

FRactal Analysis of Monthly Evaporation and Precipitation Time Series at Central Mexico

Análisis Fractal de Series de Tiempo de Evaporación y Precipitación Mensual en el Centro de México

Rafael Magallanes Quintanar¹, Ricardo David Valdez Cepeda^{2,3}, Santiago de Jesús Méndez Gallegos⁴, Arturo Moreno Báez¹, Guillermo Medina García⁵, and Fidel Blanco Macías^{2*}

¹ Universidad Autónoma de Zacatecas, Unidad Académica de Ingeniería Eléctrica. Ramón López Velarde 801, Centro. 98000 Zacatecas, Zac., México.

² Universidad Autónoma Chapingo, Centro Regional Universitario Centro Norte. Zacatecas, Zac., México.

* Autor responsable (fiblama63@gmail.com)

³ Universidad Autónoma de Zacatecas, Unidad Académica de Matemáticas. Paseo La Bufa, Calzada Solidaridad. 98060 Zacatecas, Zac., México.

⁴ Colegio de Postgraduados, Campus San Luis Potosí. Calle de Iturbide 73, Salinas de Hidalgo. 78622 San Luis Potosí, S.L.P., México.

⁵ INIFAP, Campo Exp. Zacatecas. Km 24.5 Carretera Zacatecas-Fresnillo. 98500 Calera de V. R., Zacatecas, México.

SUMMARY

Advances on climate change research, as well as the assessment of the potential impacts of climate change on water resources, would allow the understanding of the spatial and temporal variability of land-surface precipitation and evaporation time series at local and regional levels. In the present study, the spectral analysis approach was applied on monthly evaporation and precipitation anomaly time series with the aim of estimating their self-affinity statistics. The behavior of estimated fractal dimension values of evaporation time series throughout Zacatecas State territory is irregular, and noise in all the evaporation anomaly time series tends to have a persistent behavior. On the other hand, the behavior of estimated fractal dimension values of most of the precipitation time series throughout Zacatecas State territory tends to be like the Brownian motion. Self-affinity statistics of monthly evaporation or precipitation anomaly time series and geographic coordinates of 32 stations were used to estimate correlation coefficients; the results are compelling evidence concerning monthly precipitation anomaly behavior tends to be more regular toward North of Zacatecas State territory, that is, toward driest areas.

Index words: *self-affinity; fractal dimension; spectral analysis.*

RESUMEN

Los avances de investigación sobre cambio climático en México, así como la evaluación de

los impactos potenciales de dicho cambio sobre los recursos hídricos pueden conllevar a un mejor entendimiento de la variación temporal y espacial sobre la superficie terrestre al considerar las series de tiempo de evaporación y precipitación a niveles local y regional. En el presente estudio se aplicó la técnica de análisis espectral sobre series mensuales de anomalías de evaporación y precipitación con el objetivo de estimar sus estadísticos de autoafinidad. El comportamiento de los valores estimados de dimensión fractal de las series de tiempo de las anomalías de evaporación registradas en el territorio del estado de Zacatecas fue irregular y el ruido en todas ellas tuvo un comportamiento persistente. Por otra parte, los valores estimados de dimensión fractal de las series de tiempo de las anomalías de precipitación presentaron un comportamiento parecido al del movimiento browniano. Las estadísticas de autoafinidad de las series de tiempo de anomalías de evaporación o precipitación y las coordenadas geográficas de 32 estaciones fueron empleadas para estimar coeficientes de correlación; los resultados muestran que el comportamiento de las anomalías de la precipitación mensual tiende a ser más regular hacia el norte del territorio del estado de Zacatecas; es decir, hacia las áreas más secas.

Palabras clave: *autoafinidad; dimensión fractal; análisis espectral.*

INTRODUCTION

Generally, the surface temperatures play a key role in increasing the evaporation from the oceans and land,

leading to an increase in globally averaged precipitation. Those changes in rainfall distributions have attracted much attention because of the particular vulnerability of human activities to hydrological extreme events such as flood-producing rains and droughts (Kharin *et al.*, 2007). It is widely known that hydrological droughts are caused by lack or scarce rainfall.

It has been evidenced that precipitation trends vary by regions and over time, although land-surface precipitation has generally increased North of 30° N over the past century and decreased over much of the tropics since the 1970's (IPCC, 2007). On the other hand, the evaporation of water as measured from pan evaporimeters has decreased in many regions of the world over the past half-century (Roderick and Farquhar, 2004; Blanco-Macías *et al.*, 2011), thus this suggests a recent decrease in the terrestrial evaporation component of the hydrologic cycle (Lawrimore and Peterson, 2000).

In addition to the traditional statistical analysis, evaporation and precipitation time series could be analyzed using other approaches; for instance, they could be treated like fractal profiles (Blanco-Macías *et al.*, 2011; Valdez-Cepeda *et al.*, 2012). The fractal concept is very useful for interpretation of time series data in various branches of earth science, like horizontal variability of temperature, humidity, rainfall, and cloud water in the atmosphere, among others. All these phenomena obey power law behavior over well-defined wavenumber ranges. These results are of great importance for understanding the variability of the atmosphere and for an improved characterization of these fields into large-scale models of the climate system (Dimri, 2005).

Hence, the aim of this study was to analyze long-term anomaly time series of evaporation and precipitation registered at 32 meteorological stations located within the Mexico's State of Zacatecas by means of the power spectrum analysis in order to acquire knowledge at local and regional levels.

