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It may be cited using the following DOI

DOI: 10.20937/ATM.52541
Acceptance date: 26 November 2019

The published manuscript will replace this preliminary version at the above DOI.
Relationship between precipitation anomalies and multivariate ENSO index through wavelet coherence analysis

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RESUMEN

Una mejor comprensión de la variación espacial y temporal de la precipitación pluvial a niveles local y regional es indispensable para poner en contexto la investigación sobre cambio climático. La precipitación mensual de 59 estaciones (de 1976 a 2010, es decir, 34 años) en el estado de Zacatecas en México se transformó en anomalías de precipitación mensual estandarizadas. El análisis de conglomerados de las nuevas series de tiempo identificó tres grupos (regiones: semiáridas, altiplano y cañones) con regímenes de precipitación similares. Análisis de espectro de potencia se llevaron a cabo para identificar frecuencias importantes. Análisis de coherencia de ondeletas se realizaron para detectar relaciones significativas entre cada una de las tres series temporales de anomalías de precipitación media mensual regional (SAMP) y el Índice de Oscilación del Sur (MEI) multivariado. Se identificaron tres regiones: Semiárida, Altiplano y Cañones. En las tres series de tiempo regionales las frecuencias de 0.5, 1, 2 y 3 años estuvieron presentes en su espectro de potencias. Las regiones del Altiplano
y Cañones tuvieron frecuencias importantes de 13 y 12 años respectivamente. Las frecuencias de 3 años pueden estar relacionadas con el fenómeno El Niño Oscilación del Sur. Tres períodos con correlación significativa entre SAMP y MEI fueron identificados: 1993 a 2003 para la región Semiárida, 1995 a 2003 para el Altiplano y 1988 a 2003 para la región de los Cañones. Los resultados sugieren que las anomalías de precipitación varían según las regiones y con el tiempo. Además, los resultados indican fuertemente que la precipitación es modulada por el MEI.

**ABSTRACT**

A better understanding of the local and regional spatio-temporal variability of past precipitation is needed to contextualize climate change research. Monthly precipitation data from 59 stations in the state of Zacatecas in Mexico were transformed into standardized monthly precipitation anomalies for the period 1976-2010 (34 years). Cluster analysis of the new time series was used to identify regions with similar precipitation regimes. Power-spectrum analysis was carried out to identify important frequencies. Wavelet coherence analysis was performed to detect significant relations between each of the regional monthly mean precipitation anomaly time series (SAMP) and the Multivariate El Niño Southern Oscillation Index (MEI). Three regions were identified: Semi-arid, Highlands and Canyons. In all the three regional SAMP series, the 0.5-, 1-, 2- and 3-year frequencies are present in the power–spectrum; the Highlands and Canyons regions showed important frequencies of 13 and 12 years, respectively. The 3-year frequencies may be linked to the El Niño Southern Oscillation phenomenon. Three periods with significant correlation between regional SAMP time series and the MEI were identified: 1993 to 2003 for the Semi-arid region, 1995 to 2003 for Highlands region and 1988 to 2003 for the Canyons region. The results suggest that
precipitation anomalies vary over time and according to regions. The results also strongly indicate that precipitation is modulated by the MEI.

1. INTRODUCTION

Climate change triggers severely negative effects on global water resources (Fares et al., 2016). In fact, changes in rainfall distribution have attracted so much attention because of the vulnerability of human activities to extreme hydrological events such as flood–producing rains and droughts (Kharin et al., 2007). These precipitation changes could also have a dramatic effect on agriculture (Yue, et al., 2010). Record-breaking rainfall events around the world during the last decade have had a severe impact on human society and the environment including agricultural losses and flooding (Lehmann et al. 2015). Changes in water availability or more importantly, the shortage of water in the future could have negative impacts as well on hydropower generation and on agricultural activities in Central America and Mexico (Karmalkar et al., 2011) such as the arid and semiarid irrigated land areas (150,000 ha) in the state of Zacatecas located in Central Mexico.

The state of Zacatecas is one of the main providers of basic grains in Mexico, primarily dry beans (Cid et al., 2018) and corn, but several of its 34 aquifers are overexploited with a deficit of about 433 Mm$^3$ per year (Diario Oficial de la Federación, 2015). A better understanding of the spatial and temporal variability of precipitation over land, at local and regional levels, is necessary for advancing climate change research, as well as for estimating the potential impact of climate change on water resources (Nickl et al., 2010). Several studies suggest that precipitation trends vary over time and according to regions, although precipitation over land has generally increased in the north at 30° N over the past century and decreased over much of the tropics since the 1970s (The Intergovernmental Panel on Climate Change (IPCC),...
Recent studies on precipitation during the last 20 years suggest that the current climate is becoming wetter compared with the climate of the 1950s in North America (Huang et al., 2016). Precipitation at higher latitudes has generally increased notably over North America, Eurasia and Argentina (Trenberth, 2011).

