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Predicting the Temporal Structure of the Atlantic Multidecadal Oscillation (AMO) for Agriculture Management in Mexico's Coastal Zone

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ABSTRACT

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The influence of global-scale modes of climate variability on Mexico's coastal zone is investigated through the analysis of the Atlantic Multidecadal Oscillation (AMO) effect on the long-term (decadal) behavior of three climatic variables (rainfall, maximum and minimum temperatures) and agricultural production in 17 coastal states. Statistical methods to predict the annual and decadal behavior of the AMO index were proposed, assessed, and used to predict the long-term production phase (above or below the production trend) for the principal crops in the states where the highest correlation among climate signals and agricultural production was found. The near-term (1 y to decades) temporal variability structure of the AMO index was modeled by analytic functions (decadal component) and through discrete simulation (yearly component), using the fractal dimension as a nonlinear measure to assess and mimic the irregularity of the original time series with good results. For the decadal signals, significant correlations ($p < 0.05$) were found between AMO and climatic variables in 13 of 17 states with rain and 14 of 17 states with maximum and minimum temperatures. AMO and total production correlate in 12 of 17 states, and for specific crops, 34 of 51 values were significant. For the purposes of coastal management, the long-term forecasts obtained may be good enough to propose adaptation measures to climate variability related to agricultural activity in 5-year horizons, which closely correspond to periods of government in Mexico.

ADDITIONAL INDEX WORDS: *Modes of climate variability, agriculture, coastal management, Mexican coastal zone.*

INTRODUCTION

Coastal zones are fragile and dynamic regions in which oceanic, atmospheric, and terrestrial phenomena interact, generating environments with high biological diversity and a series of ecosystem services and functions that have allowed the development of civilization throughout human history. Taking into account different definitions of coastal zone, some authors have established that over 50% of the world population lives within 200 km of the coast (Hinrichsen, 1998), around 1.2 billion at a distance less than 100 km from the coast (Small and Nicholls, 2003), and 625 million below the altitude of 10 m (Neumann *et al*., 2015). These coastal areas also support a large part of global productive activities such as agriculture, forestry, industry, commerce, tourism, transport, aquaculture, and mining; strategic facilities for defense, navigation, power generation, and oil extraction; and are the most visited places for recreational, leisure, and contemplation purposes (Cicin-Sain and Knecht, 1998; Crossland *et al*., 2005; Kay and Alder, 2005).

Coastal systems, composed of elements, flows, and interactions, both natural and anthropogenic, are continually disturbed by processes of pollution (Vikas and Dwarakish, 2015), urban expansion (Rodriguez and Brebbia, 2015), industrialization, land-use changes, eutrophication (Sinha, Michalak and Balaji, 2017), introduction of exotic species (Olenin *et al*., 2017; Williams and Grosholz, 2008), overfishing, natural resource exploitation, biodiversity loss (Ramírez *et al*., 2017), and even bad governance practices, just to mention some stress factors, which unceasingly affect the sustainability of the coastal environment (Dronkers and Stojanovic, 2016; Sandberg, 2011; Turner and Bower, 1999). In addition to these factors, coastal areas around the world are the places where the effects of climate change are first manifested and where their impacts will be strongest (Wong *et al*., 2014). The increase in atmospheric temperature and in the upper layers of the ocean, the accelerated sea-level rise, the acidification of the ocean, changes in precipitation patterns, and the increase in intensity and frequency of extreme meteorological events, among others factors, will produce a continuous intensification in the vulnerability levels of coastal areas (McFaden, 2007; Weissenberger and Chouinard, 2015).

In addition to the impacts of climate change, the natural variability of the global climate system (*i.e*. atmosphere, hydrosphere, cryosphere, land surface, and biosphere) strongly influences the vulnerability and adaptive capacity of coastal zones. Following the definition proposed by the Intergovernmental Panel on Climate Change (IPCC, 2013), climate variability refers to variations in the mean state of the climate on all spatial and temporal scales beyond that of individual weather events. The climate system exhibits several large-scale phenomena, such as the El Niño–Southern Oscillation,

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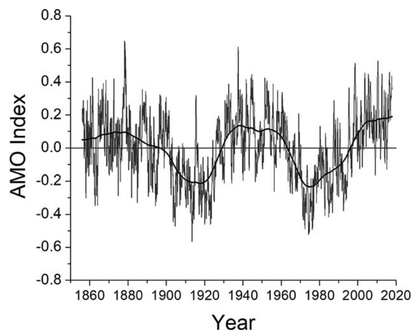

Figure 1. Atlantic Multidecadal Oscillation (AMO) index (1856–2015). Yearly values (dark gray) and 10-year smoothed values (bold line).

the Atlantic Multidecadal Oscillation (AMO), or the Pacific Decadal Oscillation (PDO). Although these modes of variability are not exactly periodic, they are oscillatory in character, and their state is monitored using indices (De Viron, Dickey, and Ghil, 2013). A mode of climate variability can be understood as an underlying space–time structure with preferred spatial pattern and temporal variation that helps account for the gross features in variance and for teleconnections—correlations between climate variables and climate index at different spatial locations (Christensen *et al*., 2013).

One of the most prominent modes of climate variability in the Northern Hemisphere is the AMO (Kerr, 2000), also called more recently Atlantic Multidecadal Variability (*e.g.,* Yeager and Robson, 2017). This global signal was identified in four long-term records (starting in 1854, 1856, 1880, 1881, and ending in 1992) of the North Atlantic sea surface temperature (SST) by Schlesinger and Ramankutty (1995) when observing oscillations in the SST with periods of 65 to 70 years covering the entire basin. Climate models and analysis of surface heat fluxes have suggested that the AMO is an internal mode of climate variability originating from changes in the circulation of the Atlantic Ocean, but its origin is still debated (Gulev and Latif, 2015; McCarthy *et al*., 2015; Zhang, 2017). The temporal structure of the AMO index is shown in Figure 1. This index is defined as the area-average SST anomaly over the North Atlantic (0–70° N) minus the global mean SST. In the existing record, it is possible to observe in the decadal structure three positive or warm phases (two of them partial) with approximate durations of 41, 34, and 22 years, and two negative or cool phases (complete) with durations of nearly 32 years. The spatial pattern, obtained by linearly regressing the SST anomalies at each location on the AMO index, exhibits positive values over the entire North Atlantic, with the largest magnitudes (approximately 0.5°C) south of Greenland (Deser *et al*., 2010). This spatial pattern (*e.g*., Deser *et al*., 2010; Hartman *et al.,* 2013) extends and influences the Mexican littorals (both east and west coasts) with positive anomalies in the southern part, and negative anomalies in the Gulf of California (West Coast) and Tamaulipas State (East Coast).

The AMO is linked with decadal or multidecadal climate fluctuations, such as the winter climate of East China (Li and Bates, 2007), Indian and Sahel rainfall (Zhang and Delworth, 2006), Atlantic hurricanes (Poore and Brock, 2011), European and American summer precipitations and temperatures (Ionita *et al.,* 2013; O'Reilly, Woollings, and Zanna, 2017; Sutton and Dong, 2012; Veres and Hu, 2013), Arctic temperatures (Chylek *et al*., 2011), and river flows (Enfield, Mestas-Nuñez, and Trimble, 2001; Kelly, 2004). In the coastal areas of the world, the effects of the AMO and other modes of climate variability have been observed, for example in the sea-level rise acceleration along the European and American coasts (Ezer, Haigh, and Woodworth, 2016; Karamperidou *et al*., 2013; McCarthy *et al*., 2015), sediment accretion/erosion cycles and beach morphology (Ortega *et al.,* 2013; Tătui, Vespremeanu-Stroe, and Preoteasa, 2014), number and intensity of tropical cyclones (Briggs, 2008; Maxwell *et al*., 2013), abundance of coastal species (Manta *et al*., 2017; Mieszkowska *et al*., 2014), potential impacts on coastal upwelling (Cropper, Hanna, and Bigg, 2014), and wave climatology and coastline evolution (Dada *et al*., 2016; Duan *et al*., 2014; Seymour, 2011).

