of 420 m asl, see Figure 1. This lake, also known as Tacarigua, is the largest endorheic freshwater body in Venezuela (Díaz *et al.*, 2010). Lake Valencia occupies a tectonic depression called *Graben de Valencia*, between the Cordillera de la Costa, at the north, and the Serranía del Interior, at the south. The body of the water of lake has a volume of 6.30 km$^3$, an average depth of 18 m, and maximum depth of 39 m approximately. There are 18 sub-basins taxing in the lake (Trejo *et al.*, 2015).

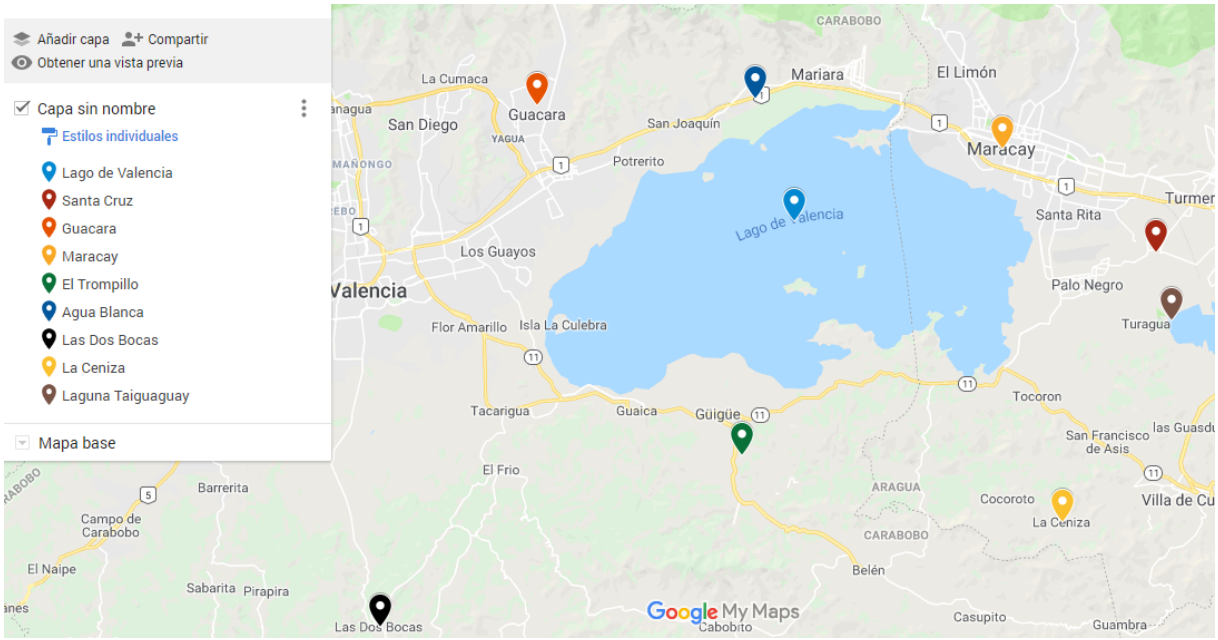


Fig. 1: Map of the studied area. (Source: Google maps.)

The database used for this article was provided by the Instituto Nacional de Meteorología e Hidrología (INAMEH). We used a small network of $J = 8$ rainfall stations located in the Lake Valencia basin. These stations represent a good spatial coverage across the region under study. The weather stations names, geographical positions and number of observed years are shown in Table 1.

The calculation of SPI requires that there are no missing data in the time series. Additionally, the data record length must be at least 30 years, according to the World Meteorological Organization (McKee *et al.*, 2012). The amount of precipitation was evaluated with regard to the monthly arithmetic means of daily precipitation. In this work we complete the data of missing periods by using a moving average process of order 3.

Table 1: Weather stations and years observed.

| Station code | Locality name | Coordinates | | | Years | | |
|---|---|---|---|---|---|---|---|
| | | Lat | Long | Height | Period | Missing | Observed |
| 417 | Santa Cruz | 10,167 | -67,488 | 444 | 1966-1999 | 3 | 30 |
| 452 | Guacara | 10,236 | -67,884 | 300 | 1949-1993 | 1 | 43 |
| 466 | Maracay | 10,25 | -67,65 | 436 | 1934-1992 | 0 | 58 |
| 488 | Colonia El Trompillo | 10,061 | -67,772 | 450 | 1960-1993 | 0 | 35 |
| 489 | Agua Blanca | 10,046 | -67,838 | 515 | 1951-2005 | 3 | 68 |
| 491 | Las Dos Bocas | 9,961 | -67,995 | 550 | 1949-2005 | 4 | 52 |
| 497 | Las Cenizas | 10,027 | -67,599 | 670 | 1960-2003 | 3 | 43 |
| 1494 | Embalse Taiguaiguay | 10,147 | -67,5 | 438 | 1951-1999 | 3 | 45 |

We used the ENSO index series data as reported by the National Oceanic and Atmospheric Administration (NOAA) on its World Wide site. We considered the SOI index and the MEI index over the period 1951-2017.

## 3. Precipitation Modeling

Let $Y_t(j)$ represent the observed precipitation amount on time $t$ at station $j = 1, \ldots, 8$. We will model $Y_t(j)$ as a random variable. We proceed with a classic time series analysis. First, the stationarity and stationality of the precipitation series were analyzed by the autocorrelation function and partial autocorrelation function methods. We investigated the series of the rainfall at each station. See Figure 2 for an example of such data series. The autocorrelation and the partial autocorrelation obtained indicated stationarity, as it is illustrated in Figure 3.