Variations and trends of precipitation may be affected by quasi-periodic phenomena, that is, phenomena that happen repeatedly at irregular intervals. For instance, El Niño-Southern Oscillation (ENSO), the most important coupled ocean-atmosphere phenomenon, causes global climate variability in inter-annual time scales (Wolter and Timlin, 2011). Precipitation increases over northwestern Mexico during El Niño winters but decreases in the region around the Isthmus of Tehuantepec. A southward shift in the location of the subtropical jet stream also increases the number of cold fronts over the southern part of the Gulf of Mexico (Magaña et al., 2003). Research should nonetheless include the possible association between precipitation and periodic phenomena (Valdez-Cepeda et al., 2012) such as ENSO at local and regional levels. An interesting teleconnection between precipitation anomalies registered at the Litter River Watershed, Tifton, Georgia, United States of America and the ENSO 3.4 index of sea surface temperature was confirmed by Keener et al. (2010) through the wavelet coherence analysis.

Several studies suggest important relationships between ENSO and local or regional precipitation patterns (e.g. Magaña et al., 2003; Kane, 2009; Keener et al., 2010; Li and Chen, 2014), but a relation between ENSO and rainfall in Central Mexico (i.e. Zacatecas state) has not been reported. The aims of this study were therefore: 1) To cluster standardized anomalies of the monthly precipitation (SAMP) time series into groups that represent regions under the basis of similar precipitation regimes, 2) To generate regional SAMP time series
using all the members (time series) for each cluster, 3) To identify important frequencies in
each regional SAMP time series and possible connections with quasi-periodic phenomena,
and 4) To detect coupling signals using each estimated regional SAMP and the MEI.

2. MATERIAL AND METHODS

2.1 Precipitation Data

Monthly precipitation data from 59 sites located within the state of Zacatecas, Mexico (Fig. 1) were analyzed. Table I provides information on location. Data sets were kindly provided by the ‘Comisión Nacional del Agua’, the official National Institution in charge of recording climatic and meteorological data in Mexico. Time series of 34 years (1976-2010) were checked for outliers or missing values.

2.2 Precipitation linear trends and anomaly time series

Precipitation time series are in general non–stationary and frequently present long–term trends. Identifying the trends and detrending the data are both of great interest and importance in data analysis. Moreover, detrending climate data is often a necessary step before meaningful spectral results can be obtained (Wu et al., 2007). Linear trends of the 59 precipitation time series were estimated through a linear regression analysis, considering this simple model:

\[ Y_i = a + bX_i, \]  \hspace{1cm} (1)

where \( Y_i \) is \( i_{th} \) monthly precipitation and \( X_i \) is \( i_{th} \) month.

Before carrying out the fractal analysis with the power spectrum density approach, linear trends of the series were removed following Equation 2:

\[ Y_{di} = Y_i - (a + bX_i), \]  \hspace{1cm} (2)
where $Y_{di}$ is the $i_{th}$ detrended monthly precipitation.

After removing the trends, the standardized anomalies were computed simply by subtracting the sample mean and dividing by the corresponding sample standard deviation, as pointed out by Wilks (2006). The new time series were then referred to as “standardized anomalies of the monthly precipitation time series” (SAMP) and could be analyzed by using common statistical analysis and other approaches like the spectral analysis which uses several algorithms such as maximum entropy, autoregressive moving average, non-harmonic method, singular spectral analysis and the traditional Fourier analysis (Lana et al., 2005).

2.3 Cluster analysis

Cluster analysis is an effective statistical tool to find homogeneous climate regions based upon observed values of meteorological parameters (Unal et al., 2003; Mahlstein and Knutti 2010; Karmalkar et al., 2011). This approach groups data objects based only on information found in the data that describes the objects and their relationships. The goal is that the objects within a group be similar to one another and different from the objects in other groups (Tan et al., 2005). The greater the similarity within a group and the greater the difference between groups, the better or more distinct the clustering becomes (Tan et al., 2005). In this study, we used a tree clustering algorithm to join objects (i.e. standardized anomalies of the monthly precipitation) into successively larger clusters (i.e. regions under the basis of similar precipitation regimes). The 1-Pearson’s $r$ (Everitt et al., 2011) was used as linkage distance and Ward’s method was used as linkage rule.

The joining, or tree clustering, method uses the similarities or distances between objects when forming the clusters. Similarities are a set of rules that serve as criteria for grouping or separating items. The distances can be based on a single dimension or on multiple
dimensions, with each dimension representing a rule or condition for grouping objects. In the case of the 1-Pearson’s r (Everitt et al., 2011) as linkage distance, low values mean that both involved elements are highly positively correlated, while two elements having low positive correlation are more distant from each other. Ward’s method (Ward, 1963) is generally regarded as very efficient although it tends to create small-sized clusters (Unal et al., 2003) and uses an analysis of variance approach to evaluate the distances between clusters. This method defines the proximity or distance between two clusters as the increase in the squared error that results when two clusters are merged (Tan et al., 2005). The cluster analysis was performed in this research using Statistica version 8.0 (StatSoft, Inc., 2007).

