Prediction of MJ rainfall season using CCA models

ERIC J. ALFARO[1,2,3], HUGO G. HIDALGO[1,2], NATALIE P. MORA[1]

Abstract

The prediction of the May-June (MJ) precipitation as the first peak of the rainy season is important in the Central American isthmus because wetter (drier) MJ seasons tend to be associated with early (late) onsets of the rainy season on the Pacific slope. Having a late start of the rains, followed by a drier season in MJ in conjunction with a deep Mid-Summer Drought (MSD), would affect significantly key socioeconomic sectors in the isthmus like hydropower generation, water supply for human consumption (as main cities in the isthmus are located on the Pacific slope) and agriculture. Using 162 gauge stations, we built skillful Canonical Correlation Analysis (CCA) prediction models for MJ season as the first peak of the rainy season, using as predictands monthly rainfall accumulations and Standardized Precipitation Index (SPI) values over Central America. Sea Surface Temperature anomalies (SSTA) were used as predictors handling a domain bounded by 63° N-10° S and 152° E-15° W, along with the Palmer Drought Severity Index (PDSI) values covering the isthmus. Leading times from December to April were explored in the predictor fields. CCA models, using February´s SSTA and April´s PDSI showed significant skill values for the prediction of MJ accumulations and the SPI over an important portion of Central America. Models´ loadings showed that warmer (cooler) Eastern equatorial SSTAs in the Pacific along with cooler (warmer) SSTAs in the Tropical North Atlantic (TNA) during February, tend to be related with drier (wetter) conditions in almost all the isthmus during the next MJ season. It is suggested that Sea Surface Temperature (SST) mode could modulate MJ precipitation in Central America influencing the position of the Intertropical Convergence Zone (ITCZ) and the strength of the trade winds. Additionally, it was observed that drier (wetter) soil moisture (PDSI) in April tends to be related with drier (wetter) precipitation conditions in almost all the isthmus during next MJ season.

KEYWORDS: SEASONAL CLIMATE PREDICTION, CENTRAL AMERICA, STANDARDIZED PRECIPITATION INDEX, STATISTICAL MODELS, PALMER DROUGHT SEVERITY INDEX

Resumen

Predecir la precipitación durante mayo-junio (MJ), como primer pico de la estación lluviosa en el istmo de América Central, es muy importante ya que se ha observado que condiciones más o menos húmedas durante MJ tienden a estar precedidas por inicios tempranos o tardíos de la época lluviosa. Un inicio tardío de las lluvias, por ejemplo, seguido de condiciones más secas que lo normal durante MJ y por un periodo posterior de veranillo o canícula intensa, puede afectar significativamente sectores socioeconómicos clave en el istmo como la generación hidroeléctrica, el abastecimiento de agua potable o la agricultura. En este trabajo se usaron los datos de 162 estaciones pluviométricas para construir modelos predictivos para MJ como primer pico de la estación lluviosa, usando el Análisis de Correlación Canónica (ACC). Los aspectos a predecir durante MJ son los acumulados de lluvia y el Índice Normalizado de Precipitación (INP) en América Central. Se usaron dos campos como predictores. El primero fue las anomalías de la temperatura superficial del mar (TSM) observada en el dominio 63° N-10° S y 152° E-15° W. El segundo fue el Índice de Severidad de Sequía de Palmer (ISSP), cubriendo la totalidad del istmo. Se estudió el potencial predictivo de estos dos campos desde diciembre hasta abril. Los modelos del ACC, usando las anomalías de la TSM en febrero y el ISSP en abril, evidencian una buena habilidad predictiva de los acumulados y del INP durante MJ, en una región importante de América Central. Los resultados mostraron que condiciones más cálidas (frías) en las anomalías de

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[1] Center for Geophysical Research, University of Costa Rica.

[2] School of Physics, University of Costa Rica.

[3] Center for Research in Marine Sciences and Limnology, University of Costa Rica.

Emails: erick.alfaro@ucr.ac.cr, hugo.hidalgo@ucr.ac.cr, natali.morasandi@ucr.ac.cr.

la TSM del Pacífico ecuatorial del este, junto con condiciones más frías (más cálidas) en el Atlántico Tropical Norte durante febrero, tienden a estar correlacionadas con periodos más secos (húmedos) durante el siguiente bimestre de MJ en prácticamente todo el istmo. Lo anterior sugiere que la TSM podría modular la lluvia durante MJ en América Central al influenciar la posición de la Zona de Convergencia Inter-Tropical y la magnitud de los vientos alisios. En forma adicional, se observó que condiciones más secas (húmedas) en la humedad del suelo (ISSP) durante abril, tendieron a estar relacionadas con periodos de lluvia más secos (húmedos) en casi todo el istmo durante el siguiente periodo de MJ.

PALABRAS CLAVE: PREDICCIÓN CLIMÁTICA ESTACIONAL, AMÉRICA CENTRAL, ÍNDICE NORMALIZADO DE PRECIPITACIÓN, MODELOS ESTADÍSTICOS, ÍNDICE DE SEVERIDAD DE SEQUÍA DE PALMER.

1. Introduction

Amador, Alfaro, Lizano, and Magaña (2006); Amador et al. (2016a); and Taylor and Alfaro (2005), describe extensively the key drivers of the Central American climatic variability. Those works explain that the most dominant synoptic influence is the North Atlantic subtropical high. Subsidence associated with the spreading of the North Atlantic subtropical high to the North American landmass dominates during boreal winter, as do the strong easterly trades found on its equatorward flank. Coupled with a strong trade-winds inversion, a cold ocean and reduced atmospheric humidity, the region is generally at its driest condition during the winter. With the onset of boreal spring, however, the subtropical high moves offshore and trade wind intensity decreases, with downstream convergence. The variation in the strength of the trades is an important determinant of climate throughout the year for Central America. There is also a weak trade-winds inversion with altitude, the ocean warms and atmospheric moisture is abundant. The region is consequently at its wettest in the boreal late spring-summer-early autumn half-year. Besides the subtropical high, other significant synoptic influences include:

a) The seasonal migration of the Intertropical Convergence Zone (ITCZ) – mainly affecting the Pacific side of southern Central America (Hidalgo, Durán-Quesada, Amador, & Alfaro, 2015).

b) The intrusions of polar fronts, originated at mid-latitudes, which modify the boreal dry winter and early spring climates of the northern Caribbean and north Central American regions (Zárate-Hernández, 2013).

c) The westward propagating tropical disturbances (Amador, Alfaro, Rivera, & Calderón, 2010) – a summer seasonal feature associated with much rainfall, especially over the Caribbean region.