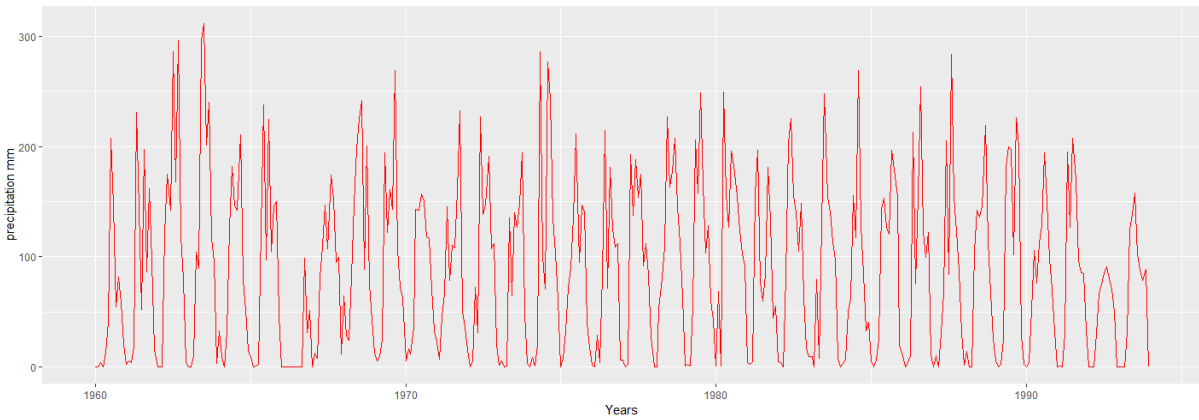


Fig. 2: Precipitation time series from station Agua Blanca.

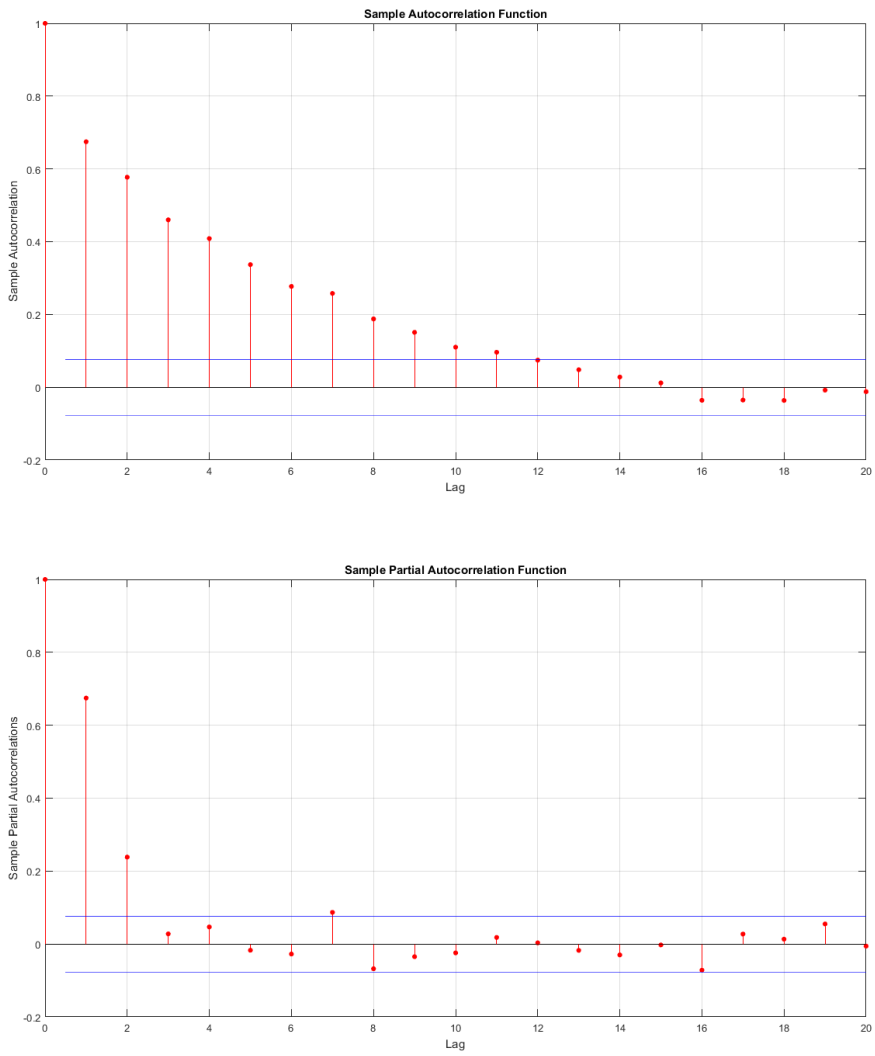


Fig.3: Autocorrelation (top) and partial autocorrelation (bottom) at Agua Blanca station.

Indeed, we distinguished two seasons, one dry and one wet. The graph of monthly averages shows that the months of January, February, March, April and December are the months of the lowest rainfall amounts. While the months between May and November are the months with the highest amount of rainfall (Figure 4).