Climate change and climate variability present a profound challenge to food security and development around the word (Padgham, 2009; Rosenzweig and Hillel, 2008). In a study with ample spatial coverage, Ray *et al*. (2015) established that approximately 60% of the variations in maize, rice, soybean, and wheat crop yields worldwide can be explained by climatic variability. The impact of climate change and decadal temperature trends on yields of the main global crops has also been reported by Porter *et al*. (2014). Climate variability has been, and continues to be, the principal source of fluctuation in food production around the globe (Piao *et al*., 2010; Sivakumar, Das, and Brunini, 2005; Zhao *et al*., 2005). Different mitigation and adaptation strategies that consider the effect of climate variability have been proposed for specific regions and products (Ahmed and Stockle, 2017; Ali, Tedone, and De Mastro, 2017; Ali and Erenstein, 2017; Anandhi, Steiner, and Bailey, 2016; Daouda and Bryant, 2016; Deichert, Gedamu, and Nemomsa, 2017; Olayide and Tetteh, 2017).

The analysis of the response of specific crops to climate change and variability has been the subject of studies in different regions of the world. For Indonesia, Schroth *et al*. (2014) identified potentially suitable cultivation areas for Arabica coffee crops on the basis of local topography, climate observations, and models and, for the same crop but in Tanzania, Craparo *et al*. (2015) provided evidence of negative climate impacts on it; several studies on the United States showed decadal climate variability influence on wheat and maize production (Kucharik and Ramankutty, 2005; Tian *et al*., 2015) and, for East Africa, Ogutu *et al*. (2018) use a probabilistic climate forecast for maize yield; the effects of climate on cocoa production in Nigeria have been reported by Oyekale, Bolaji, and Olowa (2009); the links between climate variability and maize, millet, rice, and groundnuts in Ghana were discussed by Abdul-Rahaman and Owusu-Sekyere (2017), and for the same country, Williams *et al*. (2017) show the impact of climate variability on pineapple production. In Mexico, the relationship between climate and agriculture has been studied mainly from the perspective of climate change (AIACC, 2006; Arce-Romero *et al*., 2018; Gay *et al*., 2006; Hellin, Bellon, and Hearne, 2014). The impacts of climate variability on agricultural production have been addressed

Table 1. *Irrigated and rain-fed planted areas in Mexican coastal states.*

Coastal State Name	Total Area Planted (ha)	Rain-Fed Area (ha)	Rain-Fed Area (%)	Irrigated Area (ha)	Irrigated Area (%)
Baja California	217,823.82	27,708.74	12.72	190,115.08	87.28
Baja California Sur	42,964.25	—	0.00	42,964.25	100.00
Sonora	634,601.60	37,574.40	5.92	597,027.20	94.08
Sinaloa	1,269,627.30	368,751.17	29.04	900,876.13	70.96
Nayarit	383,846.64	299,128.68	77.93	84,717.96	22.07
Jalisco	1,569,812.69	1,280,634.00	81.58	289,178.69	18.42
Colima	158,951.43	86,930.76	54.69	72,020.67	45.31
Michoacan	1,152,215.94	694,829.88	60.30	457,386.06	39.70
Guerrero	890,979.00	784,327.27	88.03	106,651.73	11.97
Oaxaca	1,384,571.57	1,294,424.80	93.49	90,146.77	6.51
Chiapas	1,445,690.48	1,389,286.36	96.10	56,404.12	3.90
Tamaulipas	1,399,126.91	945,425.65	67.57	453,701.26	32.43
Veracruz	1,504,815.77	1,380,427.25	91.73	124,388.52	8.27
Tabasco	256,827.63	248,800.43	96.87	8,027.20	3.13
Campeche	314,812.03	285,697.43	90.75	29,114.60	9.25
Yucatan	755,414.13	689,220.05	91.24	66,194.08	8.76
Quintana Roo	139,454.94	132,356.87	94.91	7,098.07	5.09

from geographically localized studies like Granados, Soria, and Cortina (2016) in Guanajuato or with specific products such as maize in Oaxaca (Dilley, 1997; Rogé and Astier, 2015) and Tlaxcala (Conde, Ferrer, and Orozco, 2006; Ziervogel *et al.*, 2006); however, to the best knowledge of the authors, there is no work that analyzes the impact of the AMO on agricultural production in all of Mexico's coastal states.

From the point of view of coastal management (*e.g.*, Scialabba, 1998), the practice of agriculture in coastal areas can be perceived as a socially beneficial activity (*e.g.*, provides livelihoods for the coastal population, is a local source of employment and nutrition), but also negatively from the environmental point of view, as an element that encourages the change of use of soil affecting biodiversity and ecosystem services, or as a potential land-based source of contaminants—agrochemicals, pesticides, and fertilizers—that many times generate conflicts among coastal stakeholders and sectors (Brugere, 2006; Gowing, Tuong, and Hoanh, 2006; Neumann, Ott, and Kenchington, 2017). However, in countries such as Mexico, where approximately 60% of agricultural production is generated in coastal states and 74% of crops are rain fed (Table 1), the influence of weather, extreme meteorological events, climate, water availability, and soil conditions is critical. In this sense, it is essential to understand the effects and potential impacts of climate variability on this economic resource, to take adaptive measures and mitigation strategies that reduce vulnerability, and, as far as possible, generate predictive models that help decision making to deal with these long-term phenomena.

Despite unresolved questions about origin and mechanisms, several studies agree that the AMO's variability is predictable on multiyear timescales (Boer, 2004; Griffies and Bryan 1997; Murphy *et al.*, 2010; Seitola and Järvinen, 2014). Some attempts to model, predict, or generate useful information from the spatial and temporal structure of the AMO have been presented using coupled global atmosphere–ocean models (Chikamoto *et al.*, 2013; Han *et al.*, 2016; Wei and Lohmann, 2012), probabilistic approaches (Elsner and Jagger, 2006; Suckling *et al.*, 2017), and statistical methodologies (DelSole and Tippett, 2009; DelSole, Tippett, and Shukla, 2011; Luo *et al.*, 2012; Yang *et al.*, 2013). Comprehensive reviews of the state of knowledge and progress made in understanding the variability and predictability of the AMO and other modes of climate variability can be found in Latif *et al.* (2006), Latif and Keenlyside (2011), Meehl *et al.* (2009, 2014), and Yeager and Robson (2017).

A central hypothesis of this research is the fact that near-term (1 y to 1 decade) climatic variability can affect the agricultural productivity of entire regions, directly modifying rain and surface atmospheric temperature patterns and, indirectly, through changes in humidity, soil moisture, nutrient availability, pests, and presence/absence of pollinating bees. Specifically, the aim of this paper is to analyze the possible relationships between the temporal behavior of the AMO (*i.e.* annual and decadal) and the time series of the production of selected agricultural crops of commercial importance for the coastal states of Mexico. In accord with the results obtained, it will seek to stablish simple predictive models for the AMO's temporal structure that allow them to anticipate the behavior of agricultural products beyond seasonal periods with the idea of supporting long-term decision making related to coastal management.

METHODS

The following paragraphs will describe the study area, the sources of information, and the methodology followed for the analysis of climatic variables, the AMO index, the total agricultural production of each coastal state of Mexico, and the selected crops. In a detailed manner, the simulation process followed to estimate the behavior of the AMO index will be explained.

Study Area

Surrounded by the Pacific and Atlantic oceans and with two semienclosed seas, the Sea of Cortez and the Gulf of Mexico (which communicates with the Caribbean Sea), Mexico is highly susceptible to the dynamics of the ocean–atmosphere system. Mexico's marine area is larger than its terrestrial area and comprises an economic exclusive zone of 2,997,679 km^2. The Mexican coastal zone includes different climatic regions in

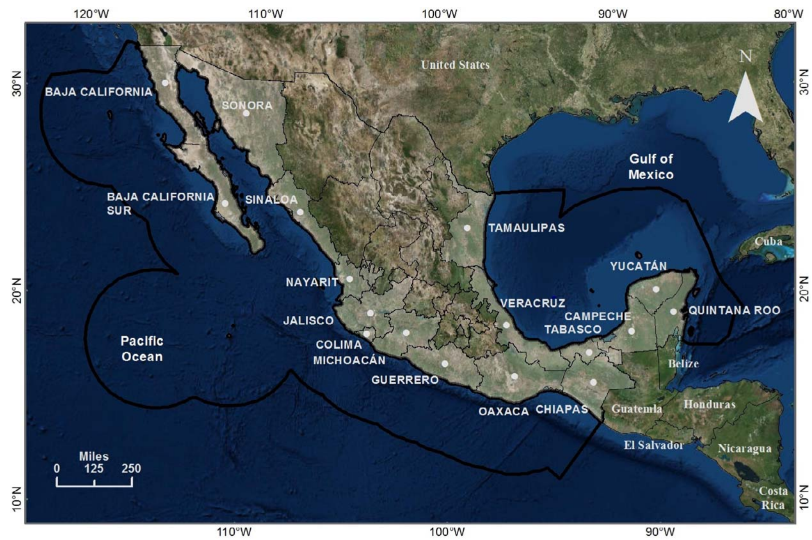

Figure 2. Study area. Mexican coastal states (light color) and economic exclusive zone (bold line). Source of images: (a) Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community; (b) CONABIO EEZ, and (c) INEGI state division. (Color for this figure is available in the online version of this paper.)