MATERIAL AND METHODS

Data

The original data were long-term records of monthly evaporation and precipitation. We acquired those data sets from 32 meteorological stations located

within the territory of the Mexico's State of Zacatecas. Generalities for each station and series are presented in Table 1. Data were kindly provided by the Comisión Nacional del Agua, the national official institution in charge of registration of climatic and meteorological data in Mexico. For the analysis, we considered stations with at least 30 years of records, within a period from January 1943 to May 2006. In other words, we involved time series without missing data.

Linear Trends

Experimental series are often affected by non-stationarity and fractality (Ming, 2010). Climate time series are in general non-stationary, and frequently present long-term trends. Among several methods to calculate the trend of a climatological time series, the simplest and broadly used one is the interpretation of the time series as a superposition of a linear trend (Trömel and Schönwiese, 2008). This technique has been used by Muhlbauer *et al.* (2009), Guerreiro *et al.* (2010), Nickl *et al.* (2010), Xie *et al.* (2010), and Xie *et al.* (2011). Therefore, linear trends were estimated through least squares linear regression analyses, taking into account the following simple model (Draper and Smith, 1966).

$$\hat{Y} = b_0 + b_1 X \quad (1)$$

The presence of a trend can make it more difficult to analyze other components of interest, such as the cycle or the seasonal (White and Granger, 2011). Thus, the purpose of removing a trend is then simplifying the analysis of those other components (White and Granger, 2011). In other words, removing the trend is an important issue in order to avoid that non-stationary behavior accompanying these data which will give spurious results (Peng *et al.*, 1994; Hausdorff and Peng, 1996).

Then, the series' precipitation and evaporation linear trends were removed following the Eq. 2:

$$\hat{Y}_{di} = Y_i - \hat{Y} \quad (2)$$

where \hat{Y}_{di} is the detrended monthly precipitation or evaporation. When the above step is performed, the new time series is known as anomaly time series

Table 1. Generalities of meteorological stations and time series.

Station	Municipality	Latitude	Longitude	Altitude	Precipitation period	Evaporation period
				m		
Cedros	Mazapil	24° 20'	101° 46'	1781	1970 - 2005	1970 - 2005
Chalchihuites	Chalchihuites	23° 28'	103° 52'	2260	1972 - 2006	1966 - 2005
Col. González Ortega	Sombrerete	23° 57'	103° 26'	2195	1970 - 2006	1970 - 2003
El Platanito	Valparaíso	22° 36'	104° 03'	1030	1957 - 2006	1957 - 2005
El Rusio	Villa Hidalgo	22° 26'	101° 47'	2122	1967 - 2006	1967 - 2005
El Sauz	Fresnillo	23° 16'	103° 06'	2096	1947 - 2006	1947 - 2005
Excame III	Tepechitlán	21° 38'	103° 20'	1740	1946 - 2006	1946 - 2005
Fresnillo	Fresnillo	23° 10'	102° 53'	2201	1949 - 2006	1949 - 2005
Gral. Guadalupe Victoria	Noria de Ángeles	22° 43'	101° 49'	2132	1966 - 2006	1966 - 2005
Gruñidora	Mazapil	24° 12'	101° 55'	1809	1963 - 2006	1963 - 2005
Huanusco	Huanusco	21° 46'	102° 58'	1490	1968 - 2005	1972 - 2005
Jerez	Jerez	22° 38'	103° 00'	2000	1962 - 2006	1962 - 2005
Jiménez del Teúl	Jiménez del Teúl	23° 14'	103° 48'	1924	1963 - 2006	1962 - 2005
Juchipila	Juchipila	21° 24'	103° 06'	1259	1947 - 2006	1947 - 2005
La Florida	Valparaíso	22° 41'	103° 36'	1840	1954 - 2006	1954 - 2005
La Villita	Tepechitlán	21° 36'	103° 20'	1786	1957 - 2006	1957 - 2005
Loreto	Loreto	22° 15'	101° 59'	2077	1963 - 2006	1963 - 2005
Monte Escobedo	Monte Escobedo	22° 18'	103° 33'	2182	1964 - 2006	1963 - 2005
Nochistlán	Nochistlán	21° 21'	102° 50'	1853	1960 - 2006	1949 - 2001
Ojocaliente	Ojocaliente	22° 34'	102° 16'	2062	1961 - 2006	1959 - 2006
Palomas	Villanueva	22° 20'	102° 47'	2025	1969 - 2006	1969 - 2005
Pinos	Pinos	22° 16'	101° 34'	2025	1947 - 2006	1947 - 2006
Presa El Chique	Tabasco	22° 00'	102° 53'	1648	1951 - 2006	1963 - 2005
Ramón López Velarde	Jerez	22° 49'	102° 57'	2045	1966 - 2006	1966 - 2006
San Gil	Gral. Fco. Murguía	24° 11'	102° 58'	1829	1969 - 2006	1969 - 2006
San Pedro Piedra Gorda	Cuauhtémoc	22° 27'	102° 20'	2053	1943 - 2006	1943 - 2006
Santa Rosa	Fresnillo	22° 55'	103° 06'	2236	1947 - 2006	1947 - 2005
Teúl	Téul de González Ortega	21° 28'	103° 27'	1909	1963 - 2006	1962 - 2005
Tlaltenango	Tlaltenango	21° 46'	103° 18'	1685	1949 - 2006	1949 - 2005
Villa de Cos	Villa de Cos	23° 17'	102° 20'	1991	1962 - 2006	1962 - 2005
Villanueva	Villanueva	22° 21'	102° 53'	1935	1963 - 2006	1963 - 2005
Zacatecas	Zacatecas	22° 45'	102° 34'	2352	1953 - 2006	1953 - 2006

(i.e. monthly precipitation anomaly or monthly evaporation anomaly), which is the time series of deviations of a quantity from some mean (Wilks, 2011).

