Changes in large-scale controls of Atlantic tropical cyclone activity with the phases of the Atlantic Multidecadal Oscillation

Louis-Philippe Caron * [1,2], Mathieu Boudreault [3] and Cindy L. Bruyère[4,5]

[1]Rossby Centre, Swedish Meterological and Hydrological Institute (SMHI), Sweden

[2]Climate Forecasting Unit, Institut Català de Ciències del Clima (IC3), Spain

[3]Department of Mathematics, Université du Québec à Montréal (UQAM), Canada

[4]National Center for Atmospheric Research (NCAR), USA

[5]Environmental Sciences and Management, North-West University, South Africa

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*Corresponding author: louis-philippe.caron@ic3.cat

Abstract

Atlantic tropical cyclone activity is known to oscillate between multi-annual periods of high and low activity. These changes have been linked to the Atlantic Multidecadal Oscillation (AMO), a mode of variability in Atlantic sea surface temperature which modifies the large-scale conditions of the tropical Atlantic. Cyclone activity is also modulated at higher frequencies by a series of other climate factors, with some of these influences appearing to be more consistent than others. Using the HURDAT2 database and a second set of tropical cyclone data corrected for possible missing storms in the earlier part of the record, we investigate, through Poisson regressions, the relationship between a series of climate variables and a series of metrics of seasonal Atlantic cyclone activity during both phases of the AMO.

We find that, while some influences, such as El Niño Southern Oscillation, remain present regardless of the AMO phase, other climate factors show an influence during only one of the two phases. During the negative phase, Sahel precipitation and the North Atlantic Oscillation (NAO) are measured to play a role, while during the positive phase, the 11-year solar cycle and dust concentration over the Atlantic appear to be more important. Furthermore, we show that during the negative phase of the AMO, the NAO influences all our measures of tropical cyclone activity, and we go on to provide evidence that this is not simply due to changes in steering current, the mechanism by which the NAO is usually understood to impact Atlantic cyclone activity. Finally, we conclude by demonstrating that our results are robust to the sample size as well as to the choice of the statistical model.

Keywords: Tropical cyclones; Atlantic variability; Poisson regression, Atlantic Multidecadal Oscillation

1 Introduction

Atlantic tropical cyclone (TC) activity has been observed to vary over a wide range of timescales, from (sub)seasonal to decadal (and possibly longer), and multiple attempts have been made to relate these variations to a large array of climate variables. The lower frequency variations are generally considered to be related to the slowly varying thermodynamic conditions(Emanuel et al., 2013), driven in large part by changes in local SSTs, whereas higher (annual) frequencies tend to be driven by teleconnections from factors external to the tropical Atlantic, such as El Niño Southern Oscillation (ENSO). Table 1 offers an overview of the different climate factors that have been linked to annual and decadal changes in Atlantic cyclone activity (the timescale we are interested in here) as well as a non-exhaustive list of references discussing these relationships.

The understanding of the relationship between large-scale fields and Atlantic TC activity has led to the development of TC seasonal forecasts and, more recently, to multi-annual forecasts. If decadal forecasts are still in the early stages of development (Smith et al. (2010); Caron et al. (2013)), seasonal forecasts are now routinely performed by numerous groups using a range of different techniques (Camargo et al., 2007a). Often, such techniques rely on linking the presence or absence of certain large-scale features to an increase or decrease in TC activity above or below the climatological mean. For example, the presence of El Niño (La Niña) conditions in the tropical Pacific are usually associated with a decrease (increase) in Atlantic TC activity.

Another well-known influence on Atlantic hurricane activity is Western Sahel rainfall, which was previously used as a predictor in hurricane seasonal forecasts. Landsea and Gray (1992) and Landsea et al. (1992) showed that Sahel rainfall was highly correlated with the strongest Atlantic cyclones. However, the link between these two variables began to deteriorate in the late 1990's to the point where Western Sahel precipitation is no longer included in these seasonal forecasts. Fink et al. (2010) later showed that the influence of Western Sahel precipitation on Atlantic TC activity is cyclical and tends to be strong in years when conditions over the Atlantic are unfavourable to TC formation, and much weaker in years where conditions are more favourable. Although not as dramatic, a similar behaviour was highlighted by Klotzbach (2011a) and Klotzbach (2011b) which showed that the influence of ENSO on Atlantic cyclone activity tends to be stronger/weaker when the background thermodynamic conditions are unfavourable/favourable to cyclogenesis.

Since the influence of at least one parameter from table 1 can be "switched on/off" by the general conditions over the tropical Atlantic whilst another can be strengthened/weakened, this begs the question as to whether or not other known influences on TC activity are also modulated in a similar fashion. Here, we are investigating whether the links between different measures of Atlantic TC activity and the various predictors from table 1 remain stationary between more active and quieter periods of TC activity.

Changes in the Atlantic Multidecadal Oscillation (AMO) have been linked to the slow (decadal) variation in Atlantic cyclone activity (see AMO references in table 1). Defined as the (linearly) detrended Atlantic SST anomaly north of the equator (Knight et al. (2006); Zhang and Delworth (2006)), the positive (negative) phase produces climate conditions more conducive (detrimental) to TC formation, such as higher (lower) SSTs and lower (higher) wind shear. Thus, the AMO index provides a straightforward way to sort conducive from non-conducive years. The AMO timeseries is shown in figure 1a, while table 2 shows the years sorted according to their AMO value.

Section 2 describes the different datasets used for this study while section 3 gives a short description of the Poisson regression, the technique used here to investigate the relationship between TC activity and various climate indices. Section 4 contrasts the relationship between different climate indices and TC activity during both phases of the AMO and section 5 discusses the robustness of the results presented. Section 6 concludes with a short discussion.

2 Data

2.1 Tropical cyclone data

The HURDAT2 database (HURDAT second version; Landsea and Franklin (2013)) maintained by the National Hurricane Centre is the most comprehensive collection of tropical cyclone information for the Atlantic basin, with yearly TC information (location, wind intensity, minimum pressure, 34/50/64 kt wind radii per quadrant, landfall location) available from the mid-19th century to the present. The origin of the data that went into creating this best-track database changed over time as technology improved and as the observational network evolved: TC information up to the mid-20th Century comes exclusively from ship encounters and data collected at landfalls, whereas starting in the mid-20th Century, additional data was collected using aircraft reconnaissance missions and, from the 1960's onward, from orbiting satellites (Vecchi and Knutson, 2008). The evolution in observational practices over the Atlantic is reflected in the increased quality and reliability of this dataset with time. Due to patchy coverage, it is likely that a fair number of storms were missed in the earlier period, this number decreasing as coverage improved.

Landsea et al. (2010) showed that a steady increase in the number of short-lived systems[1] was present in the hurricane database and argued that it was the result of changing observational practices. Similarly, by comparing data of Atlantic TC activity over the 20th century against large-scale environmental variables, Villarini et al. (2011) concluded that the increase in short-lived tropical cyclones present in the database was spurious. Bruyère et al. (2012) additionally noted a spurious discontinuity in these short-lived storms around 1960, at the advent of satellite imagery, but further observed that the proportion of short-lived storms to the total number of storms remained constant both before and after that discontinuity, suggesting that part of the detected increase might indeed be real. An increase in the number of short-lived storms was also detected in downscaled simulations performed over the 20th century (Emanuel, 2010). Thus, the

[1] A short-lived system is one for which the lifetime is shorter than 48 hours.

extent to which the upward trend in short-lived systems is real is not yet entirely established, however, any uncertainty which these storms may introduce into the database can be circumvented by limiting the focus to those storms which lasted more than two days.

Recent work by Landsea et al. (2008) and Landsea et al. (2012) has led to the detection of previously missed storms and thereby to corrections in HURDAT for the early part of the 20th century. Continuing work of this nature will no doubt contribute to further reducing any artificial biases in the database. Unfortunately, there is no substitute for storms that were completely missed by the observational network of the day. This has led Vecchi and Knutson (2008), Landsea et al. (2010) and Vecchi and Knutson (2011) to attempt to estimate, respectively, the number of tropical cyclones, long-lived tropical cyclones (>48h) and hurricanes that could have been missed given the deficient coverage present in the early years of the database using TC tracks from other years. Obviously, these estimations are subject to high uncertainties.[2] For example, any shift in geographical distribution of storms over time, or any increase in activity in an area where coverage used to be poor (e.g. Eastern Atlantic) will be mistakenly interpreted as missed storms thus causing the database to be over-corrected. Nonetheless, we believe that these three studies offer the best current estimates of bias-corrected timeseries of tropical cyclone activity in the HURDAT2 database and they will therefore be used in this study. For comparison purposes, we will also include the non-corrected values for the same three timeseries (total number of TCs, long-lived TCs and hurricanes) taken directly from the HURDAT2 database[3], as well as the total number of major hurricanes (category 3-5 on the Saffir-Simpson scale), for which there currently exists no corrections. It should be mentioned that these timeseries are constructed using all of the storms that occurred during any given year. Finally, we also use the number of US landfalling hurricanes taken directly from HURDAT2. This assumes that the U.S. coastline was sufficiently

[2]For a full discussion on this issue, we refer the interested reader to Vecchi and Knutson (2008).

[3]We are using the latest version of HURDAT2, which was last updated in June 2013 to revise the 1851-1945 hurricane seasons.

populated to record every U.S hurricane landfall since 1878. Although this assumption is likely overly optimistic (Landsea, 2007), the number of missed storms is also likely to be sufficiently small to have a negligible impact on the conclusion of this study.

Figure 2 shows the five timeseries, both in their original and bias-corrected forms (when applicable). Decadal variability in basin-wide TC activity can be observed (figure 2a-d), with periods of both high (e.g. 1940's+1950's, 1995 to present) and low (e.g. early 20th century, 1980-1994) activity. As mentioned earlier, this variation in TC activity has been previously linked to the slowly varying AMO. And although landfalling hurricanes (figure 2e) show no such obvious signs of decadal variability, a regression between U.S. landfalling hurricanes and the AMO is significant at the 5% level.