which there is a high biological diversity and numerous coastal environments distributed along 11,122 km of coastline. There are 17 coastal states with a territorial extension of 1,111,766 km^2; of them, 11 are located on the West Coast (792,938 km^2) and 6 on the East Coast (318,828 km^2). Approximately 156 municipalities have direct access to the sea (coastal counties). This study analyzes the behavior of atmospheric surface temperature, rainfall, and agricultural productivity of the 17 coastal states of Mexico. Figure 2 shows the study area.

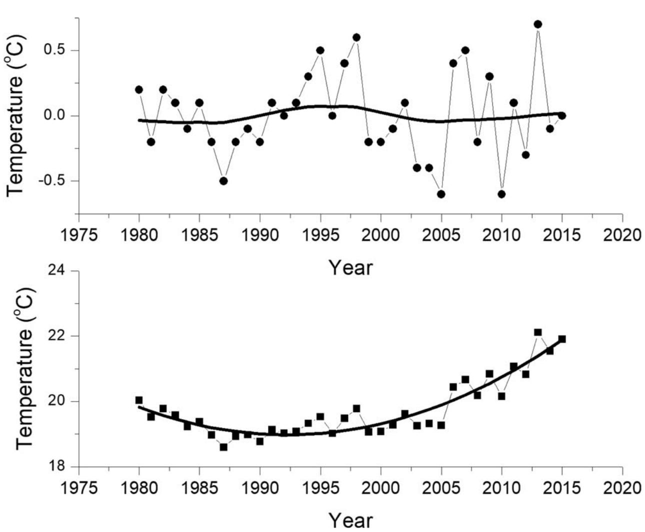

Figure 3. Schematic diagram of time-series decomposition process. Bottom: original minimum temperature signal (squares) and nonlinear trend (continuous dark gray line). Top: detrended signal or residuals (circles) and smoothed signal (continuous black line).

Surface Temperature and Rain

For the annual and decadal analysis of rainfall (Rn) and maximum (TMAX) and minimum (Tmin) temperatures of each coastal state, monthly records from the Mexican National Weather Service (SMN, 2017) were used for the period 1980–2015. Monthly values of the three climate variables (*i.e.* Rn, TMAX, and Tmin) were used to obtain the yearly average. The yearly time series were detrended and smoothed using moving-average techniques (10-y period) to extract the decadal component for each climate variable signal. Detrending is a key issue in climatic time-series analysis. Before selecting the most appropriate technique, several methods were explored: (1) analytical linear and nonlinear polynomial models (up to fourth order); (2) spectral methods removing sequentially the components with higher energy, and (3) empirical methods like the empirical mode decomposition (Wu *et al.*, 2007). Although it is not possible to generalize the results to all the climatic variables analyzed (rain, TMAX, and Tmin), considering the mean square error (MSE), the determination coefficient (R^2), and the behavior of the residues in the long term, it was decided to work with the nonlinear model of second order (see Figures S3a,b,c and S4a,b,c in Supplementary Materials). Figure 3 shows an example of the methodology followed with all the climatic variables; in this case the plot shows the minimum temperature in the State of Campeche.

AMO Index

The historical record of monthly values of the AMO index was obtained from the Earth System Research Laboratory of the National Oceanic and Atmospheric Administration. The data cover 1856 to date (see Figure 1) and the index was calculated from the Kaplan SST record using the HadlSST1 data set (Enfield, Mestas-Nunez, and Trimble, 2001; Rayner *et al.*, 2003). A spectral analysis of the complete signal was performed

Table 2. *Agricultural production crops selected for this study.*

Coastal State Name	Product 1	Product 2	Product 3
Baja California	Tomato	Wheat	Strawberry
Baja California Sur	Tomato	Chili	Potatoes
Sonora	Wheat	Grapes	Potatoes
Sinaloa	Maize	Tomato	Chili
Nayarit	Sugarcane	Beans	Mango
Jalisco	Maize	Sugarcane	Pastures
Colima	Lemon	Sugarcane	Pastures
Michoacan	Avocado	Maize	Blackberries
Guerrero	Maize	Mango	Pastures
Oaxaca	Maize	Pastures	Sugarcane
Chiapas	Maize	Pastures	Coffee
Tamaulipas	Sorghum	Sugarcane	Maize
Veracruz	Sugarcane	Maize	Oranges
Tabasco	Banana	Sugarcane	Cocoa
Campeche	Maize	Sugarcane	Soybeans
Yucatan	Pastures	Maize	Lemon
Quintana Roo	Sugarcane	Maize	Chili

to identify the most adequate frequency to extract the long-term signal. For the purposes of this work, the frequencies with higher energy correspond to those centered around a period of 10 years (see Figure S1 in Supplementary Materials). Several smoothing and nonlinear filtering techniques were analyzed to extract the decadal component of the AMO index used in this study: double-smoothed moving average with 10-year period, fast Fourier filter with 10-year period, fast Fourier low-pass parabolic filter with a frequency $f = 0.05$, and fast Fourier low-pass parabolic filter with amplitude threshold $A = 7.013$. Although in the first three cases the level of error was similar, the lowest MSE value in all cases was that associated with the moving-average technique (see Figure S2 in Supplementary Materials).

The detrended, unsmoothed AMO index (ESRL-NOAA, 2017) part used during this study corresponds to the period from 1980 to 2015. In this paper only one section of the total AMO index was analyzed; for this reason, it was necessary to extract the local trend and then proceed with the decadal smoothing in the same way as for the climatic variables described in the previous section to obtain the decadal behavior.

Agricultural Production

The database of agricultural production was generated from the official information provided by the Agricultural and Fisheries Information Service (SIAP, 2017) of the Mexican Ministry of Agriculture, Livestock, Rural Development, Fisheries and Food (SAGARPA). This study considered, for each coastal state, the annual values of the total food production for the period 1980–2015. Likewise, it defined the three main agricultural products of each state from those that had the highest commercial value in 2010. For these three selected crops the annual production from 1980 to 2015 was considered as well. All the agricultural time series were detrended and smoothed according to the previously described methodology. Because of the lack of data with the same spatial and temporal coverage used in this research, the technological component (*e.g.,* new machines, irrigation techniques, automatization processes, improvements in fertilizers, seeds, and pesticides) and the specific needs of each crop studied (*e.g.,* local soil and humidity, solar irradiation, nutrient availability, seasonality of day length) were not considered in this study. Table 2 shows the crops selected in each Mexican coastal state and Figure 4 some selected products.

Data Analysis

The yearly time series of total agricultural production and of the three selected products for each state were correlated with the corresponding climatic variables (*i.e.* Rn, TMAX, and Tmin) and with the AMO index (correlation matrix). In the same way the analysis proceeded with all the smoothed series (decadal behavior) to define the level of correlation between signals in the long term.

The study tested the significance of the Pearson product-moment correlation coefficients according to Sheskin (2011), which computed the quantity t using the following equation:

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \tag{1}$$

in which, r is the correlation coefficient between two variables and n the number of data of each variable considered. The calculated t value is contrasted with the corresponding critical value from the t distribution with $n-2$ degrees of freedom.

The significant ($p < 0.05$) correlation values among agricultural products, climate variables, and AMO index were analyzed and the time series associated with the highest significant ($p < 0.05$) correlation coefficients between the AMO index and agricultural products were then chosen for predictive purposes.

Predictive Methodology

This analysis is based on the characteristics of the statistical and probabilistic structure of the complete time series of the AMO index (1856–2015), and its sole purpose is to generate simple forecasts that are useful for coastal management, unlike other predictive process-based models aimed at improving scientific knowledge of the phenomenon itself.