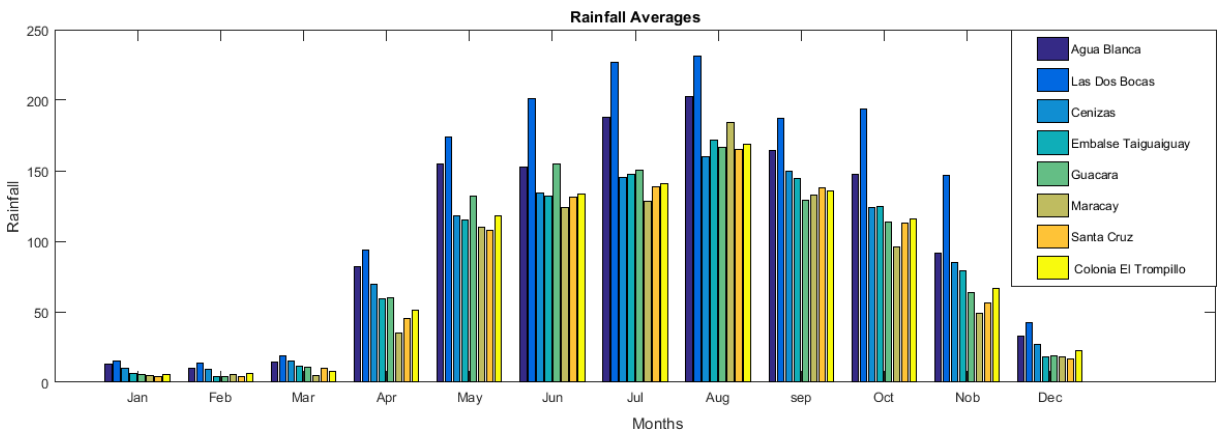


Fig. 4: Monthly average of rainfall by locality.

The partial correlation converges to 0, which is an indicative of stationarity. But, the tendency of the series is not clear. It is known, in the case of the autorregresive process with order $p$, (AR(p)), that we can study the stationarity by considering the associated characteristic polynomial, see Fermín *et al.* (2016). The test Dickey-Fuller, is used as an indicative of the stationarity. If the p-value is lower than the established $\alpha = 0,05$ level of confidence, the null hypothesis of a unit root is rejected. The result was that all stations are stationary with a p-value of 0.001 or lower.

Observing in the series of precipitation the maximums, minimums and averages values at each station, we obtain an indicative of the level of precipitation. The Table 2 shows the minimum and maximum rainfall (abbreviated as min ppn and max ppn, respectively) for each station in the study area. We computed the SPI to obtain a classification of the intensity levels of the series. We needed to complete the missing data, see Table 3. We adjust a moving average process of order 3 to the data. In this way, we completed and smoothed the data. Then we proceeded to calculate the SPI, using the 'spi' library of the statistical package R, see Neves (2015).

Tabla 2: Maximum and mininimum recorded precipitation at the stations.

| Locality | Period-years | Minimum (mm) | Maximum (mm) |
|---|---|---|---|
| Santa Cruz | 1966-1999 | 0 | 351 |
| Guacara | 1949-1993 | 0 | 419,9 |
| Maracay | 1934-1992 | 0 | 454 |
| Colonia El Trompillo | 1960-1993 | 0 | 311,7 |
| Agua Blanca | 1951-2005 | 0 | 633,6 |
| Las Dos Bocas | 1949-2005 | 0 | 475,5 |
| Las Cenizas | 1960-2003 | 0 | 446,6 |
| Embalse Taiguaiguay | 1951-1999 | 0 | 334,6 |

## 4. A Gaussian Hidden Markov model for SPI

In this section we calculate the SPI index, after using the Gaussian hidden Markov Model, intensity levels are classified. The SPI classification scheme used is

- 'EW'=Extremely Wet
- 'VW'=Very Wet
- 'MW'=Moderality Wet
- 'N'=Normal
- 'MD'=Moderality Dry
- 'VD'=Very Dry
- 'ED'=Extremely Dry

For each locality under study in Table 3, we classify the intensities according to the previous scheme, writing in the table Yes or NO if there was an occurrence. We observe in this table that 100 % of the locations have intensity level precipitation of the type (EW, VW, MW, N). While 62.50 % presented a moderately dry intensity (MD) and only 12.50 % presented a very dry precipitation (VD). Special focus was made on the intensities (EW, VW, MW, N).

Table 3: Intensity Levels at the stations.

| Localidad | EW | VW | MW | N | MD | VD | ED |
|---|---|---|---|---|---|---|---|
| Santa Cruz | Yes | Yes | Yes | Yes | Yes | NO | NO |
| Guacara | Yes | Yes | Yes | Yes | NO | NO | NO |
| Maracay | Yes | Yes | Yes | Yes | Yes | NO | NO |
| Colonia El Trompillo | Yes | Yes | Yes | Yes | Yes | NO | NO |
| Agua Blanca | Yes | Yes | Yes | Yes | Yes | NO | NO |
| Las Dos Bocas | Yes | Yes | Yes | Yes | NO | NO | NO |
| Las Cenizas | Yes | Yes | Yes | Yes | Yes | Yes | NO |
| Embalse Taiguaiguay | Yes | Yes | Yes | Yes | NO | NO | NO |

Let $Z_t(j)$ be the SPI index value on time $t$ at station $j = 1,\ldots,8$. In the following expresion, the index $j$ that indicates the station is omitted, with the purpose of simplifying the notation. The GHMM is defined by

$$Z_t = \mu_{X_t} + \sigma_{X_t} e_t \tag{1}$$

where $\{X_t\}_{t\geq 0}$ is a homogeneous discrete Markov chain, the space state is the discrete set $\{1,\ldots,m\}$. Assume that $\{e_t\}$ is a Gaussian standard independent observation. The unknown paramaters are the intensity levels $\mu_i$, the noisy variance $\sigma_i^2$ in each regime, with $i = 1,\ldots,m$, as well as the state transition probability distribution $A = \{a_{ij}\}$, with transition probability defined by $a_{ij} = \mathbb{P}(X_t = j|X_{t-1} = i)$, $i, j = 1,\ldots,m$.