2.2 Climate Indices

The choice of the climate indices used in this study is based on previous literature discussing climate-cyclone interactions and is summarized in table 3. The influence of ENSO is studied using the Niño3.4 index (Trenberth, 1997), during the months of ASO. The Niño index is computed using the mean of NOAA extended reconstructed SSTs (ERSST; Smith et al. (2008)) and Hadley Center reconstructed SSTs (HadISST; Rayner et al. (2006)) based on a 30-year sliding climatology, updated every five years. The absolute Atlantic SST (AtlSSTs) and relative SST (RelSST) are also computed using the average of ERSSTs and HadSSTs, defined respectively by the mean SST limited by 10°N, 25°N, 80°W and 20° (the Main Development Region, or MDR) and by the difference between the former and the mean tropical SST limited by 30°N and 30°S. The West African Monsoon (WAM) influence is represented by the Western Sahel rainfall anomalies compiled at Washington University. The NAO index is provided by the Climate Research Unit (CRU) of East Anglia (Jones et al., 1997). Sunspot numbers (SSNs) are produced by the Solar Influences Data Analysis Center (SIDC) of the Royal Observatory of Belgium and are obtained through the NOAA.[4] The Quasi-Biennial Oscillation (QBO) is given by

[4]Following results from the available literature, we performed our analyses using both September SSNs and SSNs averaged over ASO. We found that September SSNs generally returned smaller p-values.

zonal winds at 30 hPa, which are provided by the University of Berlin (Naujokat, 1986). Information on dust concentration over the tropical Atlantic can be found in Evan and Mukhopadhyay (2010). Finally, since timeseries of stratospheric ozone concentration which currently exist do not cover a sufficiently long period to be useful here, we have instead selected the 100 hPa temperature directly, keeping in mind that other factors besides ozone concentration might influence temperature at that level. The temperature at 100 hPa over the MDR is calculated by averaging temperatures in NCEP (Kalnay et al., 1996) and a combination of ERA-40 (Uppala et al., 2005) and ERA-Interim (Dee et al., 2011) reanalyses. Finally, the AMO is taken from NOAA's database (Enfield et al., 2001). Figure 1 shows the different timeseries of these indices for the available period.

2.3 Genesis Potential Index

Gray (1979) showed that it was possible to assess the potential for TC genesis through the use of environmental parameters, and over the years, this concept has been used to develop a number of different genesis indices. These indices aim to communicate whether or not the atmosphere-ocean system is conducive to cyclogenesis over a particular area. Here, we use a Genesis Potential Index (GPI) recently developed by Emanuel (2010):

$$GPI = |\eta|^3 \, \chi^{-\frac{4}{3}} \, max((PI - 35), 0)^2 \, (25 + V_{shear})^{-4} \tag{1}$$

where η is the absolute vorticity (s^{-1}) at 850 hPa, χ is the moist entropy deficit in the middle atmosphere, PI is the potential intensity ($m\ s^{-1}$; Emanuel (1995), Bister and Emanuel (1998)) and V_{shear} is the vertical wind shear ($m\ s^{-1}$) between 850 and 200 hPa. The large-scale fields used to compute the GPI are taken from the NCEP reanalyses for the August-October seasons spanning the period 1960-2012. Figure 3 shows the mean GPI values for that period as well as the location of all the $\sim$600 cyclogenesis events observed during that 53-year period. Changes in the GPI field will be used to explain some of the detected changes in cyclogenesis locations.

We thus chose to include only those results obtained using September SSNs.

3 Poisson Regression

To analyze the effect of the various climate indices on the number of TCs, we use a Poisson regression, which is a classical approach to analyze count data. The Poisson regression has been applied successfully in climatology to analyze the determinants of TC frequency in Solow and Nicholls (1990), Elsner (2003), Elsner and Jagger (2006), Villarini et al. (2010), Tippett et al. (2011), and Kozar et al. (2012). The Poisson regression is a type of generalized linear model (GLM) with a Poisson distribution and a logarithmic link function.

When we represent by N_k the number of TCs during year k, then a Poisson *distribution* (or Poisson *process*), given by

$$\Pr(N_k = n) = \frac{e^{-\lambda}\lambda^n}{n!}, n = 0, 1, 2, ... \tag{2}$$

assumes that the mean number of events during any given year k is constant at λ. The apparent presence of cycles in figure 2 shows that it is very unlikely that TC formation is consistent with the Poisson process of equation 2 (with constant mean).

When it is believed that the mean number of events may evolve over time due to p time-varying determinants (also known as predictors or covariates), then a Poisson regression is considered a more appropriate approach. In a Poisson regression, the covariates influence the mean number of events such that

$$\Pr(N_k = n) = \frac{e^{-\lambda_k}\lambda_k^n}{n!}, n = 0, 1, 2, ... \tag{3}$$

where

$$\log(\lambda_k) = \beta_0 + \beta_1 X_{1,k} + \beta_2 X_{2,k} + ... + \beta_p X_{p,k} \tag{4}$$

is a logarithmic link function and $X_{1,k}, X_{2,k}, ..., X_{p,k}$ are a set of p covariates observed at time k.

One can also view the Poisson regression as

$$\mathrm{E}[N_k|\mathbf{X}_k] = \exp\left(\mathbf{X}_k\boldsymbol{\beta}\right) \tag{5}$$

meaning that

$$\beta_i = \frac{\frac{\partial \mathrm{E}[N_k|\mathbf{X}_k]}{\partial X_{i,k}}}{\mathrm{E}[N_k|\mathbf{X}_k]}, i = 1, 2, ...p.$$

In other words, β_i represents the *relative* variation (or percentage change) in $\mathrm{E}[N_k|\mathbf{X}_k]$ per unit of $X_{k,i}$. Note that we have collapsed the predictors $X_{i,k}$ into a single vector $\mathbf{X}_k$ and done similarly for β_i to simplify the presentation.

3.1 Methodology

As a first step, we select the years when the AMO was positive and perform regression analyses on that subset of the data. Only one predictor is used ($p = 1$) for each regression, meaning that for each of the 8 count variables, 10 regressions were carried out (one per climate index). The process is then repeated for those years when the AMO was negative. The value of the various β_1's can be found in table 4.

β's are obtained using maximum likelihood estimation (MLE) which is a standard (frequentist) approach to estimate coefficients in Poisson regressions (see for instance McCullagh and Nelder (1989), Winkelmann (2010)). To assess the statistical significance of a predictor, we use the (asymptotic) p-value associated with that variable, where the null hypothesis is $\beta_1 = 0$ and the alternative hypothesis is $\beta_1 \neq 0$. The p-value associated to a given estimate of β is the probability that the statistic associated to the aforementioned hypothesis test is at least as high as the one observed in the sample, if the true value of β was 0 (which is the null hypothesis). The computation is based upon a normal distribution because β_1 obtained with MLE is asymptotically Gaussian. When facing uncertainty with respect to the true model while being additionally limited to a small sample size, it is always more prudent to use low significance levels, in the order of 1% or below. In this vein, we perform a robustness analysis in section 5 to validate the results, specifically with respect to the sample size and the choice of regression model.

Another potential challenge here is that by analyzing multiple indices, we increase the likelihood of finding a significant variable only by chance, which is common when carrying out multiple testing. In the statistics literature, there are methods that correct for multiple testing biases, namely the Bonferroni or Sidak corrections (Dickhaus (2014); Shaffer (1995)). The effective p-value that is equivalent to the usual 5% cut-off lies between 0.5% and 2%, depending on the level of correlation observed between the 10 covariates used in this paper.

This being said, however, predictors that generate p-values between 2% and 5% will also be considered in this analysis for various reasons. Firstly, there might be a true physical or natural explanation linking a predictand and its predictor but the relationship may be hard to observe because data is noisy or the phenomenon is too complex. Second, some of these relationships which are borderline significant might nonetheless be supported by the literature. And thirdly, the goal of this paper being the assessment of the significance of usual TC predictors during the positive and negative phases of the AMO, the difference in p-values during both phases might also be a very interesting metric to evaluate. Hence, a variable that has a p-value of 90% (which is extremely unsignificant) during the positive AMO phase and a borderline p-value of 5% during the negative AMO phase, would still merit some attention. The significance of each covariate as well as the sign of that relationship for both phases of the AMO are displayed in figure 4.

4 Modulation of large-scale influences on Atlantic cyclones

4.1 Local and remote Sea Surface Temperatures

Results from figure 4 suggest that some large-scale influences remain stationary during both phases of the AMO. Both the MDR SST with respect to the mean tropical SST (RelSST) and the absolute MDR SST (AtlSST) generally remain very significant predictors of Atlantic tropical cyclone activity, with RelSST returning the smallest p-values. Since both Atlantic and tropical SSTs influence the local thermodynamic conditions (i.e. instability of the ocean-atmosphere system), the prime modulator of TC activity in the

Atlantic over the recent past, this result is not entirely unexpected. Of course, RelSST and AtlSST are not entirely independent from one another, as RelSST is simply a measure of how warm the Atlantic is with respect to the other tropical oceans or, put another way, how fast the tropical Atlantic warms with respect to these oceans.

At the interannual timescale, the prime driver of Atlantic TC variability is generally considered to be El Niño Southern Oscillation (ENSO). ENSO is driven by changes in ocean temperature in the tropical Pacific, where above average conditions (El Niño) in the Central and Eastern Pacific shift the convective activity in the tropical Pacific eastward, and modify the Walker cell throughout the tropics. The influence of ENSO on Atlantic TC activity is well documented and is understood to occur mainly through local changes in vertical wind shear: during El-Niño (La Niña) conditions, the eastward (westward) shift in convection in the tropical Pacific leads to anomalous upper-level westerlies (easterlies) over the Atlantic, which then increases (decreases) the vertical wind shear, thus decreasing (increasing) TC activity (Camargo et al. (2007b); Goldenberg and Shapiro (1996); Klotzbach (2011a)). The strong influence of ENSO can be seen clearly here with significant p-values for all the regressions between Niño3.4[5] and basin-wide predictands, regardless of the phase of the AMO. And although the differences between AMO+ and AMO- are small, our results are consistent with Klotzbach (2011a) and Klotzbach (2011b) which showed that the influence of ENSO on major hurricanes and landfalling hurricanes was stronger during the negative phase of the AMO.

It is interesting to note that the significance of the remaining predictors (NAO, Sahel rainfall, SSNs, dust, stratospheric temperature) varies considerably depending whether we are in a positive or a negative phase of the AMO. During the negative phase, only the NAO and the Western Sahel precipitation consistently return significant coefficients,

[5]We performed the regressions using a range of ENSO indices and found the Niño3.4 and Niño4 indices to return the smallest p-values. Regressions performed using the Southern Oscillation Index (SOI), Niño3 and Niño1+2 indices were, in general, also significant, but returned larger p-values. Only the results obtained with the Niño3.4 are shown here.

and neither the dust nor sunspot numbers appear to have any significant influence. On the other hand, during the positive phase, the significance of the predictors tends to be opposite: the NAO and the Western Sahel do not appear to play a role, whereas dust and sunspot numbers appear to be significant. Finally, the upper-tropospheric temperature shows indications of influencing different measures of TC activity during both phases of the AMO. We investigate the influence of each climate variable more closely in the following sections.