To predict the temporal structure of the AMO index using statistical methods, it was considered that the original signal (ST) could be separated into two components: (1) decadal part or low-frequency signal (SD) and (2) the yearly component (SY), plus the error (e) according to the following equation:

$$ST_i = SD_i + SY_i + e_i \tag{2}$$

The decadal part was modeled by nonlinear analytic functions using common best-fit procedures with error criteria such as mean absolute percentage error (MAPE), mean absolute deviation (MAD), mean squared deviation (MSD), or accuracy ratio (ACRA) for acceptance (Tofallis, 2015). Two schemes were proposed to model the nonlinear part: (1) a simple moving-average method with a 9-year period ($\mathrm{SD1}_i$), and (2) an oscillatory function ($\mathrm{SD2}_i$) defined by the next equation:

$$\mathrm{SD2}_i = A\sin\left(\pi\frac{\mathrm{ST}_i - \mathrm{ST}_{\mathrm{cen}}}{W}\right) \tag{3}$$

in which, A is the wave amplitude, $\mathrm{ST}_{\mathrm{cen}}$ is the center of the wave in time, and W is the width of the semiwave.

The yearly component forecast was done using discrete simulation techniques (Law and Kelton, 1991). Following

Figure 4. Selected agricultural products used in this study. Top row (from left to right): sugarcane field, chili crop, and wheat field. Middle row (from left to right): potato farm, bean crops, and lemon trees. Bottom row (from left to right): mango, maize field, and banana plantation. Source of Images: SAGARPA (http://www.sagarpa.gob.mx/saladeprensa/Banco/Forms/Miniaturas.aspx). (Color for this figure is available in the online version of this paper.)

Golestani and Gras (2014), the nonlinear properties of the original and simulated time series were used as an acceptance measure. Specifically this study introduces the fractal dimension as a selection criterion among several discrete simulation forecasts.

Once the best nonlinear function (SD) was defined, then it was subtracted from the original AMO index to obtain the residuals, in this case the yearly component (SY). Later on, looking at the probability distribution function followed by these residuals, it can be determined that the appropriate discrete function to perform the simulation was established. After a best-fit test for the residuals, their normality was tested by a Kolmogorov–Smirnov test at a significance level of $\alpha = 0.05$. Several runs of simulated random residuals (NSY) were performed using the following equation (Azarang and García-Dunna, 1996):

$$\mathrm{NSY}_i = \left(\sum_{i=1}^{12} r_i - 6\right)\sigma + \mu \tag{4}$$

in which, r_i are independent uniform random numbers between 0 and 1, σ the standard deviation, and μ the mean of the normal distribution followed by the residuals. According to Golestani and Gras (2014), no significant improvement was observed for the data considered when the number of runs was greater than 10; however, in this analysis the number of runs was extended to 20.

The fractal dimension (D) of a time series measures how irregular the given time series is. For each time series of simulated residuals, their fractal dimension was calculated using the Hurts exponent (H) with the relationship $D = 2 - H$. This study estimates H using the rescaled range analysis according to Kale and Butar-Butar (2011). The estimation procedure involves three basic steps: (1) for a time series over a total duration N, the deviation of each piece of data is calculated with respect to the total average (data – whole mean). For these deviations the range R = maximum value – minimum value is obtained and the rescaled range defined as R/S, where S is the standard deviation of the data; (2) the next step is to divide the original series into two equal parts $N = N/2$ and repeat the procedure shown in (1) for the two segments. The average value of R/S is then calculated for the two segments. Then the entire procedure is repeated for $N = N/4$, $N = N/8$, $N = N/16$ and so on; (3) finally H can be estimated by the slope of the best-fit line that is obtained when plotting $\log_{10}(R/S)$ *vs*. $\log_{10}(N)$.

The resulting residuals were added to the nonlinear functions defined to obtain the simulated series of the AMO index. Five performance criteria of the simulated series were used before proceeding with the forecasts: the similarity between the mean and standard deviation of the original AMO index and the simulated one; the difference between maximum and minimum values among original and simulated series; and finally the match between the fractal dimensions of the original time series and the simulated one. In addition, the MAPE, MAD, MSD, and ACRA measures of accuracy were calculated (Tofallis, 2015).

Using the best hindcast for the long AMO index time series (1856–2015), a 5-year forecast was performed (2015–2020) for the AMO's temporal structure. This forecast was used to predict the agricultural production of specific products in selected coastal states (highest correlations between AMO and agricultural products) using as a predictor, in linear or quadratic regression models, the simulated AMO index. The measured values of agricultural production for 2016 (latest information officially reported) were used to assess the yearly predictive capacity of the model.

RESULTS

In this section the results obtained in the correlational analysis carried out among the different variables considered in all the Mexican coastal states are presented, for both annual and decadal behaviors. The relationships obtained between the climatic variables (Rn, TMAX, and Tmin) and the AMO, the climatic variables and the agricultural production, and the AMO and the agricultural production are taken into consideration. Finally, the annual and decadal forecasts of the total agricultural production and selected crops are presented.

Climatic Variables and AMO

The yearly values of the three climatic variables used in this study, Rn, TMAX, and Tmin, show, in general, an increase in their values for the period 1980–2015. Considering the linear trends, six coastal states present significant ($p < 0.05$) slopes in the precipitation level, going from 6.8 ± 3.3 mm/y in Quintana Roo to 21 ± 4.5 mm/y in Colima; for the maximum temperature, seven states present significant increases, from 0.017°C ± 0.008°C/y in Tamaulipas to 0.091°C ± 0.012°C/y in Oaxaca, and, for the minimum temperature, 14 coastal states (82%) show significant positive linear trends ranging from 0.02°C ± 0.008°C/y to 0.13°C ± 0.018°C/y. In 5 of the 6 states that had significant increases in Rn, significant positive correlations ($p < 0.05$) were observed with the AMO index using yearly data. It was also found in the analysis that 6 of 7 states with significant increases in TMAX correlated positively with AMO, and 9 of 14 with significant increases in Tmin correlate positively as well. The total significant correlations observed using yearly information between the climate variables and the AMO index were 23 of 51 (45%), of which only one was negative (TMAX in Campeche State).

The low-frequency signals (decadal behavior) show 41 of 51 (80%) significant ($p < 0.05$) correlations among climatic variables and AMO index. In this case 23 were positive (the majority with TMAX) and 18 negative (most of them with Tmin). Considering the decadal structure of the data, all coastal states feel the influence of the AMO—in a correlational sense—at least in one climate variable, as it is possible to observe in Table 3.

The AMO's spatial pattern (see by example Deser *et al.*, 2010) corresponds very well with the sense of correlations obtained in this study between AMO index and rain patterns. For the northern half of the country, the AMO spatial pattern exhibits negative SST anomalies on both coasts, with a positive patch in the northern Pacific corner. In this analysis (see Table 3), the northern half of the Pacific coastal states (until Michoacan) shows negative correlations between AMO index and Rn except Baja California State (positively correlated), which is located in the northern corner of the Pacific littoral. For the East Coast (Gulf of Mexico and Caribbean Sea) the AMO's spatial pattern shows a kind of horseshoe form with negative SST anomalies in the north (Tamaulipas State) and in the south parts (Yucatán and Quintana Roo states) of Mexico, with positive anomalies in the central states (Veracruz, Tabasco, and Campeche). This behavior is repeated almost exactly in the decadal correlational analysis performed in this study between AMO index and Rn. During the AMO positive phase (warm), the northern Mexican states see less than normal rainfall, whereas the central states see the opposite, which corresponds to what was observed by Enfield, Mestas-Nuñez, and Trimble (2001) for the United States. For the other phase of the AMO (negative or cool) the pattern is reversed.