2.4 Fractal analysis

The temporal variation of natural phenomena has been difficult to characterize and quantify which is why Mandelbrot (1982) introduced the fractal analysis. Time series can be characterized by a non–integer dimension (fractal dimension) when treated as random walks or self–affine profiles. These series can be treated as self-affine systems because they are invariant only under anisotropic magnifications (Bunde and Havlin, 2013). Self–affine systems are often characterized by roughness, which is defined as the fluctuation of the height over a length scale. For self–affine profiles, the roughness scales with the linear size of the surface by an exponent called the Hurst exponent (Turcotte, 1997). This exponent, however, only gives limited information about the underlying distribution of height differences (Evertsz and Berkner, 1995). The Hurst exponent as well as the fractal dimension measure how far a fractal curve is from any smooth function used to approximate it (Moreira et al., 1994). There are several approaches to estimate fractal dimension for self–affine profiles but
we only used the power spectrum technique because it is very sensitive and is a good exploratory tool for real data (Weber and Talkner, 2001).

2.5 Power spectrum approach

Self–affine fractals are generally treated quantitatively through spectral techniques. The variation of the power spectrum $P(f)$ with frequency $f$ appears to follow a power-law (Turcotte 1997):

$$P(f) \sim f^{-\beta}.$$  \hspace{1cm} (3)

The power spectrum $P(f)$ is defined as the square of the magnitude of the Fourier transform of the SAMP. Denoting SAMP as a function of time by $Z(t)$, we have:

$$P(f) = \left| \int_{t_0}^{t_1} Z(t)e^{-i2\pi ft} \, dt \right|^2,$$  \hspace{1cm} (4)

where $t_0$ and $t_1$ are the limits of time over which the series extend. The discrete version of Equation 4 should be used for such a standardized anomaly sampled at discrete time intervals:

$$P(f) = \left| \sum_{t=t_0}^{t_1} Z(t)e^{-i2\pi ft} \right|^2.$$  \hspace{1cm} (5)

The next step is to obtain a relationship between the power $\beta$ and the fractal dimension $D$.

After considering the time series $Z_1(t)$ and $Z_2(t)$ separated by distance $r$ and related by

$$Z_2(t) = \frac{1}{r^D}Z_1(rt),$$  \hspace{1cm} (6)
it can be observed that $Z_1(t)$ has the same statistical properties as $Z_2(t)$, and since $Z_2$ is a properly rescaled version of $Z_1$, their power spectral densities must also be properly scaled. We can then write:

$$P(f) = \frac{1}{r^{2H+1}} P \left( \frac{f}{r} \right).$$  \hspace{1cm} (7)

It follows that

$$\beta = 2H + 1 = 5 - 2D_s,$$  \hspace{1cm} (8)

$$D_s = \frac{5 - \beta}{2},$$  \hspace{1cm} (9)

and

$$H = 2 - D_s,$$  \hspace{1cm} (10)

where $D_s$ denotes the fractal dimension estimated from the power spectrum and $H$ is the Hurst exponent (see Valdez-Cepeda et al., 2003a,b, 2007).

Since the periodogram is a poor estimate of the power spectrum, we used the Welch method of averaging periodograms (Welch, 1967). We also used the ‘running sum’ transformation to shift the slope by a factor of $\pm 2$. The Hurst exponent and the $D_s$ (because of data-trace) had a slope between $-1$ and $1$ on the log-log plot. Major modal contributors could then be identified in such a plot.

In order to obtain an estimate of the fractal dimension $D_s$, one must calculate the power spectrum $P(f)$ (where $f = \frac{2\pi}{l}$, $f$ is the wavenumber, and $l$ is the wavelength), and plot the logarithm of $P(f)$ versus the logarithms of $f$. This plot should follow a straight line with a negative slope $-\beta$ if the profile is self-affine (Valdez-Cepeda et al., 2003a, b).
The power spectrum approach involving the SAMP was carried out using the Benoit 1.3 software (TruSoft Int’l Inc., 1997). The important frequencies of SAMP were estimated through the plot yielded by power–spectral density $\Phi_x(f)$ versus frequency, considering significant ($p \leq 0.05$) peaks.

2.6 Multivariate El Niño Southern Oscillation Index Data

The ENSO is arguably the most important coupled ocean-atmosphere phenomenon causing global climate variability on inter-annual time scales (Wolter and Timlin, 2011). The MEI is calculated based on the six main observed variables over the tropical Pacific (Wolter 1987; Wolter and Timlin 1993, 1998). These six variables are sea-level pressure, zonal and meridional components of the surface wind, sea surface temperature, surface air temperature, and total sky cloudiness fraction. The MEI is computed separately for each of twelve sliding bi-monthly seasons (Dec/Jan, Jan/Feb,…, and Nov/Dec). After spatially filtering the individual fields into clusters (Wolter 1987), the MEI is calculated as the first un-rotated Principal Component (PC) of all six observed fields combined. This is accomplished by normalizing the total variance of each field first and then performing the extraction of the first PC on the covariance matrix of the combined fields (Wolter and Timlin, 1993). All seasonal values are standardized with respect to each season in order to keep the MEI comparable. A MEI database with a length matching our precipitation records (1976-2010) was downloaded from the National Oceanic and Atmospheric Administration website http://www.esrl.noaa.gov and used to couple it with each of the standardized anomaly regional means of the monthly precipitation time series. The MEI was used because it has been related to precipitation in several regions around the world and takes into account ENSO’s seasonality. For instance, precipitation was positively and significantly correlated
with the MEI during the boreal winter (Nov-Apr), mainly in northeastern and northwestern Mexico (Mendez-Gonzalez et al., 2009).