In addition, the warm pools of the Americas constitute an important source of moisture for the North American Monsoon System (Wang & Enfield, 2001, 2003).

Alfaro (2002) calculated the mean dominant annual cycles in the Central American region using Empirical Orthogonal Functions (EOFs) analysis for 94 daily rain gauge stations dataset. This allowed the determination of some important aspects of this cycle such as the start and end of the rainy season and the Mid-Summer Drought (MSD; Magaña, Amador, & Medina, 1999). Some latitudinal variations were found in these variables. The region is dominated by one mean annual cycle that captures 72% of the variance. This cycle implies mainly a combination of systems and parameters that involves the latitudinal migration of the ITCZ, the seasonal variation of solar radiation that influences latent heat flux, and the low level wind and its interaction with local orography. The second annual cycle in importance explains only 8% of the variance, and it dominates in stations located over the Caribbean Coast of Honduras, Costa Rica and Panama. In the inter-annual scale, the wettest (driest) years in the region are dominated, in general, by warmer (colder) sea surface temperatures in the tropical Atlantic compared to the eastern tropical Pacific.

Regularly, in Central America, Regional Climate Outlook Forums (RCOFs) have taken place in an effort to predict precipitation accumulations for the following target seasons: May-June-July (MJJ), August-September-October (ASO) and December-January-February-March (DJFM) (Donoso & Ramírez, 2001; Garcia-Solera & Ramirez, 2012). Currently, the RCOFs also include Outlooks for the Standardized Precipitation Index or SPI (WMO, 2012). Our objective is to build skillful Canonical Correlation Analysis (CCA) prediction models for the May-June (MJ) season, the first peak of the rainy season (Alfaro, 2002), using as predictands monthly rainfall accumulates and SPI values over Central America. The prediction of the MJ as the first peak of the rainy season is important because wetter (drier) MJ seasons tend to be associated with early (late) onsets of the rainy season. The early summer rainfall tends to be rather heterogeneous spatially across the Caribbean (Alfaro, 2002; Jurya & Malmgren, 2012).

So, having a late start of the rains, like in 2015 (Amador et al., 2016b), followed by a significantly drier than normal season in MJ, in conjunction with a deep MSD in July and August (Alfaro, 2014; Hernandez & Fernandez, 2015; Solano, 2015; Maldonado, Rutgersson, Alfaro, Amador, & Claremar, 2016), can affect significantly key socioeconomic sectors in Central America. Some of these socioeconomic sectors are hydropower generation, water supply for human consumption (as main cities in the isthmus are located on the Pacific slope) and agriculture.

Previously, Alfaro (2007) used a statistical model based on CCA to explore the predictability of the rainfall season in Central America, including MJJ. Explanatory variables were seasonal Atlantic and Pacific Ocean Sea Surface Temperature (SST) for the region inside 112.5° E-7.5° W and 7.5° S-62.5° N, during 1958-98. He found that for the early rainfall season, MJJ, positive (negative) tropical Atlantic SST anomalies were associated with positive (negative) rainfall anomalies over a broad area located at the north of the studied region. The model results were cross-validated, showing significant skill values over an important portion of the studied region.

Fallas-López and Alfaro (2012a) used the statistical technique of contingency table analysis (Alfaro, Soley, & Enfield, 2003) to produce predictive schemes associated with rainfall in Central America. As a first step, a principal component analysis was used to produce indices, using daily weather records from 146 stations. Two rainfall components associated with Central American Pacific and Caribbean slopes were obtained.

Keeping in mind that one of the work objectives was to support the RCOFs process; the predictive schemes used by Fallas-López and Alfaro (2012a) in the rainfall predictions included the MJJ trimester. Different climate indices were used as predictors, which were associated with several climate variability sources that influence the climate patterns in Central America. This was done using a lead-time of one or two bimesters previous to the predicted season.

Useful predictive schemes were found by Fallas-López and Alfaro (2012a) for practically all the relationships previously mentioned. Notice that most of the Central American climate variability could be explained by the El Niño – Southern Oscillation (ENSO; e.g. inter-annual variability) and by the Atlantic Multidecadal Oscillation indices (AMO; Enfield, Mestas-Nuñez, & Trimble, 2001, mainly, e.g. multidecadal variability).

Also, Fallas-López and Alfaro (2012b) elaborated a seasonal climate prediction scheme for Central America based on CCA, for the same seasons used by Fallas-López and Alfaro (2012a). SSTs from the oceans around the isthmus were used as predictors. Precipitation accumulations were used as the predictand field, using 146 meteorological stations located in Mesoamerica with monthly records from 1971 to 2000. The sea surface temperature area used is 60° N - 60° S and 270° E - 0° W. In general, the SST associated with the previous quarter was used for every predicted season, including MJJ. Some of the identified modes in the analysis display spatial patterns associated with known climate variability sources as ENSO, AMO and Pacific Decadal Oscillation (PDO; Mantua, Hare, Zhang, Wallace, & Francis, 1997), meaning that CCA is useful for seasonal prediction in Central America. The predictor patterns could be explained by studying their association with different climate indices.

