North Tropical Atlantic influence on western Amazon fire season variability

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Received 7 March 2011; revised 26 April 2011; accepted 2 May 2011; published 17 June 2011.

[1] The prevailing wet climate in the western Amazon is not favorable to the natural occurrence of fires. Nevertheless, the current process of clearing of humid forests for agriculture and cattle ranching has increased the vulnerability of the region to the spread of fires. Using meteorological stations precipitation and the Moderate Resolution Spectroradiometer (MODIS) Active-Fires (AF) during 2000–2009, we show that fire anomalies vary closely with July-August-September (JAS) precipitation variability as measured by the Standardized Precipitation Index (SPI). The precipitation variability is, in turn, greatly determined by sea surface temperature (SST) anomalies in the North Tropical Atlantic (NTA). We develop a linear regression model to relate local fire activity to an index of the NTA-SST. By using seasonal forecasts of SST from a coupled model, we are able to predict anomalous JAS fire activity as early as April. We applied the method to predict the severe 2010 JAS season, which indicated strongly positive seasonal fire anomalies within the 95% prediction confidence intervals in most western Amazon. The spatial distribution of predicted SPI was also in accordance with observed precipitation anomalies. This three months lead time precipitation and fire prediction product in the western Amazon could help local decision makers to establish an early warning systems or other appropriate course of action before the fire season begins.
Citation: Fernandes, K., et al. (2011), North Tropical Atlantic influence on western Amazon fire season variability, *Geophys. Res. Lett.*, *38*, L12701, doi:10.1029/2011GL047392.

1. Introduction

[2] Increases in fire incidence in the Amazonian regions reflect shifts in many aspects of development, including logging, land use change, infrastructural development, demographic and social change and climate variability [*Aragão and Shimabukuro*, 2010; *Cochrane and Laurance*, 2008; *Morton et al.*, 2008; *van der Werf et al.*, 2008]. In the western Amazon the wetter climate is less conducive to fires [*Bush et al.*, 2007] when compared to eastern and southern Amazon, where far more research has been conducted [*Alencar et al.*, 2006; *Ray et al.*, 2005]. Nevertheless, the drought of 2005 set in motion conflagrations that burned more than 300,000 ha of forests in the western Amazon state of Acre and it was averred "a disaster never previously experienced by modern societies in this part of Amazonia" [*Brown et al.*, 2006]. The severity of the 2005 drought was even more intriguing given that the usual suspect, the El Niño Southern Oscillation (ENSO) known to affect the Amazonian climate [*Ropelewski and Halpert*, 1987; *Zeng*, 1999], was neutral during most of 2005 [*Climate Prediction Center*, 2011]. On the other hand, the North Tropical Atlantic (NTA) was unusually warm and it has been shown to impact the Amazon dry season precipitation anomalies [*Fu et al.*, 2001; *Marengo et al.*, 2008; *Yoon and Zeng*, 2010; *Zeng et al.*, 2008].

[3] We investigate further the extent to which NTA-SST fluctuations affect the dry season fire anomalies in the western Amazon through the impact on the regional climate. We compare the JAS Standardized Precipitation Index (SPI) [*McKee et al.*, 1993] against the MODIS-AF product [*Justice et al.*, 2002] to determine the relationship between fire and climate. We further explore the forecasts from a coupled ocean-atmosphere general circulation model (GCM) for sea surface temperature (SST) as possible predictors of JAS droughts and fire anomalies. We show that the seasonal SST forecasts, made in April, can predict western Amazon JAS fire and precipitation anomalies.

2. Data and Methods

2.1. Rainfall Datasets and Standardized Precipitation Index (SPI)

[4] We use a precipitation record, provided by the Peruvian Meteorological Service (Servicio Nacional de Meteorologia e Hidrologia-SENAMHI) to develop a regional gridded rain gauge-only dataset. This dataset overcomes the limitation of sparsely distributed rain gauges in the western Amazon in publicly available rain-gauge only datasets [*Liebmann and Allured*, 2005; *Silva et al.*, 2007] and inconsistent satellite-based precipitation estimates in the tropics [*Juarez et al.*, 2009]. We complemented our stations network from SENAMHI with data obtained from the Brazilian Agência Nacional de Águas (ANA) website. This dataset provided a uniform daily average number of stations of about 400 reporting non-missing values in the 1970s, 1990s and 2000s, with a reduction of about 12% in the 1980s. The data were interpolated to 0.25° × 0.25° spatial resolution using