Fractal Analysis

Temporal variation of natural phenomena has been difficult to characterize and quantify. To solve

these problems, fractal analysis was introduced by Mandelbrot (1982). Time series can be characterized by a noninteger dimension (fractal dimension), when treated as random walks or self-affine profiles (Valdez-Cepeda *et al.*, 2003). Self-affine systems are often characterized by roughness, which is defined as the fluctuation of the height over a length scale (Moreira *et al.*, 1994). For self-affine profiles, the roughness

scales with the linear size of the surface by an exponent called the roughness or Hurst exponent (Valdez-Cepeda *et al.*, 2003). However, this exponent gives limited information about the underlying distribution of height differences (Evertsz and Berkner, 1995). There is the fact that the Hurst exponent, as well as the fractal dimension, measures how far a fractal curve is from any smooth function which one uses to approximate it (Moreira *et al.*, 1994). There are a lot of approaches to estimate fractal dimension for self-affine profiles, but we only used the power spectrum technique, because it is sensitive and a good exploratory tool for real data (Weber and Talkner, 2001).

Power spectrum approach. Self-affine fractals are generally treated quantitatively using spectral techniques. The power spectrum variation $P(f)$ with frequency f appears to follow a power law (Turcotte, 1992):

$$P(f) \sim f^{-\beta} \quad (3)$$

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

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

where t_0 and t_1 are the limits of time over which the series extend. Regarding such precipitation or evaporation anomalies record, which is sampled at discrete time intervals, we should use the discrete version of Eq. 4:

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

The next step is to obtain a relationship between the power β and the fractal dimension (D). By considering two time series $Z_1(t)$ and $Z_2(t)$ separated by the distance r , and related by

$$Z_2(t) = \frac{1}{r^H} Z_1(rt), \quad (6)$$

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. Thus, we can write

$$P(f) = \frac{1}{r^{2H+1}} P\left(\frac{f}{r}\right), \quad (7)$$

It follows that

$$\beta = 2H+1 = 5 - 2D_s, \quad (8)$$

$$D_s = \frac{5-\beta}{2}, \quad (9)$$

and

$$H = 2 - D_s, \quad (10)$$

where D_s is the fractal dimension estimated from the power spectrum and H is the Hurst exponent. The Hurst exponent provides a measure for long-term memory and fractality of a time series; it quantifies the relative tendency of a time series to either regress to a long-term mean value in certain direction.

Since the periodogram is a poor estimate of the power spectrum because the estimate of power at any frequency is very noisy, with the amplitude of the noise being proportional to the spectral power, we followed the strategy proposed by Valdez-Cepeda *et al.* (2007), that is, we rather use the Welch's method of averaging periodograms in order to obtain 50 regular logarithmic intervals of the two records (complete series and partial series); in addition, we used the 'running sum' transformation to shift, by a factor of + 2, the slope, and thereby the Hurst exponent and the D_s because data trace had a slope between -1 and 1 on the log-log plot.

In practice, with the aim of obtaining an estimate of the fractal dimension D_s , one calculates the power spectrum $P(f)$ (where $f = 2\pi/l$, f is the wave-number, and l is the wavelength), and plots the logarithm of $P(f)$ versus the logarithms of f . If the profile is self-affine, this plot should follow a straight line with a negative slope $-\beta$.

Correlation

In addition, in order to find possible bivariate associations between geographical coordinates of the

stations and the estimated self-affinity statistics, as well as trends in Zacatecas territory, correlation coefficients were estimated. Pearson's correlation coefficient (r), sometimes also called the cross-correlation coefficient, is a quantity that gives the quality of a least squares fitting to the original data. This value allowed the authors to analyze the relationship among self-affinity statistics of the monthly evaporation and precipitation anomaly time series, and geographic coordinates of the stations.

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(\hat{Y}_{di} - \bar{\hat{Y}})^2}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (\hat{Y}_{di} - \bar{\hat{Y}})^2}} \quad (11)$$

where X_i is the geographic coordinate latitude or longitude, and Y_{di} is the monthly precipitation or evaporation anomaly.

RESULTS AND DISCUSSION

Advances on climate change research, apart from assessing the potential impacts of climate change on water resources, would allow understanding the spatial and temporal variability of land-surface precipitation and evaporation time series at local and regional levels. In addition to common statistical analysis, evaporation and precipitation time series could be analyzed using other approaches, like the spectral analysis that uses several algorithms such maximum entropy, autoregressive moving average, non-harmonic method, singular spectral analysis, and the traditional Fourier analysis (Lana *et al.*, 2005). In the present study, spectral analysis approach was applied on monthly evaporation and precipitation anomaly time series in order to estimate their self-affinity statistics: Fractal dimension (D_s), Hurst exponent (H) and slope ($-\beta$). All analyzed evaporation and precipitation anomaly time series yielded straight lines on the log-log plot with slope ($-\beta$) (Table 2), suggesting that $P(f) \propto f^\beta$. Therefore, it means that each spectrum is singular and that it is represented by a curve on the complex plane for monthly evaporation or precipitation anomaly time series.

Evaporation Anomaly Time Series

Most of the spectral fractal dimension (D_s) values varied from 1.087 to 1.478, and H values changed from 0.521 to 0.913 (Table 2); consequently, the behavior of estimated D_s values throughout Zacatecas State territory is very irregular (Figure 1), although noise in most of the evaporation anomaly time series tends to have persistent (long-term memory) behavior. Notably, most of the D_s values fall in the 1.243-1.322 range, and they represent an area that may be covering almost 62.60% of the State area (Figure 1). On the other hand, time series with D_s values in the range of 1.4-1.478 represent only 0.67% of the State area. These results indicate most of the monthly evaporation anomaly time series showed long-term positive autocorrelation, which means that a high value in these series will probably be followed by another high value. In addition, a few monthly evaporation anomaly series (those with D_s near to 1.5) tend to have a behavior like the Brownian movement or random walk.

