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Key Points:

- Estimates of missing storms are not sufficient to account for the increase in hurricane activity in the eastern tropical Atlantic
- Recent upward trends, artificial or not, affect the selection of key determinants of tropical cyclone activity, especially the SST variable
- Despite previous results to that effect, the May–June NAO does not provide predictive skill for Atlantic landfalling hurricanes

Supporting Information:

- Data Set S1
- Data Set S2

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Reanalysis of climate influences on Atlantic tropical cyclone activity using cluster analysis

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Abstract We analyze, using Poisson regressions, the main climate influences on North Atlantic tropical cyclone activity. The analysis is performed using not only various time series of basin-wide storm counts but also various series of regional clusters, taking into account shortcomings of the hurricane database through estimates of missing storms. The analysis confirms that tropical cyclones forming in different regions of the Atlantic are susceptible to different climate influences. We also investigate the presence of trends in these various time series, both at the basin-wide and cluster levels, and show that, even after accounting for possible missing storms, there remains an upward trend in the eastern part of the basin and a downward trend in the western part. Using model selection algorithms, we show that the best model of Atlantic tropical cyclone activity for the recent past is constructed using Atlantic sea surface temperature and upper tropospheric temperature, while for the 1878–2015 period, the chosen covariates are Atlantic sea surface temperature and El Niño–Southern Oscillation. We also note that the presence of these artificial trends can impact the selection of the best covariates. If the underlying series shows an upward trend, then the mean Atlantic sea surface temperature captures both interannual variability and the upward trend, artificial or not. The relative sea surface temperature is chosen instead for stationary counts. Finally, we show that the predictive capability of the statistical models investigated is low for U.S. landfalling hurricanes but can be considerably improved when forecasting combinations of clusters whose hurricanes are most likely to make landfall.

1. Introduction

The first seasonal hurricane forecasts for the Atlantic basin were issued in the 1980s [*Gray*, 1984a, 1984b; *Camargo et al.*, 2007a], and since then there has been a growing number of organizations (the complete list of current seasonal forecasts can be found at http://www.seasonalhurricanepredictions.org), ranging from national weather services to universities and private companies, which have started issuing such products. While these forecasts are typically made for the Atlantic basin as a whole, recent studies are suggesting that skillful seasonal forecasts at the subbasin level [*Vecchi et al.*, 2014; *Camp et al.*, 2015; *Camp and Caron*, 2017] and of landfalling storms [*Murakami et al.*, 2016a] are also becoming possible. It is worth pointing out that these studies relied on so-called dynamical forecasts, wherein upcoming seasonal hurricane activity is estimated by directly detecting and tracking the storms in initialized climate simulations.

On the other hand, many seasonal forecast systems are based on statistical relationships between a selection of local and remote climate factors and basin-wide seasonal hurricane characteristics. The El Niño–Southern Oscillation (ENSO) is probably the most well known of these influences, in no small part because the detection of a robust link between ENSO and Atlantic hurricane activity is what lead to hurricane seasonal forecasts in the first place [*Gray*, 1984a, 1984b]. The influence of ENSO has been found to occur primarily through modulation of upper tropospheric zonal winds, and consequently on vertical wind shear, over the northern tropical Atlantic [*Goldenberg and Shapiro*, 1996; *Bell and Chelliah*, 2006], but changes in tropospheric humidity have also been implicated [*Camargo et al.*, 2007b]. The presence of El Niño (La Niña) conditions in the tropical Pacific is usually associated with conditions more detrimental (favorable) to cyclogenesis and with a general decrease (increase) in Atlantic tropical cyclone (TC) activity.

Thermodynamical conditions, driven by underlying sea surface temperature, over the Northern Atlantic also play a dominant role in modulating hurricane activity, especially over multiannual time scales [*Emanuel et al.*, 2013]. Changes in the thermodynamical Atlantic background have been associated with changes in the

Atlantic Multidecadal Oscillation (AMO) or more directly through changes in Atlantic sea surface temperature (SST) [*Zhang and Delworth*, 2006; *Knight et al.*, 2006; *Shapiro and Goldenberg*, 1998; *Emanuel*, 2005]. The positive phase of the AMO, associated with positive SST anomalies over the North Atlantic, produces climate conditions more conducive to TC formation (and vice-versa). The case was also made that the SST of the tropical Atlantic taken with respect to the rest of the tropics was a more relevant parameter than the absolute temperature of the tropical Atlantic itself [*Villarini et al.*, 2016; *Camargo et al.*, 2013; *Villarini et al.*, 2011a; *Vecchi et al.*, 2008] due to the impact of remote SST on Atlantic vertical wind shear [*Latif et al.*, 2007] and potential intensity (PI) [*Emanuel*, 1988]. PI represents the thermodynamically based maximum cyclone intensity that the ocean-atmosphere system will support and is a parameter influencing tropical cyclone activity [*Vecchi and Soden*, 2007; *Swanson*, 2008].

Changes in the upper troposphere and tropical tropopause layer temperature were also shown to impact PI [*Vecchi et al.*, 2013; *Emanuel et al.*, 2013; *Wing et al.*, 2015] since PI depends, in part, on the difference in temperature between the ocean and the upper troposphere [*Emanuel*, 1986]. Everything else being equal, decrease in upper troposphere temperature will increase PI and, incidentally, Atlantic TC activity.

Another well-known influence on Atlantic hurricane activity is the amount of rainfall that falls over the Western Sahel region in the months preceding and overlapping with the busiest months of the hurricane season. Precipitation over that region of Africa was previously found to be highly correlated with Atlantic hurricanes [*Goldenberg and Shapiro*, 1996; *Bell and Chelliah*, 2006], and in particular with the strongest storms [*Landsea and Gray*, 1992; *Landsea et al.*, 1992], and was afterward used as a predictor in hurricane seasonal forecast models [*Gray and Landsea*, 1992]. The influence of Sahel precipitation was shown to occur, like ENSO, through modulation of the vertical wind shear over the tropical Atlantic, with positive precipitation anomaly being linked to increase convective activity over the Sahel region and, consequently, to negative anomaly in the upper zonal flow over the tropical Atlantic. Changes in the general characteristics of African Easterly Waves (AEWs), which are the precursors to a large number of Atlantic hurricanes, might also have a role to play [*Thorncroft and Hodges*, 2001]. However, despite a promising start, Sahel precipitation was later abandoned as a predictor as the link with Atlantic hurricane activity began to deteriorate in the late 1990s to the point where it no longer had any predictive power. More recently, *Fink et al.* [2010] showed that the influence of Western Sahel precipitation on Atlantic TC activity is cyclical and tends to be stronger (weaker) in years when conditions over the Atlantic are unfavorable (favorable) to TC formation. Further supporting the connection between Sahel rainfall and hurricane activity is the detection of this link in high-resolution climate models [*Caron et al.*, 2012]. As such, it is entirely possible that this predictor will be reinstated in seasonal forecasts, especially if we are entering a more quiescent era of Atlantic hurricane activity, as some have recently speculated [*Klotzbach et al.*, 2015].

It was also argued that the influence of Sahel precipitation on Atlantic hurricane activity is in fact a proxy influence of the Atlantic Meridional Mode (AMM) [*Kossin and Vimont*, 2007]. The AMM is the leading mode of variability in the Atlantic, and it impacts, among other things, precipitation over the Sahel region. A positive AMM has been associated with warmer SST across the north tropical Atlantic, a southward displacement of the Intertropical Convergence Zone as well as lower vertical wind shear across the main development region (MDR) [*Kossin and Vimont*, 2007; *Vimont and Kossin*, 2007], all conditions favorable to cyclogenesis. It is also worth mentioning that variations in the AMM, unlike the AMO, have been linked to Atlantic hurricane variability at both the annual and multiannual time scales.

Although the aforementioned climate variables are arguably the most well-known modulators of Atlantic tropical cyclone activity, hurricane activity has also been linked to the North Atlantic Oscillation (NAO) [*Elsner and Kocher*, 2000; *Elsner et al.*, 2000; *Villarini et al.*, 2012], the 11 year solar cycle [*Hodges and Elsner*, 2010; *Elsner and Jagger*, 2008], natural and anthropogenic tropospheric aerosols [*Dunstone et al.*, 2013; *Evan et al.*, 2006, 2008], and the North Atlantic subpolar gyre temperature [*Smith et al.*, 2010; *Dunstone et al.*, 2011; *Caron et al.*, 2015a].

Statistical hurricane forecast models, which incorporate a certain number of these relationships, typically manage to capture the overall effect of these various climate factors on the basin-wide hurricane activity but usually miss regional differences in these influences. For example, it is well known that while El Niño has an overall negative effect on Atlantic tropical cyclone activity, the effect within the basin itself can vary with the flavor of ENSO [*Kim et al.*, 2009; *Caron et al.*, 2010]. In that context, analyzing the variability of a subgroup of storms, or cluster, with similar characteristics as opposed to the basin as a whole might highlight the relationship between regional activity and some particular climate factor. This could then be expected to lead to some insight on hurricane variability and possibly an improvement in the forecast itself. In fact, the recent use of clusters in a hybrid dynamical-statistical seasonal forecast system has been shown to improve upon the skill given by the dynamical forecasts alone [*Murakami et al.*, 2016b].

A few studies have used a clustering approach to study Atlantic tropical cyclones [*Kossin et al.*, 2010; *Kozar et al.*, 2012; *Corporal-Lodangco et al.*, 2014; *Daloz et al.*, 2015]. In particular, *Kossin et al.* [2010], and later on *Kozar et al.* [2012], have used Poisson regressions to link the variability of four clusters of tropical cyclones to different climate features.

Here we follow up and expand on these studies by (i) increasing the number of climate predictors considered in those studies, (ii) using multiple tropical cyclone time series as a measure of TC activity, (iii) increasing the analysis time period, and (iv) investigating how the deficiencies in the hurricane database can propagate at the cluster level in this type of studies.

We use a similar approach and the same clustering technique as both *Kossin et al.* [2010] and *Kozar et al.* [2012] [*Gaffney*, 2004], but whereas they considered all tropical cyclones (tropical storms and hurricanes), we also extend the analysis to tropical cyclones that survived 48 h or longer and storms that have reached hurricane intensity. By comparing the variability of the different sets of clusters, we hope to both increase the robustness of the previous findings and provide some additional insights on the influence of some climate factors.

We also look at the impact that artificial trends in HURDAT2 have on the resulting statistical relationship and attempt to mitigate their impact through a first order correction. This type of correction has typically been performed at the basin-wide scale [*Villarini et al.*, 2010, 2012; *Caron et al.*, 2015b], but here we apply it at the cluster level as well. Finally, we use these results to develop statistical models of tropical cyclone and hurricane counts and suggest an alternative to modeling landfalling storms.