As explained by Maldonado, Alfaro, Fallas, and Alvarado (2013), meetings in Central America with different socioeconomic stakeholders takes place after every RCOFs to translate the probable climate impacts from predictions. From the feedback processes of these meetings, it has emerged that extreme event predictions, like droughts or floods, are necessary for different sectors. As shown by their work of the ASO season, these predictions can be tailored using CCA, showing that extreme events in Central America are influenced by interannual variability related to ENSO and decadal variability associated mainly with AMO and PDO. The previously mentioned socioeconomic sectors, regularly participate at RCOFs meetings, in the called Applications Fora. Therefore, providing them with an Outlook based on the SPI can help in the managing and planning activities for the upcoming season.

2. Methodology

A dataset of 162 gauge stations with monthly observations of precipitation provided by the meteorological services of Central America were used. Their location is shown in figure 1. Since each meteorological station has distinct time coverage, a common time series length is determined according to the stations' data availability. Therefore, the selected time series length covers from January 1979 to December 2008 (30 years). Gaps in the time series were filled using the methodology described by Alfaro and Soley (2009), which combines autoregressive models and EOFs methods.

From the gauge stations data, we calculated the monthly rainfall accumulations and the SPI. According to the World Meteorological Organization (WMO, 2012), the SPI is based on the probability of precipitation on any time scale. The probability of the observed precipitation is then transformed into an index. The SPI was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, streamflow and reservoir storage reflect the longer-term precipitation anomalies (WMO, 2012). The SPI calculation at any location is based on its long-term precipitation record over

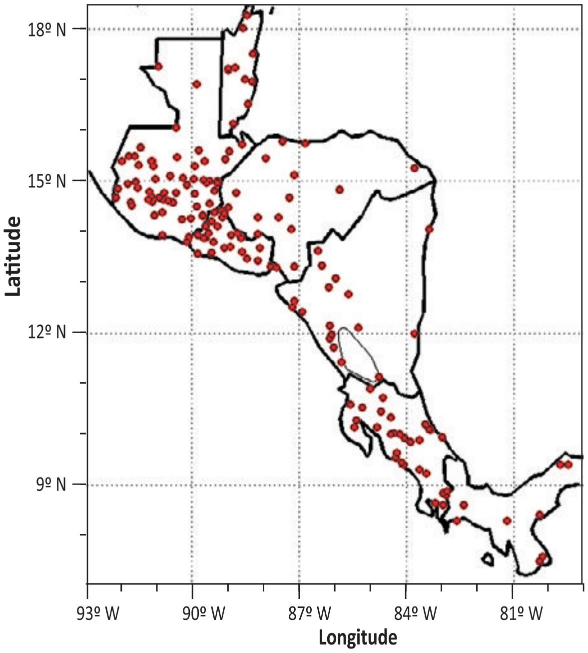

Figure 1. Location of the rain gauge stations used (red dots).

a desired period of time. This long-term record is fitted into a probability distribution, which is then transformed into a normal distribution, so that the mean SPI for the location and desired period is zero. Positive SPI values indicate precipitation totals greater than the median precipitation, and negative values indicate totals less than the median precipitation. Because the SPI is normalized, wetter and drier climates can be represented in the same way; thus, wet periods can also be monitored using the SPI (WMO, 2012).

As stated by Maldonado et al. (2016), the extended reconstructed sea surface temperatures were used (ERSSTv3b; Xue, Smith, & Reynolds, 2003; Smith, Reynolds, Peterson, & Lawrimore, 2007). The SST anomalies are constructed using a combination of observed data along with models and historical sampling grids. This global database has a horizontal resolution of 2.5° by 2.5°. The domain bounded by 63° N - 10° S and 152° E - 15° W is taken into account in order to capture the signal of the most important climate variability modes of the Central American isthmus, such as ENSO, PDO, AMO, the North Atlantic Oscillation (NAO; Hurrell & Deser, 2009), and the Tropical North Atlantic (TNA; Enfield, Mestas, Mayer, & Cid-Serrano, 1999). These modes have shown to be relevant in terms of rainfall variability during the MJ season (Fallas-López & Alfaro, 2012a, 2012b).

As a predictor, we used also the monthly Palmer Drought Severity Index (PDSI), calculated according to Dai, Trenberth, and Qian (2004). To build the PDSI, Dai et al. (2004) used the Climate Research Unit (CRU) surface air temperature data and the precipitation data were acquired from the National Centers for Environmental Prediction (NCEP) Climate Prediction Center, and were created by gridding data using the optimal interpolation scheme. For field water-holding capacity (awc), they used a soil texture–based water-holding-capacity map (Webb, Rosenzweig, & Levine, 1993). This global database has a horizontal resolution of 2.5° by 2.5°. From this PDSI database, we selected the grid points covering the Central American isthmus.

The PDSI and SST anomalies are used as predictors in the CCA models. CCA is used as a predictive tool in a classic scheme, i.e. predictor fields lead to the predictand ones.

Consequently, following Maldonado et al. (2013, 2016), CCA is employed to find the relationship between SSTs monthly anomalies (SSTA) and PDSI normalized fields (field X) with the MJ seasonal rainfall accumulations and SPI fields of each gauge station used in this study as predictands (each index would be the field Y, for the corresponding model).

In other words, we looked for a statistical relationship between the large and the regional scale features of the SSTA or PDSI, and the characteristics of the rainfall accumulations or SPI in each of the stations (local scale). Experiments using the junction of SSTA and PDSI were conducted, but they did not provide any additional information compared to using the predictor fields separately. We also conducted experiments splitting the precipitation data in a model calibration period (depended period) and in another one to verify the predictions (independent period), but in this case the results also did not show improvement, mainly because the records are relatively short records for the models calibrations.

The above CCA methodology is based on Maldonado et al. (2013, 2016) and is implemented and summarized as follows: the fields (SSTA or PDSI as predictors, and accumulations or SPI fields as predictands) are first reduced by means of EOFs analysis to ensure stability of the CCA parameters.