2.7 Wavelet coherence analysis

Wavelet analysis is a spectral method of decomposing a time series into time and frequency space. This allows the identification and analysis of dominant localized variations of power, i.e., where the variance of the time series is largest for a given frequency (Keener et al., 2010). Transferring the concept of the Fourier analysis, a wavelet power spectrum (WPS) can be defined as the wavelet transformation of the autocorrelation function (Maraun and Kurths, 2004). This can be implemented following the Wiener-Khinchin theorem (Maraun and Kurths, 2004):

\[
WPS_x(s) = \langle W_x(s) W_x(s)^* \rangle, \quad (11)
\]

where the brackets denote expectation values and \(WPS_x(s)\) describes the power of the signal \(x(t)\) at a certain time \(t_i\) on a scale \(s\).

As in the Fourier analysis, the univariate WPS can be extended to compare time series, for instance, \(x(t_i)\) and \(y(t_i)\). One can define the wavelet cross-spectrum \([WCS_x(s)]\) as the expectation value of the product of the corresponding \(W_x^+(s)\) and \(W_y^+(s)\):

\[
WCS_x(s) = \langle W_x^+(s) W_y^+(s)^* \rangle. \quad (12)
\]

In contrast to the WPS, the WCS is a complex value (analogous to Fourier cross spectra) and can be decomposed into amplitude \(|WCS_x(s)|\) and phase \(\Phi_x(s)\):

\[
WCS_x(s) = |WCS_x(s)| e^{i\Phi_x(s)}. \quad (13)
\]
The phase $\Phi_i(s)$ describes the delay between the two signals at time $t_i$ on a scale $s$.

A normalized time and scale resolved measure for the relationship between the time series $x(t_i)$ and $y(t_i)$ is the wavelet coherency (WCO), defined as the amplitude of the WCS normalized to two single WPS:

$$WCO_i(s) = \frac{\|WCS_i(s)\|}{\left(WPS_i^*(s)WPS_i^j(s)\right)^{\frac{1}{2}}}.$$  \hfill (14)

A value of 1 means a linear relationship between series $x(t_i)$ and $y(t_i)$ around time $t_i$ on a scale $s$. A value of zero is obtained for vanishing correlation.

Spurious peaks can occur for areas of low wavelet power due to normalization. Note the importance of estimating the expectation values of the single terms in Equation (14). If they are not considered separately, numerator and denominator will equal each other and the result will be identical to 1 no matter what the real WCO is. When computing WCO from observational data, one must thus smooth the numerator and denominator separately (Maraun and Kurths, 2004). In the current case, WCO was performed involving the MEI series and each of the three regional SAMP under the basis of a 95% confidence level. We used the MatLab code developed by Grinsted et al. (2004) for this purpose. The code is available at http://noc.ac.uk/marine-data-products/cross-wavelet-wavelet-coherence-toolbox-matlab.

3. RESULTS AND DISCUSSION

3.1 Cluster analysis

A cluster analysis was performed using 59 SAMP with the aim of grouping them into successively larger groups (i.e., regions under the basis of similar precipitation regimes). The dendrogram (Fig. 2) revealed three clusters or regions (Table I) when using a linkage distance
value of 1: I, Semi-arid region (11 out of 59 stations); II, Highlands region (27 out of 59 stations); and III, Canyons region (21 out of 59 stations).

A map showing the stations and their corresponding regions is presented in Fig. 3. Those regions are distributed from NE to SW of the state territory, that is, from the driest to the wettest areas. As expected, cluster analysis results agree with the spatial distribution of the annual mean precipitation throughout the Zacatecas state territory (Fig. 4). Thus, cluster I (Semi-arid region) includes weather stations with annual precipitation from <300 to 400 mm, cluster II (Highlands region) includes stations with annual precipitation from 400 to 500 mm, and cluster III (Canyons region) includes stations with annual precipitation from 500 to >700 mm.

The regions identified in this research agree well with the three Floristic Districts reported by Balleza et al. (2005) on the basis of the geographic distribution of 456 species of the Asteraceae family. Considering results from both studies, the Semi-arid region covers the Floristic District named Ia; the Highlands region agrees with the Floristic District named Ib; and the Canyons region covers the Floristic District named II. This implies Asteraceae family species richness and their distribution could depend on the rainfall patterns as suggested by our results. In this context, Balleza et al. (2005) results suggest that the species of the Asteraceae family distributed in the Zacatecas territory can be divided in two main groups: i) Those thriving mostly in the dry environments (Semi-arid region), and ii) Those thriving in the temperate, warm habitats along the Highlands and Canyons regions. In fact, the flowering plant family Asteraceae is one of the most influential in the diversification and evolution of many animals that heavily depend on their inflorescences to survive (Barreda et al. 2015). Species of the Asteraceae family are found almost everywhere in the world except
in Antarctica (Barreda et al. 2015) which means that their climatic requirements are very
diverse, although it seems that climatic factors restrict the phenological period of most
species as pointed out by Torres and Galetto (2011).