Precipitation Anomaly Time Series

Spectral fractal dimension (D_s) values varied from 1.411 to 1.791, and H values changed from 0.209 to 0.589 with a mean of 0.47. Most of the D_s values are in the range of 1.486 to 1.562; so their corresponding area in the map could be covering 49.08% of the State area (Figure 2). In addition, a time series (El Sauz) showed $D_s \approx 1.5$. Hence noise in that monthly precipitation anomaly time series tend to be like the Brownian movement or random walk. Results for these series suggest that autocorrelations at small time lags can be positive or negative, but where the absolute values of the autocorrelations decay exponentially quickly to zero.

On the other hand, high D_s values are in the range of 1.638 to 1.796. However, they may represent as much as 0.16% of the State area. Therefore, noise in the corresponding monthly precipitation anomaly series tends to have anti-persistent (short-term memory) behavior. As a consequence, prediction of these time series values is not an easy task since a single high value will probably be followed by a low value or vice versa.

Table 2. Statistics for monthly evaporation and precipitation anomaly time series for Zacatecas State meteorological stations.

Station	Evaporation						Precipitation					
	Mean	Median	SD	Ds	H	β	Mean	Median	SD	Ds	H	β
	----- mm -----						----- mm -----					
Cedros	167.88	163.18	42.29	1.32	0.68	2.36	27.59	16.00	32.27	1.48	0.52	2.03
Chalchihuites	160.50	150.10	44.93	1.18	0.82	2.64	43.72	16.60	61.46	1.41	0.59	2.18
Col. González Ortega	169.33	155.40	52.03	1.23	0.77	2.53	38.32	17.20	52.21	1.46	0.54	2.08
El Platanito	196.18	190.54	68.45	1.32	0.68	2.36	48.08	20.70	60.39	1.58	0.42	1.84
El Rusio	181.23	172.76	51.23	1.27	0.73	2.46	28.98	15.00	38.93	1.66	0.35	1.69
El Sauz	164.04	153.42	55.20	1.27	0.73	2.45	34.88	13.80	44.98	1.51	0.49	1.99
Excame III	168.89	151.35	64.28	1.20	0.80	2.61	61.91	23.50	80.07	1.62	0.38	1.76
Fresnillo	188.72	179.49	60.92	1.48	0.52	2.04	34.10	15.60	42.30	1.55	0.45	1.89
Gral. Guadalupe Victoria	167.63	164.86	44.31	1.30	0.70	2.40	30.19	14.90	39.60	1.79	0.21	1.42
Gruñidora	155.64	151.08	59.84	1.15	0.85	2.70	28.39	16.20	36.25	1.41	0.59	2.18
Huanusco	179.06	169.06	53.96	1.31	0.70	2.39	50.29	16.85	67.89	1.50	0.50	2.01
Jerez	183.639	177.12	61.05	1.09	0.91	2.83	41.55	19.84	51.21	1.50	0.50	2.01
Jiménez del Téul	160.79	154.62	47.00	1.25	0.75	2.50	39.87	16.60	51.12	1.44	0.56	2.11
Juchipila	190.44	184.90	52.46	1.28	0.72	2.44	60.27	24.10	76.98	1.45	0.55	2.10
La Florida	142.67	128.74	50.30	1.24	0.76	2.53	48.43	20.40	61.45	1.61	0.39	1.79
La Villita	178.33	159.50	63.11	1.42	0.59	2.17	65.67	23.40	85.09	1.59	0.41	1.82
Loreto	161.07	154.95	51.22	1.14	0.86	2.71	36.69	18.00	49.17	1.56	0.44	1.88
Monte Escobedo	159.92	142.33	54.83	1.26	0.74	2.48	59.30	24.60	74.53	1.57	0.43	1.85
Nochistlán	178.04	166.39	55.84	1.12	0.88	2.76	60.13	20.00	76.78	1.63	0.37	1.74
Ojocaliente	161.46	158.05	46.41	1.25	0.75	2.50	31.82	13.50	43.31	1.41	0.59	2.17
Palomas	198.23	175.27	66.98	1.45	0.55	2.10	43.55	17.80	57.87	1.55	0.45	1.89
Pinos	166.06	158.08	47.44	1.10	0.90	2.80	36.20	19.70	46.60	1.46	0.54	2.08
Presa El Chique	189.42	169.55	65.04	1.17	0.83	2.66	44.72	19.00	56.32	1.53	0.48	1.95
Ramón López Velarde	169.83	157.00	53.49	1.23	0.77	2.53	37.98	17.20	49.22	1.60	0.40	1.80
San Gil	186.67	177.91	55.64	1.27	0.73	2.47	27.85	12.00	37.98	1.49	0.51	2.01
San Pedro Piedra Gorda	176.73	167.49	54.16	1.21	0.79	2.58	34.49	16.00	46.00	1.52	0.48	1.95
Santa Rosa	181.33	168.32	56.59	1.39	0.61	2.22	37.81	15.90	51.04	1.45	0.55	2.10
Téul de González Ortega	150.43	141.30	49.73	1.27	0.73	2.47	66.12	20.00	88.79	1.56	0.44	1.87
Tlaltenango	173.05	163.80	54.68	1.27	0.73	2.45	58.46	18.75	76.16	1.54	0.46	1.92
Villa de Cos	176.81	169.12	52.69	1.26	0.74	2.48	34.24	18.50	44.41	1.47	0.53	2.07
Villanueva	174.95	162.98	54.63	1.30	0.70	2.40	40.61	18.50	53.44	1.48	0.52	2.04
Zacatecas	185.80	172.04	54.50	1.17	0.83	2.66	38.92	19.00	49.86	1.58	0.42	1.84