The paper is structured as follows. In section 2, we present an overview of the data and of the methodology used in this paper. In section 3, we investigate the relationship between various climate predictors and Atlantic tropical cyclone activity, both at the basin-wide scale and for different storm clusters. Section 4 analyzes the impact of artificial trends in the data, whereas in sections 5 and 6, we design statistical models of tropical cyclone frequency and we investigate the predictive power of these models and of individual climate variables. We conclude the paper in section 7.

2. Data and Methodology

2.1. Climate Data

The various climate indices used in this study are similar to the ones used in *Caron et al.* [2015b] and are based on past literature linking Atlantic hurricane activity and various large-scale climate features. We use both the absolute Atlantic SST (AtlSST) and relative SST (RelSST) over the main development region (MDR) [*Goldenberg and Shapiro*, 1996], both computed using the average of NOAA extended reconstructed SSTs (ERSST) [*Smith et al.*, 2008] and Hadley Center reconstructed SSTs (HadISST [*Rayner et al.*, 2006]). AtlSST and RelSST are defined, respectively, by the mean SST limited by 10°N, 25°N, 80°W, and 20°W (the MDR region) and by the difference between the former and the mean tropical SST limited by 30°N and 30°S [*Vecchi et al.*, 2008, 2011]. Similarly, we also include the subpolar gyre (SPG) temperature, computed as the average of ERSST and HadISST over 50°N, 70°N, 60°W, and 20°W [*Smith et al.*, 2010]. The Atlantic SPG was linked to Atlantic hurricane activity through its impact on the Hadley circulation and on large-scale vertical motion over the MDR. [*Dunstone et al.*, 2011].

Time series for the AMO, defined as the linearly detrended SST averaged between 0° and 70°N [*Knight et al.*, 2006; *Zhang and Delworth*, 2006], and the AMM were obtained directly from the Earth System Research Laboratory (ESRL) database. The influence of ENSO is measured using SST anomalies over the Niño3.4 region [*Barnston et al.*, 1997], while for the NAO we use both the standard NAO [*Jones et al.*, 1997], taken as the difference in pressures between Iceland and the Azores, and the mobile NAO, derived from principal component analysis [*Folland et al.*, 2009]. Niño3.4 and NAO time series were also obtained from the ESRL database.

The sunspot numbers (SSNs) [*Elsner and Jagger*, 2008; *Hodges and Elsner*, 2010] are taken from the Solar Influences Data Analysis Center (SIDC) of the Royal Observatory of Belgium [*Van der Linden and Team*, 2016]. Sahel rainfall data are taken from the Joint Institute for the Study of the Atmosphere and Ocean [*Mitchell*, 2013].

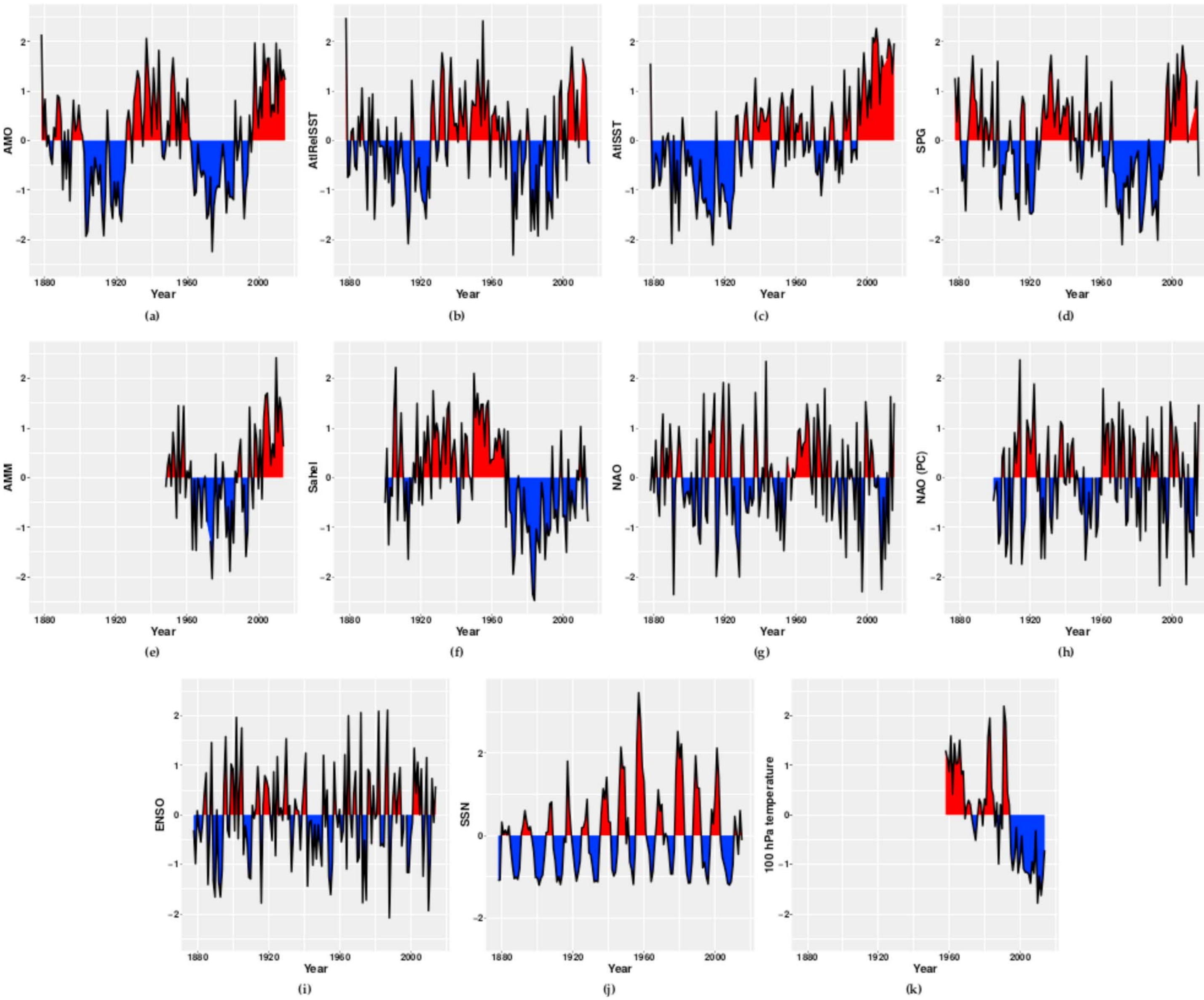


Figure 1. Standardized time series of various climate indices used in this study: (a) AMO, (b) Atlantic relative SST, (c) Atlantic SST, (d) subpolar gyre temperature, (e) AMM, (f) Sahel rainfall, (g) standard NAO, (h) mobile NAO, (i) SST anomaly over the Nino3.4 region, (j) SSNs, and (k) 100 hPa temperature over the MDR.

In this case, the Sahel region is bounded by (10°N, 20°N, 20°W, 10°E), as in *Janowiak* [1988]. Finally, the temperature at 100 hPa [*Vecchi et al.*, 2013; *Emanuel et al.*, 2013] is computed over the MDR using the Japanese 55-year Reanalysis (JRA-55) [*Kobayashi et al.*, 2015].

Climate indices are taken as the average for August-September-October (ASO), which corresponds to the peak of the Atlantic hurricane season, except for the Sahel precipitation (JJAS), the NAO (MJ), and the sunspot numbers (September only). While most climate time series cover the 1878–2015 period, the Sahel precipitation is limited to 1900–2014 and the upper tropospheric temperature to 1955–2014. The different time series are shown in standardized form in Figure 1.

2.2. Hurricane Data

The tropical cyclone time series are constructed using the HURDAT2 database (downloaded on 16 May 2016) [*Landsea and Franklin*, 2013]. This database includes information on Atlantic tropical cyclones going all the way back to the middle nineteenth century, but it is also incomplete, especially for the period preceding reconnaissance flights introduced in the mid-1940s [*Landsea*, 2007]. The increase in coverage of the Atlantic basin

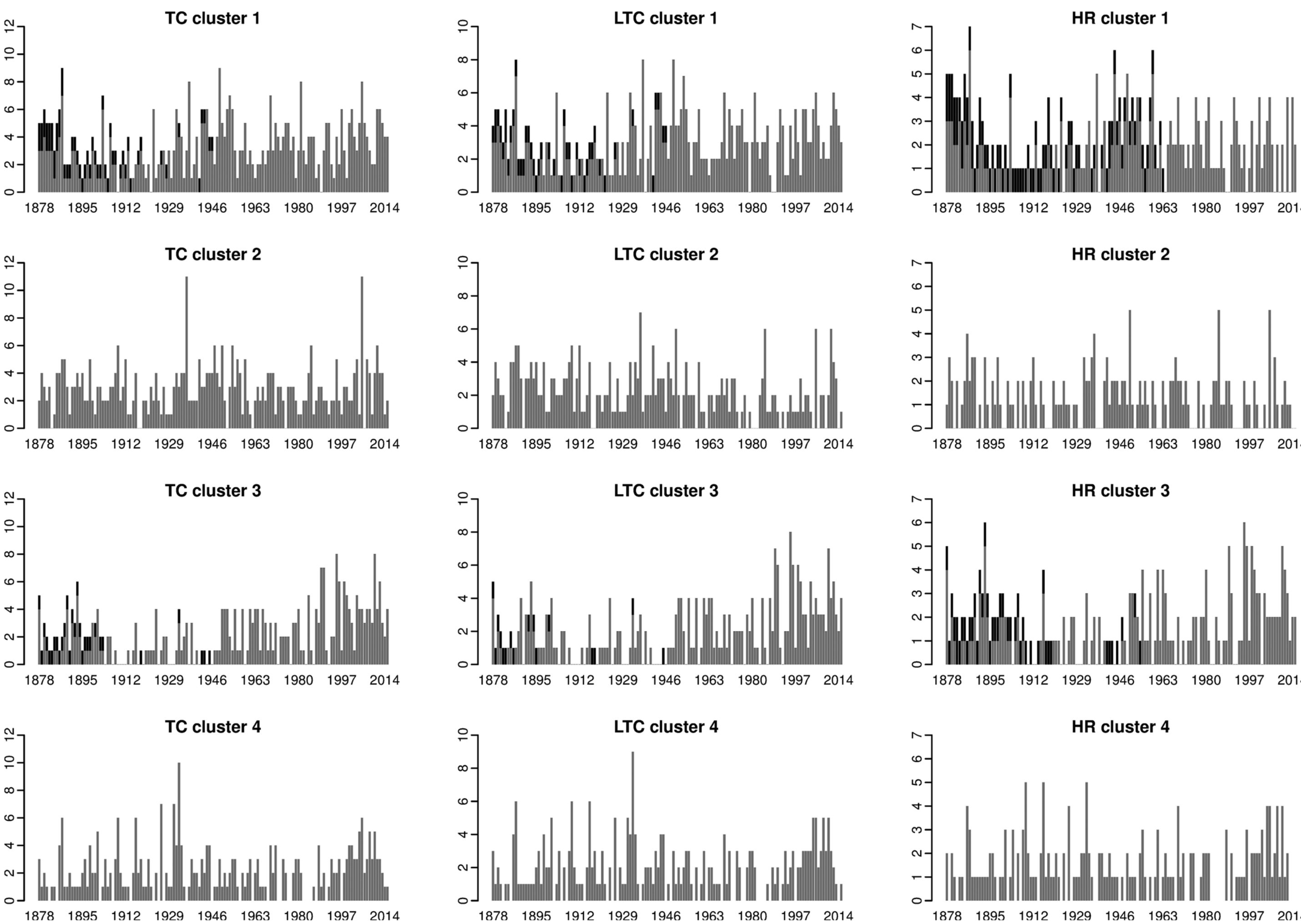


Figure 2. Time series of clusters 1–4 tropical cyclones (TCs), long-duration tropical cyclones (LTCs), and hurricanes (HRs). The data originating from HURDAT2 are in gray, and the corrections are in black.