4.2 Western Sahel Precipitation

As stated earlier, previous studies have shown that Sahel rainfall used to be strongly correlated with the strongest storms of the Atlantic (Landsea and Gray (1992); Landsea et al. (1992)). The influence of Western Sahel precipitation on TC activity has been explored by Goldenberg and Shapiro (1996), which linked changes in convective precipitation over the Sahel region to anomalous zonal winds in the upper-troposphere, which in turn modulate vertical wind shear over the MDR and the likelihood of cyclogenesis over that region. This link between Sahel precipitation, vertical wind shear over the MDR and Atlantic TC activity has also been observed in high-resolution climate models (Caron et al., 2012). It is possible that changes in the nature of the African Easterly Waves (AEWs) coming off the African continent might be playing a role (Thorncroft and Hodges, 2001).

Figure 4 clearly shows that the relationship varies considerably between the negative and positive phase of the AMO and confirms the findings of Fink et al. (2010), which showed, using simple linear regressions, that the influence of Western Sahel precipitation on Atlantic TC activity is cyclical and tends to be strong (weak) in years where conditions over the Atlantic are detrimental (favorable) to cyclone formation.[6] During the negative phase of the AMO, Western Sahel precipitation data shows no relationship to the total number of TCs, yet shows a positive relationship with the number of long-

[6]Whereas Fink et al. (2010) used data covering the period 1921-2007, we used data covering 1900-2012. We repeated our analysis using their dataset and the results were not significantly affected.

duration TCs, hurricanes, major hurricanes and U.S. landfalling hurricanes, with the significance of the relationship increasing with the intensity category of the storms. For long-duration cyclone and hurricane numbers, we note that the significance increases when one uses the corrected data as opposed to the uncorrected HURDAT2 data. Since the strongest storms are likely to require a certain amount of time to reach high intensities, the results are consistent with Landsea and Gray (1992) and Landsea et al. (1992). However, during the positive phase of the AMO, the relationship breaks down and the Western Sahel precipitation does not appear to influence TC activity.

In figure 5, we compare the difference in cyclogenesis density of major hurricanes constructed using the 15 years with the largest positive Western Sahel rainfall anomalies and the 15 years with the largest negative Western Sahel rainfall anomalies, during both phases of the AMO. During AMO- (figure 5a), we see an increase in major hurricanes associated with high Western Sahel precipitation. During AMO+ (figure 5b), we detect a similar increase (shifted slightly northward) in years of high precipitation, but it is compensated, in years of low Sahel precipitation, by an increase in major hurricanes in two different areas of the tropical Atlantic: i) at the eastern edge of the MDR and ii) off the coast of South America, at around $60^{\circ}W$.

We suggest that the increase in i) is caused by more favourable background conditions in AMO+ compared to AMO- which allow for more rapid development of AEWs into TCs such that these storms can better sustain the higher shear conditions prevailing over the Atlantic basins during years of low Sahel precipitation, whereas the increase in ii) likely represents AEWs which will have been sustained as they propagated along the southern edge of the MDR such that they avoid most of the higher shear conditions. It is not clear why years of lower precipitation over the western Sahel region would yield more TCs in these two particular areas compared to years of high precipitation during AMO+, but it seems clear that increase TC formation in the MDR region in years of low Sahel precipitation during AMO+ explains the different behaviour between AMO+ and AMO- as well as the breakdown of the significant relationship between major hurricane number and Western Sahel precipitation. At this stage, we cannot yet speculate whether or not changes in AEW characteristics also play a role.

4.3 North Atlantic Oscillation

The North Atlantic Oscillation is a north-south dipole of sea level pressure anomalies between Iceland and the Azores: when pressures are high (low) over Iceland, they tend to be low (high) over the Azores (the NAO index is commonly taken as the difference in pressures between the two locations). Here we consider the NAO in two different seasons: spring NAO (May-June), and NAO (ASO) during the active hurricane season. We find that during the negative phase of the AMO, the NAO index is negatively correlated to basin-wide Atlantic TC activity as well as to the number of U.S. landfalling hurricanes. This relationship holds only if the NAO is measured over the preceding months of May and June (MJ) however, and is not significant when measured during the hurricane (ASO) season, in accordance with previous results (Villarini et al., 2012). However, this coupling between NAO (MJ) and cyclone activity appears to break down during the positive phase of the AMO.

The influence of the NAO on landfalling hurricanes has been previously documented (see references in table 1) and is generally assumed to occur through changes in the strength and location of the Atlantic subtropical high, which in turn impact the steering current in which the Atlantic TCs propagate (Elsner (2003); Kossin et al. (2010)). During the negative phase of the NAO, the subtropical high is weaker and extends further south, which would favour westward propagation of TCs towards the U.S. In addition, such systems would tend to spend more time over the warm tropical waters than do early-recurving systems, thus also increasing the seasonal total of hurricanes. However, a recent paper by Colbert and Soden (2012) found no significant differences in TC tracks in NAO+ years compared to NAO- years and furthermore showed no simultaneous association between the NAO and the steering flow during the peak of the hurricane season. Here, we suggest a different mechanism by which the NAO impacts cyclone activity.

Figure 6 shows the difference in cyclogenesis density between the 15 most negative NAO (MJ) years and the 15 most positive NAO (MJ) years, during the negative (figure 6a) and the positive phase of the AMO (figure 6b). More storms are seen forming in the MDR during AMO+ compared to AMO- (as expected), and although there appear to be regional differences during AMO+ years (e.g. east-west shift over the MDR), the influence of the NAO (MJ) during AMO+ appears to be neutral overall, in terms of the total number of storms. The situation is noticeably different during AMO-. In the negative phase, fewer storms are observed in the MDR, with most of them forming exclusively during NAO- years. Furthermore, there is a large increase in cyclogenesis events east of the Caribbean Sea and east of Cuba and Florida during NAO- (MJ) compared to NAO+ (MJ) years.

These changes can be contrasted with changes in GPI (second row in figure 6), where the difference in detrended GPI between NAO- (MJ) and NAO+ (MJ) years is expressed as a percentage change with respect to the mean climatological value.[7] Red (blue) colours mean higher GPI values during NAO- (NAO+) years. During NAO- (MJ) years, there is a large increase in GPI east of the Florida panhandle and Cuba, where a large increase in cyclogenesis is also detected. Westward propagating AEWs will thus encounter more favourable conditions upon reaching the western part of the MDR and will be more likely to develop into TCs. The large increase in GPI over this part of the Atlantic during NAO- (MJ) years seems to be driven mostly by a decrease in vertical wind shear, itself driven by changes in upper-level winds.

Although this result requires further study, it suggests that the influence of the May-June NAO on TCs goes beyond that of simply modulating the direction of propagation,

[7]The difference has been constructed using the ten most negative and ten most positive NAO (MJ) years during the period for which NCEP reanalysis is available, 1960-2012. Furthermore, failure to remove the linear trend from the GPI timeseries does not significantly impact the result.

but rather acts to change the overall large-scale conditions such that it can be detected in basin-wide cyclogenesis statistics. This influence appears to occur through anomalous upper-level easterlies over the western Atlantic, suggesting a (new) possible interaction between the NAO and TC activity through changes in the position or velocity of the subtropical jet stream during AMO- years. Exactly how the May-June NAO could be associated with these wind anomalies remains to be explained.

4.4 Solar Activity

Elsner and Jagger (2008) were the first to detect a negative relationship between sunspot numbers and U.S. landfalling hurricanes. They suggested that the eleven-year solar cycle can influence Atlantic cyclone activity in two counteracting ways. First, increased solar activity increases downward radiation, which in turn increases the heat content of the ocean, a condition favourable to cyclone formation. On the other hand, higher levels of UV emission during years of high solar activity also increase interactions with the ozone layer in the upper-troposphere/lower stratosphere, which then raise upper-level temperature and reduce potential intensity (increasing vertical stability) and cyclone formation. More recently, Hodges and Elsner (2012) showed that there was a clear west-east shift in Atlantic cyclone activity between minimum and maximum solar activity, with an increase in the eastern part of the basin partly compensating for the decrease in the west during years of high solar activity. They attributed this shift to the two competing effects of the solar cycle, the first being predominant in the Eastern part of the tropical Atlantic where SSTs are cooler, and the second in the western part where SSTs are warmer. Here, we find that solar activity, as measured by the September sunspot numbers (SSNs), has a significant negative impact on long-duration storms (adjusted and non-adjusted), total number of TCs (adjusted) and landfalling hurricanes only during the positive phase of the AMO. This result is consistent with Hodges and Elsner (2010), which showed that correlations between solar activity and hurricane activity increase with Atlantic SSTs.

Figures 7a,b show the difference in cyclogenesis density in long-duration TCs for years with low and high SSNs. In both phases of the AMO, we observe the east-west shift detected by Hodges and Elsner (2012). However, while during the AMO- the shift is seen to be globally neutral, during the positive phase of the AMO the large increase in activity in the western part of the MDR (when SSNs are low) is not entirely compensated by the increase in the eastern part of the basin (when SSNs are high). There thus seems to be an asymmetry in the strength of the response to lower solar activity between the two phases of the AMO. Whereas higher solar activity produces a similar increase in TC activity in the eastern part of the MDR during both phases of the AMO, lower solar activity leads to a much stronger increase in TC activity in the western part during AMO+ than during AMO-. These results suggest that high solar activity is very efficient at decreasing TC activity in the western Atlantic during AMO+.

Composites of potential intensity do not show any obvious east-west shift during either AMO+ or AMO- (not shown). This could be due to limitations of the NCEP reanalysis in estimating PI, or it could be that the east-west shift in cyclone activity is caused by some other factor(s). For example, changes in the steering flow linked to solar activity could potentially steer cyclones towards the subtropics sooner (the exact mechanism for this remains unknown). The shift could also be due to the beta-drift, whereby storms forming earlier due to higher SSTs also recurve earlier towards the subtropics. On the other hand, inspection of wind composites reveals an area of lower wind shear collocated with the area of higher cyclogenesis detected during years of low SSNs during AMO+ periods (not shown), which suggests that changes in the dynamic, driven by solar activity, could also be playing a role.

Although we cannot conclude at this stage which mechanism is responsible for this east-west shift or for the asymmetrical response, the negative relationship measured here between SSNs and the number of U.S. landfalling storms and long-duration storms is consistent with the results obtained in the publications listed in table 1.

4.5 Dust

Given the comparatively shorter length of the remaining timeseries (all three climate indices are only available for ∼50 years, resulting in less than 30 years of data for either AMO+ and AMO-), conclusions relative to the influence of these parameters are somewhat more uncertain than the other parameters discussed so far, which go back to 1878, with the exception of the Sahel rainfall record which began in 1900.