A maximum of 10 EOFs and CCA modes in the filtering stage are allowed. This threshold is suggested here to avoid over-parameterization. The optimal combination of EOFs and CCA modes are calculated by means of the goodness index (mean Kendall τ). Notice that any set of EOFs will produce unique CCA modes for that specific set. Once the best combination of EOFs is determined, that set of EOF is capturing the maximum variability in each field (X and Y), separately, for each specific CCA model (MJ accumulations and SPI).

The minimum number of EOFs between both fields, however, first determines the maximum possible number of CCA modes. Then, with the goodness skill, the maximum number of CCA modes is found for the best fit to avoid any over-parameterization in the model $Y_1 = b^T \cdot X$, where the elements of b are the ordinary least-squares regression coefficients computed with CCA, and Y_1 is the predicted value of Y. The Kendall τ is computed using cross-validation models with a 5-month window from 1979–2008 for each station in all the models. This metric also allows identifying the best month to predict any of the MJ accumulates and SPI fields. It is worth mentioning that the resulting models would not necessarily have 10 EOF and CCA modes. Monthly SSTA or PDSI fields from December to April were analyzed as potential predictors; thus, 4 months before the MJ season were studied for a classic prognosis scheme (lead time). Each experiment was conducted with and without the persistence observed in March-April (MA), prior to MJ accumulates and SPI. The CCA models were calculated using the Climate Predictability Tool or CPT, elaborated by the International Research Institute for Climate and Society (IRI; Mason & Tippett, 2016, http://iri.columbia.edu/our-expertise/climate/tools/cpt/). The CPT tool was chosen because it is currently in use for operative seasonal climate prediction in Central America. The performance of the CCA model predictions was evaluated using the LEPS score (Wilks, 2011).

One of the main concerns about the former predictive schemes by Alfaro (2007), and Fallas and Alfaro (2012a, 2012b), is that they included the month of July in the predictand. Compared with May and June as a season, the extra month (of July) is associated with reinforcement of the trade winds and of the Caribbean Low Level Jet or CLLJ (Amador, 2008) in addition to the MSD in the Eastern Tropical Pacific (Magaña et al., 1999; Herrera, Magaña, & Caetano, 2015; Maldonado et al., 2016). For this reason, here we do not include July in the predictive schemes associated with the first peak of the rainy season, maintaining just -MJ as the predictand target season. Another important difference is that Alfaro (2007) and Fallas-López and Alfaro (2012a, 2012b) used the previous two or three monthly average, as the leading predictor, and what we propose here is to use the monthly values separately, to better identify the potential sources of variability. Nevertheless, results from Alfaro (2007) and Fallas-López and Alfaro (2012a, 2012b) showed that the use of CCA models in Central America could also help in the RCOF tasks, providing an objective analysis tool for the predictive relationships found in the region.

The Niño 3.4 index (Trenberth, 1997) was obtained from the National Oceanic and Atmospheric Administration (NOAA; http://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices) as well as the AMO index (http://www.esrl.noaa.gov/psd/data/correlation/amon.us.long.data). The PDO index was provided by the University of Washington (http://research.jisao.washington.edu/pdo/PDO.latest). We also used horizontal wind data at 925 hPa, provided by the NCEP and the National Center for Atmospheric Research (NCAR) reanalysis (Kalnay et al., 1996; Kistler et al., 2001), which has a horizontal resolution of 2.5° by 2.5°. The wind data is used to calculate the CLLJ index, as in Amador (2008), Amador et al. (2010), and Maldonado et al. (2016).

3. Results and Discussion

The results from the different models adjusted performance are summarized in figure 2. It presents the box plots of the MJ season LEPS cross validation at the different stations shown in Fig. 1. From this figure, some points could be enhanced based on the observed median values. In general, compared with MJ accumulations (Figs. 1a, c), better cross validation results were obtained for MJ SPI (Figs. 1b, d). The inclusion of the MA persistence improved the predictability of the models (Figs. 1c, d vs. Figs. 1a, b). Models adjusted in Fig. 1d, showed that using PDSI as predictor increases predictability for shorter lead times, with April having the highest median values. Better predictions were achieved using SST as predictor in boreal winter, with February having the highest median values. A decrease in the median predictability in March was observed in all models adjusted using SSTA as predictor.

Fig. 3 shows the spatial distribution of LEPS scores using SST in February as the predictor field. Fig. 3a is for the MJ accumulations, and Fig. 3b is for MJ SPI. The best combination of X, Y and CCA modes for accumulations and SPI were 10, 5, 1 and 10, 6, 1, respectively. Both models considered the persistence observed in MA and were optimized for 1 CCA mode. Correlations for the CCA leading modes are 0.89 and 0.88 respectively, with an associated p-value < 0.01 in both cases. Except for some few stations located near the El Salvador-Guatemala border and in Nicaragua Pacific north coast, positive values were observed across the isthmus, showing good predictability skill for the adjusted models.