Yet oddly enough, there is a recent report (Velásquez-Valle *et al.*, 2013) about the H spatial variability of the daily rainfall series for almost all the same stations considered by us. Velásquez-Valle *et al.* (2013) presented a map and a figure showing a close positive relationship ($r = 0.57$) between H and Longitude (westwards). By carefully looking that map, anybody may be able to identify that H value diminishes

from Northeast to Southwest and from Northwest to Southeast in the upper half of the territory (the driest); in such a map, H values also diminishes from Southwest to Northeast in the lower half of the State. Thus, it might seem eerie but our results partially match those of the map from these authors, although used rainfall scales were different (monthly versus daily). In the present case, Ds values appear to decrease toward the

Northwest and Northeast, in the upper half of the State, and toward small areas in the Southwest, South and Southeast in the lower half of the territory (Figure 2). It is worth pointing out that both maps (Figures 1 and 2) were developed using a digital elevation model in order to correct a potential orographic influence.

Correlation Analysis

Monthly evaporation or precipitation anomaly time series self-affinity statistics and the stations' geographic coordinates were used in order to estimate correlation coefficients. Results can be appreciated in Tables 3

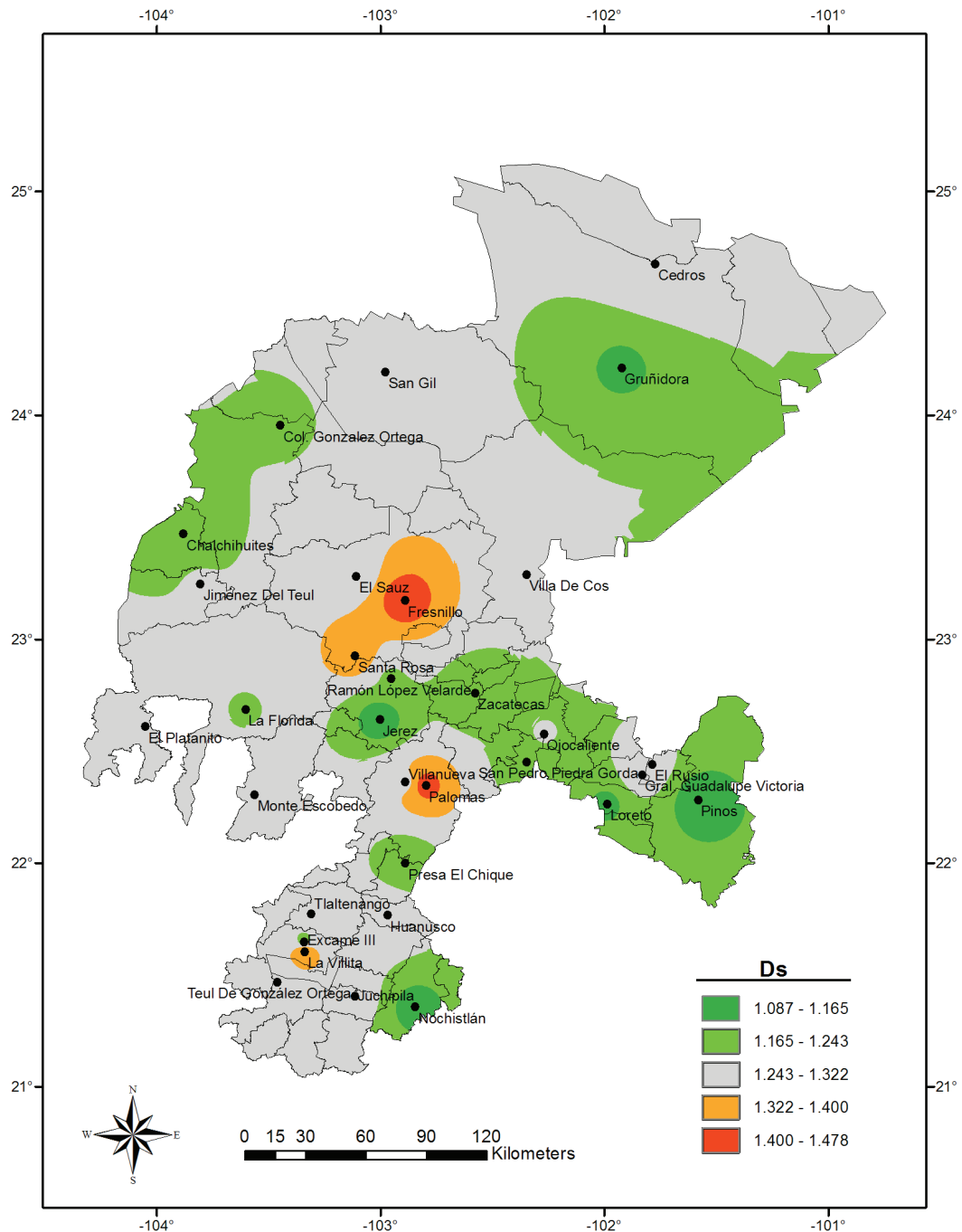


Figure 1. Evaporation time series anomalies fractal dimension (Ds) through Zacatecas State territory.

and 4. High correlations between fractal statistics mean a great interdependence, whereas these significant correlations between geographical coordinates and central tendency or dispersion statistics suggest the strong influence of orography on the precipitation case.