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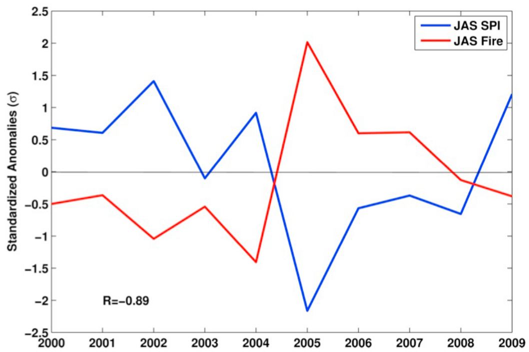

Figure 1. Timeseries of the JAS standardized precipitation index (SPI) and standardized fire anomalies averaged over the western Amazon domain (14°S–3°S, 76°W–70°W).

Cressman's [1959] method, which determines the average distance between the available stations at each time step and applies a multiplier factor to extend the radius of influence of neighboring stations on the target station. The daily-interpolated precipitation is then averaged to monthly means, but only for grid cells with 75% of the days reporting non-missing data. The monthly gridded precipitation data from 1970–2009 was used as the baseline period for the three months SPI calculation.

[5] The SPI is the number of standard deviations that the observed cumulative precipitation deviates from the climatological average. A continuous period of at least 30 years of monthly precipitation data is necessary to estimate the appropriate probability density function. The associated cumulative probability distribution is then estimated and subsequently transformed to a normal distribution. Negative (positive) SPI values indicate deficient precipitation, and positive values indicate abundant precipitation.

[6] We also require rainfall data for verifying the forecast made for 2010. Due to the delay in availability of the observational data described above, the 3B43v6 Tropical Rainfall Measuring Mission (TRMM) [*Huffman et al.*, 2007] is used to obtain the 2010 precipitation anomaly at 0.25° × 0.25° spatial resolution, relative to the 1998–2010 period of record for this data. Qualitative comparison is then made between the predicted SPI and observed precipitation anomaly.

2.2. Fire Dataset

[7] The active fire data from MODIS consists of gridded fire pixels count at 1 km^2 resolution aggregated to a 100 km^2 grid and monthly time steps. The units are given as "hot pixels" per 100 km^2 per day [*Justice et al.*, 2002]. The focus of our study is the climate impact on the spread of large fires, which are successfully detected in the MODIS active fire product [*Morisette et al.*, 2005; *Schroeder et al.*, 2008]. We re-gridded the data to 0.25° × 0.25° spatial resolution and standardized by subtracting the JAS 2000–2009 mean and dividing by standard deviation at each grid cell.

2.3. Study Area

[8] The relationship between western Amazon SPI and fire anomalies is evaluated initially for a domain of coordinates 14°S–3°S and 76°W–70°W. This domain was defined to avoid high Andean altitudes as well as Bolivia and Colombia for which we do not have precipitation data. The North Tropical Atlantic (NTA) SST index time series is calculated for the domain 10°N–23°N and 75°W–35°W.

2.4. Seasonal Climate Forecast Data-ECHAM-GML Model

[9] To explore the potential of using GCM seasonal forecasts to predict dry season precipitation and fire anomalies we used the thermodynamic ocean model (TOM) coupled to the atmospheric model ECHAM4.5 [*Lee and Dewitt*, 2009; *Roeckner et al.*, 1996], hereafter referred to as ECHAM-GML [*Lee and Dewitt*, 2009; *Roeckner et al.*, 1996]. The ECHAM-GML retrospective forecasts are available from the International Research Institute for Climate and Society (IRI) Data Library for the period 1982 to present. It was chosen for this study because of its high forecast skill of tropical Atlantic SSTs compared to other statistical and dynamical SST forecasts [*Lee and Dewitt*, 2009].