Rainfall patterns define the agricultural activities performed by peasants and growers of each
region. Such activities represent important economic income to most of the families settled
throughout Zacatecas territory. In the Semi-arid region, goats are kept for dairy and meat
production although those activities represent only low income at a family level; the major
production systems are characterized by small flocks (<100 animals), feeding based on
grazing and browsing native vegetation, following regular routes and keeping the animals
overnight in rudimentary shelters. The main products of these systems are kid goats
(‘cabritos’) and culled goats (Tovar-Luna, 2009). In the Highlands region, the main crop is
dry beans (*Phaseolus vulgaris*), followed by species for forage such as corn (*Zea mays*) and
oats (*Avena sativa*), and horticultural species such as peppers (*Capsicum annum*), onions
(*Allium cepa*) and garlic (*Allium sativum*). In the Canyons region, the main activity refers to
the cow-calf production system followed by the production of guava (*Psidium guajava*), and
a great variety of horticultural products.

3.2 Power Spectrum Analysis

A spectral analysis was performed on each regional SAMP series to estimate their self-
affinity statistics (Table II): Mean, Median, Standard Deviation (Std), Fractal dimension (Dₙ),
Hurst exponent (H) and slope (-β). All three regional SAMP series yielded straight lines on
the log-log plot with slope (-β), suggesting that P(f) ∝ f^β (Valdez-Cepeda et al., 2003a, b).

This means that each spectrum is singular and is represented by a curve on the complex plane
for the SAMP series of the case.
Spectral fractal dimension \( (D_s) \) values vary from 1.354 to 1.527, and H values change from 0.473 to 0.646. The \( D_s \) and H values of 1.354 and 0.646, respectively, suggest that the Semi-arid region SAMP series tends to show persistent behavior (\( D_s < 1.5 \) and \( H > 0.5 \)). The Highlands region SAMP series has \( D_s \) and H values of 1.497 and 0.503, respectively, while the Canyons region SAMP series has \( D_s \) and H values of 1.527 and 0.473, respectively. These results indicate that the SAMP series in both regions tend to be like the Brownian movement or random walk (\( D_s \approx 1.5 \)), as pointed out by Mandelbrot (1985).

### 3.3 Important frequencies

Plots of power spectrum density \([\Phi_x(f)]\) against frequency allows us to identify the dominant frequencies on the regional SAMP series in terms of the dominant frequencies (1/year) that are likely to be important to the precipitation process (Figures 5a, 5b, and 5c). This approach gives us some frequency components that do not consider time and length because the analysis gives us a resolution in a frequency that is determined for the window size over the analyzed time series. In other words, the results give us useful information about the frequency content of the analyzed series, but they do not indicate at which time these frequencies occur. The detected frequencies were those from confidence bands of 95% in the adjusted linear model and are likely to be important to the precipitation process. Significant peaks of the power spectrum were detected at \( p \leq 0.05 \).

The 0.5-, 1-, 2- and 3-year frequencies are present in the power–spectrums of all analyzed regional SAMP series. The Highlands and Canyons regions showed important frequencies of 13 and 12 years, respectively.

The 0.5- and 1-year frequencies may be linked to the seasonal cycle while the 2-year frequency could be related to the Quasi-Biennial Oscillation (Kane, 2009), which is a 26-
month cycle explaining solar activity and wind reversal in the lower stratosphere of the North Pole (Labitzke and Loon, 1989; Mendoza et al., 2001). The 3-year frequency suggests a possible effect of a quasi-periodic event like ENSO. It is widely recognized that ENSO has an erratic cycle from 3 to 5 years (Weber and Talkner, 2001), 3 to 6 years (Monetti et al., 2003), 4.3 years (Luo et al., 2015) or 2 to 7 years (Zubair, 2002; MacMynowski and Tziperman, 2008). These discrepancies may be explained by the physical dependence of ENSO frequency on the structure of the coupled mode provided by diagnosing the relative contributions of the thermocline feedback and zonal advection feedback on ENSO evolution (An and Wang, 2000). The 12- and 13-year frequencies indicate that there may be effects from the sunspot cycle, which varies from 8 to 14 years (Mendoza et al., 2001) or 11 years (Hu et al., 2009) with a long-term average of 11.3 years. We then carried out a wavelet coherence analysis on each of the SAMP and the MEI time series, each with a significant 5.5-yr frequency, to identify possible relationships.

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a wavelet coherence analysis on each of the SAMP and the MEI time series, which have a
significant 5.5-yr frequency, to identify possible relationships.

3.4 Wavelet coherence analysis

Results of phase and wavelet coherence between each regional SAMP series and the
Multivariate ENSO Index series are shown in Figure 6. Figures 6a, 6b and 6c correspond to
the Semi-arid, Highlands and Canyons regions, respectively. Black figure outlines indicate
areas significant to 95% confidence, that is, cones of influence; spots limited by a thick black
line point out a possibly significant relation between both phenomena; and vectors indicate
the phase difference between the regional SAMP and the MEI series with arrows pointing
clockwise to indicate in-phase behavior and arrows pointing counter-clockwise to indicate
anti-phase behavior (Keener et al., 2010).