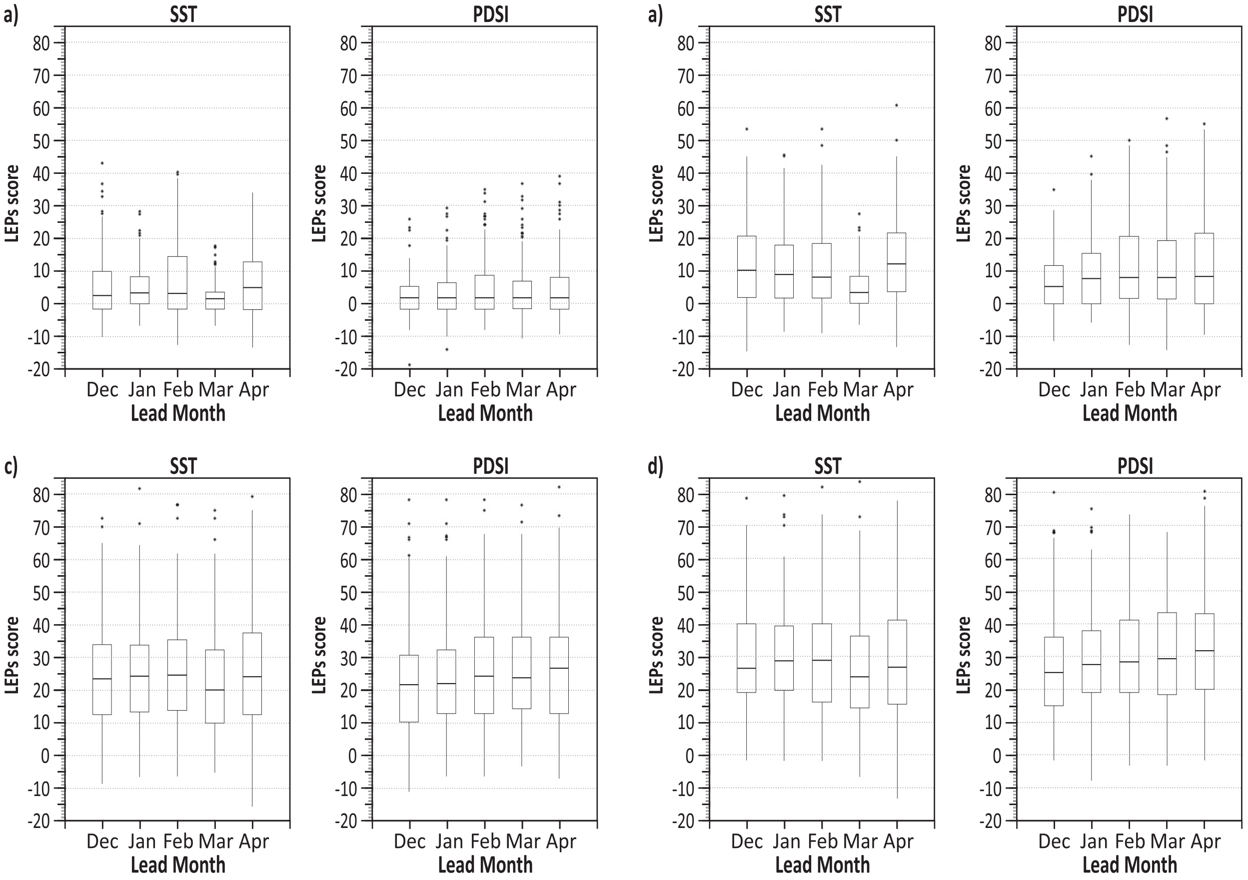

Figure 2. Box plots of the MJ season median LEPS scores for the different adjusted CCA models, comparing the use of SST and PDSI fields as predictors. Values are from the cross validation at the different stations presented in Fig. 1. Results in a) and b) do not consider the persistence observed in MA, as c) and d) do. Left panels, a) and c), are for MJ accumulates and the right panels b) and d), are for MJ SPI as predictand values. The boxplots represent the variability of the LEPS scores for the 162 stations.

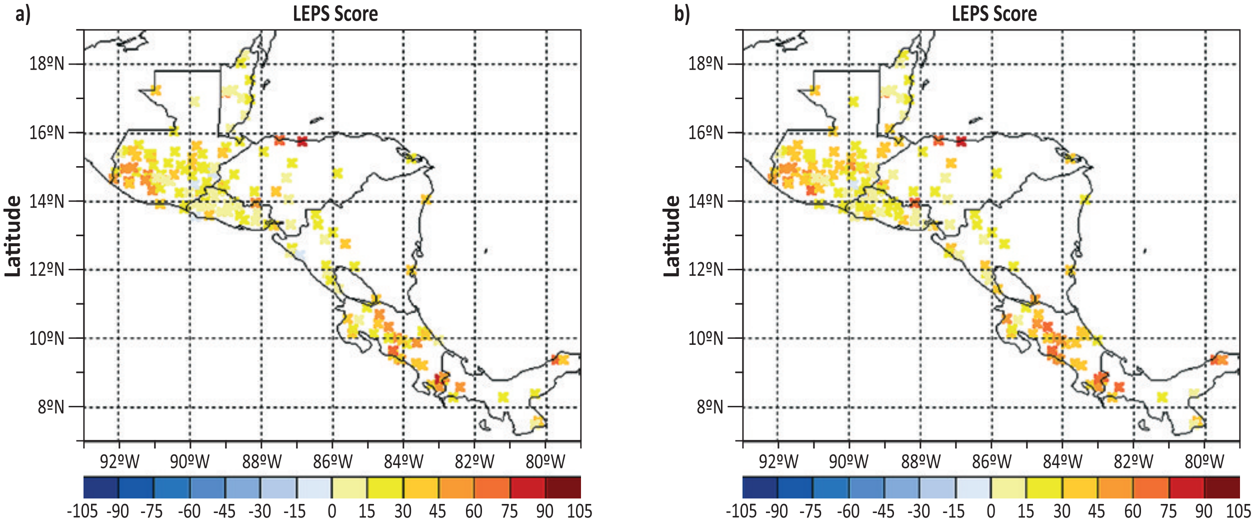

Figure 3. Spatial distribution of LEPS scores using SST in February as predictor field for MJ a) accumulates and b) SPI. Both models considered the persistence observed in MA. Models associated Kendall´s τ was 0.138 and 0.126 respectively.

coast, positive values were observed across the isthmus, showing good predictability skill for the adjusted models.

Figure 4 is the equivalent of figure 3, but for LEPS scores using PDSI in April as predictor field. As for figure 3, both models considered the persistence observed in MA and were optimized for 1 CCA mode. The best combination of X, Y and CCA modes for both, accumulates and SPI, were 2, 7, 1. Correlations for the CCA leading modes are 0.78 and 0.77, respectively, with an associated p-value < 0.01 in both cases. Positive LEPS score were also observed for almost all the stations in Central America.