There, significant correlations between each fractal statistic and latitude were estimated; for instance, a significant negative correlation ($r = -0.41$) between D_s values for the precipitation anomaly time series and latitude. In addition, significant positive

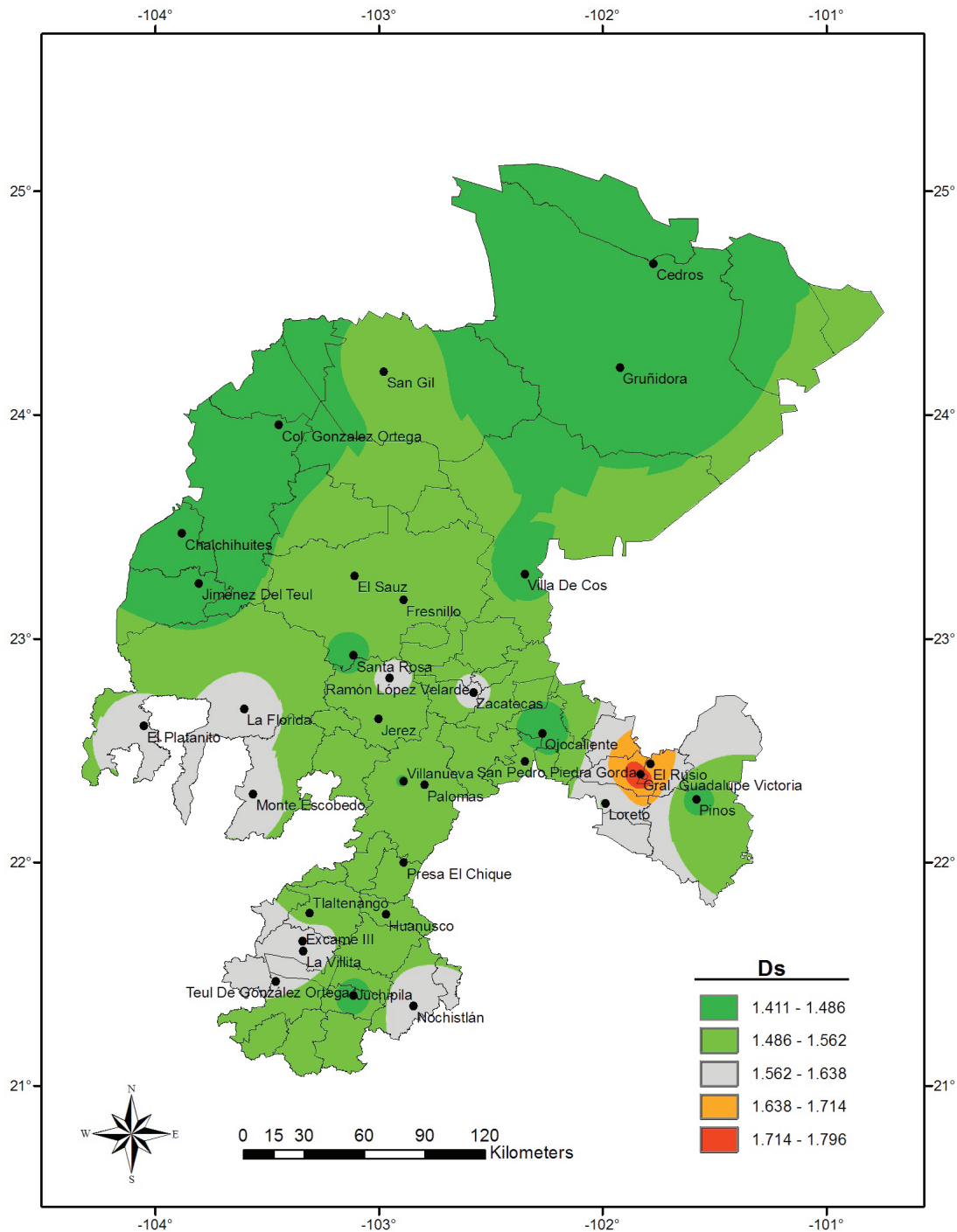


Figure 2. Precipitation time series anomalies fractal dimension (D_s) through Zacatecas State territory.

correlations ($r = 0.41$) between H and β values of the precipitation anomaly time series and latitude were evidenced. The present findings strongly suggest that D_s values of the monthly precipitation anomaly decrease as latitude increase, and H and β values of the monthly precipitation anomaly increase as latitude does within Zacatecas State territory. In order to test such possible associations, linear relationships were estimated. Results showed clearly that the model was significant ($P = 0.019$) for monthly precipitation anomalies D_s against latitude, as can be appreciated in Figure 3. Thus, such results are compelling evidence that monthly precipitation anomalies behavior may be

more regular toward North of Zacatecas State territory, that is, toward driest areas.

Future research to gain knowledge about the behavior of the monthly evaporation and precipitation time series for each station (punctual) or area should take into account their fractal level and their possible association with periodic phenomena, such as the sun cycle and El Niño Southern Oscillation. This might be possible when using other techniques, such as wavelet cross spectrum and wavelet coherency analyses (Maraun and Kurths, 2004; Hartmann *et al.*, 2008), among others.

Table 3. Correlation matrix among geographic coordinates and fractal statistics for monthly evaporation anomaly time series at Zacatecas State.