We assume that $m$ is known. In fact, the previous analysis, done using the SPI, leads us to consider $m = 4$, then $\mu_i \in \{N, MW, VW, EW\}$, $i = 1,\ldots,4$. Hence, the parameters to be estimated are,

$$\Psi = (A, \mu_1, \ldots, \mu_4, \sigma_1, \ldots, \sigma_4).$$

To estimate $\Psi$, we considered the maximum likelihood estimator. The log-likelihood of the model can be written in the following form:

$$L(\Psi) = \sum_{X_{1:T}=x_{1:T}} \sum_{t=1}^{T} \log\left(\psi(Z_t - \mu_{x_t}, \sigma_{x_t}) a_{x_t,x_{t-1}} \pi_{x_t}\right)$$

where $\psi(x,v)$ is a density $\mathcal{N}(0,v^2)$. The log-likelihood estimator of $L(\Psi)$ is a root of the equation $\nabla L(\Psi) = 0$. The solution of this equation can be computed efficiently with an EM algorithm, see Fermín *et al.* (2016) and its references. The EM algorithm is divided into two stages: the expectation stage (E) and the maximization stage (M). In the step E, we calculate the expectation of the log-likelihood of the complete data conditioned on the observed data. In the next step M, this function is maximized. This procedure is repeated iteratively.

In order to illustrate the results when modeling the SPI with a GHMM, we chose the Trompillo locality. This station has the shortest historical period and more Extremely Wet (EW) rainfall was recorded. This locality will be representative when calculating the correlation with the ENSO events.

The results of estimation by means of the EM procedure in Trompillo station are: transition matrix,

$$\hat{A} = \begin{bmatrix} 0,8875 & 0,08571429 & 0,01071429 & 0,01607143 \\ 0,76666667 & 0,11666667 & 0,06666667 & 0,05 \\ 0,54545455 & 0,27272727 & 0,09090909 & 0,09090909 \\ 0,84615385 & 0,15384615 & 0 & 0 \end{bmatrix}$$

intensity levels $\mu$ and variance $\sigma^2$,

$$\hat{\mu} = \begin{bmatrix} 0.064991721582782 \\ 1.237921717425580 \\ 1.859111513498231 \\ 2.200000000000000 \end{bmatrix} \quad \hat{\sigma^2} = \begin{bmatrix} 0.064991721582780 \\ 0.000000000000002 \\ 0.000000000000004 \\ 0 \end{bmatrix}$$

The Figure 5 shows the percentages of the precipitation states of the Trompillo locality. It was observed that more than 8.3544 % of rainfall were Extremely Wet (EW), 7.3417 % were Very Wet (VW), 9.1139 % MW (MW), 12.92 % of moderately dry intensity (MD) and the 62.27 % were rainfall with normal intensities (N).

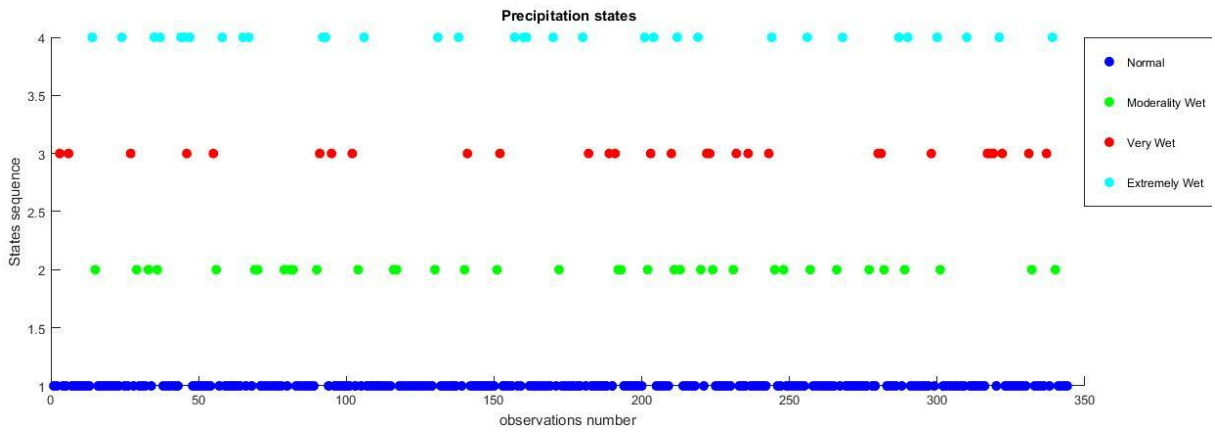


Fig. 5: Intensity levels at the Trompillo station.

We build a plot with the classified precipitation series according to their levels. This allows us to have a complete idea of the intensities, in a single graphic representation (Figure 6).