over the course of the twentieth century has led to well-documented biases in the HURDAT database [*Landsea et al.*, 2010] and there are ongoing reanalysis efforts aiming to correct its shortcomings [*Landsea et al.*, 2008, 2012; *Chenoweth*, 2014]. While we may never know the exact number of storms missed by the observational network of the day, some studies [*Vecchi and Knutson*, 2008, 2011; *Landsea et al.*, 2010] have offered estimates on the number of possible missed storms (tropical cyclones (TCs), hurricanes (HRs), tropical cyclones lasting longer than 48 h (LTCs), respectively) during the presatellite era. Thus, in addition to using the raw HURDAT2 data for the number of TCs, LTCs ,and HRs, we also make use of the corrected time series suggested by the three aforementioned studies. These adjustments are of course just an estimate of what was possibly missed due to a patchy coverage, but using both the original and the corrected time series provides a sensitivity test for this type of correction and allows us to examine whether the results we obtained are significantly impacted by the deficiency of the database.

2.3. Clusters: Description and Characteristics

The cluster analysis applied here was first developed in *Gaffney* [2004] and applied to North Atlantic extra-tropical cyclones in *Gaffney et al.* [2007], where it is described in detail. The cluster technique is based on a mixture of polynomial regression models (quadratic here), which are used to fit the geographical shape of the tropical cyclone tracks by finding parameters that maximize the likelihood of the observations. The cluster algorithm has as input the location of each storm, and is repeated 100 times, randomizing the order that the tracks are included in the analysis. The final cluster assignment is chosen as the best fit among them. One of the advantages of this cluster analysis is the ability to deal with tracks with different lengths.

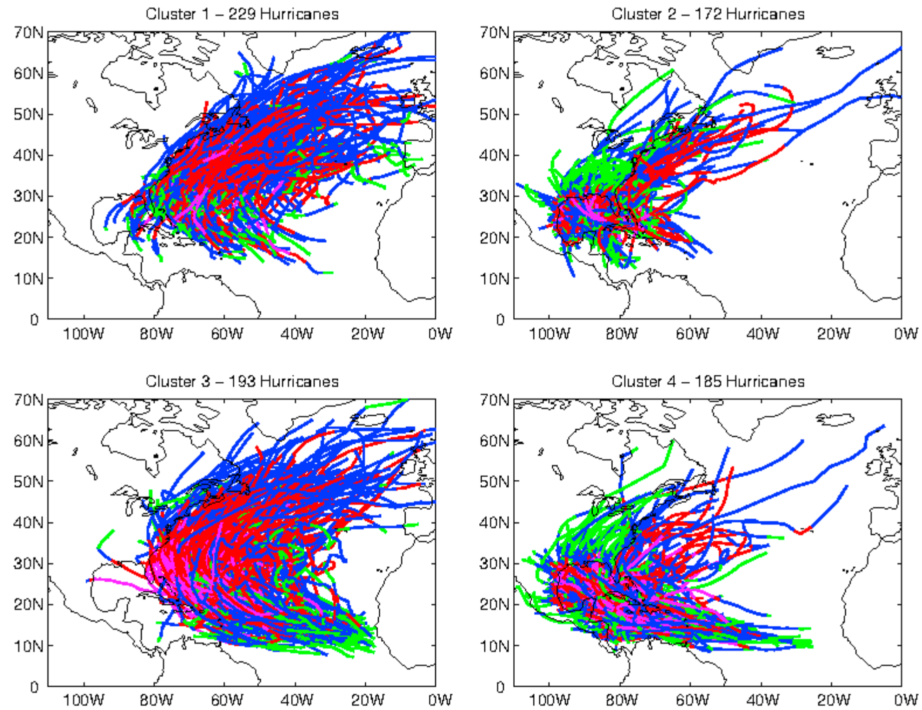


Figure 3. The four clusters of North Atlantic hurricane tracks for the 1878–2015 period. The different colors indicate the intensity of the storms. Green, tropical depression; blue, tropical storm; red, hurricane categories 1–2; magenta, hurricane categories 3–5.

This technique has been extensively applied to observed tropical cyclones tracks in the western [*Camargo et al.*, 2007c, 2007d] and eastern [*Camargo et al.*, 2008; *Caron et al.*, 2015c] North Pacific, Southern Hemisphere [*Ramsay et al.*, 2012], and in North Atlantic TC model tracks [*Daloz et al.*, 2015]. In the case of observed North Atlantic tropical cyclones, *Kossin et al.* [2010] applied the cluster analysis for the period 1950–2007. As discussed by the authors, similar to other cluster techniques, the number of clusters is not uniquely determined in this technique. We used the in-sample log-likelihood, within-cluster spread, and qualitative arguments to choose a final number of four clusters. In *Kozar et al.* [2012], the original data set was extended to include an earlier period and the analysis of four clusters was done for the period 1878–2007. Here we use the updated observed HURDATA2 data set and further extend the cluster analysis to the period until 2015, keeping the choice of four clusters, as in the previous studies. Furthermore, we consider not only all TCs but also the characteristics of the hurricane-only clusters as well as tropical cyclones lasting 48 h or more. Figure 2 shows the time series of the number of these events along with their corrected counterpart, whereas Figure 3 displays the tracks of TCs that reach hurricane intensity in each cluster.

Storms in cluster 1, which is the largest cluster (Table 1), tend to form relatively northward and eastward in the basin and tend to propagate in a north-eastern direction, generally without making landfall. In contrast, storms in cluster 2 tend to form in or at the edge of the Gulf of Mexico and generally make landfall. Clusters 3 and 4 consist of storms forming the most southward, generally from AEWs, but while storms in cluster 3 generally recurve out to sea, a large number of storms in cluster 4 are found to propagate westward and make landfall in the Caribbeans, Central America, or the U.S.

Table 1. Distribution of Storms Per Cluster

	TCs	LTCs	HRs	% of Landfalling HRs
Cluster 1 (U.S. Coast storms)	426	390	229	44.5%
Cluster 2 (Gulf of Mexico storms)	394	297	172	93.6%
Cluster 3 (MDR - East/Cape Verde storms)	279	261	193	37.8%
Cluster 4 (MDR - West/Caribbean storms)	283	259	185	94.1%

Besides differences in geographical distribution, it was shown in *Kossin et al.* [2010] that these different clusters also had different general characteristics: significant differences were detected in longevity, intensity, landfall rate, and destructiveness. Not surprisingly, the storms from clusters 3 and 4, which form in the deep tropics, tend to be more intense than the storms in clusters 1 and 2, as evidenced by the largest proportion of hurricanes in those two clusters, and storms from clusters 2 and 4, which are closer to land, have a much higher landfall rate than clusters 1 and 3 (roughly >90% versus ∼40%; Table 1). There also exists clear differences in frequency between the clusters, both at the interannual and the decadal level. For example, the recent active period (1995–2015) is due mostly to a high number of clusters 3 and 4 hurricanes, whereas cluster 1 hurricane activity is relatively low compared to previous periods. The differences in the variability of the different clusters was explained by the different climate factors that they are sensitive to. *Kossin et al.* [2010] linked cluster 3 and 4 to northern tropical Atlantic SST and the AMM as well as ENSO. On the other hand, they could only link cluster 2 to the Madden-Julian Oscillation (MJO), a subseasonal oscillation (the focus of the study being on seasonal activity, we do not consider subseasonal oscillations here). Similarly, attempts to model the variability of this cluster in *Kozar et al.* [2012] were relatively unsuccessful.

Finally, *Kossin et al.* [2010] linked the variability of cluster 1 to the May-June NAO, with the rate of cluster 1 storms increasing during the negative phase of the NAO. The link between the NAO and Atlantic TC activity was postulated to occur through changes in the strength and location of the Atlantic subtropical high: a negative NAO is associated with a subtropical high that has a more south-west location during the hurricane season, forcing TCs that form equatorward of the high to remain at lower latitudes and in conditions generally more favorable to their intensification [*Elsner*, 2003]. On the other hand, a later study [*Colbert and Soden*, 2012] found no significant differences in the mean hurricane tracks in negative NAO years compared to positive NAO years and showed no simultaneous association between the NAO and the steering flow during the peak of the hurricane season, so it is possible that the mechanism by which the NAO influences TC activity is not yet fully understood. Interestingly, using a longer time period, *Kozar et al.* [2012] did not report a strong link between cluster 1 TCs and the May-June NAO but reported a link with cluster 4 TCs, which are the storms one would expect to be most impacted by the mechanism described above.

2.4. Poisson Regression

The results presented in this paper are derived from Poisson regressions, which is a conventional approach to analyzing the determinants of count variables. Let $X_{j,k}$ be the value of the jth predictor (or covariate) at time k and N_k be the number of events at time k. Then, a Poisson regression is a modeling approach that links N_k to $X_{1,k}, X_{2,k}, \dots, X_{p,k}$ such that

$$\log\left(\mathrm{E}[N_k|X_{1,k}, X_{2,k}, \dots X_{p,k}]\right) = \beta_0 + \beta_1 X_{1,k} + \beta_2 X_{2,k} + \cdots + \beta_p X_{p,k} \tag{1}$$

i.e., the conditional mean of the Poisson distribution at time k is a log-linear function of the predictors. In this structure, it is important to note that each coefficient β_j of the regression is rather interpreted as the *percentage* change in $E[N_k|X_{1,k}, X_{2,k}, \dots X_{p,k}]$ when $X_{j,k}$ is varied by one unit.

The Poisson regression is a popular approach in hurricane climatology, and it has been applied by various authors [*Solow and Nicholls*, 1990; *Elsner and Jagger*, 2006; *Villarini et al.*, 2010; *Kozar et al.*, 2012; *Camargo et al.*, 2014; *Caron et al.*, 2015b, 2015c]. For more details on Poisson regressions, *Elsner and Jagger* [2013] (Chapter 7) present a more hurricane-specific approach whereas *Cameron and Trivedi* [2013] provide a rigorous treatment of the statistical model.