The loadings for the first CCA modes that optimized the models are shown in figure 5, using February

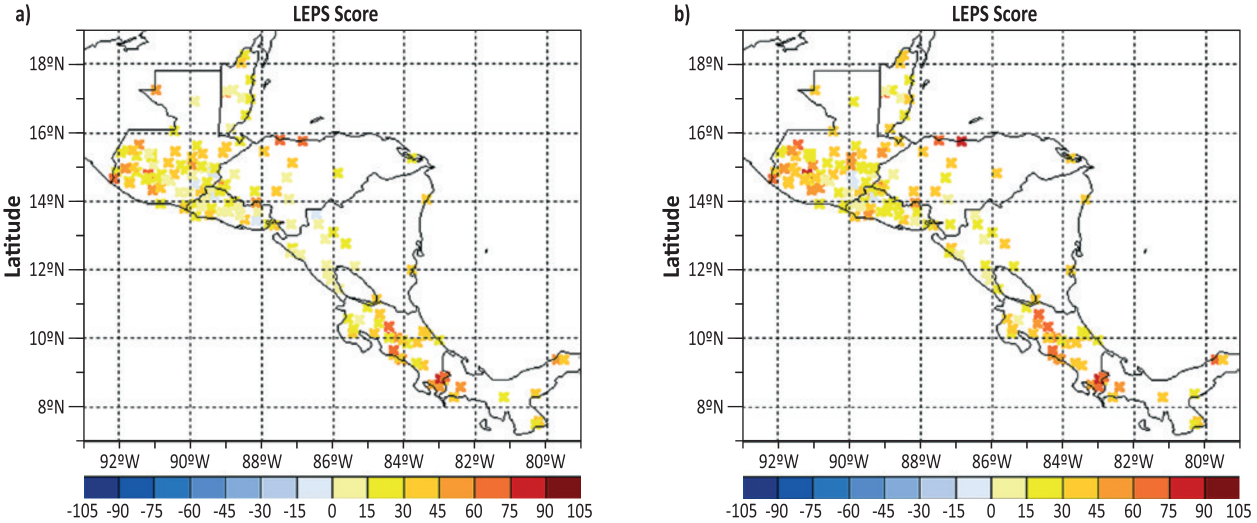

Figure 4. Spatial distribution of LEPS scores using PDSI in April as predictor field for MJ a) accumulations and b) SPI. Both models considered the persistence observed in MA. Models associated Kendall´s τ was 0.185 and 0.183 respectively.

SSTA as predictor and MJ accumulations and SPI as predictands. Please note that correlations between loading time series are negative in Figs. 5a,c and 5b,d. It is observed that warmer (cooler) Eastern equatorial SSTAs in the Pacific, along with cooler (warmer) SSTAs in the TNA during February, tends to be related with drier (wetter) conditions in almost all the isthmus during next MJ. Warmer (cooler) TNA conditions are associated with weaker (stronger) trade-winds, and this favors (does not favor) the formation of deep convective mesoscale systems in the region (Alfaro, 2007, 2002). Additionally, this mode also shows that SST loadings in the eastern equatorial Pacific are positively correlated with the phases of the North Pacific modes of variability, according to Hartmann (2015). Hidalgo et al. (2015) explain that warmer (cooler) conditions in the equatorial Pacific delay and maintain the ITCZ in western-southern (eastern-northern) positions, offshore (nearshore) of Central America, decreasing (increasing) the stability over the isthmus, and this does not favor (favors) the formation of deep convective mesoscale systems in the region (Hidalgo et al., 2015). This response could be enhanced during the positive (negative) phases of the North Pacific SST modes of variability (Gershunov & Barnett, 1998; Muñoz, Wang, & Enfield, 2010; Fallas-López & Alfaro, 2012a; Hartmann, 2015). So, this mode could modulate MJ precipitation in Central America, influencing the position of the ITCZ and the strength of the trade winds.

As in figure 5, figure 6 shows the loadings for the first CCA modes that optimized the models, using April PDSI as predictor and MJ accumulations and SPI as predictand. Notice that correlations between loading time series are negative in Figs.