2.5. The Linear Regression Models

[10] The 2000–2009 time series of SST averaged over the NTA domain were calculated from one-month lead ECHAM-GML retrospective SST forecasts for May-June-July (MJJ), June-July-August (JJA) and JAS (i.e., made in April, May and June respectively). The MJJ, JJA and JAS NTA-SST forecast time series were regressed onto the gridded values of the JAS SPI. The same procedure was done between the NTA-SST forecast and observed fire anomalies. The regression models built using the 2000–2009 data were used to predict the JAS 2010 SPI and fire anomalies. The 2000–2009 data used to derive the linear regression models were also tested for temporal independence. The SPI and fire temporal autocorrelation (not shown) is not statistically significant ($P<0.1$) in 98% of the grid cells in both cases. The 95% prediction confidence interval (CI) used to verify the JAS 2010 fire anomalies prediction is given in equation (1):

$$CI = \hat{y}_{(i)} \pm 1.96\ RMSE_v \quad (1)$$

where $\hat{y}_{(i)}$ is model predicted values and $RMSE_v$ is the cross-validated root mean square of validation as in equation (2).

$$RMSE_v = \sqrt{\frac{PRESS}{n}} \quad (2)$$

where PRESS (equation (3)) is the prediction residual sum of squares (PRESS). This is referred to as "leave-one-out" cross validation method, where n is number of time steps used in the regression.

$$PRESS = \sum_{i=1}^{n} \left(y_i - \hat{y}_{(i)}\right)^2 \quad (3)$$

where y_i and $\hat{y}_{(i)}$ are the observed and predicted values in timestep i that was not used in fitting the model that generated $\hat{y}_{(i)}$ [*Weisberg*, 1985].

3. Results

3.1. Relationship Between Droughts and Fires

[11] The JAS SPI and fire anomalies, averaged over the western Amazon domain, are highly correlated ($R = -0.89$, $P = 0.0006$) during the period 2000–2009 (Figure 1). Six

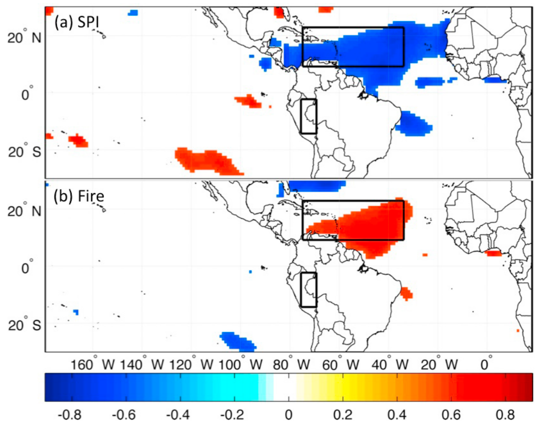

Figure 2. Western Amazon domain averaged (a) JAS SPI and (b) fire anomalies correlations with MJJ tropical SST forecast (2000–2009). Only 90% significant correlations are shown. The boxes show the western Amazon (14°S–3°S, 76°W–70°W) and the NTA-SST index (10°N–23°N, 75°W–35°W) domains.

months SPI (April, May, June, July, August and September) is also highly correlated to fire variability but less so ($R = -0.81$, $P = 0.0043$), thus we focus our analysis on 3 months JAS SPI. Nearly 80% of JAS fire variance is explained by JAS SPI, indicating that the climate component is the main driver of fire anomalies seasonally in the region, with contributors such as land use and management likely accounting for much of the remaining fraction.

3.2. Large Scale Forcing of Dry Season SPI and Fire Variability

[12] SSTs fluctuations in the North Tropical Atlantic determine to a large extent the western Amazon dry season precipitation anomalies [*Marengo et al.*, 2008; *Yoon and Zeng*, 2010; *Zeng et al.*, 2008]. We examine whether SST forecast can be used for seasonal precipitation and fire anomalies prediction in the region.

[13] The earliest ECHAM-GML SST forecast season to show a region of tropical North Atlantic correlating significantly to western Amazon domain averaged JAS SPI is MJJ (Figure 2a). The relationship between domain JAS SPI and the following seasons (JJA and JAS) SSTs, show very similar patterns to those shown in Figure 2a, only the correlations widen in area and become more significant (not shown). The physical mechanism linking the North Tropical Atlantic to reduced precipitation in the Amazon is related to the northward displacement of the Intertropical Convergence Zone (ITCZ) when the NTA-SST is anomalously warm [*Marengo et al.*, 2008]. The ITCZ migration away from South America's northern coast results in net water vapor divergence and anomalous subsidence in the Amazon leading to reduced precipitation [*Knight et al.*, 2006; *Yoon and Zeng*, 2010]. Our results showing negative correlation between domain JAS SPI and SST in the NTA sector during the 2000s are in agreement with the expected response linking warmer NTA-SST and reduced precipitation in the western Amazon, and oppositely for colder NTA-SST. Not surprisingly, the remote NTA SST relationship to western Amazon JAS fire variability shows correlations of the opposite sign (Figure 2b), indicating that over the region fire season anomalies are strongly determined by the local climate response to the NTA large scale forcing. One implication of NTA-SST leading the western Amazon local response by a few months is that JAS SPI and fire anomalies can be predicted from NTA-SST forecast as early as April each year.