The *significance* of the relationship between a given predictand and a predictor is summarized by the p value of its two-tailed test. However, this significance can be affected by model misspecification, i.e., any material deviation between the model's assumptions (Poisson) and the characteristics of the data. Therefore, in sections 3 and 4, we have conducted additional robustness analyses using alternative models (such as quasi-Poisson, geometric, or negative binomial regressions) and using Huber-White (sandwich) standard errors. Unless stated otherwise, these results are provided in the supporting information.

3. Climate Influences on Atlantic Tropical Cyclone Activity

3.1. Method

We would like to determine the extent to which the climate indices (predictors; Figure 1) help explain the storm counts (predictands), both at the basin-wide level and at the cluster level (Figure 2). As an initial first step, we study each pair of predictand and predictor using the Poisson regression of section 2.4. This is meant

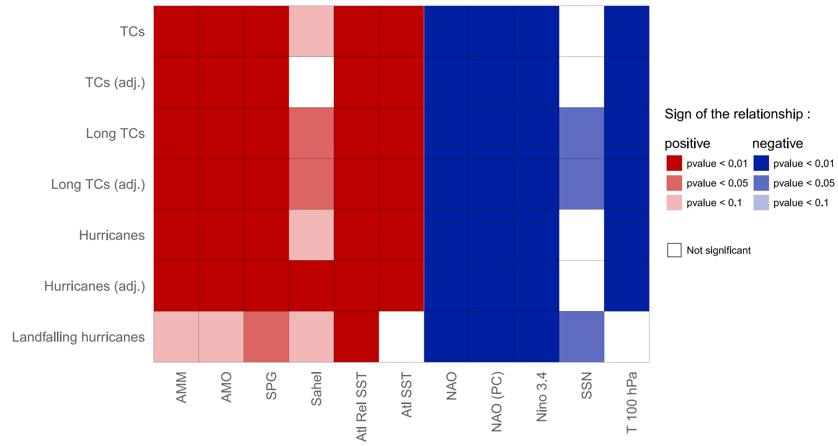


Figure 4. Heatmap showing the relationship, based on Poisson regressions, between different measures of Atlantic tropical cyclone activity (listed on the left) and different climatological factors (listed at the bottom). The color indicates the sign of the βs (negative, blue; positive, red), while the shading indicates the actual p value of the covariate.

as a preliminary analysis of covariates before combining them in a complete statistical model. It gives a sense of how a covariate may help explain a predictand or how it correlates with the predictand.

Looking at each of these pairs may lead to what is known as the multiple testing bias, i.e., the nonnegligible possibility of finding a significant relationship by chance. To make sure this bias has negligible impact on the results of this section, we focus on predictors that have a physical relationship with TC activity, thus using a rather small number of potential predictors (compared to many studies outside of climate sciences). Moreover, when we account for the correlation between climate indices (dependence between climate indices and the resulting collinearity is discussed extensively in the Appendix of *Villarini et al.* [2012]), typical corrections for this bias (e.g., Bonferroni) recommend to use a p value of about 1% instead of the common 5%.

3.2. Basin Wide

This method has been applied to the data of sections 2.1 and 2.2. The results are summarized in Figure 4. For each pair, the cell color indicates the direction of the relationship (red is positive, and blue is negative), whereas the tone indicates the significance of the relationship (p value of two-tailed test). The three color tones indicate whether the relationship is significant at a 1% level (darkest color, strong relationship), 5% level, or 10% level (lightest color, very weak relationship). Note that the supporting information contains all values to complement the figures.

Table 2 shows the linear correlation coefficients between the different climate indices used in Figure 4. We note that some of the predictor time series are highly correlated among themselves (Table 2), in part due to the fact that they are proxies for the thermodynamical conditions present over the northern tropical Atlantic during the hurricane season. Indices linked to these thermodynamics conditions (AMM, AMO, and AtlSST) are, not surprisingly, among the strongest predictors (Figure 4). Similarly, regressions between different measures of basin-wide TC activity and upper tropospheric temperature, ENSO and the NAO, are significant and negative. Moreover, regressions with Sahel precipitation are only significant (and positive) for LTCs and HRs, and regressions with SSNs are only significant for LTCs (and negative). The influence of both Sahel precipitation and SSNs was shown to be concentrated during one of the two phases of the AMO: AMO+ for SSNs and AMO− for Sahel precipitation [*Caron et al.*, 2015b; *Fink et al.*, 2010].

It is also worth noting that RelSST is consistently the strongest single predictor (having the smallest p value), while the SSN and Sahel precipitation are the weakest predictors (largest p values), whether or not we account for missing storms in the presatellite era. We also note that the relationship between hurricanes and Sahel precipitation becomes stronger (smaller p value) once we correct for missing storms, suggesting that this relationship is robust across the twentieth century.

The regressions for U.S. landfalling hurricanes offer, on the other hand, a different picture. While some of the time series linked to thermodynamic conditions over the tropical Atlantic are significant and positive (RelSST and SPG), others are not statistically significant or only weakly so (absolute SST, AMO, and AMM).

Table 2. Correlation Coefficients Between the Various Atlantic Climate Indices[a]

	AMM	AMO	SPG	Sahel	AtlRelSST	AtlSST	NAO	NAO (PC)	Nino3.4	SSN	T 100 hPa
AMM	1	**0.81**	**0.62**	**0.37**	**0.86**	**0.83**	−0.17	−0.17	**−0.25**	0.07	**−0.50**
AMO		1	**0.74**	**0.20**	**0.74**	**0.78**	**−0.20**	−0.17	0.03	0.05	**−0.55**
SPG			1	**0.27**	**0.56**	**0.47**	**−0.31**	**−0.38**	−0.07	−0.06	**−0.60**
Sahel				1	**0.44**	0.01	−0.02	−0.06	**-0.20**	0.01	−0.05
AtlRelSST					1	**0.72**	**−0.20**	**−0.27**	**−0.29**	0.05	**−0.46**
AtlSST						1	**−0.18**	−0.17	0.14	0.10	**−0.63**
NAO							1	**0.79**	0.06	0.07	**0.28**
NAO (PC)								1	0.07	0.00	0.20
Nino3.4									1	0.02	0.14
SSN										1	0.22
T 100 hPa											1

[a]Statistically significant (5% level) correlations are highlighted in bold.

Interestingly, only the landfalling hurricane regression is not statistically significant with respect to upper troposphere temperature. On the other hand, regressions with the NAO, ENSO, and SSNs are all significant and negative, as previously highlighted by *Elsner and Jagger* [2006], *Klotzbach* [2011], and *Elsner and Jagger* [2008], amongst others.

We have also checked the robustness of these analyses using alternative models or methods to compute the significance of the relationships (see section 2.4). As expected, only weak relationships (p value slightly below 5%) have been affected by the use of one of latter approaches. Therefore, the results shown above are robust to model misspecification (see supporting information for more details).

3.3. Clusters

We now repeat the analysis, but instead of performing the regressions at the basin-wide level, we used the different tropical cyclone clusters as predictands. Using different TC clusters allows us to investigate how the different predictors identified in the previous section vary within the Atlantic basin, whereas using multiple measures of TC activity allows us to evaluate the robustness of that relationship. Figure 5 summarizes the results of the different Poisson regressions for each possible pair of predictand and predictor. The cluster time series are constructed using the HURDAT2 database directly and thus do not include the corrections to the time series considered in Figure 4.

We note large differences in the climate factors modulating the variability of each of these clusters, as noted previously by *Kossin et al.* [2010] and *Kozar et al.* [2012]. While the regressions for clusters 3 and 4 are reminiscent of the results obtained from the basin as a whole, there are fewer climate influences that can explain the variability observed in clusters 1 and 2.

For cluster 1, indices constructed using Atlantic SSTs (AMO and both RelSST and AtlSST) are the only significant predictors. Interestingly, *Kossin et al.* [2010] linked TCs from cluster 1 to the standard May-June NAO. Using the standard NAO but a much longer time period, we detect only a weak relationship with TCs and LTCs and no significant relationship with HRs. When using the PC NAO, the significance of the relationship slightly improves for the first two but the link remains relatively weak (p value of 2–3% at best).

With respect to cluster 2, only ENSO consistently returns highly significant relationships for all three predictands. Other predictors sometimes appear significant, but there is no consistent pattern and their statistical relationships tend to be relatively weak. In particular, the relationship between TCs and Atlantic SST (either absolute or relative) is much weaker for LTCs and nonexistent for HRs. It is likely that the failure to link cluster 2 TCs to ENSO in *Kossin et al.* [2010] is due to the shorter period considered in that study.

On the other hand, covariates tend to be very significant for the two southern clusters, especially for cluster 4, which is linked to all the predictors investigated here. In particular, cluster 4 is the only one showing a robust link to Sahel precipitation. Because the influence of the latter occurs through the modulation of vertical wind shear over the MDR [*Goldenberg and Shapiro*, 1996], it is not surprising that this predictor is primarily associated with storms that originated as African Easterly Waves (AEWs). Furthermore, the western part of the MDR

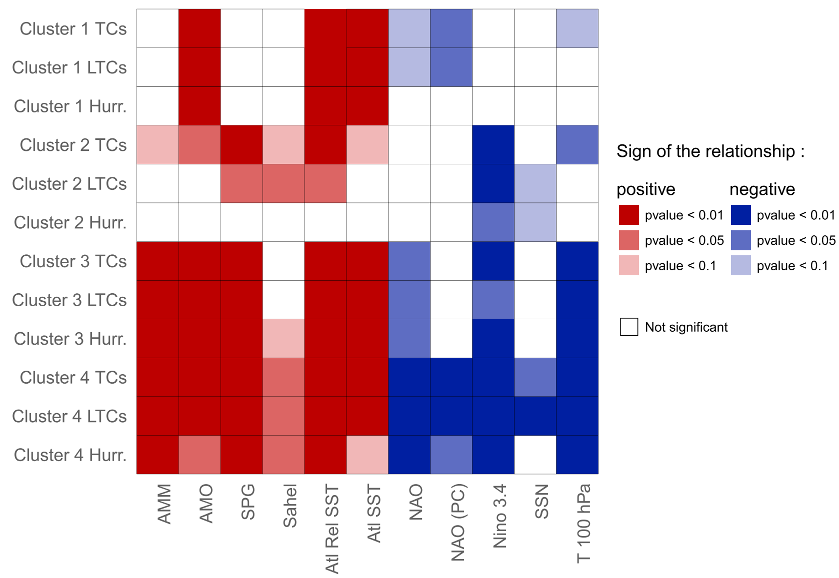


Figure 5. Heatmap showing the relationship, based on Poisson regressions, between the different tropical cyclone clusters (listed on the left) and different climatological factors (listed at the bottom). The color indicates the sign of the βs (negative, blue; positive, red), while the shading indicates the p value of the covariate.

is the region with the largest difference in track density between years with high and low Sahel precipitation [*Caron et al.*, 2015b], which is consistent with the result found here.