Dust outbreaks from West Africa over the tropical North Atlantic have been shown to be linked to Atlantic TC activity (Evan et al., 2006). These outbreaks impact TC activity through changes in underlying tropical SSTs, with dust optical depth anomalies and monthly mean SSTs showing a maximum in cross-correlation when the SST lags the dust by one to three months (Evan and Mukhopadhyay, 2010). Furthermore, episodes of dust outbreak are associated with extremely dry air coming from the Sahara, which is another factor detrimental to cyclone formation. We find that the amount of dust in the atmosphere, measured over the months of August-October, has a significant and negative impact on all measures of TC activity, but only during the positive phase of the AMO. Figures 8a,b show the difference in cyclogenesis density between years with low and high dust concentration during the negative (8a) and positive (8b) phase of the AMO. In both cases, years with lower dust concentration are associated with more storms over the MDR. This increase in activity appears to be stronger during AMO+, which is not surprising since the MDR is more conducive to TC formation. However, during AMO-, the increase observed when dust is low is compensated by an increase in TC activity in the western, subtropical part of the basin. It is not clear at this stage if this apparent link between increased dust concentration and higher TC activity in the subtropical Atlantic is a real feature, with the dust possibly acting as an inhibitor and delaying cyclogenesis of AEWs, or is simply due to the fact that we don't have a sufficiently long dust dataset to produce an appropriate composite.

4.6 Ozone Concentration - Upper tropospheric temperature

A recent paper by Emanuel et al. (2013) suggests that the recent decrease in ozone concentration in the upper-troposphere is in part responsible for the large and recent increase in power dissipation index (PDI) in the Atlantic. They argue that the decrease in ozone concentration influences Atlantic hurricane activity by decreasing the temperature near the tropopause, which in turn modifies the thermodynamic environment in which Atlantic hurricanes develop, more specifically their outflow temperature. The influence of ozone concentration on Atlantic TC activity is supported by the inability of dynamically downscaled AGCM simulations driven by observed SSTs to capture the recent increase in hurricane activity, unless the decrease in tropopause temperature is taken into consideration (Caron and Jones (2011); Emanuel et al. (2013)).

As indicated earlier, the existing timeseries of stratospheric ozone concentration over the MDR do not cover a sufficiently long period to verify this hypothesis using the technique we are applying here. Instead, we have selected the MDR 100 hPa temperature directly. We find a strong and negative impact between temperature at 100 hPa and the total number of TCs and long-duration TCs during AMO+, as well as a weaker but still significant impact on the total number of TCs, hurricanes and major hurricanes during AMO-. Given that the recent increase in PDI is largely driven by an increase in storm numbers (Emanuel, 2007), these two results are consistent with one another. On the other hand, p-values for landfalling hurricanes are not measured to be significant in either phase of the AMO. In order to rule out the possibility that this relationship comes from the influence of the 11-year solar cycle on stratospheric temperature, we repeated the regressions after filtering out the ASO MDR 100 hPa temperature using a 9-13 year bandstop filter. Doing so tends to slightly decrease the p-values, but the significance levels were not impacted.

It can be seen in figure 1j that MDR temperatures at 100 hPa differ significantly between ERA and NCEP for most of the available reanalysis period. NCEP reanalyses display a stronger cooling trend than other reanalysis products at that level and some of this trend is likely to be spurious (see figure 1a in Vecchi et al. (2013)). As such, we also computed our regressions using individual reanalysis timeseries instead of the average of the two. The p-values obtained using ERA (NCEP) data are smaller (larger) than those obtained using the mean, but generally remain significant in all cases.[8] Since our results tend to improve with what is generally considered the better reanalysis while the second set of reanalysis still returns significant p-value, we conclude that our results are not dependent upon the choice of the reanalysis.

We suggest that the difference in significance measured between AMO+ and AMO- is due to the relatively short length of the record combined with the fact that the downward trend in stratospheric temperature which began in the early 90's occurs almost entirely during an AMO+ phase. Besides the fact that there are fewer storms during AMO- and thus a signal of ozone concentration/stratospheric temperature might be weaker, we see no apriori reasons as to why that influence should differ during the negative and positive phase of the AMO. This interpretation is supported by results shown in figures 9, 10 and 11. If this is indeed the case and the negative temperature anomaly in upper-tropospheric temperature were to persist during the next negative AMO period, we could observe an above average number of cyclones during that period (with respect to past AMO- years).

4.7 The Quasi-Biennal Oscillation

The quasi-biennial oscillation (QBO) is an oscillation of the tropical zonal winds in the stratosphere. Its highly predictable nature, even a year in advance, initially made it very interesting in the context of long-range seasonal forecasts. However, the relationship between the QBO and Atlantic TC activity seems to have broken down in recent years and as such is no longer used as a predictor by any of the groups producing such fore-

[8]The exact p-values are given as supplementary information.

casts. The reason behind this change in behaviour is currently unknown and the physical mechanism possibly linking the QBO to Atlantic hurricane activity still remains to be established (Camargo and Sobel, 2010). In this study, we found no influence of the QBO on Atlantic TC activity in either phase of the AMO.

5 Robustness analysis

Before we conclude, we analyze the results presented in section 4 in terms of their robustness to various factors. There are two main elements here which require further investigation, namely model error and sample size.

5.1 Model error

It is well known that the Poisson regression assumes equidispersion, that is, the conditional (upon regressors) mean is identical to the conditional variance. We now investigate whether the preceding results are robust to the presence of overdispersion (variance greater than expectation), which is a common feature in many count variables. Although Gourieroux et al. (1984b) and Gourieroux et al. (1984a) showed that the value of β_1 is robust to model mis-specification in regressions with count data (consistent estimator), overdispersion or underdispersion can have an effect on standard errors and hence on any other significance measure (such as confidence intervals and p-values).

To analyze the robustness with respect to overdispersion, two different approaches are used. First, we compute a standard error that is robust to such mis-specification using the sandwich covariance estimator. Second, we use a GLM that is not based upon the Poisson distribution. Hence, we use the quasi-Poisson model and the negative binomial regression (and its special case, the geometric distribution). That leaves us with a total of four robustness checks with respect to the regression model.

Instead of presenting the p-values (or the various shades of grey) for each of the latter robustness checks, we show in figure 9 the number of times (out of four) which the p-value of a given predictand/predictor combination was below 5% for any given check. In the very large majority of cases, the relationships obtained in section 4 are maintained, thus validating earlier results.[9]

5.2 Sample size

Although annual climate data usually spans over 130 years of data, the experiments presented in this paper rely on a sample that is approximately split in two (AMO+ and AMO- years). Thus, the effective sample size generally drops to about 65-70, and even to $\sim$30 for some of the climate indices observed only from the 1950's onward. Small sample sizes may affect the reliability of significance tests and in this section we check if it might have affected the results.

To do so, we use both a non-parametric and a parametric bootstrap, which are standard techniques in such cases. Quantiles of the bootstrapped parameters are used in order to assess the significance of a predictor. Figure 10 shows the significance of each predictand/predictor pair, for both bootstrap methods, using various shades of grey. We observe that the results are generally robust to the size of the sample; the non-parametric bootstrap being the method which adjusts standard errors the most, especially for indices starting in the 1950's. For example, with the non-parametric bootstrap, the relationship between the dust concentration and the number of TCs (in general) is weak or non-existent, whereas it appears to be relatively strong for almost all TC counts when using the parametric bootstrap. Therefore, the overall conclusions seem to be unaffected by the split in the sample size.

[9] For the exact p-values of each regression, please consult the two Excel files associated with the supplementary information.

6 Concluding remarks

The results presented here suggest that climate controls of Atlantic TC activity vary along with the slowly varying AMO. While the influence of local and remote SSTs remains present in both phases of the AMO, the influence of other factors is distinctly concentrated in either one phase or the other. During the negative phase of the AMO, when hurricane activity is in a lull, TC activity is linked, through changes in large-scale circulation, to precipitation over the Western Sahel and the phase of the May-June NAO, whereas during the positive phase of the AMO, when the basin is generally more active, TC activity is strongly associated with solar variability and dust concentration over the Atlantic basin. Finally, upper-tropospheric temperatures show a significant relationship to different measures of cyclone activity during the two phases of the AMO and we speculate that, if it were available, a longer timeseries of upper-level temperature would likely reduce the p-values in both phases of the AMO.

For comparison purposes, we also evaluate the significance of the covariates for the entire 1878-2012 period. In doing so, we are also considering the lower frequency timescale which was essentially filtered out in our previous analysis. The p-values are shown in figure 11 and the β values are provided in table 5. We observe that whenever a covariate is important in either the AMO + or AMO - phase, it is generally relevant when the entire timeseries is considered.

Since that by sorting years according to their AMO index we are isolating the years when a given physical influence is strongest, one might expect to obtain more significant relationships when the sample is divided into AMO + and AMO - than when we use the full sample (figure 4 compared to figure 11). Although intuitive, this might not be the case for two reasons. First, by splitting the sample into two, we are also increasing the statistical uncertainty on a parameter estimate, potentially increasing the resulting p-value. Furthermore, the transition of relevant climate influences on Atlantic TC activity between AMO+/- is likely to be progressive, shifting with the background conditions as the latter go from conducive to marginal or vice-versa, and the effect of a covariate is unlikely to change abruptly from one regime to another as the AMO reaches 0, a somewhat arbitrary cutoff point. Therefore, by isolating AMO +/- periods, we have removed some of the noise, but we likely also rejected some years during which a given covariate would still be influencing TC activity. One notable exception appears to be the influence of solar activity, which tends to decrease when the entire period is taken into consideration (compared to AMO+ only), thus suggesting that the influence of solar activity on basin-wide TC statistics is concentrated in years when the general thermodynamic conditions over the Atlantic are most favourable to cyclone formation.

The results of this paper have important implications for hurricane seasonal forecasts, as they suggest that such forecasts could be improved by making a pre-selection of the appropriate factors simply based upon the phase of the AMO. We are currently investigating this avenue.