	Longitude	Latitude	Altitude (m)	D_s	H	β	Mean	Median	SD	Yearly mean
Longitude	1.00	0.16	0.37 [†]	-0.19	0.19	0.19	0.00	0.14	-0.31	0.02
Latitude		1.00	0.24	0.03	-0.03	-0.03	-0.14	-0.03	-0.25	-0.10
masl			1.00	-0.14	0.14	0.14	-0.26	-0.30	-0.34	-0.24
D_s				1.00	-1.00 [†]	-1.00 [†]	0.34	0.26	0.22	0.34
H					1.00	1.00 [†]	-0.34	-0.26	-0.22	-0.34
β						1.00	-0.34	-0.26	-0.22	-0.34
Mean							1.00	0.93 [†]	0.60 [†]	0.97 [†]
Median								1.00	0.40 [†]	0.91 [†]
SD									1.00	0.59 [†]
Yearly mean										1.00

[†] Correlations are significant at $P \leq 0.05$; $n = 32$; D_s = fractal dimension; H = Hurst exponent; SD = standard deviation.

Table 4. Correlation matrix among geographic coordinates and fractal statistics for monthly precipitation anomaly time series at Zacatecas State.

	Longitude	Latitude	Altitude (m)	D_s	H	β	Mean	Median	SD	Yearly mean
Longitude	1.00	0.16	0.37 [†]	0.09	-0.09	-0.09	-0.60 [†]	-0.38 [†]	-0.61 [†]	-0.61 [†]
Latitude		1.00	0.24	-0.41 [†]	0.41 [†]	0.41 [†]	-0.74 [†]	-0.60 [†]	-0.75 [†]	-0.74 [†]
masl			1.00	0.04	-0.04	-0.04	-0.40 [†]	-0.29	-0.38 [†]	-0.37 [†]
D_s				1.00	-1.00 [†]	-1.00 [†]	0.20	0.18	0.18	0.22
H					1.00	1.00 [†]	-0.20	-0.18	-0.18	-0.22
β						1.00	-0.20	-0.18	-0.18	-0.22
Mean							1.00	0.81 [†]	0.99 [†]	1.00 [†]
Median								1.00	0.76 [†]	0.80 [†]
SD									1.00	0.99 [†]
Yearly mean										1.00

[†] Correlations are significant at $P \leq 0.05$; $n = 32$; D_s = fractal dimension; H = Hurst exponent; SD = standard deviation.

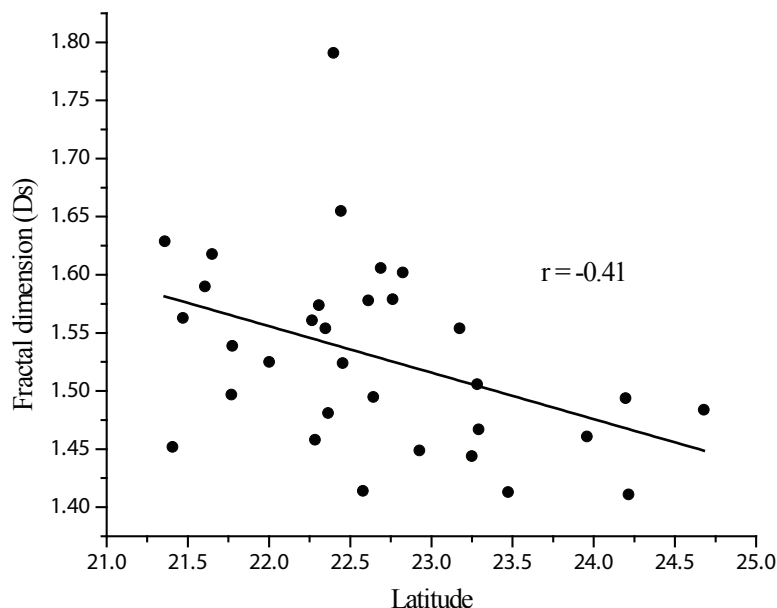


Figure 3. Linear model and Pearson correlation between geographic latitude and fractal dimension ($D_s = 2.4354 - 0.04 \text{ Latitude}$; $P = 0.0191$; $R^2 = 0.1699$) for Zacatecas State monthly precipitation anomaly time series.

CONCLUSIONS

The spatio-temporal behaviour of monthly evaporation in almost the whole Zacatecas territory showed a persistent behavior when measured through self-affinity statistics; that is, most of the evaporation anomaly time series tend to have long-term memory behavior ($D_s < 1.5$). Regarding monthly precipitation, our results suggest small areas in the Southwest, South and Southeast (areas in grey, orange, and red in Figure 3) of the territory showed an anti-persistent behavior; this means that what predominates in the involved time series are high values of monthly rainfall, followed by low values or vice versa, hence monthly precipitation is practically unpredictable in these cases. In addition, monthly precipitation behavior tends to be more regular toward North of Zacatecas State territory, that is, toward driest areas. We recommend carrying out research about a possible association between monthly evaporation and precipitation time series for each station (punctual) or area by taking into account their fractality level and periodic phenomena, such as the sun cycle and *El Niño* Southern Oscillation, among others. In this context, using other scales (hourly, daily, weekly) may be advisable in order to gain more detailed knowledge about time series fractal properties.

ACKNOWLEDGEMENTS

The authors are grateful for FoMix Zacatecas-CoNaCyT because of the financial support throughout grant number M0024-2005-1-16085.