3.3. Prediction of Dry Season SPI and Fire Anomalies

[14] Our empirical approach to predict fire anomalies from the ECHAM-GML NTA-SST index time series is based on the local climate response to the SSTs remote forcing alone, not considering any land use change or socio-economic variables that may influence fire dynamics in the region. Figure 3 shows locally the percentage of fire variance explained by the NTA-SST, suggesting that factors other than climate play an important role in determining the interannual fire variability during the dry season.

[15] Nevertheless, it is clear that the regression model is able to predict past fire activity in the region. The fire season of 2010 was very active in the Amazon [*de Melo and Gan*, 2010], but this data did not contribute to the regression

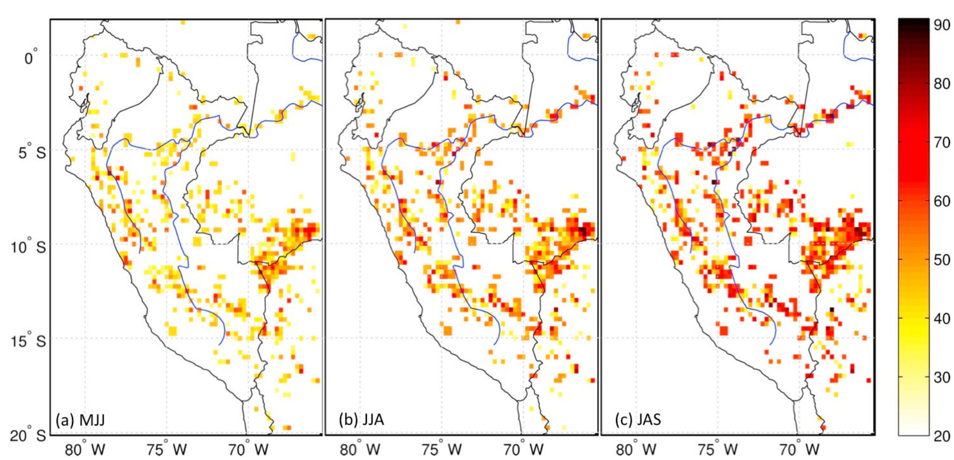

Figure 3. Percentage of JAS fire variance explained at each grid point by the 1-month lead time NTA-SST index forecast for (a) MJJ, (b) JJA and (c) JAS seasons.

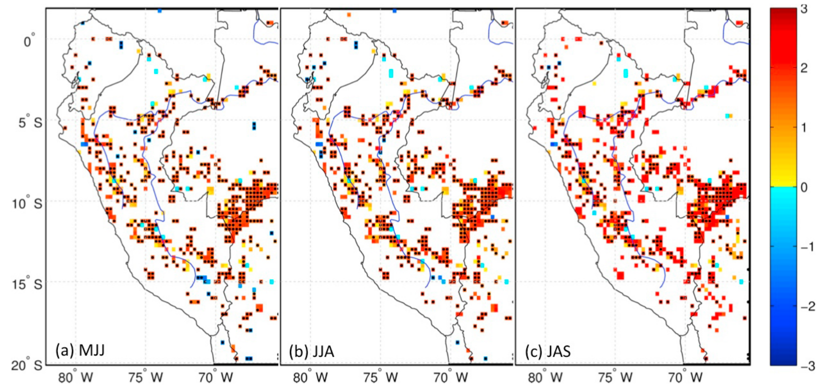

Figure 4. Predicted JAS 2010 fire anomalies, in units of standard deviation, based on 1-month lead NTA-SST forecasts for (a) MJJ, (b) JJA, and (c) JAS. The dots mark gridcells where the observed values are within the 95% confidence interval of validation.

model. Thus, we can treat this extreme case as an independent test of our prediction system. The linear regression models used to predict fire anomalies (in units of standard deviation), consistently show large, positive values in JAS 2010 predicted from MJJ, JJA and JAS NTA-SST forecast (Figure 4). The anomalies are mostly within the 95% confidence interval of prediction marked in Figure 4 as dots.