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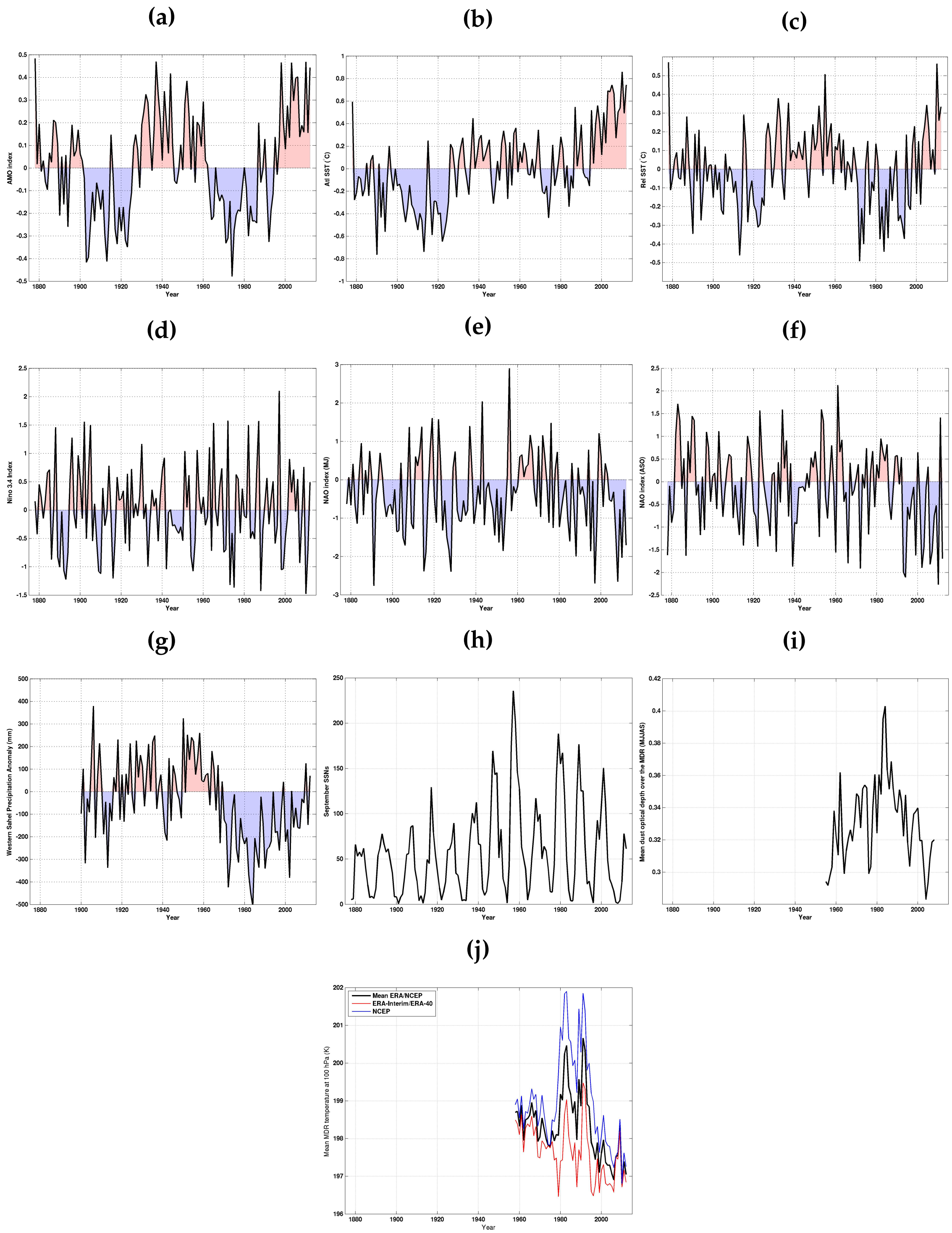


Figure 1: Timeseries of a) AMO index, b) MDR SST, c) Relative SST, d) Niño3.4 index, e) NAO (MJ), f) NAO (ASO), g) Sahel rainfall anomaly (w.r.t. 1900-2012 climatology), h) SSNs, i) MDR dust concentration, j) MDR 100 hPa temperature. MDR SST and relative SST are expressed as anomalies with respect to the climatological mean. The period over which each index is calculated is given in table 3.

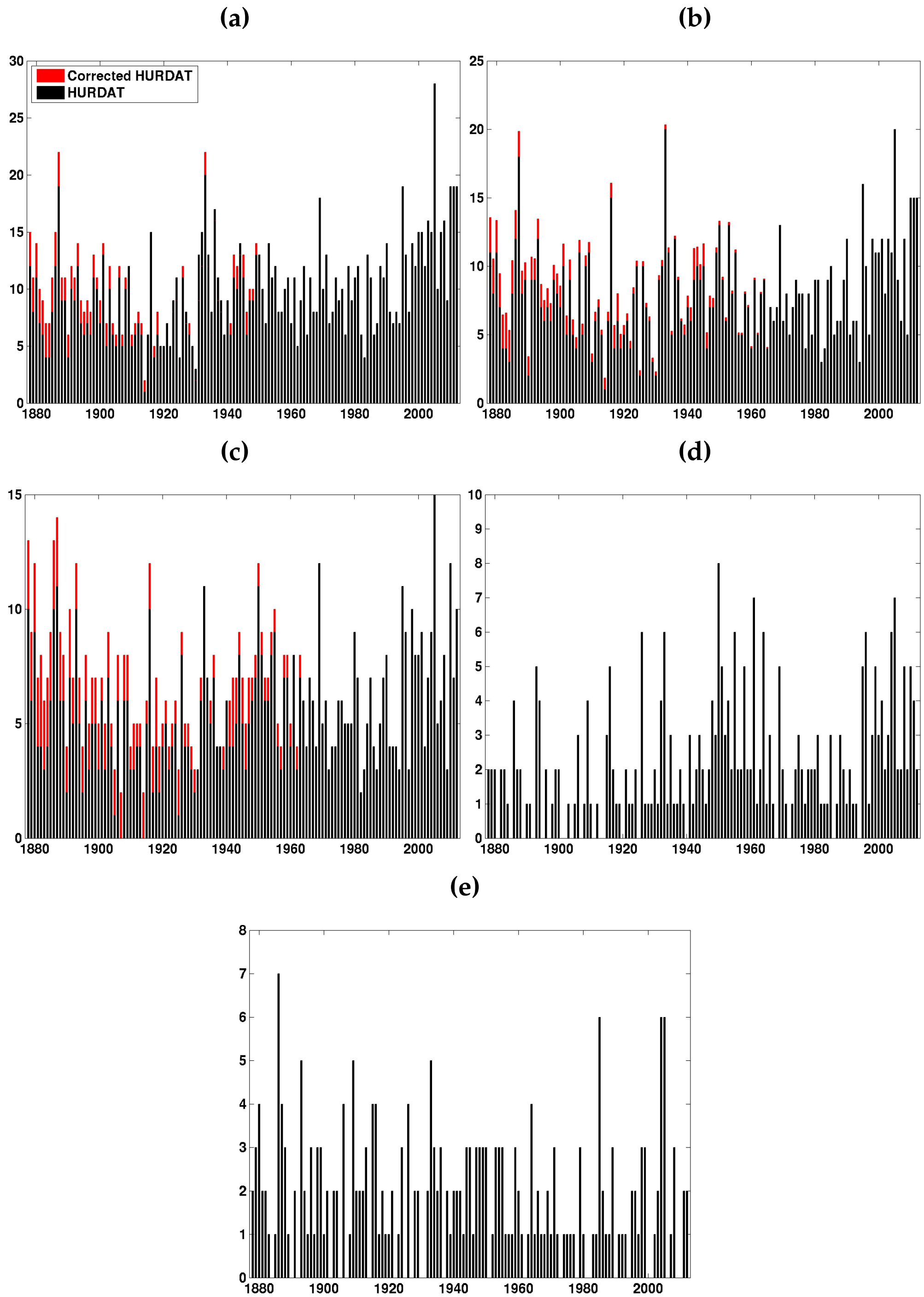


Figure 2: Timeseries for all Atlantic a) tropical cyclones, b) long-lived tropical cyclones, c) hurricanes, d) major hurricanes and e) U.S. landfalling hurricanes. Original HURDAT2 data are in black and bias-corrected data are in red.

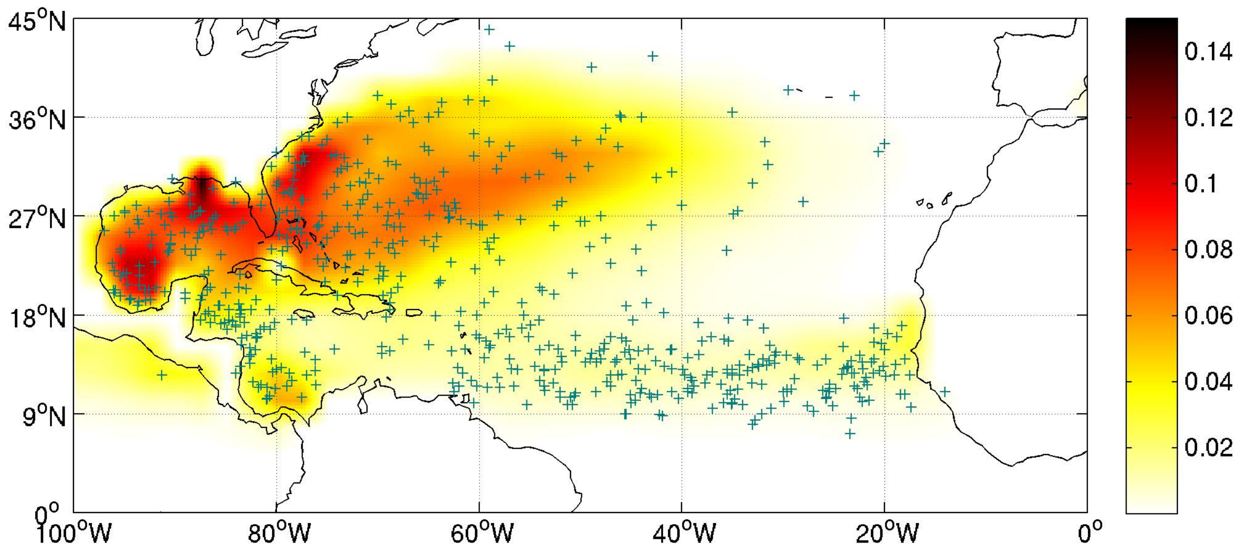


Figure 3: Mean ASO GPI, for the period 1960-2012. Only values greater than 0.005 are shown. Green cross: total cyclogenesis events detected during the period 1960-2012.