Similar to cluster 1, the link between the NAO and cluster 3 is dependent on how the NAO is defined. However, this is not the case for cluster 4, which shows a robust link to either standard or PC NAO. The fact that cluster 4 is the cluster for which the link to the NAO appears the strongest seems to support the physical mechanism suggested by *Elsner* [2003], wherein the influence of the NAO occurs through modulation of the North Atlantic subtropical high and the steering currents in which Cape Verde TCs propagate.

Cluster 4 and, to a lesser extent, cluster 2 are the only clusters showing a link with solar activity, but in both cases, the relationships are relatively weak compared to the those of the other factors considered here: only LTCs in cluster 4 return p values smaller than 1%. *Elsner et al.* [2010] suggest that the influence of the solar radiation occurs primarily through changes in upper troposphere temperature (thus changes in PI) driven by changes in UV radiation: increase in solar activity increases the temperature aloft, which negatively impact hurricanes. *Elsner and Jagger* [2008] showed that this negative relationship was more pronounced in the western part of the basin, which is consistent with clusters 2 and 4 being the clusters returning the smallest p values for this predictor.

As observed previously with data from the entire basin, using alternative models or methods to compute the significance of these relationships only has an influence on the weakest relationships but does not impact the overall conclusions. More details on the robustness of these results can be found in the supporting information.

Overall, there is no single predictor that is statistically significant for all the different measures of TC activity across the different clusters, confirming the regional influences of the different climate factors. Atlantic SST-derived predictors (e.g., AtlSST, RelSST, and AMO) appear generally as the strongest, but none of these time series is statistically significant for HRs in cluster 2, perhaps because SST in the Gulf of Mexico tends to be well above the 26°C threshold required for cyclogenesis.

However, there is one important difference between AtlSST and the other Atlantic SST-derived predictors: the AtlSST time series shows a significant upward trend, while the other time series are detrended by construction or show only a small trend over the period considered here (Figure 1). Thus, it is important to determine to what extent the significance of AtlSST is due to its ability to explain seasonal variability in TC counts and/or trends in the data. Furthermore, we know that HURDAT2 is incomplete and shows an upward trend in TC count due to improvements in the observational network. Thus, there is the possibility that the highly significant

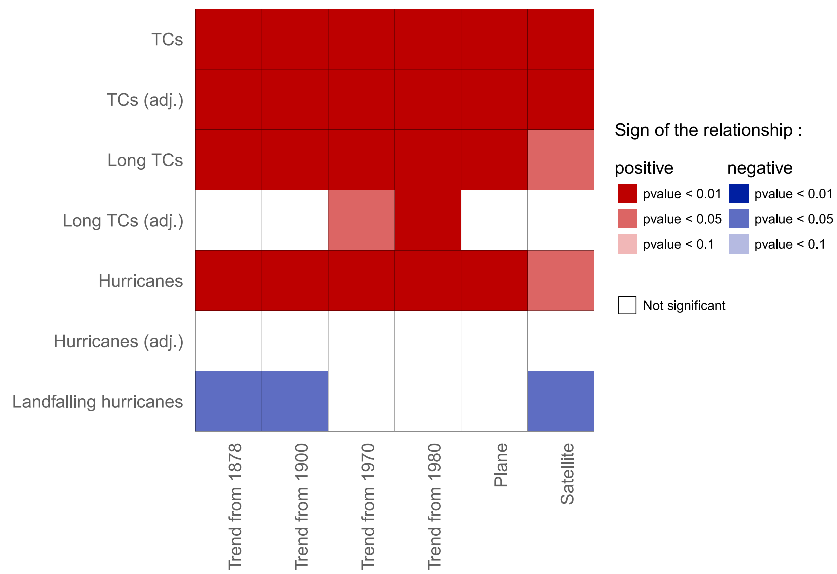


Figure 6. Heatmap showing the significance of various trend variables (listed at the bottom) in Atlantic tropical cyclone activity (listed at the left) based on Poisson regressions. The color indicates the sign of the trend (negative, blue; positive, red), while the shading indicates the *p* value of the covariate.

relationship to AtlSST is due to the artificial trend in HURDAT2 data. Therefore, before determining the best predictors of Atlantic TCs, we now investigate the presence of trends in the various clusters.

4. Trends in Hurricane Data Set

4.1. Method

Six different trend indices were analyzed. First, we used linear trend variables starting from either 1878, 1900, 1970, or 1980. Mathematically, these predictors are written as

$$X_k = \max(k - T, 0), k = 1878, 1879, \dots, 2015$$

for $T = 1878, 1900, 1970,$ and 1980. Each of these functions is used to identify the presence of trends from different starting points in the various TC time series. We use both 1878 and 1900 to test the sensitivity of the starting point on the results, as the difference between those two start dates was previously shown to have an impact on the significance of the detected trends [*Vecchi and Knutson*, 2008].

In addition to these four trend indices, we also consider two step functions: (1) 1 from 1944 onward (and 0 before), and (2) 1 from 1966 onward (and 0 before). These two step functions are meant to detect the impact on TC time series of reconnaissance flights and satellites, respectively. If either or both step functions are found to be significant, this would indicate a sudden upward shift in the later part of the time series which would be consistent with the influence of reconnaissance mission and satellite coverage on the time series.

For each of these six trend indices, we will consider that it is statistically significant if the two-tailed test linked to the β coefficient has a very small *p* value (well below 5% or 1%).

4.2. Basin Wide

Figure 6 shows the trend results for basin-wide measures of tropical cyclone activity, for both HURDAT2 data and the corrected time series. The presence of a significant upward trend is detected for all the noncorrected TCs, LTCs, and HRs time series, starting in 1878, 1900, 1970, and 1980. Furthermore, the step functions meant to represent the impact of satellite and flight reconnaissance are also very significant in these three time series. As mentioned previously, part of the detected upward trend has been identified before and is due, at least in part, to the expanding observational network, from the late nineteenth century to the beginning of the satellite era (and possibly later).

For the corrected time series, the results are significantly different for both LTCs and HRs. While an upward trend remains for LTCs from 1970 or 1980, there are no significant upward trend starting in 1878 or 1900 for neither LTCs nor HRs. Similarly, the regressions onto the two step functions are not statistically significant.

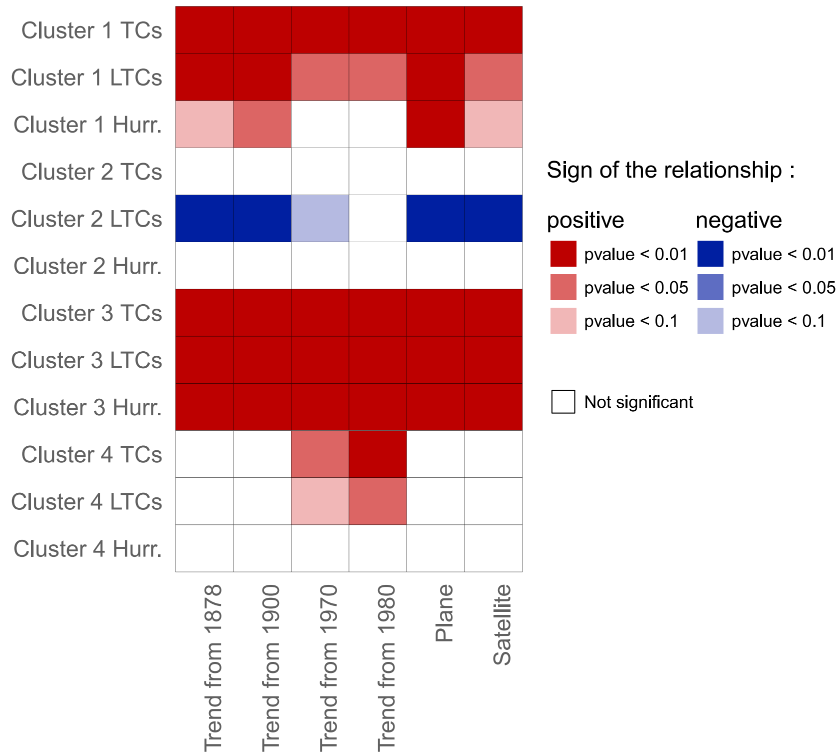


Figure 7. Heatmap showing the significance of various trend variables (listed at the bottom) in different tropical cyclone clusters (listed on the left) based on Poisson regressions. The color indicates the sign of the trend (negative, blue; positive, red), while the shading indicates the *p* value of the covariate.

On the other hand, all the trends remain significant when all corrected TCs are considered. This is the result of a significant upward trend in short duration storms (<48 h) since the late nineteenth century, as pointed out by *Landsea et al.* [2010]. It is not clear whether this upward trend is genuine and driven by physical mechanisms linked to increasing SSTs [*Emanuel*, 2010; *Bruyère et al.*, 2012] or is spurious [*Villarini et al.*, 2011b] and simply due to the fact that the corrective term introduced to account for the changing coverage, including improvement in satellite technology, is underestimated.

With respect to landfalling hurricanes, a weak (*p* values of about 3–4%) downward trend is present starting in both 1878 and 1900, as pointed out by *Vecchi and Knutson* [2008]. The fact that the satellite era step function is negative and significant suggests that there have been fewer hurricanes making landfall over the recent past compared to the 1878–1964 period. However, these regressions are sensitive to modeling assumptions because when the relationship is measured with geometric, negative binomial or quasi-Poisson regressions, the significance of the trend collapses (with *p* values between 5 and 10%). We also get similar results with Huber-White standard errors meaning that overall the weak significant downward trend detected might be due to model misspecification (see supporting information).

4.3. Clusters

Figure 7 shows a similar trend analysis performed for each of the four clusters. We detect significant and positive trends in clusters 1 and 3. The storms in these two clusters tend to propagate over the central Atlantic, away from the coast, and are also less likely to make landfall. Therefore, clusters 1 and 3 are more likely to be missing storms compared to clusters 2 and 4. In particular, cluster 3 contains the Cape Verde storms which tend to form just off the coast of Africa and recurve at sea, never making landfall or even coming close to land. This type of storm is a prime candidate for having been missed in the presatellite era in the HURDAT2 data set.