Table 3. *Correlation coefficients between AMO index and climate variables (decadal time series). Bold numbers represent significant values at p < 0.05.*

Coastal State Name	Rain	Maximum Temperature	Minimum Temperature
Baja California	**0.7785**	**−0.6597**	**−0.8295**
Baja California Sur	−0.3023	**0.4152**	**−0.8952**
Sonora	**−0.8612**	**0.7233**	**−0.3472**
Sinaloa	**−0.6981**	**0.6671**	**−0.5759**
Nayarit	−0.2620	**0.8703**	**−0.7025**
Jalisco	**−0.7118**	**0.8039**	**0.5569**
Colima	**−0.6218**	**0.8369**	**0.8594**
Michoacan	**0.7069**	**−0.7042**	**−0.4937**
Guerrero	−0.1398	**0.8509**	**−0.6211**
Oaxaca	**0.7848**	0.3241	0.3008
Chiapas	**0.6136**	**0.6833**	**−0.5269**
Tamaulipas	**−0.8390**	**0.9049**	**0.5972**
Veracruz	**0.7154**	**0.9345**	**0.8687**
Tabasco	**0.4895**	−0.1213	−0.2321
Campeche	**0.7990**	**−0.8324**	−0.1954
Yucatan	**−0.8505**	−0.0173	**0.8707**
Quintana Roo	0.0058	**0.9212**	**−0.8789**

The locally detrended and smoothed values of the AMO index (1980–2015) show a negative phase between 1983 and 1995 and a positive one for the period 1996–2009. The behavior of the climatic variables that presented the highest correlations with the AMO can be observed in Figure 5 (standardized values). It is important to note the marked similarity between the time periods during which the variables analyzed are in a positive or negative phase. For the selected states, Rn and Tmin are negatively correlated with AMO, and with TMAX, positively.

Since some climatic variables do not react immediately to changes in some major climate indices, like the AMO, the use of a longer AMO series (extending the time series some years) and a cross-correlation analysis between the series was thought to be useful to see if there are better correlations at certain lags. Considering the decadal behavior of AMO, Rn, TMAX, and Tmin after a quadratic detrending in the climatic variables was performed, the results showed a short-term (0 to 3 y) influence of the AMO on Rn and TMAX in 13 of 17 coastal states, and for Tmin in 11 of 17 states; a medium-term (4 to 7 y) influence in 4,

Table 4. *Significant ($p < 0.05$) correlation coefficients obtained between climatic variables and agricultural products in Mexican coastal states (decadal component).*

Specific Agricultural Products by Location	Correlation Coefficients		
	Rn†	TMAX	Tmin
West Coast			
Baja California			
Tomato	−0.4878	0.3325	−0.8813
Wheat	0.5923	−0.7895	
Strawberry	0.5910		0.9320
Baja California Sur			
Tomato			
Chili		0.3487	−0.5843
Potatoes	0.6693	−0.6492	0.9598
Sonora			
Wheat	0.5628	−0.7738	0.5699
Grapes		0.6097	−0.4009
Potatoes	0.5061	−0.8074	0.6037
Sinaloa			
Maize	−0.4226		
Tomato		−0.3964	
Chili		−0.5514	
Nayarit			
Maize			
Beans			
Mango		0.5615	−0.6664
Jalisco			
Maize			0.4306
Sugarcane			
Pastures			0.3967
Colima			
Lemon	−0.9180	0.6317	
Sugarcane	0.7579	−0.8832	0.6165
Pastures	−0.5212		0.5208
Michoacán			
Avocado	−0.6124		
Maize	0.3756		0.6914
Blackberry	0.5149	0.6517	0.9050
Guerrero			
Maize		0.7845	−0.7378
Mango	0.8086	−0.4541	
Pastures	0.4123	−0.6688	
Oaxaca			
Maize	0.8115	−0.7440	−0.7601
Pastures		0.3997	0.5632
Sugarcane	−0.8547		
Chiapas			
Maize			−0.6487
Pastures	0.8056	0.4027	0.5774
Coffee	0.4156		
East Coast			
Tamaulipas			
Sorghum	−0.4844	0.5811	0.5866
Sugarcane		−0.4046	
Maize	0.6074	−0.8063	0.5629
Veracruz			
Sugarcane	0.4177	0.6391	
Maize	0.7190	0.5927	0.3839
Orange	0.7217	0.4852	
Tabasco			
Banana	−0.4314	0.4564	
Sugarcane	−0.5330	0.5375	
Cocoa	−0.6703	0.9031	
Campeche			
Maize	−0.7249		0.9365
Sugarcane	−0.7312	0.6412	0.8731
Soybeans	−0.8253	0.5536	0.9200
Yucatán			
Pastures	−0.6878		
Maize			0.4423
Lemon		−0.8313	0.6272
Quintana Roo			
Sugarcane			−0.3509
Maize	0.5636	0.4767	
Chili		−0.7626	

†*Rn = rain, TMAX = maximum temperature, Tmin = minimum temperature*

3, and 5 coastal states, respectively; and a long-term influence (>7 y) in one state for TMAX and Tmin (see Table S1 in Supplementary Materials).

Climatic Variables and Agricultural Production

Considering the yearly time series of total agricultural production and three specific crops in each coastal state, as well as the three climate variables (Rn, TMAX, and Tmin), 83 of 204 (41%) significant ($p < 0.05$) correlations were found (79 positive and 2 negative). Veracruz State—the longest state on the East Coast—presented the highest number of correlations, 10 of 12, with r values ranging from 0.349 (orange production and Tmin) to 0.558 (total production and Rn). Two states (Tabasco and Michoacán) showed only 1 of 12 significant correlations. The maximum correlation value was obtained between strawberry production and Tmin in Baja California ($r = 0.861$), followed by potato production and Tmin in Baja California Sur ($r = 0.843$). The climatic variable that showed the highest number of correlations was Tmin (42 of 83), followed by Rn (25 of 83).

With regard to the behavior of decadal time series, 128 of 204 (63%) significant correlations were found between the climatic variables and agricultural production in the 17 Mexican coastal states, 80 positives and 48 negatives. Rn and TMAX showed 44 significant correlations (25 positive and 19 negative each), whereas Tmin presented 40 (30 positive and 10 negative). The

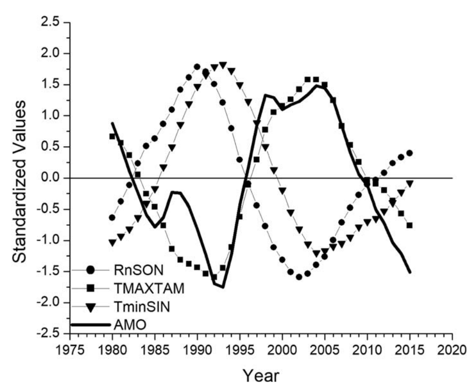

Figure 5. Highest correlations between the decadal structure of AMO index (continuous bold line) and climatic variables: (a) rain in Sonora state (circles); (b) maximum temperature in Tamaulipas State (squares); and (c) minimum temperature in Sinaloa State (triangles).

Table 5. *Significant (p < 0.05) correlation coefficients obtained between AMO index and agricultural products in Mexican coastal states (yearly and decadal components).*

Specific Agricultural Products by Location	Yearly	Decadal
West Coast		
Baja California		
Tomato	0.4925	0.5173
Wheat	0.4977	0.4273
Strawberry	0.6140	−0.5177
Baja California Sur		
Tomato	0.7182	0.6345
Chili	0.7144	0.7305
Potatoes	0.4807	−0.5722
Sonora		
Wheat		−0.3406
Grapes		
Potatoes	0.6527	
Sinaloa		
Maize	0.6849	0.5111
Tomato		
Chili	0.6986	
Nayarit		
Sugarcane	0.5949	
Beans	−0.3295	
Mango	0.6041	0.8377
Jalisco		
Maize	0.6999	0.4662
Sugarcane	0.6160	−0.4941
Pastures	0.7379	0.5263
Colima		
Lemon	0.5725	0.8860
Sugarcane	0.4631	−0.4181
Pastures	0.6261	0.7082
Michoacán		
Avocado	0.6592	−0.4365
Maize	0.6908	
Blackberry	0.4575	−0.5335
Guerrero		
Maize	0.7339	0.4612
Mango	0.5787	−0.3395
Pastures	0.6974	
Oaxaca		
Maize	0.6532	0.5733
Pastures	0.6219	−0.3728
Sugarcane		−0.6617
Chiapas		
Maize		0.7826
Pastures	0.6452	
Coffee		
East Coast		
Tamaulipas		
Sorghum	0.4928	0.5873
Sugarcane	0.4718	−0.3464
Maize	−0.4104	−0.7560
Veracruz		
Sugarcane	0.8098	0.6922
Maize	0.5615	0.4335
Orange	0.6156	
Tabasco		
Banana	0.6189	0.5115
Sugarcane	0.6172	
Cocoa	−0.4063	
Campeche		
Maize	0.6740	
Sugarcane		−0.6781
Soybeans	0.3525	−0.6244
Yucatán		
Pastures	0.5141	0.5399
Maize		0.3521
Lemon	0.6616	
Quintana Roo		
Sugarcane	0.6782	
Maize	0.4742	
Chili		−0.4302