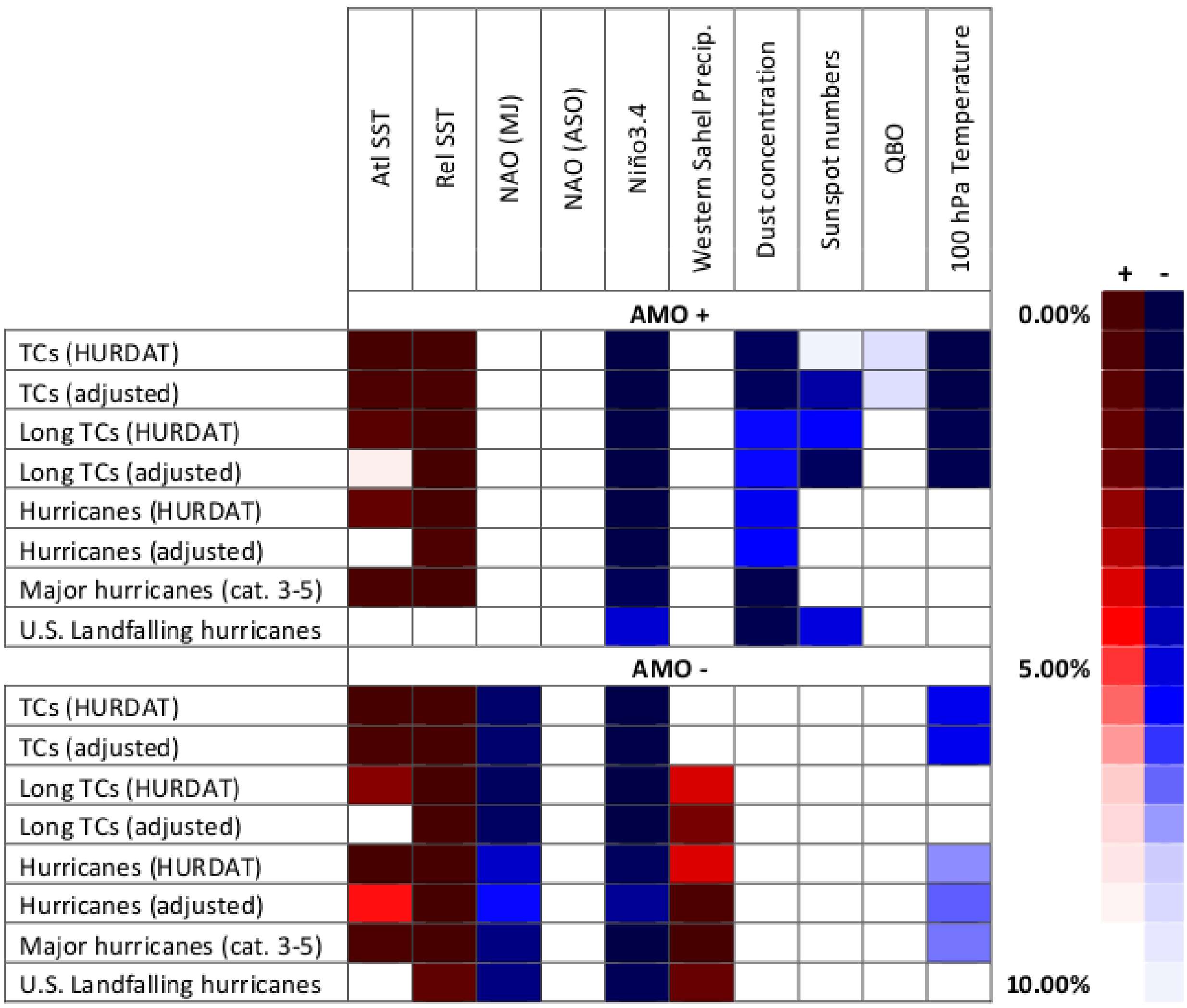


Figure 4: P-values for the significance of a given covariate. The different shadings correspond to, from darkest to lightest: < 0.1% to < 10% significance. White is > 10%. A red shading indicates that β_1>0 and a blue shading indicates that β_1<0.

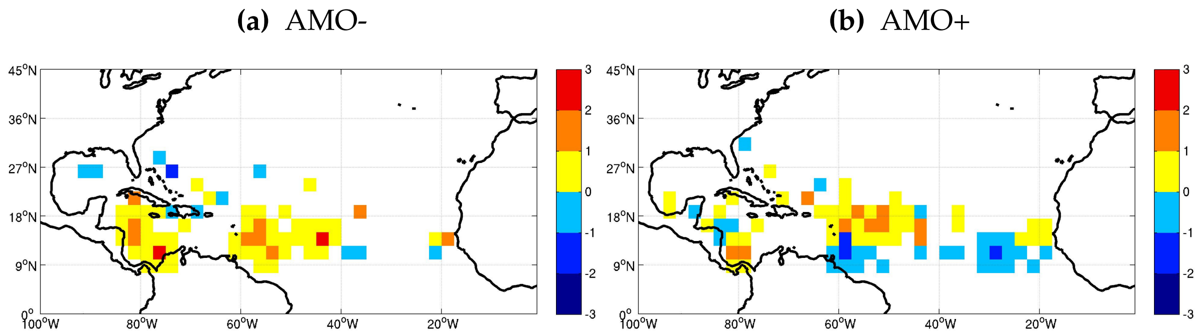


Figure 5: Difference in cyclogenesis density of major hurricanes between the 15 years with the largest positive and negative Western Sahel rainfall anomalies. Data are taken from a) AMO- years and b) AMO+ years. Yellow-red (blue) colors represent more TCs during years with positive (negative) rainfall anomalies. Units are cyclone number per $2^\circ \times 2^\circ$ grid box. Cyclogenesis density is smoothed by averaging the eight-grid points surrounding the main grid point with 1:8 weighting and the total divided by 2.

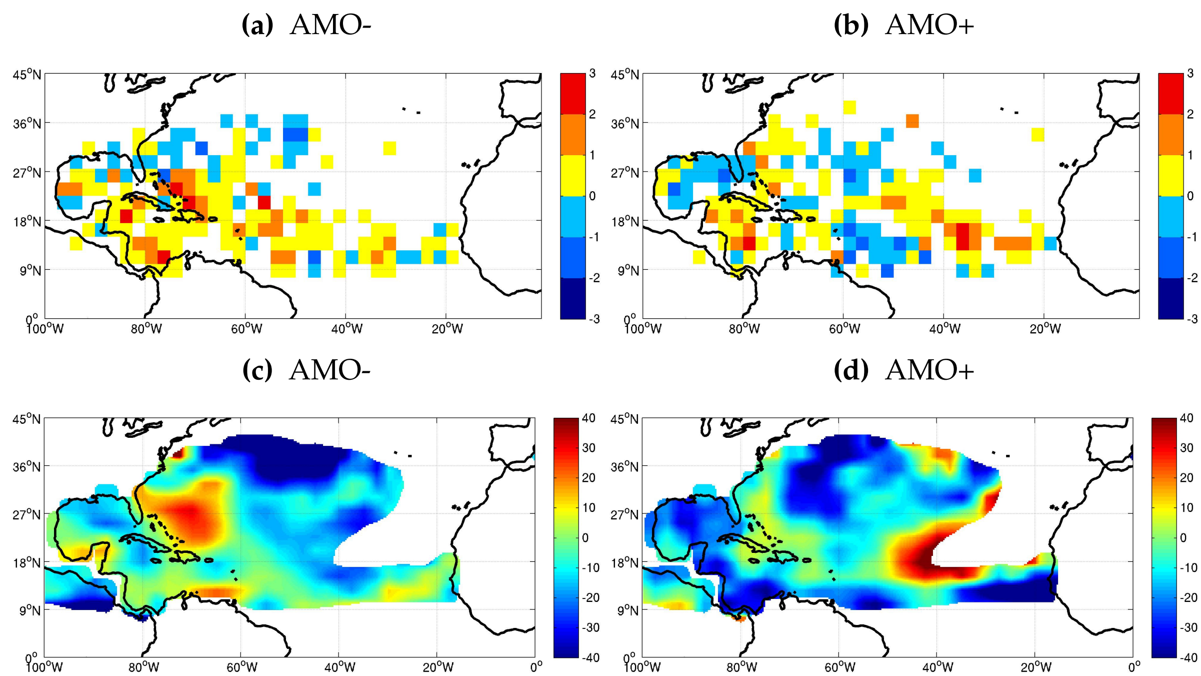
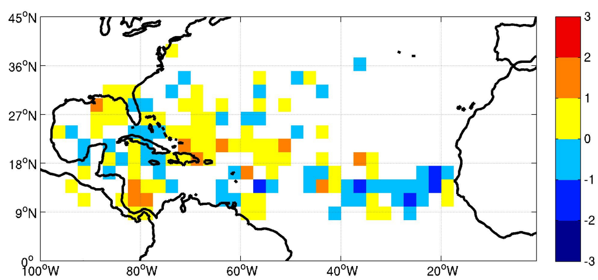


Figure 6: First row: Difference in cyclogenesis density between the 15 most negative (MJ) NAO and 15 most positive (MJ) NAO years. Data are taken from a) AMO- years and b) AMO+ years. Units are cyclone number per $2^\circ \times 2^\circ$ grid box. Yellow-red/blue colors represent more TCs during NAO-/NAO+ years. Cyclogenesis density is smoothed by averaging the eight-grid points surrounding the main grid point with 1:8 weighting and the total divided by 2. Second row: Difference in GPI between the 10 most negative (MJ) NAO and 10 most positive (MJ) NAO years. Data are taken from c) AMO- years and d) AMO+ years. Units are percent change with respect to the climatological mean. Yellow-red (blue) colors represent conditions more conducive to TC formation during NAO- (NAO+) years.

(a) AMO-



(b) AMO+

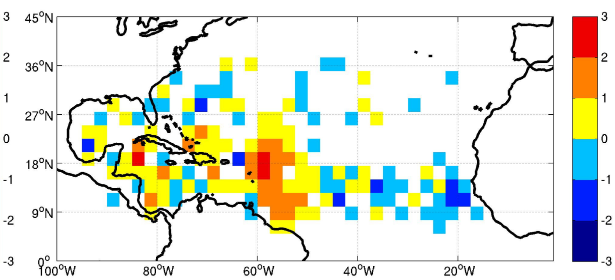


Figure 7: Difference in cyclogenesis density between the 15 years with the lowest and 15 years with the highest September SSNs. Data are taken from AMO- years (first column) and AMO+ years (second column). Units are cyclone number per $2^\circ \times 2^\circ$ grid box. Yellow-red (blue) colors represent more TCs during years with low (high) SSNs. Cyclogenesis density is smoothed by averaging the eight-grid points surrounding the main grid point with 1:8 weighting and the total divided by 2.