3.4.1 Semi-arid region

A significant spot is clearly noted from 1993 to 2003 at 5 to 12-year periodicities (Fig. 6a),
indicating a high correlation between the Semi-arid SAMP and the MEI. It should be
highlighted that 1997 was a year of El Niño at very strong intensity, whereas 2002 and 2003
were years of El Niño at moderate intensity (Wolter and Timlin, 2011); 1995, 1996, 2000
and 2001 were years of La Niña at weak intensity (Wolter and Timlin, 2011). The MEI may
have been related to precipitation in this Semi-arid region during those years. The MEI and SAMP were in phase from 1993 to 2003 as indicated by the horizontal arrows, meaning that the relative phase lag between those phenomena was nil.

Important areas are identified from 1983-1985, 1988-1990, 1996-1997, 2000-2001 and 2002-2003 in the 0.5-year period. These results suggest that seasonal components of the precipitation are important issues in this region. In fact, heavy unimodal precipitation dominates throughout the Zacatecas territory. Significant spots are also identified from 1989-1990 and 2005-2006 at the 1-year period and as such, the precipitation of those years could be related to the movement of the Earth around the sun. The significant spot from 2005 to 2006 corresponds to a period with ENSO and precipitation in phase and SAMP were positive, indicating a humid period.

3.4.2 Highlands region

A significant band of 5- to 12-years is also localized from 1995 to 2003 at 5- to 12-year periodicities (Fig. 6b). Arrows suggest that the Highlands region SAMP and the MEI were mostly in phase during this period. This also implies a strong correlation between the MEI and the Highlands region SAMP. It is widely recognized that periodicities of El Niño and La Niña are 2-5 years and 7-15 years, respectively, as pointed out by Wolter and Timlin (2011). El Niño occurred at moderate intensity from 2002 to 2003, and La Niña events were recorded from 1998 to 2000 at moderate intensity as well.

A significant spot is present from 1996 to 1999 at a 2-year period and another significant small blob is appreciated in 1983, thus implying that the MEI and Highlands region SAMP corresponding to these years were strongly correlated. Both phenomena were in anti-phase during 1996-1999, as indicated by horizontal left arrows, which may be explained by the El
Niño phenomenon with very strong intensity that occurred during 1997-1998. However, precipitation leads MEI by approximately ¼ cycle, as indicated by vertical arrows, in 1983. This implies that precipitation during that year could have adhered to El Niño with very strong intensity which occurred during 1982-1983.

Significant spots occur over 1984-1985, 1986-1988, 1994-1996, 2000-2002 and 2008-2009 at a 0.5-year period. These results suggest that seasonal components of precipitation are important issues in the Highlands region. Significant spots are also appreciated over 1989-1990 and 2000-2001 at a 1-year period. Precipitation during these years could therefore be related to the rotation of the Earth around the sun.

3.4.3 Canyons region

A large significant spot is present from 1988 to 2003 at 5- to 10-year periods (Fig. 6c). This result suggests a strong correlation between the MEI and the Canyons region SAMP that could be due to periodicities of El Niño and La Niña of 2-5 years and 7-15 years, respectively (Wolter and Timlin, 2011). Vectors indicate that the MEI and the standardized anomalies of the monthly precipitation are mostly in phase. In addition, a significant spot present over 1996-1998 at the 3-year period may suggest a strong correlation between the MEI and the Canyons SAMP. Both phenomena of the blob were in anti-phase and this could be due to the fact that 1997-1998 was a period of El Niño with strong intensity and 1998-1999 was a period of La Niña with moderate intensity.

Significant spots occur over 1984, 1988-1989, 1993-1994, 2001 and 2006-2009 at a 0.5-year period. These results suggest that seasonal components of precipitation have an important influence in this region. Another important spot was present for the period of 1988-1989 at
the 1-year period. As previously stated, precipitation during these years might have been influenced by the Earth’s orbit around the sun.

In summary, we obtained compelling evidence of important spots corresponding to 2- to 7-year periods as shown in the wavelet coherence figures. The significant spots recorded from 1993 to 2003, 1995 to 2003 and 1988 to 2003 for the Semi-arid, Highlands and Canyons regions, respectively, indicate that SAMP vary by region and over time. These results suggest important correlations between the MEI and each of the regional SAMP for the state of Zacatecas. This correlation has also been recorded in other regions around the world such as the precipitation anomaly time series registered at the Litter River Watershed, Tifton, GA, USA and the ENSO 3.4 (Keener et al., 2010).

4. CONCLUSIONS

A cluster analysis was successfully performed on 59 SAMP series to identify 3 regions: Semi-arid, Highlands and Canyons regions. These regions strongly agree with 3 Floristic Districts previously reported and results from both studies suggest that species richness of the Asteraceae family could depend on regional precipitation regimes. These regions agree with areas under the basis of annual mean precipitation in the state of Zacatecas.