[16] Similarly, the predicted 2010 JAS SPI using MJJ, JJA and JAS NTA-SST forecast indicates very dry conditions (Figure 5). It should be noted that our gridded precipitation data is derived from meteorological stations distributed over Peru and northwestern Brazil, thus the interpolated precipitation does not extend over Colombia and Bolivia. Moreover, precipitation was not interpolated at grid cells where the density of stations was insufficient, thus the patchy character of predicted SPI. Due to delay in the availability of the station data to derive our gridded precipitation data set, the 2010 JAS SPI forecast was verified by qualitatively comparing it to JAS precipitation standardized anomalies derived from TRMM (Figure 5d). The widespread negative anomalies during the 2010 dry season are in broad agreement with our JAS SPI forecast (Figures 5a–5c) as well as recently published results [*Lewis et al.*, 2011]. In addition, the Brazilian National Water Agency (ANA) reported record low water levels in the Negro River near the city of Manaus and Solimões River at Itapeuá, both in Brazil [*Agência Nacional de Águas*, 2010]. The Negro and Solimões River integrate precipitation over the northwest and west part of the Amazon basin respectively.

4. Discussion and Conclusions

[17] Fire dynamics in humid tropical forests are complex and involve a swath of socio-economic aspects, including replacement of forests by crops and pastures, fires for agricultural maintenance, timber extraction and infrastructure development all of which result in greater vulnerability of the natural system to fires. At fine spatial scales, patterns of land use most likely explain where fires are most prevalent in the western Amazon, being the climate the main driver of interannual fire variability during the dry season.

[18] Using real-time SST forecasts for the north tropical Atlantic sector we are able to predict precipitation and fire anomalies during the dry season months. The 2010 positive fire anomalies predicted by the 2010 seasonal forecasts for MJJ, JJA, and JAS are in agreement with the negative predicted 2010 JAS SPI and observed precipitation anomalies estimated by TRMM. Our results show that ECHAM-GML MJJ SST can be used to predict western Amazon JAS precipitation and fire anomalies as early as April, information that can be regionally used as an early warning product.

[19] Beyond the focus period of this study (the 2000s), the relationship between precipitation and SSTs in the North

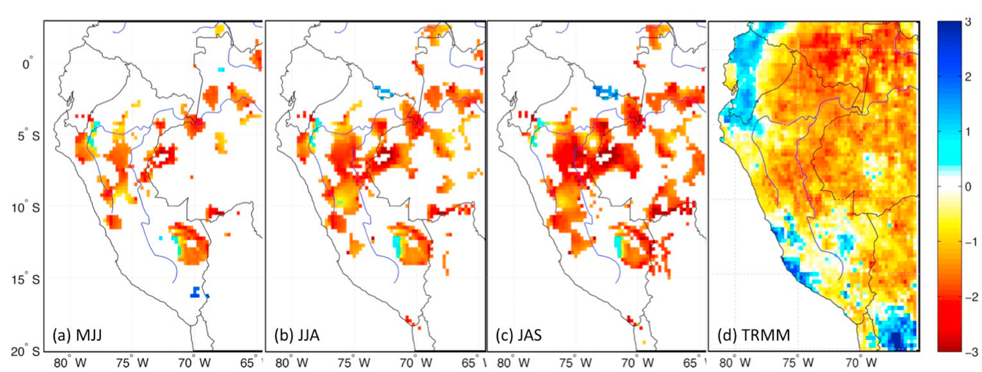

Figure 5. Predicted JAS 2010 SPI, in units of standard deviation, from based on 1-month lead SST forecasts for (a) MJJ, (b) JJA, and (c) JAS; (d) the observed standardized precipitation anomalies from TRMM in JAS 2010.

Atlantic sector weakens (1982–1999). Further research is ongoing to examine to what extent this might be related to the Atlantic Multi-Decadal Oscillation (AMO) variability [*Schlesinger and Ramankutty*, 1994], climate change trends or some combination of the two.

[20] **Acknowledgments.** This work was supported by NSF-CNH grant 0909475 and Tinker Foundation. S. Bernardes was supported by a NASA Earth and Space Science Fellowship. The Editor thanks two anonymous reviewers for their assistance in evaluating this paper.

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