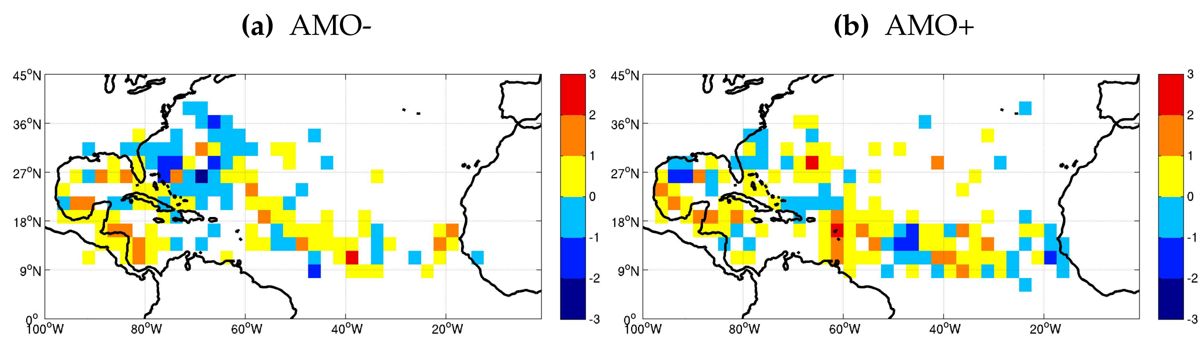


Figure 8: Difference in cyclogenesis density between the 10 years with the lowest and the 10 years with the highest concentration of dust over the MDR. Data are taken from AMO- years (first column) and AMO+ years (second column). Units are cyclone number per $2^\circ \times 2^\circ$ grid box. Yellow-red (blue) colors represent more TCs during years with low (high) dust concentration. Cyclogenesis density is smoothed by averaging the eight-grid points surrounding the main grid point with 1:8 weighting and the total divided by 2.

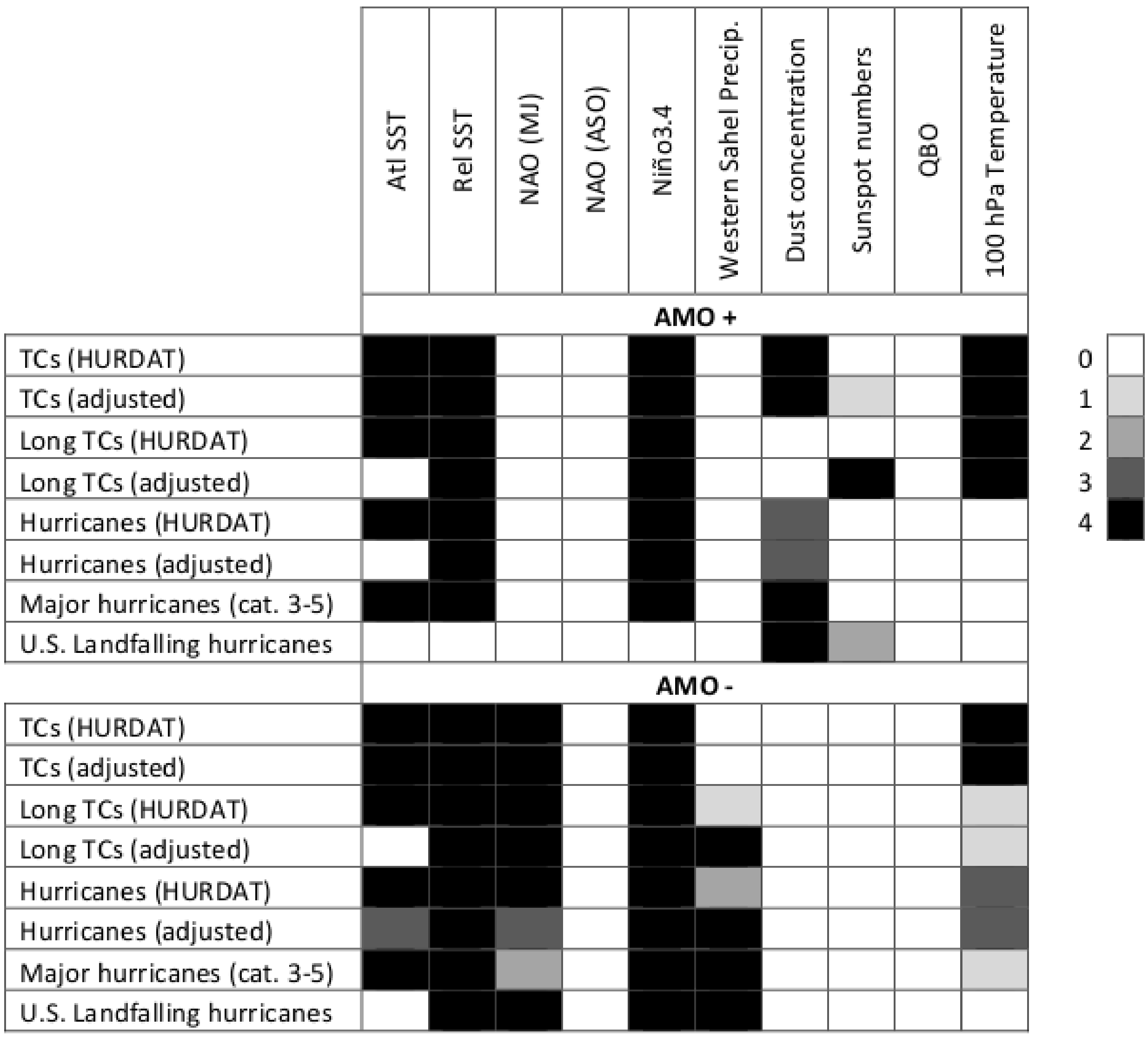


Figure 9: Number of times (out of four) the p-value of a given predictand/predictor combination is below 5% for any given robustness check (with respect to the regression model). Black corresponds to 4, dark grey corresponds to 3, grey corresponds to 2, light grey to 1, white is 0.

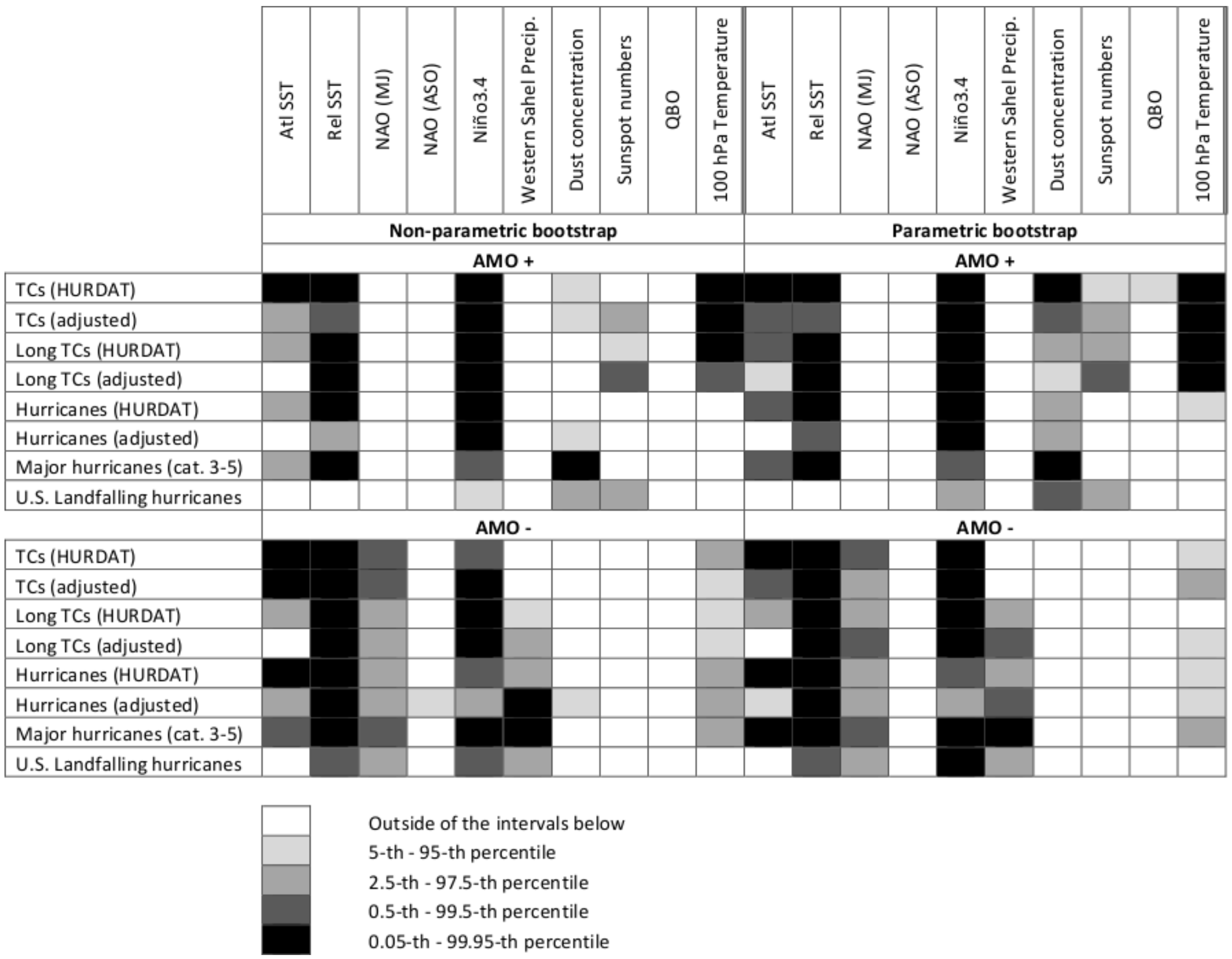


Figure 10: Significance of a predictor computed with quantiles of bootstrapped parameters (non-parametric and parametric bootstrap). Black corresponds to the case when the estimated parameter is outside the interval given by the 0.05-th and 99.95th percentiles, whereas dark grey corresponds to the interval given by the 0.5-th and 99.5th percentiles, grey is 2.5-th and 97.5-th percentile, whereas light grey is 5-th and 95-th percentiles.