Cluster 2 shows a significant downward trend starting in both 1878 and 1900 for LTCs which is also robust to model misspecification (see supporting information). Because the trend is only apparent for longer lived TCs, we speculate that this downward trend is an artifact of the better basin coverage since reconnaissance missions started in the 1940s. By improving the coverage of the basin away from the coastline through

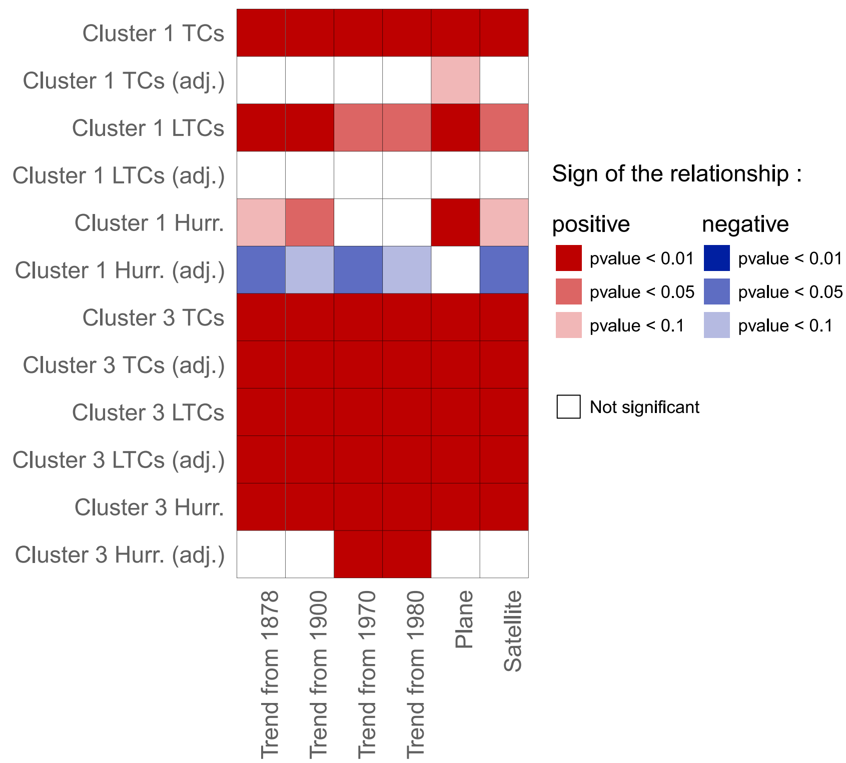


Figure 8. Heatmap showing the significance of various trend variables (listed at the bottom) in different tropical cyclone clusters corrected for missing storms (listed on the left) (based on Poisson regressions). The color indicates the sign of the trend (negative, blue; positive, red), while the shading indicates the *p* value of the covariate.

reconnaissance flights and satellite technology, many storms originating from AEWs are likely to be detected sooner (thus farther east) and, in this exercise, more likely to be categorized as cluster 4 than as cluster 2. In this case, failure to account for the earliest portion of the storm tracks will artificially inflate cluster 2 in the first half of the records. Because it is impossible to know exactly how many such storms would be reclassified as cluster 4, it is not possible to know the impact such reclassification would have on cluster 4. Since the cluster 4 LTC time series currently shows no significant downward long-term trends, it is possible such reclassification would lead to a downward trend in cluster 4 LTCs. Either way, this suggests a decrease in the number of LTCs in the western part of the basin.

Using an estimate for missed storms at the basin-wide level, we attempt a first-order correction for missed storms in the cluster time series by (i) assuming that all the missing TCs, LTCs, and HRs likely belong to either cluster 1 or cluster 3, and (ii) considering a constant corrective factor proportional to the ratio of cluster 1 or 3 with respect to the sum of the two. We also tried using varying yearly ratios instead of the climatological ratio, but the results were not significantly different. The trend results for the adjusted and original cluster time series are shown in Figure 8.

After applying the correction to cluster 1, the upward trends in TCs and LTCs completely disappear while the weak upward trend for HRs becomes negative and weakly statistically significant (and also robust to model misspecification). On the other hand, the correction is not sufficient to remove the significant upward trends in cluster 3 for TCs and LTCs. It is possible that the downward trend in cluster 1 HRs is due to the crude method used here, which might have led to an overcorrection. Reducing the correction in cluster 1 HRs and increasing the correction in cluster 3 HRs leads to a downward trend in cluster 3 HRs. Finally, it is not possible to say whether the upward trend in cluster 3 TCs and LTCs is due to an underestimation of the number of missing storms in that cluster, or whether there is an actual increase in the number of storms originating in the eastern part of the MDR, as suggested by *Holland and Webster* [2007].

5. Model Selection

Having quantified the influence of each predictor separately, we now aim to construct an adequate statistical model to explain the number of storms in the Atlantic basin. Furthermore, after having explained most upward trends found in the TC data, we seek to determine whether these trends impact the model selection process and the variables that are ultimately chosen. Whereas this section of the paper mainly focuses on the in-sample fit, the predictive power of the different variables will be analyzed in the subsequent section.

5.1. Method

To select the combination of predictors providing the best (or close to the best) in-sample fit, we have used two automated approaches: the (stepwise) forward selection method and the best subset approach. Both of these techniques look at the gain in the quality of the fit (likelihood value) balanced against the complexity of the model. This is usually done with the Akaike or Bayes Information Criteria (AIC or BIC) that penalize the model's likelihood based on its number of parameters. For more information on model selection methods in statistics or statistical learning, see, for example *James et al.* [2013] (chapters 5 and 6) and *Hastie et al.* [2009] (chapters 3 and 7).

The forward procedure is a very popular technique and has been applied by *Caron et al.* [2015c] for storms in the Eastern Pacific and by *Kozar et al.* [2012] and *Villarini et al.* [2010] for storms in the North Atlantic. The procedure consists in adding a variable in the statistical model until there is no improvement in the AIC or BIC. The best subset method is a more systematic approach that looks at every possible pairs, triplets, quadruplets (and so on) of variables until a specific combination that optimizes the AIC or BIC is found. This latter approach is very computationally intensive when the number of predictors is large, but in this study, the algorithm runs in a fraction of a second on a standard computer. In this section, the model selection is based upon the BIC, which prefers more parsimonious models. We refer to *Caron et al.* [2015c] for a more detailed discussion of the forward and best subset selection methods in a similar context.

As some climate data are not available for the entire 1878–2015 period, our analysis is divided into two parts. First, we select the 1958–2014 period, for which data are available for all predictors. In the second part, AMM, NAO (PC), Sahel precipitation, and atmospheric temperature at 100 hPa are excluded, but estimations are conducted over the entire time interval (1878–2015).

Figure 9 shows the chosen predictors, their sign and significance using heatmaps, whereas supporting information includes the exact coefficients and p values for each data set. Because forward and best subset selection algorithms agreed on the same models for the 1958–2014 period and are very similar for the 1878–2015 period, we only show the results obtained using the best subset technique. The results are analyzed in each of the following subsections.

Moreover, Table 3 shows the results of the chi-square (χ^2) goodness-of-fit (GOF) test, and the likelihood ratio test (LRT). The first test provides an indication of the quality of the fit of each selected model, whereas the LRT assesses the significance of adding the predictors (compared to a model without predictors).

5.2. All Variables: 1958–2014

The results (Figure 9) clearly show that the Atlantic relative SST should form the basis of a statistical model for all types of cyclones in the North Atlantic, regardless of strength. Moreover, the 100 hPa temperature is a significant predictor that needs to be added to the model in combination with AtlRelSST for TCs and LTCs. This holds true whether we adjust the time series for possible missing storms or not.

Our results diverge from [*Kozar et al.*, 2012] whose method selected AtlSST, Nino3.4, and the DJFM NAO as the best combination of predictors. However, a direct comparison is difficult because the time period and the list of predictors between the two studies are different. More specifically, we do not consider DJFM NAO as a possible predictor, whereas [*Kozar et al.*, 2012] did not include the upper tropospheric temperature in their predictor list. We also suspect that the selection of AtlSST in their model versus AtlRelSST is due to the presence of an upward trend in the TC time series, whereas in our case, the downward trend in the upper tropospheric temperature can account for that upward trend (more on this in the next section).

In section 3, we showed that the Sahel precipitation appears as a significant predictor, but less so than other climate factors. Now that we consider combinations of predictors including the Atlantic RelSST in the model, Figure 9 shows that the Sahel precipitation does not improve the in-sample fit. It is hence never included in these statistical models. Because the time series of Sahel precipitations is available since 1900, we reran

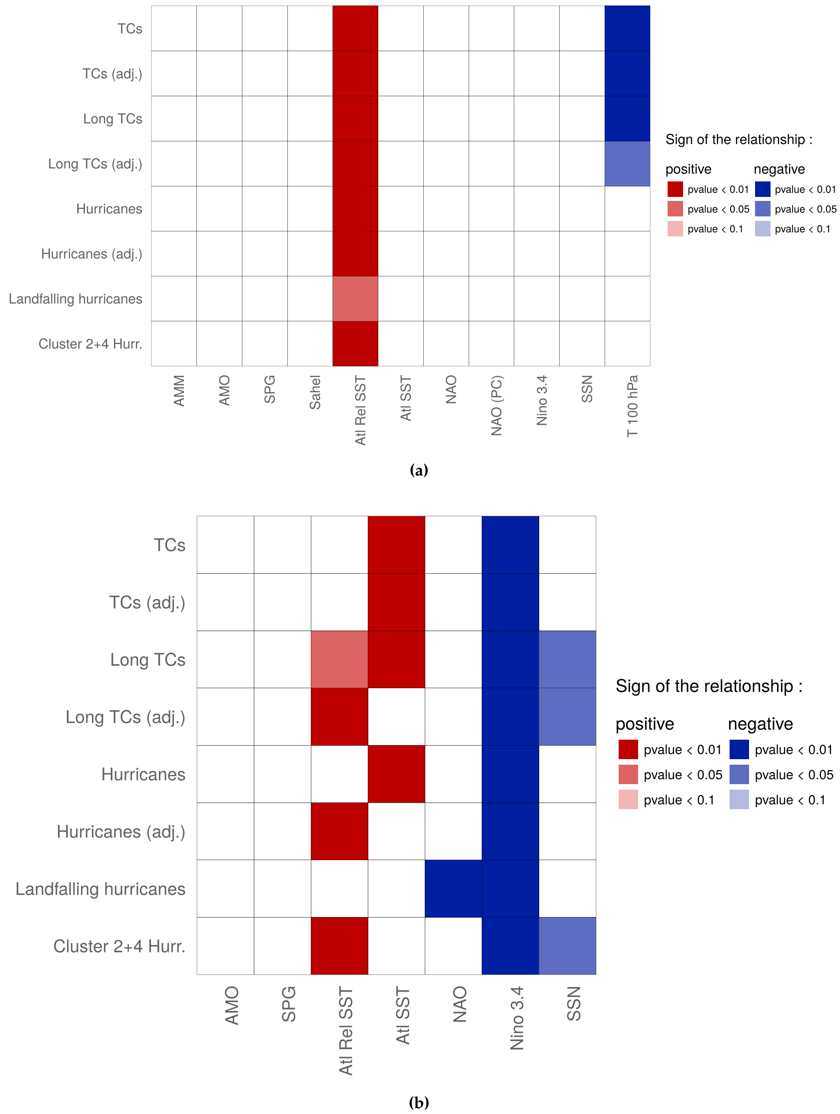


Figure 9. Heatmaps showing selected variables, sign of their coefficients, and significance for the best subset technique, for the (a) 1958–2014 period and the (b) 1878–2015 period.

the selection algorithms starting in 1900 (thus excluding the 100 hPa temperature) to determine whether that variable would appear as an important predictor in a statistical model. Those results, included in the supporting information, show that this variable does not appear in any model with either method. We are thus comfortable in excluding this variable from the next step of our analysis.