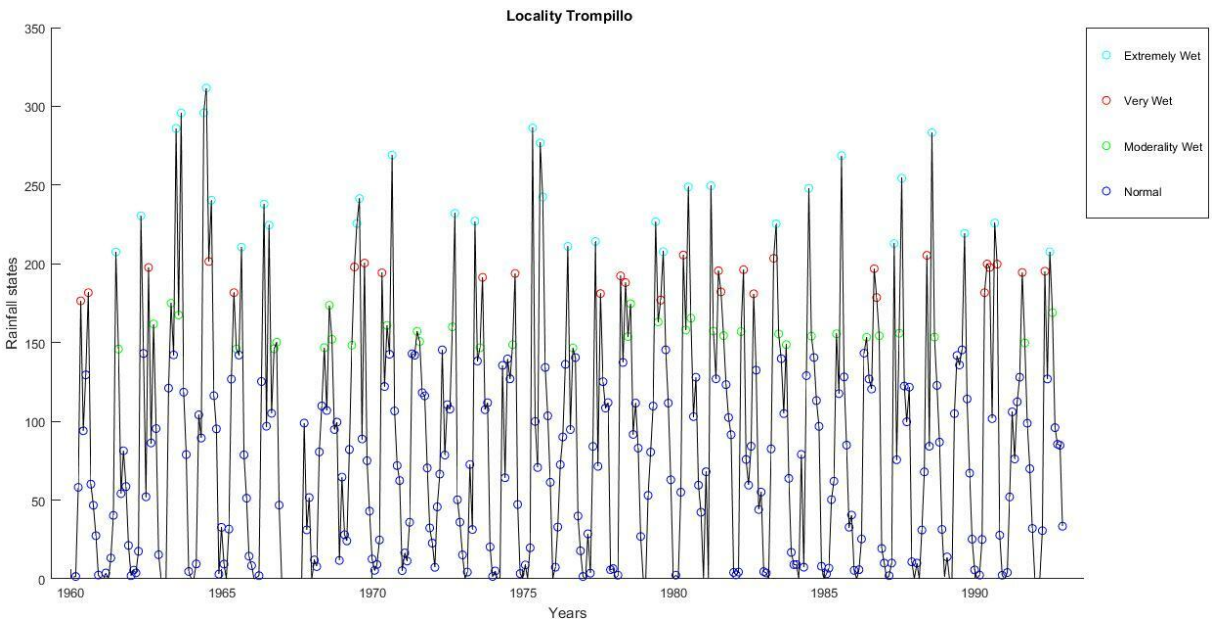


Fig. 6: Intensity levels and clasification of rainfall at the Trompillo station.

Now, we consider to separate the models for each intensity level, in the equation (1) the state is fixed,

$$Z_t = \mu_i + \sigma_i e_t \tag{2}$$

for $i = 1, \ldots, 4$. We represent each equation separately. This allows us to observe how each state of precipitation evolves over time, without having to study all precipitation phases simultaneously. The results are shown in Figure 7. The advantages of applying the models (GHMM) over the index under study (SPI) are shown.

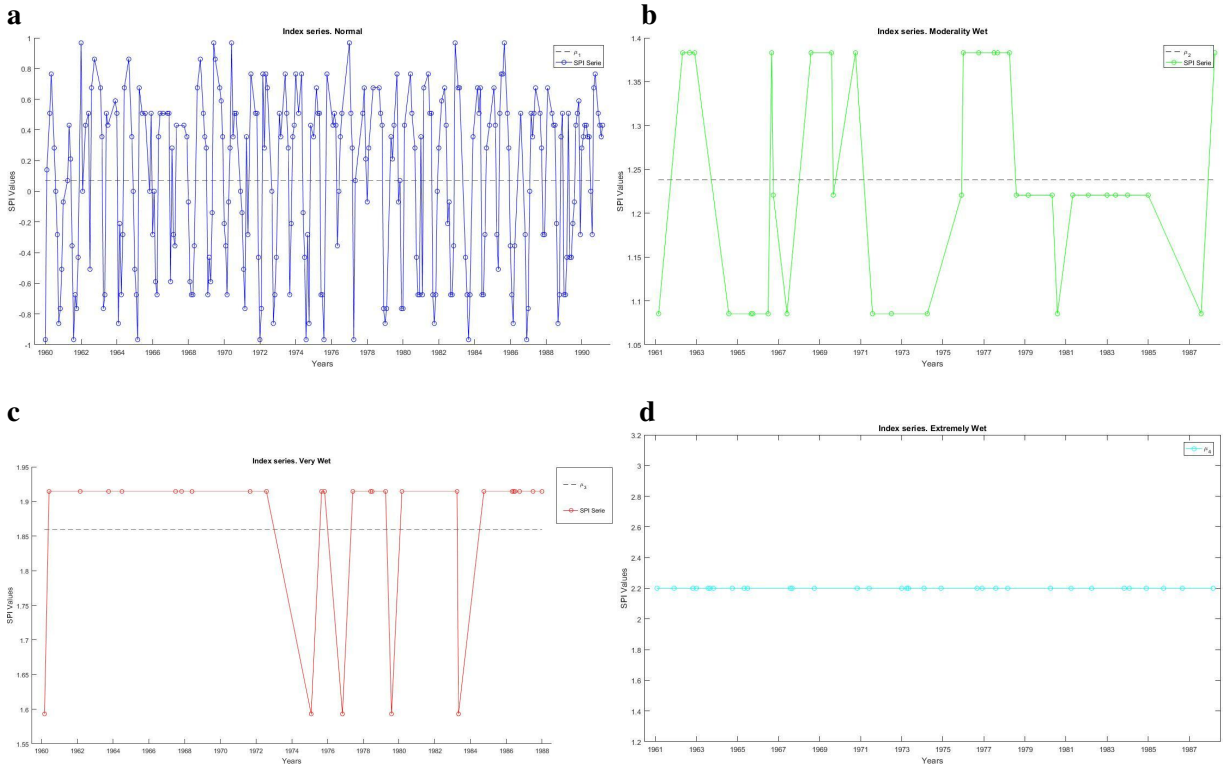


Fig. 7: SPI series states: Normal (a); Moderately Wet (b); Very Wet (c); Extremely Wet (d).