Cross correlations using wavelet coherence analysis between the MEI and each of the three regional SAMP series indicate teleconnections at different periods. In the Semi-arid region, a strong correlation from 1993 to 2003 occurred between the MEI and SAMP at a 5-12-year period showing a consistent in phase angle. In the case of the Highlands region, the results are compelling evidence regarding the influence of ENSO on precipitation. An important correlation from 1995 to 2003 occurred between both phenomena in-phase at 5-12-year period. Another strong correlation from 1996 to 1999 with an important anti-phase angle was
identified and these phenomena were strongly correlated at a delay of approximately $\frac{1}{4}$ cycle during 1983. This knowledge could be useful to policymakers since horticultural systems are performed under irrigated conditions using extracted water from aquifers without recharging. The years when El Niño occurs, implying wet seasons, could be thus taken advantage of to recharge aquifers in this region. In the Canyons region, the identified relationship between both phenomena was in phase from 1988 to 2003 and another strong correlation showing antiphase status was found from 1996-1998. There is still a need to measure the degree of association between precipitation and the MEI at regional and local levels by means of other robust statistical techniques, e.g. cross-correlation coefficients, focusing on periods lower than 1 year.

Other significant identified frequencies, i.e., 12 and 13 years for Canyons and Highlands regional SAMP (Fig. 5), respectively, indicate that their underlying relationships to physical mechanisms remain unknown. In future work, therefore, a wavelet coherence analysis between a quasi-periodic phenomenon (e.g. solar activity measured through the sunspot number time series) and the regional or local SAMP series should be performed to learn more about precipitation behavior.

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| Station | Station name         | Latitude   | Longitude   | Meters above sea level | Cluster |
|---------|----------------------|------------|-------------|------------------------|----------|
| 1       | Agua Nueva           | 23° 46' 55"/102° 09' 39" | 1932        | I                      |
| 2       | Boca del Tesorero    | 22° 49' 20"/102° 57' 05" | 2045        | III                    |
| 3       | Calera               | 22° 54' 00"/102° 39' 00" | 2192        | II                     |
| 4       | Estación Camacho     | 22° 26' 26"/102° 22' 11" | 1658        | I                      |
| 5       | Cañitas              | 23° 36' 07"/102° 43' 53" | 2025        | II                     |
| 6       | Caopas               | 24° 46' 52"/102° 10' 16" | 2000        | I                      |
| 7       | Cedros               | 24° 40' 43"/101° 46' 26" | 1763        | I                      |
| 8       | Chalchihuites        | 23° 14' 27"/102° 34' 31" | 2060        | II                     |
| 9       | Col. González Ortega | 23° 57' 22"/103° 27' 02" | 2190        | II                     |
| 10      | Concepción del Oro   | 24° 37' 16"/101° 23' 26" | 1940        | I                      |
| 11      | El Arenal            | 23° 39' 01"/103° 26' 52" | 2016        | II                     |
| 12      | El Cazadero         | 23° 41' 35"/103° 26' 50" | 1898        | II                     |
| 13      | El Platanito         | 22° 36' 43"/104° 03' 05" | 990         | III                    |
| 14      | El Rusio             | 22° 26' 34"/101° 47' 09" | 2104        | II                     |
| 15      | El Sauz              | 23° 10' 47"/103° 12' 26" | 2090        | II                     |
| 16      | Excamé III           | 21° 38' 58"/103° 20' 23" | 1740        | III                    |
| 17      | Fresnillo            | 23° 10' 22"/102° 56' 26" | 2195        | II                     |
| 18      | Gral. Gpe. Victoria  | 22° 23' 43"/101° 49' 52" | 2183        | II                     |
| 19      | Gruñidora            | 24° 16' 29"/101° 53' 05" | 1825        | I                      |
| 20      | Huanusco             | 21° 46' 01"/102° 58' 07" | 1495        | III                    |
| 21      | Jerez                | 22° 38' 31"/103° 00' 05" | 2098        | III                    |
| 22      | Jiménez del Téul     | 23° 15' 18"/103° 47' 54" | 1900        | III                    |
| 23      | Juan Aldama          | 24° 17' 14"/103° 23' 34" | 1995        | II                     |
| 24      | Juchipila            | 21° 23' 14"/103° 06' 53" | 1270        | III                    |
| 25      | La Bufa              | 22° 47' 00"/102° 34' 00" | 2612        | II                     |
| 26      | La Florida           | 22° 41' 10"/103° 36' 09" | 1870        | III                    |
| 27      | La Villita           | 21° 36' 08"/103° 20' 13" | 1790        | III                    |
| 28      | Loreto               | 22° 16' 40"/101° 59' 15" | 2029        | II                     |
| 29      | Malpaso              | 22° 37' 05"/102° 45' 15" | 2135        | II                     |
| 30      | Monte Escobedo       | 22° 19' 32"/103° 29' 38" | 2190        | III                    |
| 31      | Nochistlán           | 21° 21' 55"/103° 50' 32" | 1850        | III                    |
| 32      | Nuevo Mercurio       | 24° 13' 38"/102° 09' 09" | 1706        | I                      |
| 33      | Ojocaliente          | 22° 24' 38"/102° 16' 09" | 2050        | II                     |
| 34      | Pajaritos de la Sierra | 22° 39' 36"/104° 16' 38" | 2660        | III                    |
|   | Location       | Latitude          | Longitude          | Population | Cluster |
|---|---------------|-------------------|--------------------|------------|---------|
| 35 | Palomas       | 22° 20' 47" 102° 47' 48" | 2030              | III        |
| 36 | Pinos         | 22° 16' 54" 101° 34' 47" | 2408              | II         |
| 37 | Presa El Chique | 22° 00' 00" 102° 53' 23" | 1620              | III        |
| 38 | Puerto de San Fco. | 23° 44' 01" 103° 23' 13" | 2330              | II         |
| 39 | Río Grande    | 23° 48' 01" 103° 01' 36" | 1890              | II         |
| 40 | San Andrés    | 23° 41' 55" 101° 55' 45" | 2085              | I          |
| 41 | San Antonio del Ciprés | 22° 56' 08" 102° 29' 14" | 2145              | I          |
| 42 | San Benito    | 23° 54' 10" 101° 43' 07" | 1955              | I          |
| 43 | San Gil       | 24° 11' 43" 102° 58' 36" | 1810              | II         |
| 44 | San José de Llanetes | 22° 54' 45" 103° 16' 43" | 2176              | II         |
| 45 | San Juan Capistrano | 22° 38' 39" 104° 06' 01" | 2660              | III        |
| 46 | San Pedro Piedra Gorda | 22° 27' 09" 102° 20' 49" | 2032              | II         |
| 47 | San Tiburcio  | 24° 08' 50" 101° 28' 58" | 1887              | I          |
| 48 | Santa Lucía   | 22° 26' 03" 104° 13' 00" | 2252              | III        |
| 49 | Santa Rosa    | 22° 55' 34" 103° 06' 47" | 2240              | III        |
| 50 | Tayahua       | 22° 07' 13" 102° 51' 46" | 1549              | III        |
| 51 | Téul de González | 21° 27' 42" 103° 27' 59" | 1900              | III        |
| 52 | Tlaltenango   | 21° 46' 54" 103° 17' 45" | 1700              | III        |
| 53 | Trancoso      | 22° 44' 39" 102° 22' 10" | 2190              | II         |
| 54 | Valparaíso    | 22° 26' 03" 104° 13' 00" | 1890              | III        |
| 55 | Villa de Cos  | 23° 17' 26" 102° 20' 44" | 2050              | II         |
| 56 | Villa García  | 22° 10' 10" 101° 57' 27" | 2120              | II         |
| 57 | Villa Hidalgo | 22° 20' 49" 101° 42' 55" | 2167              | II         |
| 58 | Villanueva    | 22° 21' 43" 102° 53' 22" | 1920              | III        |
| 59 | Zacatecas     | 22° 45' 39" 102° 34' 30" | 2485              | II         |