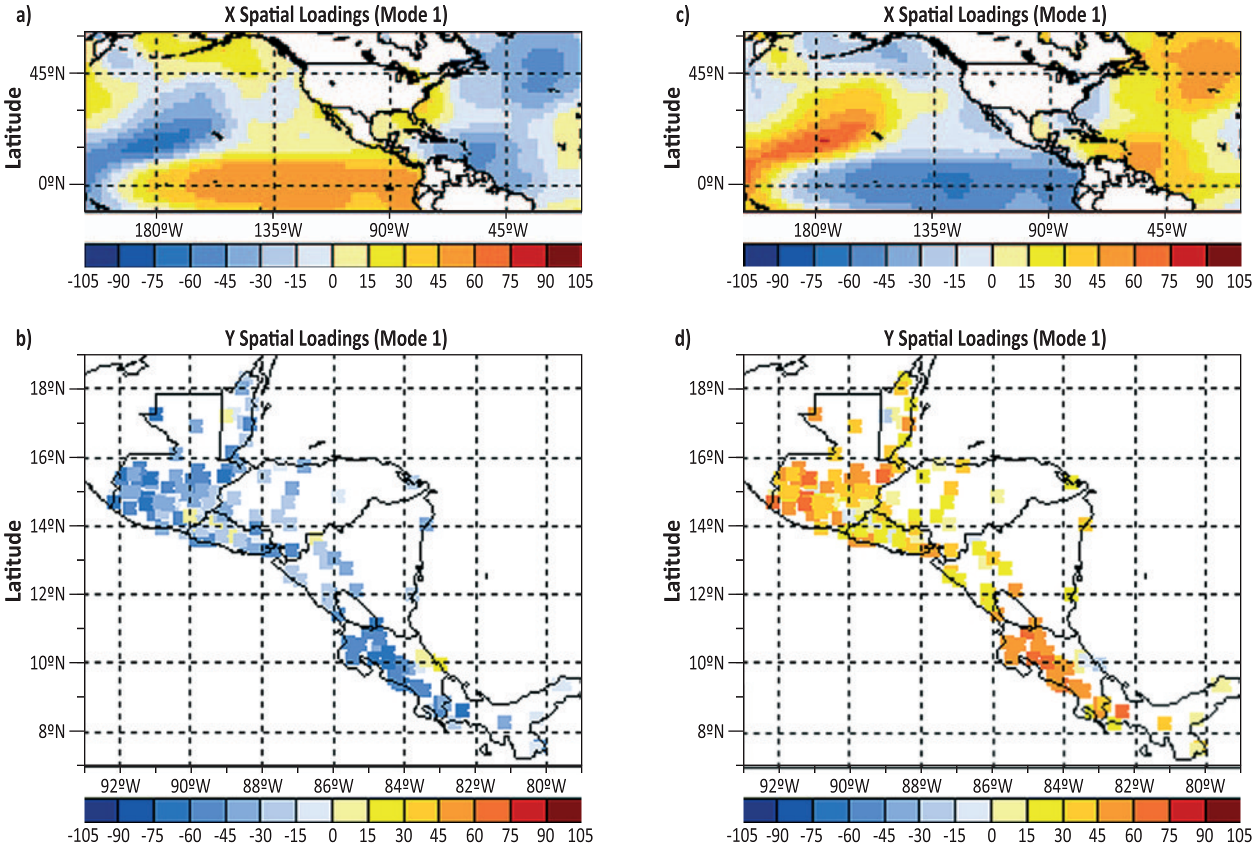

Figure 5. Loadings for the first CCA modes that optimized the models, using February SSTA as predictor (a and c) and MJ b) accumulates and d) SPI.

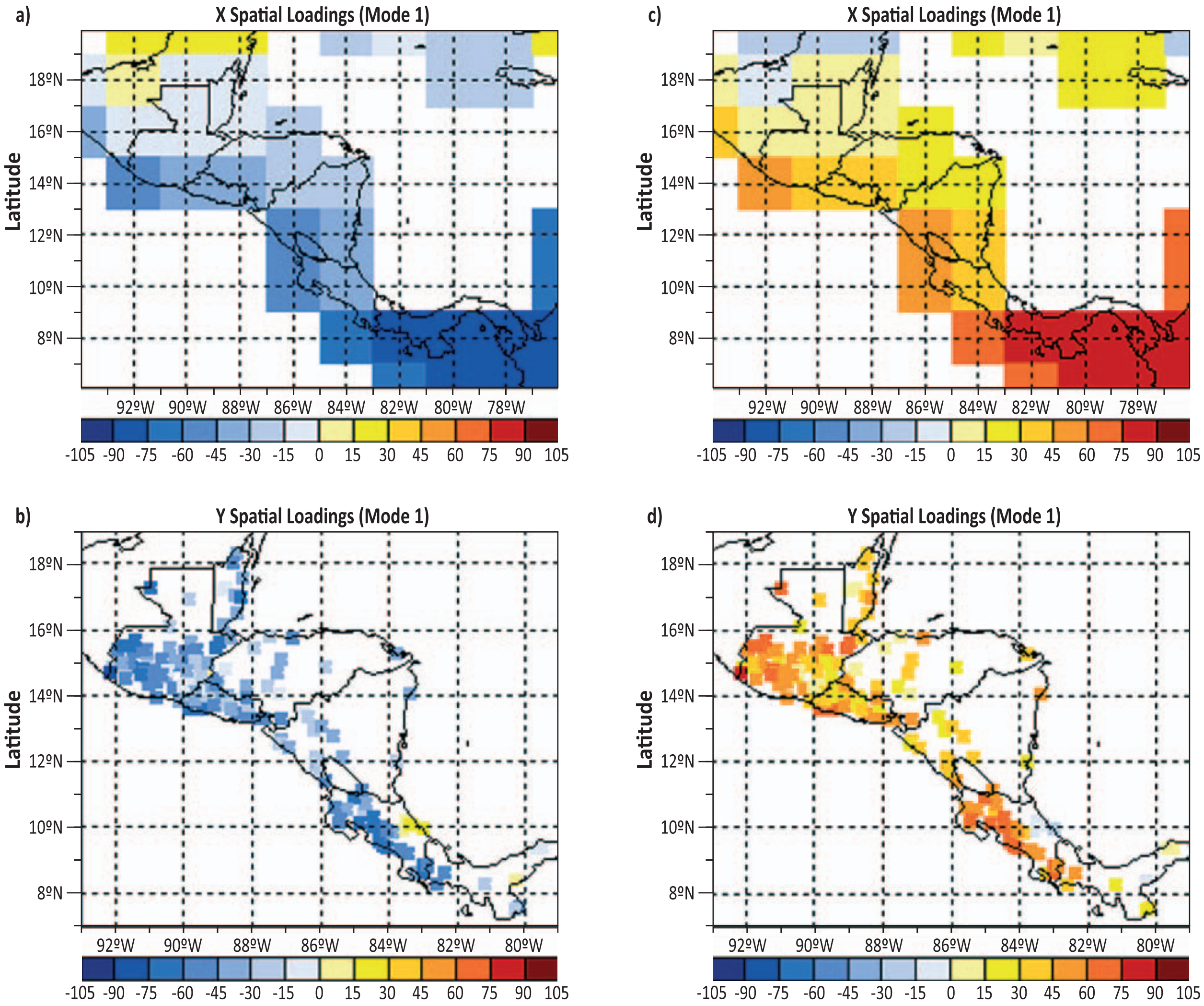

Figure 6. Loadings for the first CCA modes that optimized the models, using April PDSI as predictor in a) and c), and MJ accumulations in b) and SPI in d) as predictand.