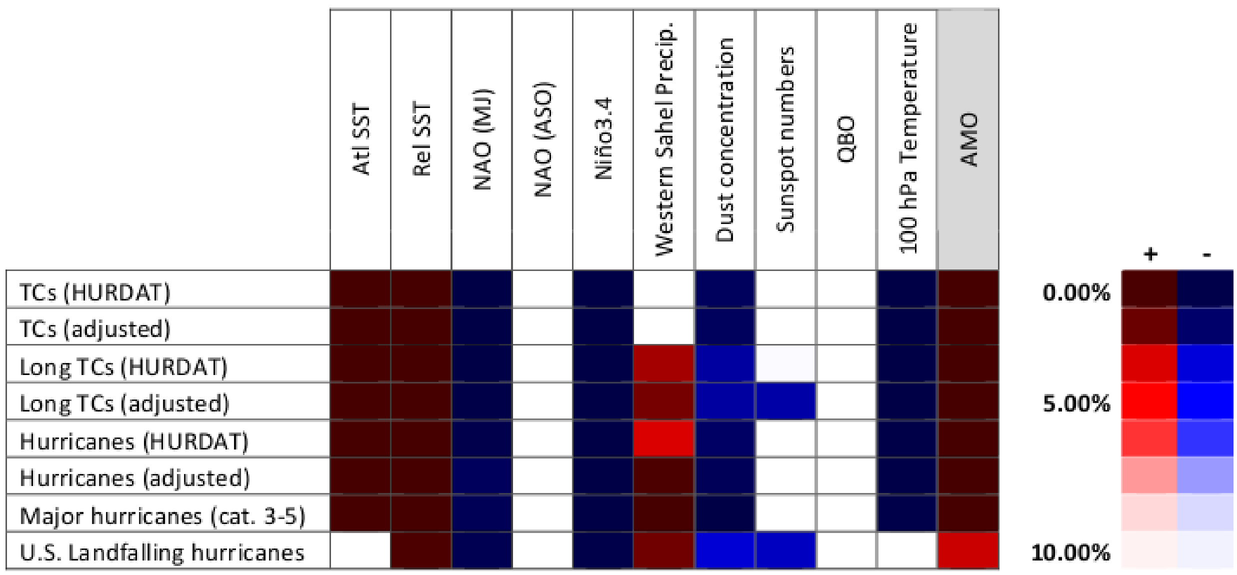


Figure 11: P-values for the significance of a given covariate. The different shadings correspond to, from darkest to lightest: < 0.1% to < 10% significance. White is > 10%. A red shading indicates that β_1>0 and a blue shading indicates that β_1<0.

Table 1: List of climate indices which have been linked to annual and multi-annual frequency variations in Atlantic tropical cyclone activity.

Climate Index	Short name	References
Atlantic Multidecadal Oscillation	AMO	Zhang and Delworth (2006); Knight et al. (2006); Goldenberg et al. (2001)
Atlantic Meridional Mode	AMM	Vimont and Kossin (2007); Kossin and Vimont (2007)
El Niño Southern Oscillation	ENSO	Kim et al. (2009); Camargo et al. (2007b); Landsea et al. (1999); Pielke and Landsea (1999) ; Shapiro and Goldenberg (1998); Gray et al. (1993) ; Klotzbach (2011a) ; Klotzbach (2011b)
Western Sahel precipitation (West African monsoon)	WAM	Fink et al. (2010); Bell and Chelliah (2006); Goldenberg and Shapiro (1996); Landsea and Gray (1992); Gray and Landsea (1992)
Atlantic SSTs	AtlSST	Saunders and Lea (2008); Bell and Chelliah (2006); Hoyos et al. (2006); Emanuel (2005); Shapiro and Goldenberg (1998);
Tropical SSTs (relative SSTs)	RelSST	Camargo et al. (2012); Vecchi et al. (2011); Swanson (2008); Latif et al. (2007)
North Atlantic Oscillation	NAO	Kossin et al. (2010); Jagger et al. (2001); Elsner and Kocher (2000); Elsner et al. (2000a); Elsner et al. (2000b); Villarini et al. (2012)
Quasi-Biennial Oscillation	QBO	Gray (1984a); Gray (1984b); Shapiro (1989); Elsner et al. (1999)
Solar activity (sunspot numbers)	SSN	Hodges and Elsner (2012); Hodges and Elsner (2010); Elsner and Jagger (2008)
Aerosols / Dust	—	Dunstone et al. (2013); Wang et al. (2012); Evan (2012); Evan et al. (2008) Evan et al. (2006)
Ozone concentration in lower stratosphere / upper tropospheric temperature	—	Emanuel et al. (2013); Vecchi et al. (2013)

Table 2: Hurricane seasons sorted by their AMO value, during ASO, 1878-2012. The 15 years with the most positive and negative AMO index are in bold.

AMO+	**1878**, 1879, 1880, 1882, 1885, 1886, 1887, 1888, 1889, 1891, 1893, 1895, 1896, 1897, 1898, 1899, 1900, 1901, 1915, 1926, 1927, 1928, 1930, 1931, **1932**, 1933, 1934, 1936, **1937**, **1938**, 1939, 1940, **1941**, 1942, 1943, **1944**, 1945, 1949, 1951, **1952**, 1953, 1955, 1957, 1958, 1959, **1960**, 1961, 1962, 1966, 1980, 1987, 1990, 1995, 1997, **1998**, 1999, 2000, 2001, 2002, **2003**, **2004**, **2005**, **2006**, 2007, 2008, 2009, **2010**, 2011, **2012**
AMO-	1881, 1883, 1884, 1890, 1892, 1894, 1902, **1903**, **1904**, 1905, 1906, 1907, 1908, 1909, 1910, 1911, **1912**, **1913**, 1914, 1916, **1917**, **1918**, 1919, **1920**, 1921, **1922**, **1923**, 1924, 1925, 1929, 1935, 1946, 1947, 1948, 1950, 1954, 1956, 1963, 1964, 1965, 1967, 1968, 1969, 1970, **1971**, **1972**, 1973, **1974**, **1975**, 1976, 1977, 1978, 1979, 1981, **1982**, 1983, 1984, 1985, 1986, 1988, 1989, 1991, **1992**, 1993, 1994, 1996

Table 3: Information on the climate indices used in this study.

Climate Index	Period	Data Provider	Years covered
AMO	ASO	Earth System Research Laboratory (NOAA)	1878-2012
Nino3.4, AtlSST RelSST	ASO	National Climatic Data Center (NOAA) / Hadley Centre	1878-2012
WAM	JJAS	Joint Institute for the Study of the Atmosphere and Ocean, University of Washington	1900-2012
NAO	MJ, ASO	Climate Research Unit, University of East Anglia	1878-2012
SSNs	September	Solar Influences Data Analysis Center / National Geophysical Data Center (NOAA)	1878-2012
Dust concentration	ASO	A. Evan (Scripps Institution of Oceanography)	1955-2008
Stratosphere temperature (100 hPa)	ASO	ECMWF (ERA40/ERA-Interim) / NCEP (Earth System Research Laboratory; NOAA)	1958-2012
QBO	ASO	Department of Earth Sciences, University of Berlin	1953-2012

Table 4: β_1 values of the Poisson regressions during both phases of the AMO.

AMO+	Atl SST	Rel SST	NAO (MJ)	NAO (ASO)	Niño3.4	Western Sahel Prec.	Dust concentration	Sunspot numbers	QBO	100 hPa Temperature
TCs (HURDAT2)	0.61	0.85	-0.052	-0.0055	-0.22	-0.00014	-8.3	-0.0012	-0.0043	-0.27
TCs (adjusted)	0.40	0.67	-0.040	0.0053	-0.22	-0.00015	-8.3	-0.0016	-0.0043	-0.27
Long TCs (HURDAT2)	0.42	0.95	-0.036	0.010	-0.24	0.000074	-6.7	-0.0016	-0.0024	-0.27
Long TCs (adjusted)	0.24	0.81	-0.026	0.016	-0.23	0.000063	-6.7	-0.0022	-0.0024	-0.27
Hurricanes (HURDAT2)	0.47	1.071	-0.055	-0.0093	-0.27	0.000074	-8.0	-0.00066	-0.0023	-0.15
Hurricanes (adjusted)	0.088	0.83	-0.036	0.020	-0.23	0.00025	-7.7	-0.0012	-0.0022	-0.12
Major hurricanes	-0.50	0.40	-0.11	0.072	-0.26	0.00044	-18.2	-0.0039	0.0018	-0.33
U.S. landfalling hurricanes	0.88	1.7	-0.063	0.038	-0.31	0.00056	-25.0	0.000033	0.0019	-0.18
AMO-										
TCs (HURDAT2)	0.74	1.05	-0.12	0.019	-0.21	0.00032	0.20	0.0011	0.0023	-0.16
TCs (adjusted)	0.59	1.07	-0.11	0.030	-0.20	0.00028	0.20	0.0011	0.0023	-0.16
Long TCs (HURDAT2)	0.50	1.37	-0.14	0.052	-0.24	0.00053	0.20	0.000013	0.0031	-0.14
Long TCs (adjusted)	0.27	1.33	-0.13	0.064	-0.23	0.00062	0.20	-0.000022	0.0031	-0.14
Hurricanes (HURDAT2)	0.94	1.64	-0.13	0.060	-0.21	0.00062	-2.42	0.00035	0.0033	-0.19
Hurricanes (adjusted)	0.44	1.56	-0.11	0.093	-0.16	0.00086	-2.93	0.00023	0.0025	-0.19
Major hurricanes	1.31	3.03	-0.24	0.13	-0.52	0.0020	-8.13	0.0019	0.0069	-0.34
U.S. landfalling hurricanes	0.14	1.78	-0.26	0.063	-0.39	0.0014	0.41	-0.0017	0.0061	-0.023

Table 5: β_1 values of the Poisson regressions for the entire 1878-2012 period.

	AMO	Atl SST	Rel SST	NAO (MJ)	NAO (ASO)	Niño3.4	Western Sahel Prec.	Dust concen-tration	Sunspot num-bers	QBO	100 hPa Tem-pera-ture
TCs (HURDAT2)	0.92	0.70	1.06	-0.11	-0.026	-0.19	0.00021	-4.86	-0.00033	0.00001	-0.26
TCs (adjusted)	0.83	0.59	1.00	-0.10	-0.015	-0.19	0.00018	-4.86	-0.00055	0.00001	-0.26
Long TCs (HURDAT2)	0.91	0.60	1.21	-0.11	-0.0065	-0.22	0.00042	-4.64	-0.0010	0.0018	-0.27
Long TCs (adjusted)	0.83	0.47	1.12	-0.10	0.0025	-0.21	0.00045	-4.64	-0.0014	0.0018	-0.27
Hurricanes (HURDAT2)	0.93	0.67	1.27	-0.11	-0.014	-0.22	0.00046	-6.36	-0.00032	0.0015	-0.22
Hurricanes (adjusted)	0.76	0.40	1.10	-0.092	0.020	-0.18	0.00065	-6.61	-0.00066	0.0013	-0.22
Major hurricanes	1.35	0.97	1.90	-0.17	0.031	-0.36	0.0014	-15.4	0.00069	0.0067	-0.35
U.S. landfalling hurricanes	0.61	0.12	0.98	-0.19	0.046	-0.30	0.0010	-9.93	-0.0030	0.0045	-0.17