## 5. AR-RM for SOI

ENSO is a cyclical phenomenon in which it is possible to identify two regimes over time (La Niña and El Niño). The behavior patterns during each of the two phases are opposite and differentiable. On the other hand, the duration and the change between regimes is variable over time. These types of models for the ENSO phenomenon have been used for example by Xuan (2004) and Cárdenas-Gallo *et al.* (2015).

An autorregressive process with Markov Regime is defined for the SOI by

$$Y_t = \rho_{X_t} Y_{t-1} + b_{X_t} + \sigma_{X_t} e_t \tag{3}$$

where $\{X_t\}_{t\geq 0}$ is a homogeneous discrete Markov chain, the space state is the discrete set $\{1, \ldots, m\}$. Assume that $\{e_t\}$ is a Gaussian standard independent observation. The unknown parameters are the $\rho_i$, $b_i$, the noisy variance $\sigma_i^2$ in each regime, with $i = 1, \ldots, m$, as well as the state transition probability distribution $A = \{a_{ij}\}$, with transition probability defined by $a_{ij} = \mathbb{P}(X_t = j | X_{t-1} = i)$, $i, j = 1, \ldots, m$. We assume that the state number is $m = 3$. We consider three states $X_t$, since ENSO is divided in three phases: El Niño, La Niña, and the transition state we call Normal.

Hence, the parameters to be estimated are,

$$\Psi = (A, \rho_1, \rho_2, \rho_3, b_1, b_2, b_3, \sigma_1, \sigma_2, \sigma_3).$$

To estimate $\Psi$, we considered the maximum likelihood estimator. The log-likelihood of the model can be written in the following form:

$$L(\Psi) = \sum_{X_{1:T}=x_{1:T}} \sum_{t=1}^{T} \log\left(\psi(Z_t - \rho_{x_t} - b_{x_t}, \sigma_{x_t}) a_{x_t, x_{t-1}} \pi_{x_t}\right)$$

where $\psi(x, v)$ is a density $\mathcal{N}(0, v^2)$. The log-likelihood estimator of $L(\Psi)$ is a root of the equation $\nabla L(\Psi) = 0$. In order to avoid local minima in the solution of this equation, we have used a stochastic approximation of the EM algorithm, the SAEM algorithm, see Fermín *et al.* (2016) and its references. The E stage in the algorithm EM is replaced by a simulation stage and an approximation procedure.

The results when modeling the SOI with an AR-RM. The parameters estimated are the transition matrix, the slope,

$$\hat{A} = \begin{bmatrix} 0.4274 & 0.4597 & 0.1129 \\ 0.1976 & 0.5836 & 0.2188 \\ 0.0426 & 0.5674 & 0.3901 \end{bmatrix} \quad \hat{b} = \begin{bmatrix} -0.7113 \\ 0.0237 \\ 0.7486 \end{bmatrix}$$

the variance, and the intercept

$$\hat{\sigma^2} = \begin{bmatrix} 0.998952924206662 \\ 0.968681703610350 \\ 0.602621116771551 \end{bmatrix} \quad \hat{\rho} = \begin{bmatrix} 0.98520 \\ -0.472054506176259 \\ 0.7486 \end{bmatrix}$$

In the 1951-2017 period, 20.84% of El Niño events were observed, 54.45% normal periods and 23.86% of La Niña phenomenon. A graphic representation of these results are shown in Figure 8.

## 6. Correlation

In this section, we analyze if there is a correlation between the rainfall regime and the ENSO phenomenon. Recall that the climate regime was classified by intensities through the SPI index denoted by $Z_t$. While ENSO occurrences are characterized by the SOI index denoted by $Y_t$. In Table 4 we show the results. For the calculation, only the months with intensities EW and MW and with the presence of the El Niño phenomenon were considered.

Table 4: Correlation between SPI and SOI.

| Locality | Time period | Correlation |
|---|---|---|
| Santa Cruz | 1966-1999 | -0,1580 |
| Guacara | 1951-1993 | 0,0463 |
| Maracay | 1951-1992 | -0,13285057 |
| Colonia el Trompillo | 1960-1993 | -0,02018438 |
| Agua Blanca | 1951-2005 | 0,0716 |
| Las Dos Bocas | 1951-2005 | -0,0475 |
| Las Cenizas | 1960-2003 | -0,11028861 |
| Embalse de Taiguaiguay | 1951-1999 | -0,02881114 |