REFERENCES

- Blanco-Macias, F., R. D. Valdez-Cepeda, and R. Magallanes-Quintanar, R. 2012. Pan evaporation analysis in central México: Trends, self-affinity and important frequencies. *Int. J. Phys. Sci.* 6: 540-549.
- Dimri, V. P. 2005. *Fractal behavior of the earth system*. Springer-Verlag Berlin Heidelberg. Germany.
- Draper, N. R. and H. Smith. 1966. *Applied regression analysis*. John Wiley and Sons, Inc. New York, NY, USA.
- Evertsz, C. J. G. and K. Berkner. 1995. Large deviation and self-similarity analysis of curves: DAX stock prices. *Chaos Solit. Fract.* 6: 121-130.
- Guerreiro, M., T. Lajinha, and I. Abreu. 2010. Precipitation indices trends and correlations at a raingauge station in Portugal. *Rev. Fac. Ciênc. Tecnol.* 7: 44-56.
- Hartmann, H., S. Becker, and L. King. 2008. Quasi-periodicities in Chinese precipitation time series. *Theor. Appl. Climatol.* 92: 155-163.
- Hausdorff, J. M. and C. K. Peng. 1996. Multi-scaled randomness: A possible source of $1/f$ noise in biology. *Phys. Rev. E.* 54: 2154-2157.

- IPCC (Intergovernmental Panel on Climate Change). 2007. Climatic Change 2007: Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press. Cambridge, UK.
- Kharin, V. V., F. W. Zwiers, X. Zhang, and G. C. Hegerl. 2007. Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations. *J. Climatol.* 20: 1419-1444.
- Lana, X., M. D. Martínez, C. Serra, and A. Burgueño. 2005. Periodicities and irregularities of indices describing the daily pluviometric regime of the Fabra Observatory (NE Spain) for the years 1917-1999. *Theor. Appl. Climatol.* 82: 183-198.
- Lawrimore, J. H. and T. C. Peterson. 2000. Pan evaporation trends in dry and humid regions of the United States. *J. Hydrometeorol.* 1: 543-546.
- Liu, Y., C. Wang, W. Hao, H. Song, Q. Cai, H. Tian, B. Sun, and H. Linderholm. 2011. Tree-ring-based annual precipitation reconstruction in Kalaqin, Inner Mongolia for the last 238 years. *Chinese Sci. Bull.* 56: 2995-3002.
- Mandelbrot, B. B. 1982. *The fractal geometry of nature.* W. H. Freeman. New York, NY, USA
- Maraun, D. and J. Kurths. 2004. Cross wavelet analysis: Significance testing and pitfalls. *Nonlin. Process. Geophys.* 11: 505-514.
- Ming, L. 2010. Fractal time series-A tutorial review. *Math. Prob. Engin.* 1-26. doi:10.1155/2010/157264.
- Moreira, J. G., J. K. L da Silva, and S. O. Kamphorst. 1994. On the fractal dimension of self-affine profiles. *J. Phys. A: Math. Gen.* 27: 8079-8089.
- Muhlbauer, A., P. Spichtinger, and U. Lohmann. 2009. Application and comparison of robust linear regression methods for trend estimation. *J. Appl. Meteorol. Climatol.* 48: 1961-1970.
- Nickl, E., C. J. Willmott, K. Matsuura, and S. M. Robeson. 2010. Changes in annual land-surface precipitation over the twentieth and early twenty-first century. *Ann. Assoc. Am. Geog.* 100: 729-739.
- Peng, C. K., S. V. Buldyrev, S. Havlin, M. Simons, H. E. Stanley, and A. L. Goldberger. 1994. Mosaic organization of DNA nucleotides. *Phys. Rev. E.* 49: 1685-1689.
- Roderick, M. L. and G. D. Farquhar. 2004. Changes in Australian pan evaporation from 1970 to 2002. *Int. J. Climatol.* 24: 1077-1090.
- Turcotte, D. L. 1992. *Fractals and chaos in geology and geophysics.* Cambridge University Press. Cambridge, UK.
- Trömel, S. and C. D. Schönwiese. 2008. Robust trend estimation of observed German precipitation. *Theor. Appl. Climatol.* 93: 107-115.
- Valdez-Cepeda, R. D., D. Hernández-Ramírez, B. Mendoza, J. Valdés-Galicia, and D. Maravilla. 2003. Fractality of monthly extreme minimum temperature. *Fractals* 11: 137-144.
- Valdez-Cepeda, R. D., O. Delgadillo-Ruiz, R. Magallanes-Quintanar, G. Miramontes-De León, J. L. Hernández-García, A. Enciso-Muñoz, and B. Mendoza. 2007. Scale-invariance of normalized yearly mean grain yield anomaly series. *Adv. Complex Syst.* 10: 395-412.
- Valdez-Cepeda, R. D., A. A. Aguilar-Campos, F. Blanco-Macías, G. Miramontes de León, S. J. Méndez-Gallegos, and R. Magallanes-Quintanar. 2012. Analysis of precipitation in Central México: Trends, self-affinity and important frequencies. *Int. J. Phys. Sci.* 7: 5314-5326.
- Velásquez-Valle, M. A., G. Medina-García, I. Sánchez-Cohen, L. K. Oleschko, J. A. Ruiz-Corral, and G. Korvin. 2013. Spatial variability of the Hurst exponent of the daily scale rainfall series in State of Zacatecas, México. *J. Appl. Meteorol. Climatol.* 52: 2771-2780. doi:http://dx.doi.org/10.1175/JAMC-D-13-0136.1.
- Weber, R. O. and P. Talkner. 2001. Spectra and correlations of climate data from days to decades. *J. Geophys. Res.* 106: 20131-20144.
- White, H. and C. W. J. Granger. 2011. Consideration of trends in time series. *J. Time Series Econ.* 3: 1-38.
- Wilks, D. S. 1995. *Statistical methods in the atmospheric sciences.* Academic Press. San Diego, CA, USA.