crops that were most planted were (1) maize in 12 states; (2) sugarcane in 8; (3) pastures in 6; and (4) chili in 3. The highest positive significant correlations found for the West Coast were strawberry and potatoes, with Tmin in Baja California and Baja California Sur ($r = 0.932$ and $r = 0.959$, respectively), and for the East Coast: maize and soybean with Tmin in Campeche ($r = 0.936$ and $r = 0.920$, respectively). The most important negative correlations were observed between lemon and rain, and sugarcane and Tmax in Colima State on the West Coast ($r = -0.918$ and $r = -0.993$, respectively) and for the East Coast between lemon and Tmax ($r = -0.831$) in Yucatan and sugarcane and Rn in Campeche ($r = -0.731$). The complete relationship of the significant correlations obtained for specific agricultural products is presented in Table 4 (this table excludes 35 significant correlations found between the total production and the climatic variables; this information can be seen in Supplementary Materials, Table S2).

Agricultural Production and AMO

The total agricultural production correlates significantly ($p < 0.05$) and positively with the AMO index in all coastal states for the yearly time series, with correlation coefficients ranging from $r = 0.498$ in Veracruz State to $r = 0.770$ in Quintana Roo State. The decadal component presents a different behavior; seven coastal states (four on the West Coast and three on the East) had significant positive correlations between total agricultural production and the AMO index, and five coastal states (four on the West Coast and one on the East) correlated negatively. In this case the maximum correlation coefficients were $r = 0.798$ in Baja California State and $r = -0.662$ in Oaxaca State (both on the West Coast).

Considering the three agricultural products defined in each coastal state, the total number of significant correlations obtained in the analysis was 42 of 51 (82%) for the yearly time series and 34 of 51 (67%) for the decadal signals. The results are shown in the Table 5.

For the yearly data, the highest positive correlation found was in Veracruz State between sugarcane production and the AMO index. This is an interesting result because—as was stated before—this coastal state is the largest on the East Coast and the cultivation of sugarcane (rain fed) involves the use of large areas of land exposed to climatic conditions and variability. Figure 6 show the behavior of the yearly time series of sugarcane and the AMO index.

For decadal behavior, two crops were selected: lemon production in Colima State (West Coast) and maize in Tamaulipas (East Coast); both products are rain fed and they represent around 9% to 13% of the total planted area in these

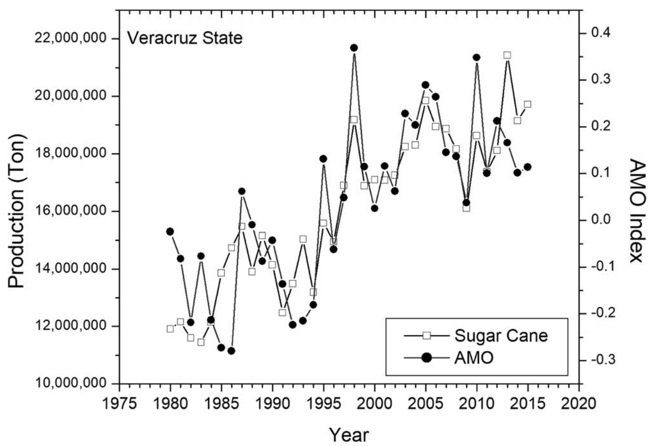

Figure 6. Yearly time series of sugarcane production (squares) in Veracruz State and AMO index (circles) ($r = 0.809$).

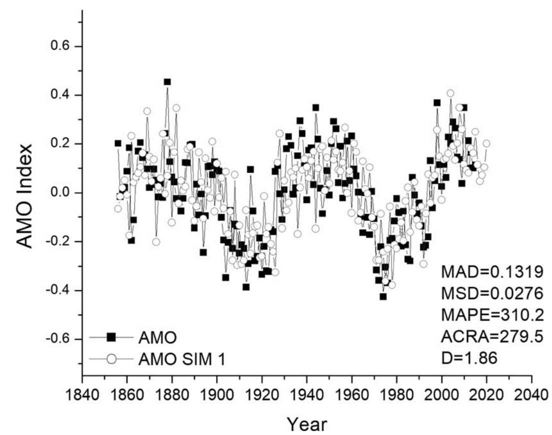

Figure 8. Original AMO index (squares) and simulated (hindcast and forecast) AMO index (circles) used for the decadal simulated part; 9-year moving-average smoothing method.

states. These cases are presented in Figure 7, which shows positive correlations between lemon and AMO ($r = 0.886$) and negative relationships among maize production and AMO ($r = -0.756$).

Predicting Agricultural Production in Coastal States

The different tests performed to simulate and forecast the temporal structure of the AMO index (long series) showed that the best option was the use of forward-moving average with a 9-year period for the decadal part of the signal ($SD1_i$) plus the best yearly component (SY_i) obtained with discrete simulation according to the accuracy criteria described in the methodology section. Figure 8 shows the time series chosen for predictive purposes. The fractal dimension (D) of the original AMO index was $D = 1.84$; in the following two figures the term D represents the fractal dimension of the simulated AMO index.

The second option for the forecast was the use, for the decadal part, of the following equation:

$$SD2_i = 0.18\sin\left(\pi \frac{ST_i - 1927}{36}\right) \quad (5)$$

In this case, the yearly part was added in the same way described in the preceding paragraph. Figure 9 shows the behavior of this predictive scheme.

Using this information and the relationships found in the correlational analysis among climatic variables, agricultural production, and AMO index, it is possible to obtain long-term (5 y in advance) forecasts for total agricultural production or for specific agricultural products, using as a predictor the simulated AMO index, and through polynomial models the response function, obtaining useful results for coastal management regarding the planning process for agriculture development in Mexico's coastal zone.

Using the yearly simulated AMO index, the best relationship found considering the accuracy ratio (Tofallis, 2015) was with

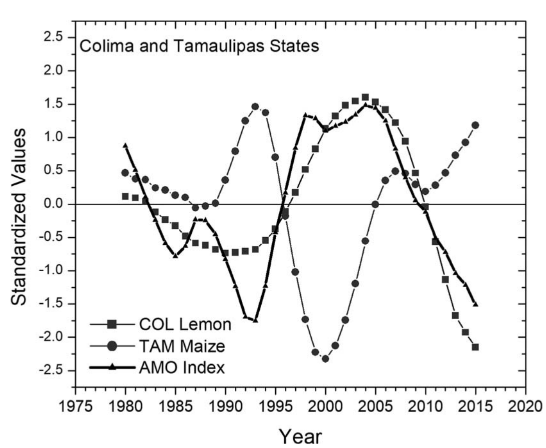

Figure 7. Decadal time series of lemon production in Colima State (squares), maize production in Tamaulipas State (circles), and AMO index (bold line).

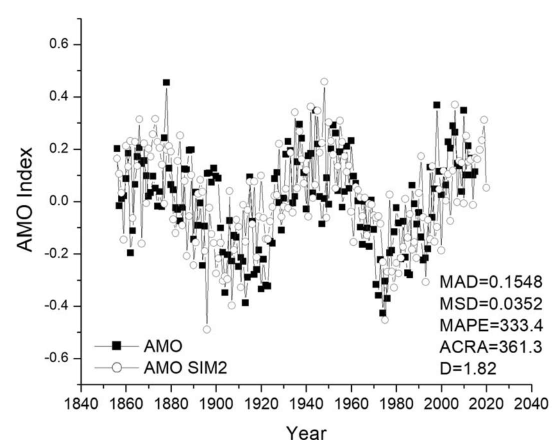

Figure 9. Original AMO index (squares) and simulated (hindcast and forecast) AMO index (circles) used for the decadal simulated part; Equation (5).