Note: Clusters: I, Semi-arid region; II, Highlands region; III: Canyons region.
Table II. Basic and fractal statistics for standardized anomalies of the monthly precipitation for the Zacatecas state regions

| Region     | Mean (mm) | Median (mm) | Std (mm) | Ds   | H    | -β  |
|------------|-----------|-------------|----------|------|------|-----|
| Semi-arid  | 29.20     | 20.71       | 29.83    | 1.354| 0.646| 2.291|
| Highlands  | 36.07     | 19.82       | 41.75    | 1.497| 0.503| 2.007|
| Canyons    | 50.26     | 23.72       | 58.17    | 1.527| 0.473| 1.946|

Note: Std (Standard Deviation), Ds (fractal dimension), H (Hurst exponent), -β (Slope)
Fig. 1. Study region of Mexican Zacatecas state territory.
Fig. 2. Dendrogram for 59 standardized anomalies of the monthly precipitation through the Zacatecas state territory using the amalgamation rule of the Ward’s method and the distance metric of 1-Pearson’s r.
Fig. 3. Location of the weather stations and their corresponding regions found through the cluster analysis in Zacatecas state territory.
Fig. 4. Distribution of annual mean precipitation along with the Zacatecas state territory.
Fig. 5. Power spectrum plots of the monthly mean standardized anomalies of the monthly precipitation time series for Semi-arid region (a), Highlands region (b) and Canyons region (c) of Zacatecas, México from January 1976 to December 2010, showing important frequencies in years. The power–spectral density is given as a function of frequency for time scales of 2 to 408 months. The fitted line was used to estimate the fractal dimension (Ds). Dashed lines indicate the confidence interval at $p \leq 0.05$. 
Fig. 6. Wavelet coherence and phase between standardized anomalies of the monthly precipitation (SAMP) of Semi-arid region (a), Highlands region (b) and Canyons region (c) and Multivariate ENSO Index (MEI) for the Zacatecas state. The vectors indicate the phase difference between the precipitation anomalies and MEI. Thick black figure outlines indicate areas significant to 95% confidence using the red noise model, and the thin black line surrounds the cone of influence.