Finally, looking at Table 3, we see that the model selected for landfalling hurricanes fails to adequately fit the data, and therefore, any conclusion based upon the Poisson regression for landfalling hurricanes must be interpreted with caution.

5.3. Entire Period: 1878–2015

In this analysis, we rely on the 1878–2015 period of hurricane data, period for which estimates of missing storms are available, but Sahel precipitations, AMM, NAO (PC), and the 100 hPa temperature are not included as possible predictors. For TCs and adjusted TCs, the best pair of predictors is AtlSST and Nino3.4 and is, in this case, consistent with results presented in *Kozar et al.* [2012]. Looking at (un)adjusted LTCs, both the absolute and the relative AtlSST are chosen as well as Nino3.4 and SSNs, as third and fourth predictors in the model.

It is important to note the upward trend in the AtlSST time series. Given that observational limitations are known to have led to many storms being missed in the earlier part of HURDAT2, leading to an artificial upward

Table 3. Chi-Square Goodness-of-Fit Test (*p* Values Shown) and Likelihood Ratio Test (*p* Values Shown) Applied to Each Model Chosen by the Best Subset and Forward Approaches for Both Time Intervals[a]

	1958–2014		1878–2015 (Best Subset)		1878–2015 (Forward)	
	χ^2 GOF	LRT	χ^2 GOF	LRT	χ^2 GOF	LRT
TCs	0.8985	< **0.0001**	0.7272	< **0.0001**	0.7266	< **0.0001**
TCs (adj.)	0.9242	< **0.0001**	0.7185	< **0.0001**	0.7236	< **0.0001**
LTCs	0.9847	< **0.0001**	0.8446	< **0.0001**	0.6650	< **0.0001**
LTCs (adj.)	0.9812	< **0.0001**	0.8621	< **0.0001**	0.8621	< **0.0001**
HRs	0.9800	< **0.0001**	0.9323	< **0.0001**	0.9562	< **0.0001**
HRs (adj.)	0.9887	< **0.0001**	0.9971	< **0.0001**	0.9971	< **0.0001**
Landfalling HRs	**0.0411**	**0.0391**	**0.0463**	< **0.0001**	**0.0463**	< **0.0001**
Cluster 2+4 HRs	0.5566	**0.0006**	0.7597	< **0.0001**	0.7597	< **0.0001**

[a]As results exactly coincide for both methods between 1958 and 2014, only one approach is shown. Boldface indicates rejection of the statistical test at a 5% level.

trend, then it is very likely that AtlSST is preferred to RelSST (which is not trended) whenever the counts have an upward trend. Similar for hurricanes, the best pair of predictors is AtlSST and Nino3.4 for the unadjusted hurricane counts, which has an upward trend, and RelSST and Nino3.4 for the adjusted hurricane counts, which does not have a trend.

As for landfalling hurricanes, both methods agree that the NAO and Nino3.4 are the best pair of predictors. It is worth mentioning, however, that contrary to all other count time series, the quality of the fit is not good as the *p* value of the χ^2-square GOF test is slightly below 5% (see Table 3). We will return in section 6.3 to the predictive power of the predictors found for landfalling hurricanes.

6. Predictive Power

The purpose of this section is to determine the skill of the previous statistical models for future predictions. To conduct this analysis, the original sample is split into a training and a validation sample. The parameters of the statistical models are first estimated on the training sample. Using these parameters and observed predictors, we compute the predicted number of TCs every year in the validation sample and compare predictions from the model and the number of observed events. Predictions (or forecasts) in a Poisson regression are computed using the conditional mean of equation (1).

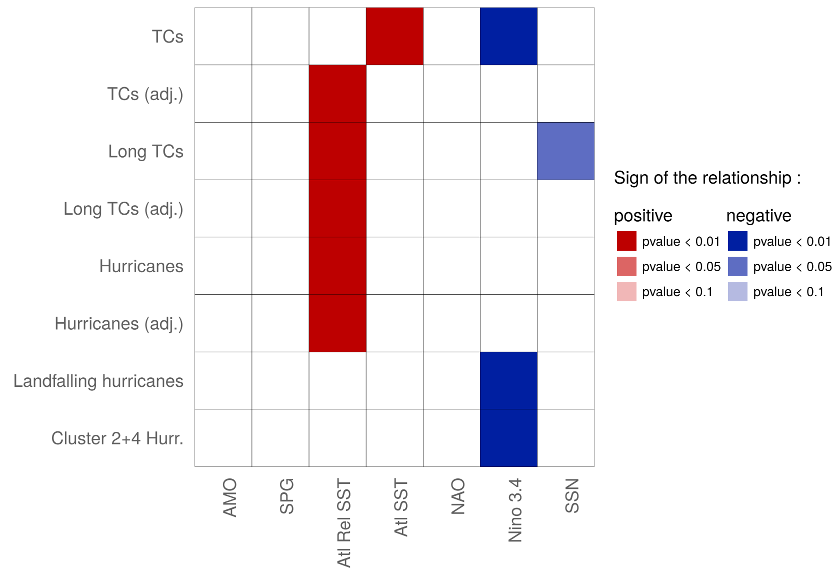
6.1. Model Selection Based Upon Predictive Power

We first look at how to build a good statistical predictive model. The *k*-fold cross validation (CV) technique is designed to build a statistical model whose variables are included only based upon their forecasting power. Therefore, the *k*-fold CV technique can be viewed as a model selection method, but instead of focusing on the in-sample fit, it focuses on the out-of-sample fit.

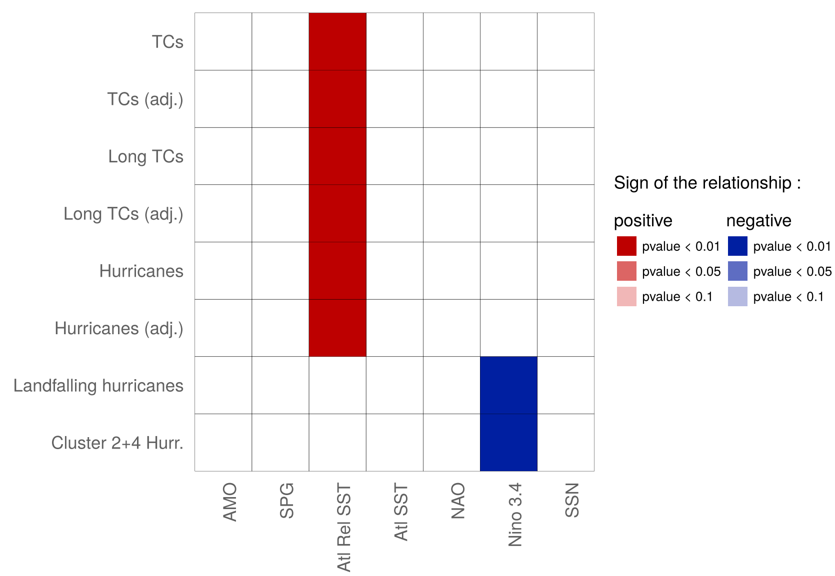
The *k*-fold CV technique consists of the following steps. The original sample is randomly split into *k* subsamples. Estimation is done on a sample combining $k-1$ subsamples, and forecasting is done on the remaining subsample. The technique chooses predictors based on their ability to minimize the forecast error when the prediction is repeated on each of the *k* subsamples. We have applied the fourfold CV and the eightfold CV to find the best combination of predictors. The chosen variables, their sign, and statistical significance (*p* value of each predictor's two-tailed test) are shown in Figure 10. Overall, RelSST is the variable that appears most often in the models, and Nino3.4 either appears as a second predictor in the model or as the sole predictor.

6.2. Forecast Analysis

To further our understanding of the forecasting capability of the number of cyclones, we have conducted the following experiment. Drawing from sections 3 and 5, we designed six simple statistical models and assessed their predictive ability. The training sample goes as far as 1878 up to 1980, whereas the validation sample corresponds to the period 1981–2015. The rationale for choosing this time interval is that it includes both an inactive period and an active period of hurricane activity, and furthermore, the validation sample represents about 25% of the entire sample (or 35% of the size of the training sample). More than a statistical analysis,



(a)



(b)

Figure 10. Heatmaps showing selected variables, sign of their coefficients, and significance for the *k*-fold CV technique ((a)fourfold and (b) eightfold).

the exercise is also meant as a preliminary step for seasonal forecasting, given that general circulation models have a fair amount of skill in predicting large-scale variables such as SST [*Villarini et al.*, 2016].

The six models analyzed are as follows (along with their corresponding color in Figure 11): (1) no predictor (simple Poisson distribution) (flat black line); (2) RelSST alone (blue); RelSST + (3) Nino3.4 (red), (4) SSNs (green), or (5) NAO (magenta); and (6) model average of the last four models (dotted black line).

The rationale behind these models is as follows. The case without any predictors (climatology) represents the baseline model. We included a model with RelSST alone because it was selected repeatedly as a good predictor in many time series in Figure 9. The following three models are based on the model selection analyses of section 5. Finally, we include a model average as it is a well-known approach to deal with model uncertainty to improve predictions.