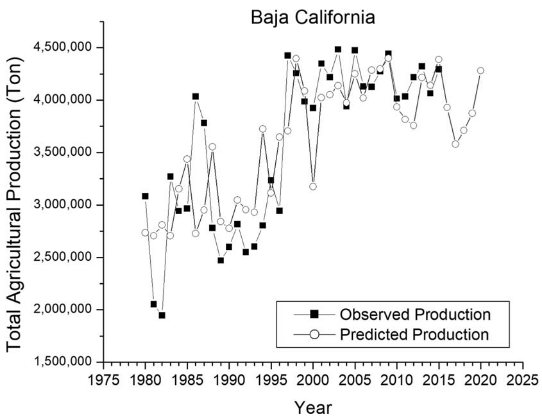

Figure 10. Total agricultural production in Baja California State. Observed production (squares) and simulated production (circles) using a regressive model with the simulated yearly AMO index as a predictor.

Baja California total agricultural production (30% error with 2016 data), which is shown in Figure 10.

The decadal behavior of specific agricultural products, which possibly is the most relevant element of the study for planning purposes in the context of coastal management, was predicted using the decadal component of the simulated AMO index (detrended and smoothed) as a predictor in linear models for the coastal states in which specific crops showed significant correlations above $r = 0.7$; the specific cases were chili in Baja California Sur ($r = 0.73$), mango in Nayarit ($r = 0.84$), lemon in Colima ($r = 0.89$), pastures in Colima ($r = 0.71$), maize in Chiapas ($r = 0.78$), maize in Tamaulipas ($r = 0.76$), and sugarcane in Veracruz ($r = 0.70$). The behavior of some of these cases is shown in Figure 11.

As could be observed in Figure 11, the selected crops are entering a period (greater than 5 y) of production below the trend values. These results allow decision makers to establish policies to substitute (maintain) crops or mechanisms to discourage (or encourage) the planting of these specific products during the periods of time estimated by the model (at least to year 2020). Some policy criteria could be defined looking at Table 6. The confidence in the prediction was established by seeing the temporal structure of the last part of the signal phase (qualitative element) plus the correlation coefficient obtained between the long-term production and the decadal simulated signal.

DISCUSSION

The results obtained in this paper showed a clear influence of the AMO on three climatic variables (Rn, TMAX, and Tmin)

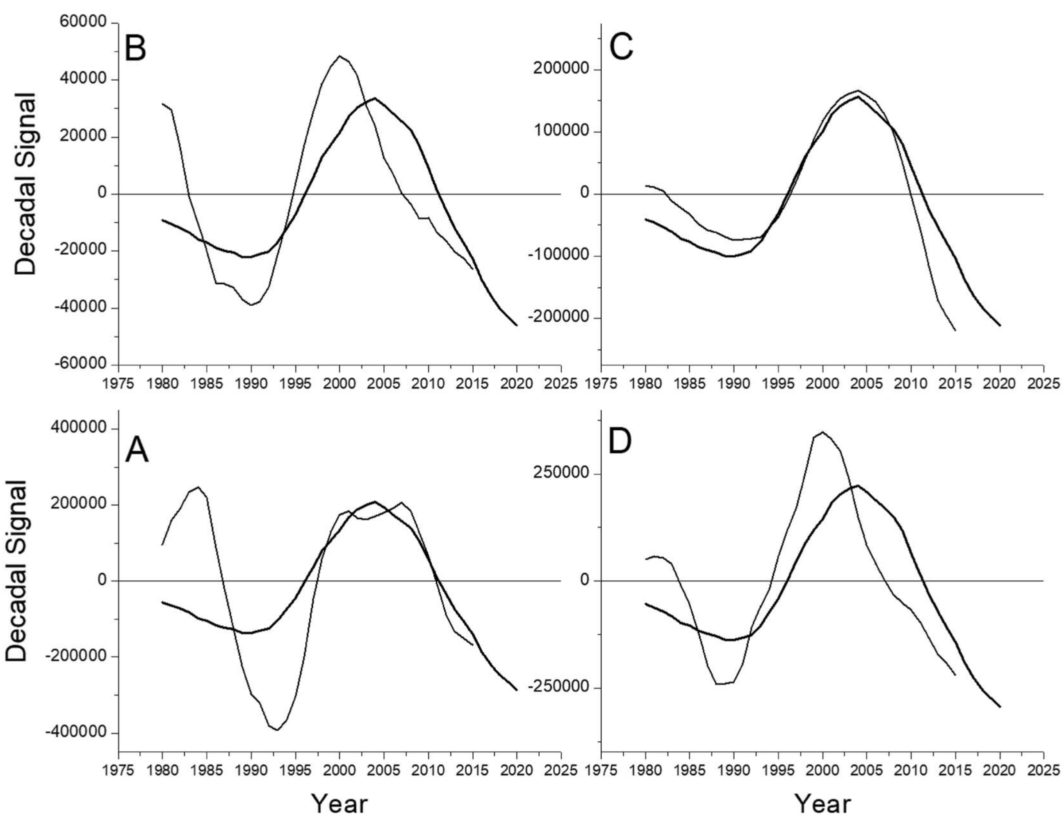

Figure 11. Observed (gray line) and predicted (bold line) long-term (decadal) production of specific crops. (A) Pastures in Colima State, (B) mango in Nayarit State, (C) lemon in Colima State, and (D) maize in Chiapas State.

Table 6. *Prediction of crop behavior for decision making in coastal management (decadal signals).*

Coastal State	Crop	Current Phase	Years in Current Phase	Expected Phase 2015–2020	Confidence	Correlation Coefficient
Baja California Sur	Chili	Negative	7	Negative	High	0.73
Nayarit	Mango	Negative	8	Negative	High	0.72
Colima	Lemon	Negative	6	Negative	Very high	0.88
Colima	Pastures	Negative	5	Negative	Moderate	0.59
Chiapas	Maize	Negative	8	Negative	High	0.73
Tamaulipas	Maize	Positive	10	Positive	Moderate	0.61
Veracruz	Sugarcane	Negative	8	Negative	Low	0.53

measured at the regional level in Mexico (coastal states). Considering the detrended and smoothed time series for the period 1980–2015, it was observed for the northern half of the country (excluding Baja California State) a negative correlation between AMO index and Rn, which means that local positive (negative) AMO phases are associated with less (more) than normal rainfall; for the southern half of the country (excluding Yucatán State) a positive correlation between AMO index and Rn was observed, producing inverse effects to those previously described. This geographically differentiated behavior responds to the spatial AMO's pattern (see Deser *et al.*, 2010). Similar behavior between AMO and rainfall has been reported in Arias, Mo, and Fu (2011) for North America; Enfield, Mestas-Nuñez, and Trimble (2001) for the United States; and in the simulation models generated by Lyu and Yu (2017) and O'Reilly, Woollings, and Zanna (2017). An explanation of the physical mechanisms underlying these interactions was proposed by Knight, Folland, and Scaife (2006) considering the multidecadal shift in the spatial position of the mean intertropical convergence zone linked with variations in the Atlantic SSTs, possibly related to the Atlantic meridional overturning circulation (Yeager and Robson, 2017).

Decadal variations in TMAX and Tmin are also modulated by AMO. For 9 of 17 coastal states significant negative correlations were found between Tmin and AMO index. Positive (negative) AMO phases were associated with decreases (increases) in the minimum temperature. This fact is important in the context of climate change because the minimum temperature is the climatic variable that showed the greatest increases in the annual analysis, with significant slopes in the linear trend in 14 of the 17 coastal states. In this sense, the synergy between global warming and climate variability—expressed by means of the AMO index—is having a very significant impact on the behavior of the Tmin; increases up to 4°C can be observed in Oaxaca state for the period 1980–2015. The TMAX experiences a behavior opposite to Tmin. This variable (TMAX) correlates positively with AMO in 11 of 17 coastal states, having maximum correlation values on the East Coast (Tamaulipas, Veracruz, and Quintana Roo). With yearly data, only 7 states showed significant increases in the slope of the linear regression model. With similar geographical characteristics (access to Pacific and Atlantic coasts), for the United States, Kurtz (2015) reported that the AMO was responsible for the atmospheric temperature increase in large areas of the country at different rates and with different influence among regions, similar to what was observed for the coastal states of Mexico in this study. Although the AMO is mainly an oceanic signal, it leads to a significant atmospheric response such as in surface air temperatures, which have been reported and analyzed by several authors using proxy records, observational data, and models (*e.g.*, Enfield, Mestas-Nuñez, and Trimble, 2001; Knight, Folland, and Scaife, 2006; Polonskii, 2008; Steinman, Mann, and Miller, 2015; Wang *et al*. 2013).