6 a,c and 6 b,d. It is observed that drier (wetter) soil moisture in April tends to be related with drier (wetter) precipitation conditions in almost all the isthmus during next MJ, except for those stations located at the Costa Rican Caribbean coast which have the opposite behavior. It is interesting to note that Hidalgo, Alfaro, and Quesada-Montano (2016) also found the opposite behavior of the Caribbean Coast of Costa Rica compared to the Pacific slope when correlating the strength of the trade-winds represented in the CLLJ Index (Amador, 2008) and precipitation in Central America. Very close to the Caribbean slope of Costa Rica there is a high mountain range, almost perpendicular to the direction of the easterly trade-winds. As the warm and humid winds encounter the mountain, orographic precipitation is favored (therefore there is a positive correlation between the strength of the wind and precipitation in the Caribbean slope). This effect only occurs in Costa Rican coast, as the others countries in Central America do not have high mountain ranges as close to the Caribbean Coast as Costa Rica. Conversely, the opposite effect occurs in the Pacific slope of Central America, as the correlation between precipitation and the CLLJ reverses (stronger easterly winds from the Caribbean result in drier conditions in

Table 1. Pearson correlation between the SST and PDSI CCA mode 1 time series from Figs. 5a,c and 6a,c and some climate variability indices during February and April.

Index	Niño 3.4	AMO	PDO	Niño 3.4 - AMO	Niño 3.4 + PDO	CLLJ
SST-Feb, accumulations model	0.57***	-0.28	0.08	0.63***	0.38**	-0.20
SST-Feb, SPI model	-0.60***	0.36**	-0.15	-0.72***	-0.45**	0.25
PDSI-Apr, accumulations model	0.53***	-0.16	0.15	0.54***	0.40**	-0.32*
PDSI-Apr, SPI model	-0.54***	0.17	-0.15	-0.54***	-0.40**	0.32

The differences between Niño 3.4 and AMO are calculated using their respective normalized index as well as the sum of Niño 3.4 and PDO. The significance levels are given by a p-value 0.10 – 0.05 (*), 0.05 - 0.01 (**) and < 0.01 (***).

the Pacific slope). In this case, the mechanism is related to the lifting of the trades at the CLLJ exit, and subsequent subsidence in the Pacific slope that suppresses convection. This mechanism is explained in detail by Hidalgo et al. (2015).

Table 1 shows the Pearson correlation values between the SST and PDSI CCA mode 1 time series, from Figs. 5a,c and 6a,c and some climate variability indices during February and April. Notice that individually, the best correlations were obtained between the leading CCA modes and Niño 3.4; however, all the correlations improved when SSTA were compared with the condition in the Atlantic using the normalized difference between Niño 3.4 and AMO. Correlations suggest that positive (negative) Niño 3.4 SSTAs, along with negative (positive) SSTAs in the AMO during February and April, tends to be related with drier (wetter) conditions in almost all the isthmus during the next MJ. It is observed that correlation signs tend to be the same during February and April, suggesting it´s persistence in the CCA models. Our models also suggest that April´s soil moisture conditions in Central America could be conditioned by the previous SSTA of the surrounding oceans during February, and by integrating the observed rain anomalies from February to April that modulate the precipitation conditions during MJ along the isthmus.

4. Conclusions

Our methodology suggests that MJ rainfall predictions can be tailored using very simple CCA models (1 CCA mode in the two cases presented here), showing that wetter or drier events in Central America are influenced by interannual variability related mainly to ENSO and TNA, and the previous soil moisture conditions. CCA models, using February SST and April PDSI, showed significant skill values for the prediction of MJ accumulations and SPI over an important portion of Central America. It means that several socioeconomic sectors, which participate regularly at RCOFs meetings in the called Central American Applications Forums, can use this information for management and planning activities for the upcoming MJ season.

In general, better cross validation results were obtained for MJ SPI when they were compared with MJ accumulates. The inclusion of the MA persistence improved the predictability of the models. Predictability using PDSI as predictor increased for shorter lead times, with April having the highest median values, while better predictions were achieved using SSTA as predictor in boreal winter, with February having the highest median values. In other words, the climatic predictability present in SSTA is longer than the climatic predictability presented in the soils. It should be mentioned here that we are not suggesting that the soil moisture, at a certain lead-time, can produce a precipitation feedback into the future atmospheric conditions (as we cannot identify the contribution of this effect using the data). Instead, we assumed that the predictive signal in the soils is mainly a reflection of the meteorological (precipitation) persistence and/or climatic predictability from other sources, including the oceans.

Warmer (cooler) Eastern equatorial SSTAs in the Pacific, along with cooler (warmer) SSTAs in the TNA during February, tend to be related with drier (wetter) conditions in almost all the isthmus during next MJ. It is suggested that SST mode could modulate MJ precipitation in Central America, influencing the position of the ITCZ and the strength of the trade-winds. Additionally, it is observed that drier (wetter) soil moisture in April, tends to be related with drier (wetter) precipitation conditions in almost all the isthmus during next MJ. Therefore, it is suggested that April soil moisture conditions in Central America could be conditioned by previous SSTA of the surrounding oceans in February and integrating the observed rainy anomalies from February to April that can modulate the observed precipitation conditions during MJ along the isthmus.

Alfaro et al. (2003) also mentioned that scientific and academic communities have discussed certain problems that arise during the development of the forums and how the research results can be better used to improve the forums' products. One of the identified problems arising during the RCOFs is that, because there is not a standardized methodology for producing the forecast, the contributions from different countries can result in a disjointed regional forecast that sometimes is physically inconsistent across political borders. Moreover, it appears that the statistics behind the tools used in the forums are not familiar to some of the participants, resulting in the problem that the national climate forecasts sometimes are based only on subjective evaluations. This work showed that CCA usage in Central America could also help in the RCOF tasks, providing objective analysis in their operational work for the predictive relationships found in the region.

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