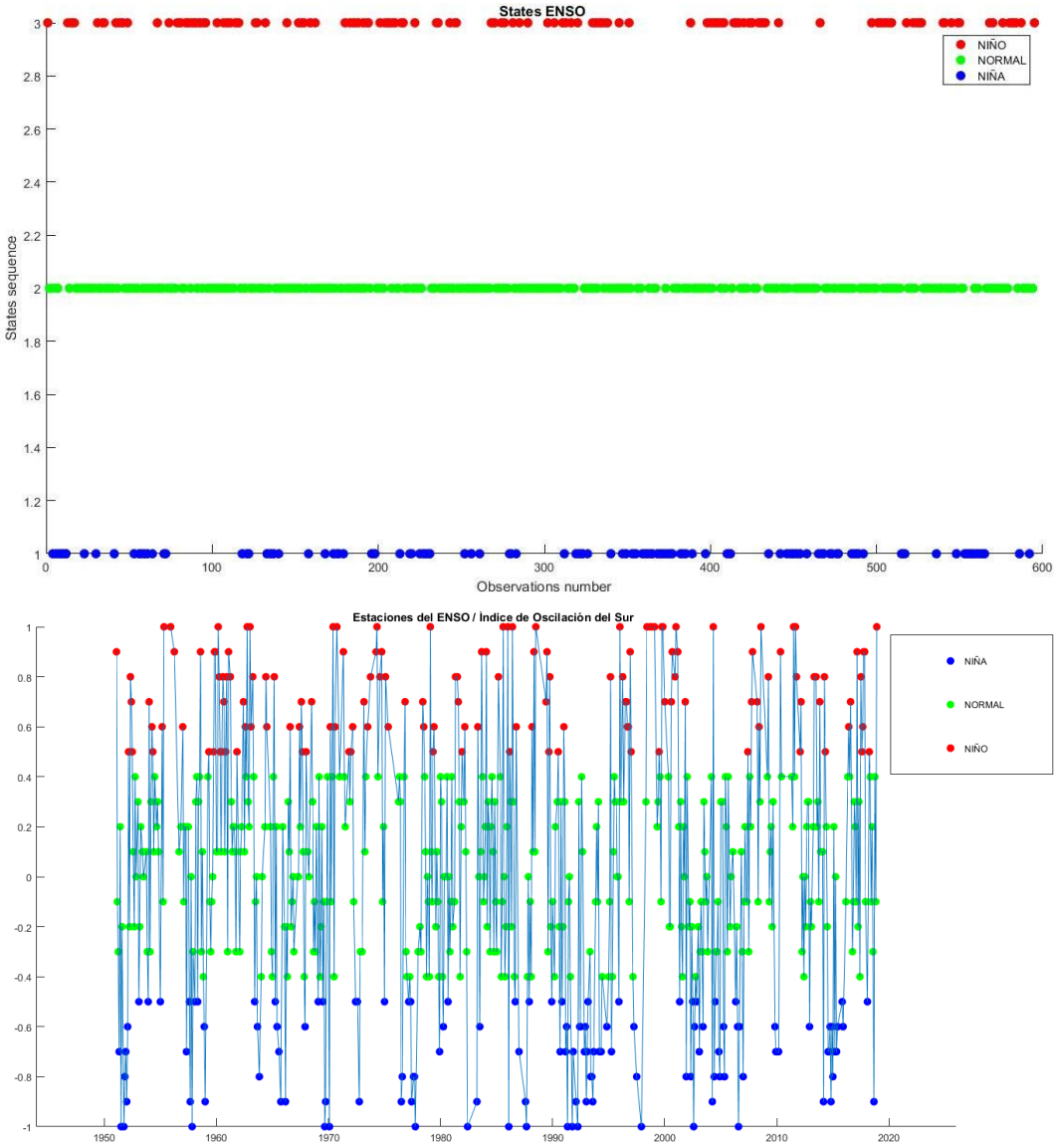


Fig. 8: States (top) and classified (bottom) SOI series.

The statistical significance of the correlation between the phenomena is measured by calculating the Pearson test. The correlation coefficients were computed using the MATLAB software, in particular the command "corrcoef". The results displayed in Table 5 show that in 7 of the 8 locations there is no correlation between the SOI and the MEI index.

Table 5: Pearson test with level of confidence $\alpha = 0.05$.

| Locality | p-value (SOI) | p-value (MEI) |
|---|---|---|
| Santa Cruz | 0,0022 | 0,2194 |
| Guacara | 0,2994 | 0,2994 |
| Maracay | 0,0028 | 0,8668 |
| Colonia El trompillo | 0,8596 | 0,9362 |
| Agua Blanca | 0,1043 | 0,0908 |
| Las dos Bocas | 0,2600 | 0,0002 |
| Las Cenizas | 0,0156 | 0,1483 |
| Embalse Taiguaiguay | 0,5089 | 0,1520 |

The ENSO phases calculated with the SOI index, can be visualized for each state by considering equation 3 separately for $i = 1, 2, 3$

$$Y_t = \rho_i Y_{t-1} + b_i + \sigma_i e_t,$$

Figure 9 shows the results.