When observing the influence of the AMO on the climatic variables of the West Coast (by means of the correlational analysis) an anomalous behavior is observed with respect to the neighboring states in the sense of the correlation coefficient in Baja California and Michoacan in Rn and TMAX. A similar behavior can be observed on the East Coast for the states of Yucatan and Quintana Roo for the three climatic variables analyzed. This fact suggests that the response of climate variables is not only influenced by the temporal behavior and spatial pattern of the AMO, but also the presence of regional effects possibly associated with oceanic phenomena such as the marked influence of the California current on the west part of the state of Baja California, the warm pool in front of Michoacán, or the dynamics of the Caribbean Sea over Quintana Roo. Also, topography, geomorphology, littoral extension, and natural vegetation cover could have an important influence among contiguous states.

From a methodological point of view, it is important to note the relevance of exploring nonlinear methods to extract trends and different smoothing schemes to obtain the low-frequency signals of time series of climatic variables. The use of linear methods for the extraction of the trend, in this study, was only justified for the agricultural series where there is a clear ascending behavior, as in the total production where the values of the coefficient of determination were generally high, oscillating between $R^2 = 0.529$ and $R^2 = 0.897$ with a mean value of $R^2 = 0.743$.

Increasingly, the global importance of the influence of climate variability and change in the agricultural sector is recognized around the world (Porter *et al.*, 2014). Studies in socially and environmentally highly vulnerable regions for these phenomena, as in Africa (Stige *et al.*, 2006), India (Khan *et al.*, 2009), or China (Liu *et al.*, 2014), demonstrate convincingly the importance of climate variability in local and regional agriculture. The regional, long-term changes observed in the rainfall and temperature patterns in response to the influence of AMO observed in Mexico's coastal states have important consequences on agricultural production in general and for specific crops in particular, and therefore have a high social impact and are important for national food security.

The total agricultural production (considering all the crops) in Mexican coastal states displays increased volumes and year-to-year variation since 1980, possibly related to advances in technology (*e.g.,* irrigation technologies, application of fertilizers and pesticides, improving crop genetics) or governmental actions (*e.g.,* subsidies, public policies, tax agreements, replacement programs for agricultural machinery), but there is also a clear climatic influence. All the coastal states analyzed showed significant correlations with AMO index at yearly scale; the correlation coefficients were between $r = 0.5$ and $r = 0.8$. For the decadal time series, significant correlations were found in 12 of 17 coastal states, with values from $r = 0.8$ to $r = -0.7$. In the long-term context, rainfall is the main source of soil moisture and probably the climatic variable that most influences crop productivity, along with changes in temperature that can alter crop development (Rosenzweig and Hillel, 2008). In this study the influence of the AMO on these climatic variables (Rn, TMAX, and Tmin) was demonstrated (see Table 3). The mechanisms through which these climatic variables act on agriculture production should be the subject of detailed studies at the regional level (for each coastal sate) and by type of crop in the country.

The results obtained in this study show an important influence of the AMO in the production of specific crops at decadal scale in all coastal states. In more than half of the coastal states, after removing the linear production trend, the decadal component of the production signal (smoothed signal) had a greater importance than the annual variation (residuals), defined in terms of the standard deviation of both signals. On average the residuals explain 64% of the crop production variability and the decadal signal explains 56% of the residuals variability. The following products should be highlighted because of the high levels of correlation obtained: chili in Baja California Sur, mango in Nayarit, lemon and pastures in Colima, maize in Chiapas and Tamaulipas, and sugarcane in Veracruz (see Figure 11 and Table 5). Most of the significant correlations found were positive (20 of 33), but there is no clear relationship between agricultural products and cultivation places that allows generalizations about how the AMO determines the behavior of particular crops.

For the three products that were planted in most states (maize, sugarcane, and pastures), the following patterns were observed: (1) the maize presented positive correlations with the AMO in all the states in which it was analyzed except Tamaulipas; (2) sugarcane showed negative correlations except in Veracruz; and (3) pastures responded with a positive relationship to the AMO in all states where this crop was analyzed, except in Oaxaca, where a low significant correlation was found. A couple of unique examples should be mentioned: (1) according to the results obtained, the AMO does not influence significantly the production of coffee in Chiapas, grapes in Sonora, and tomato in Sinaloa, the only three crops without a significant correlation with the decadal AMO index; one possible explanation for these last two products is the fact that the level of agricultural technology used in those states is among the most sophisticated in the country, which significantly reduces the influence of climate; and (2) only in two states were berry production considered, strawberry in Baja California and blackberry in Michoacan. In both states these products show negative correlations with the AMO (approximately $r = -0.52$ in both states) and very high positive correlations with Tmin ($r = 0.93$ and $r = 0.91$, respectively); when the AMO is in positive (negative) phase, Tmin as well as berry production decreases (increases). See Tables 4 and 5 as references.

The use of predictive models of probabilistic/statistical character has the advantages of simplicity, low cost, and accessibility. On the other hand, it has the disadvantage of not considering the underlying physics of the phenomena studied, as the process-based climactic models do. Besides the considerations about the filtering process and limited record lengths reported by Vincze and Jánosi (2011), the proposed models to simulate and forecast the AMO index (decadal and yearly behavior) presented in this paper can be considered good enough to propose actions related to agricultural activity in the field of management of the Mexican coastal states (see Table 6). Given that the behavior of the AMO influences—in a spatially nonhomogeneous way—the climatic variables of the different coastal states and these variables, in turn, determine to a greater or lesser extent the behavior of specific crops, even knowing, in a general way, the expected climate variability will give an advantage to this productive activity so relevant to the coastal states of Mexico.

The accuracy measures used to evaluate the performance in hindcast (see Figures 8 and 9) showed greater similarity to the simulated series using the moving average plus discrete simulation for the yearly part (residual); as an element of innovation, the use of the fractal dimension of the series to validate the level of irregularity of the observed and forecasted signal showed good results ($D = 1.84$ for the long AMO index time series and $D = 1.86$ for the simulated). The yearly measured information for the AMO index in 2016 and 2017 showed a difference with the forecast of 25% (overprediction) in 2016 and 35% (underprediction) in 2017; similar error percentages (around 30%) were found between the forecast of selected crops and the measured values for 2016. The influence of the AMO on agricultural productivity in the long term (decadal scales) has a greater potential for use in coastal management. Although the analysis carried out up to the year 2020 (see Table 6) showed good results, the behavior and the correlation between the agricultural signals and the AMO could be extended to longer periods of time (see Figure 11).

CONCLUSIONS

This research has proven that near-term climatic variability (1 y to decades) represented by the AMO affects regionally the agricultural productivity of the coastal states of Mexico and several of the most important crops of each state.

The analysis performed at yearly and decadal scales showed the influence of the AMO on the three climatic variables considered (Rn, TMAX, and Tmin), Tmin being the climatic variable with which greater numbers of significant correlations presented using yearly values for the period 1980–2015 (9 of 17); at the decadal scale the three climatic variables showed significant correlations with the AMO: 13 of 17 states with Rn and 14 of 17 with TMAX.

In all coastal states the total agricultural production correlates in a significant way with the AMO at a yearly scale and, at a decadal scale, only in 12 of 17, with correlation coefficients ranging from $r = 0.8$ in Baja California to $r = -0.7$ in Oaxaca. Considering the specific crops in each coastal state, 42 of 51 correlated significantly with the AMO index at a yearly scale and 34 of 51 at decadal. The number of significant correlations found between the selected crops and the climatic variables were 32 with Rn, 33 with TMAX, and 28 with Tmin with decadal time series.

The mechanisms by which the AMO and the climatic variables determine the production of the crops analyzed should be the subject of detailed studies for each state and product. These studies should consider the specific biological aspects of each crop, the characteristics of the soil, and local climatic conditions.

The simulated AMO index proposed in this paper generated satisfactory results for its use in coastal management, with errors of about 30% in the yearly forecast, and with the potential to know several years ahead of time the phase in which the different crops analyzed will be located.

As future research lines, the authors have begun the study of the effect of other modes of climatic variability of the order of decades relevant to fisheries, forestry, and agriculture in Mexican coastal states, such as the PDO and the North Atlantic Oscillation. Also, the use of other statistical methodologies like principal component analysis could be very useful in this kind of research.

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