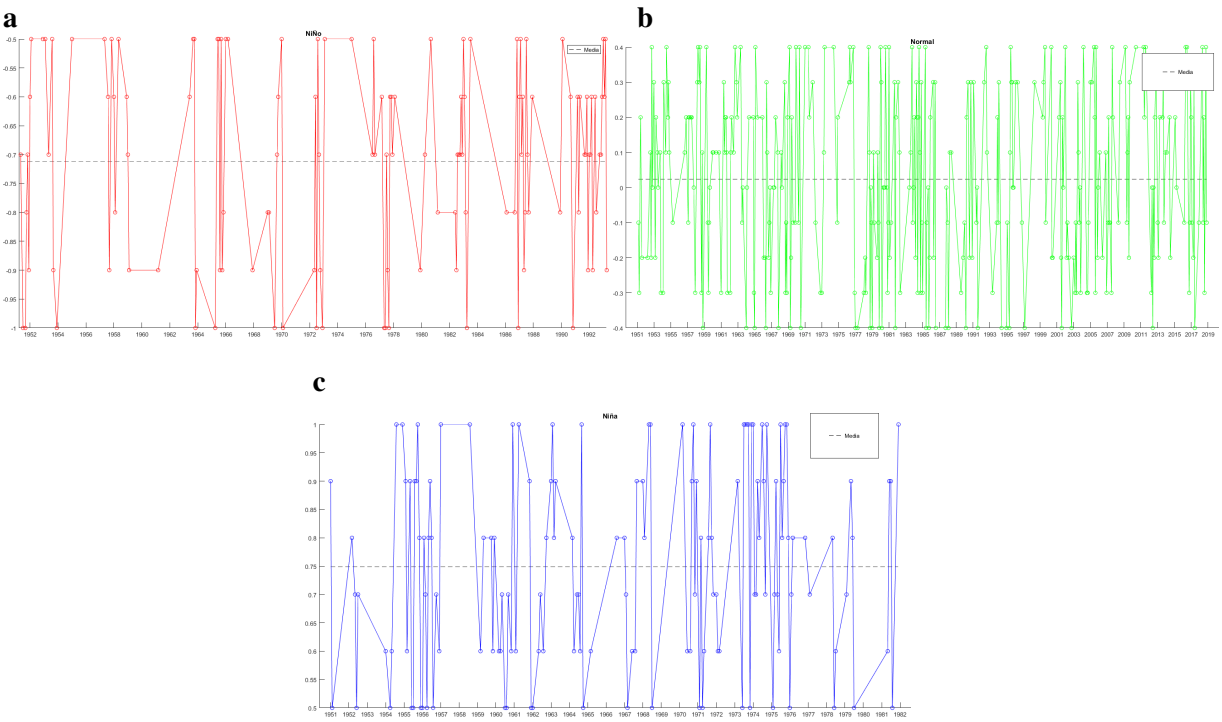


Fig. 9: ENSO phases: El Niño (a); Normal (b); La Niña (c).

In 5 of the 8 localities, the null correlation hypothesis is rejected. Therefore in these locations there is no evidence of an interrelation between the two phenomena.

In order to corroborate the results obtained, the experiments were repeated considering the MEI index for the ENSO phenomenon. In Table 6 the calculation of the correlation taking the values of the MEI are shown.

Table 6: Correlation between the SPI and the MEI.

| Locality | Time period | Correlation |
|---|---|---|
| Santa Cruz | 1979-1999 | -0,1182 |
| Guacara | 1979-1993 | 0,1351 |
| Maracay | 1979-1992 | -0,0130 |
| Colonia el Trompillo | 1979-1993 | -0,0649 |
| Agua Blanca | 1979-2005 | 0,1217 |
| Las Dos Bocas | 1979-2005 | -0,2298 |
| Las Cenizas | 1979-2003 | -0,1298 |
| Embalse de Taiguaiguay | 1979-1999 | 0,0678 |

Table 7 shows the coincidences in dates of the Extremely Wet rainfall with the ENSO stations in the Colonia el Trompillo locality. We observe that precipitation with Extremely Wet intensity occurs on 15.15% of the months where El Niño events occurred, while La Niña events occurred in 21.21% stations and 63.63% were normal events.

Table 7: ENSO phases at extremely wet months in the Colonia el Trompillo station.

| Month | ENSO | Month | ENSO | Month | ENSO |
|---|---|---|---|---|---|
| Jul-1960 | Niña | Aug-1969 | Normal | Jul-1980 | Niño |
| May-1962 | Niño | Sep-1970 | Normal | Apr-1981 | Niño |
| Jul-1963 | Normal | Oct-1972 | Normal | Jun-1983 | Normal |
| Sep-1963 | Normal | Jun-1973 | Niña | Jul-1984 | Niña |
| Jun-1964 | Niña | May-1975 | Normal | Aug-1985 | Niña |
| Jul-1964 | Normal | Aug-1975 | Normal | May-1987 | Normal |
| Sep-1964 | Normal | Sep-1975 | Normal | Aug-1987 | Normal |
| Sep-1965 | Normal | Jul-1976 | Normal | Aug-1988 | Niño |
| Jun-1966 | Normal | Jun-1977 | Normal | Sep-1989 | Niño |
| Aug-1966 | Niña | Jun-1979 | Normal | Sep-1990 | Normal |
| Jul-1969 | Normal | Sep-1979 | Niña | Jul-1992 | Normal |

## 7. Conclusion

From the results of the data analysis, we could see that rainfall shows a seasonal behavior. The months of precipitation in the lake basin show a unimodal distribution with two periods clearly differentiated, one period is characterized by above average rainfall, and occurs between May and October; the rainfall in the other period is below average, ocurring between November and April. The maximum rainfall value is presented in August and the minimum in March. The intensities, in the area of study, were classified as normal, moderately wet, very wet and extremely wet. Dry periods were recorded but only in 50 % of the localities, the most observed rainfall intensity is normal. This is one of the indicators taken into account that shows the presence of the phenomenon, since in the entire series of precipitation there were occurrences of very wet and extremely wet intensities. These occurrences were less than 7.3417 % and also 9.1139 % respectively.

On the other hand, the previous analysis does not guarantee that the phenomenom is present or not. The contribution of the models with hidden variables allowed us to study individually each phase of the ENSO and rainfall, as well as its temporal evolution. We observed that the occurrences of El Niño were 20.84 % throughout the period of study. Likewise in the locality El Trompillo, used as a reference for the other localities in the Extremely Humid precipitation series, there were coincidences with the dates only 15.15 % of the time.

The analysis of the correlation between the ENSO phenomenon and rainfall patterns in most places, shows us that for the data studied there is no statistical evidence revealing a correlation of rainfall patterns in the basin of Lake Valencia and the ENSO. This could be due to the fact that there exists a marked microoclimate behavior in this basin.

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