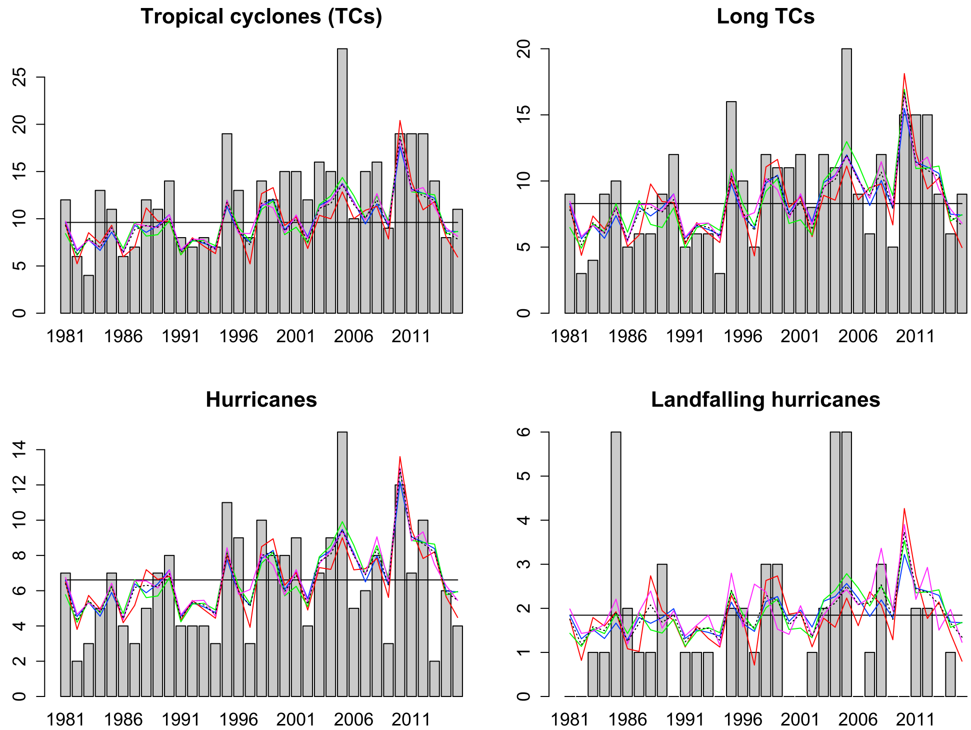


Figure 11. Observed number of events (bars) and model predictions (lines). Legend: flat black line, no predictor (climatology); blue, RelSST only; red, RelSST and Nino3.4; green, RelSST and SSNs; magenta, RelSST and NAO; and dotted black, model average.

From Figure 11 we see that with the exception of landfalling hurricanes, all models that include at least RelSST perform well in predicting the interannual variability. The low period 1991–1994 is well captured by all models and the peak around 2010–2012 as well. However, the years 1995 and 2005 generate the most important prediction errors. As it is difficult to distinguish the predictive power of each model on the graphs, Table 4 shows the relative *reduction* (in %) in the mean square error (MSE) for each model compared to the case without a predictor (positive value means forecasting ability is *improved*).

With the exception of landfalling hurricanes, Table 4 shows that the statistical models are able to reduce the MSE by a margin of 35–50% when compared to a model without a predictor. We also observe that adding a second predictor does not seem to improve the predictive capability of these statistical models because RelSST alone suffices to reduce the MSE by about 40–50%. As is often the case when analyzing predictive power, the simpler models often outperform the most complex ones. Finally, for the case of landfalling hurricanes, the reduction in MSE is very small for all these models, indicating that typical cyclone predictors do not lead to a good fit in-sample (see Table 3) and out-of-sample (Table 4).

6.3. Landfalling Hurricanes

We now further analyze the time series of the number of U.S. landfalling hurricanes. We repeat a similar forecast analysis where the training sample is obtained with data from 1878 to 1980, whereas prediction is

Table 4. Reduction (in %) of the MSE Compared to a Model Without Predictor for TCs (Adj.), LTCs (Adj.), HRs (Adj.), and U.S. Landfalling Hurricanes

% Reduction in MSE	TCs (Adj.)	LTCs (Adj.)	HRs (Adj.)	Landfalling HRs
RelSST only	41.3%	55.7%	45.7%	5.5%
RelSST and Nino3.4	35.5%	47.3%	50.2%	−1.1%
RelSST and SSNs	41.6%	50.7%	42.8%	8.6%
RelSST and NAO	43.4%	55.4%	47.8%	−0.3%
Model average	41.7%	55.1%	48.2%	5.9%

Table 5. Reduction (in %) of the MSE Compared to a Model Without Predictor for U.S. Landfalling Hurricanes. Results Are Presented by Periods of 5 Years[a]

	1981–1985	1986–1990	1991–1995	1996–2000	2001–2005	2006–2010	2011–2015	Avg	Std
Nino3.4 only	**15.2%**	−35.5%	**46.4%**	**30.7%**	−12.7%	−29.6%	**38.9%**	**7.6%**	33.5%
NAO only	**15.0%**	−55.0%	**6.8%**	−59.1%	**2.2%**	−35.1%	**37.7%**	−12.5%	37.3%
RelSST only	**4.9%**	−13.3%	**55.8%**	**33.9%**	**22.5%**	−61.8%	−17.6%	**3.5%**	38.8%
Nino3.4 + NAO	**30.2%**	−172.9%	**36.2%**	**33.1%**	−11.6%	−117.0%	**68.2%**	−19.1%	90.5%
Nino3.4 + RelSST	**16.2%**	−28.3%	**67.5%**	**43.6%**	**3.0%**	−105.4%	**20.3%**	**2.4%**	56.3%
Mod avg single	**13.4%**	−24.5%	**40.7%**	**22.2%**	**5.0%**	−36.8%	**29.1%**	**7.0%**	28.3%
Mod avg but NAO	**13.0%**	−16.6%	**57.7%**	**39.3%**	**5.2%**	−60.7%	**19.3%**	**8.2%**	38.6%

[a] Avg (Std) is the average (standard deviation) calculated over the seven time periods. Positive values are emphasized in boldface.

conducted on a 1 year ahead basis between 1981 and 2015. To improve predictions on landfalling hurricanes, we choose specific predictors for that time series (see Figures 9 and 10). The models are as follows: (1) no predictor; (2) one predictor: Nino3.4 or NAO or RelSST; (3) Nino3.4 and NAO; (4) Nino3.4 and RelSST; (5) model average on the three models based upon a single predictor; and (6) model average on the three models that do not have NAO.

To help identify the periods when predictions were more difficult, we computed the MSE by periods of 5 years for each of the models. The results are shown in Table 5.

We see that the predictive performance of the models vary a lot over time; the periods 1986–1990 and 2006–2010 being the worst for all models. The column Avg of Table 5 indicates the average % reduction over the seven periods. It is interesting to see that both models that include the NAO perform the worst overall. Using the average number of landfalling hurricanes before 1981 has an overall better predicting power after 1980 than both models constructed with the NAO.

Moreover, the table shows that the quality of the predictions based upon a single variable is more stable over time (first three rows and Std column) than both models built with two predictors (next two rows, same column). Taking a model average over the former three models helps further increase the stability of the predictions (Std of 28% over the seven periods).

Finally, it is worth mentioning that the decrease in MSE with respect to the case without a predictor is very small for all proposed models (about 5–10%). Therefore, all models have a very weak predictive power. This further confirms the difficulty of applying this approach for the U.S. landfalling hurricanes time series. Among the common predictors of tropical cyclones, many predictors have a strong relationship when taken alone (RelSST, NAO, and Nino3.4, see Figure 4). However, the best statistical models built from these variables have a poor in-sample and out-of-sample fits and therefore have difficulty explaining the interannual variability.

Instead, given that, respectively, 92% and 87% of all clusters 2 and 4 TCs make landfall, we argue that the sum of clusters 2 and 4 storms are a good proxy for landfalling hurricanes along the coast of the U.S., Mexico, and the Caribbean. Thus, we conclude this section by performing a predictive power analysis on the latter. First of all, we ran our model selection algorithms to determine the most significant predictors and best models (Figure 9). Both the forward selection method and the BestGLM method agree on the same statistical model, i.e., RelSST, Nino3.4, and, to a lesser extent, the SSNs. Neither cluster 2 nor 4 shows any significant upward trend, so the appearance of RelSST as opposed to AtlSST should not be surprising as this time series does not have a trend either.

Table 6 shows the predictive power of the proposed statistical models for the clusters 2+4 hurricanes. The best model is clearly Nino3.4 taken alone. It has the highest mean reduction in MSE, and it succeeds in out-performing a model without a predictor in each 5 year period except the 2001–2005 period. The predictive power of Nino3.4 is also shown in Figure 10 where it was selected as the sole predictor in the fourfold and eightfold model selection methods. The level of MSE reduction achieved by Nino3.4 alone is interesting (35% and over 40% when we exclude the worst period), and the quality of the predictions is more stable than with landfalling hurricanes.

Table 6. Reduction (in %) of the MSE Compared to a Model Without Predictor for Clusters 2+4 Hurricanes[a]

	1981–1985	1986–1990	1991–1995	1996–2000	2001–2005	2006–2010	2011–2015	Avg	Std
Nino3.4 only	**29.6%**	**66.6%**	**32.8%**	**42.8%**	−8.8%	**44.9%**	**38.3%**	**35.2%**	22.8%
NAO only	−22.6%	−130.4%	−46.6%	−201.0%	**9.7%**	−31.7%	−41.3%	−66.3%	73.2%
RelSST only	**0.5%**	−18.5%	**46.9%**	**49.8%**	**21.5%**	−5.4%	−14.1%	**11.5%**	28.2%
Nino3.4 + NAO	**31.8%**	**77.7%**	−32.5%	−5.6%	−39.3%	**56.2%**	**45.6%**	**19.1%**	45.4%
Nino3.4 + RelSST	−11.4%	−71.3%	**37.3%**	**24.9%**	**15.6%**	−43.4%	−24.1%	−10.3%	39.1%
Mod avg single	−16.0%	−75.2%	−63.7%	−33.4%	−3.2%	−35.8%	−16.7%	−34.9%	26.3%
Mod avg but NAO	**6.8%**	**22.3%**	**24.5%**	**27.1%**	**2.6%**	**13.0%**	**7.1%**	**14.8%**	9.8%

[a]Results are presented by periods of 5 years. Avg (Std) is the average (standard deviation) calculated over the seven time periods. Positive values are emphasized in boldface.

7. Conclusion

In this article we have reanalyzed the main climate influences of hurricane activity over the North Atlantic Basin. The main objective was to expand on previous work by increasing the list of potential predictors, using multiple tropical cyclone time series, increasing the analysis time period, and investigating the impact of artificial trends in the hurricane data set. Through the use of a clustering technique, we also linked these influences to specific regions of the North Atlantic Basin.

We found that the first cluster, which is mainly composed of the storms propagating along the U.S. seaboards, is primarily linked to the thermodynamical conditions of the North Atlantic, that the second cluster, which is mainly composed of storms forming in the Gulf of Mexico, is mainly tied to ENSO, and that storms from the third and fourth clusters, which are composed of storms forming in the deep tropics, have similar influences as that of the basin as a whole, except for SSNs, which is only linked to the fourth cluster.

While both clusters 1 and 3 show upward trends, LTCs in cluster 2 show a downward trend. We suspect that this downward trend is likely artificial and due to increasing observational capability. Indeed, earlier detection would likely have led many storms to be classified as cluster 4 storms in the early part of the record. Correction of missing storms removes the trends in cluster 1, but not in cluster 3. It is not clear if the latter remaining trend in cluster 3 is real or spurious, but these results suggest a reduction in TC activity in the western part of the basin and an increase in the eastern part.

We then ran model selection algorithms based upon the best in-sample or out-of-sample fit. We found that between 1958 and 2014, when we could use all predictors available, algorithms tended to often select upper tropospheric temperature, as well as relative Atlantic SST as good predictors of Atlantic tropical cyclone activity. For the entire time span (1878–2015), we found that SST and the Nino3.4 index were the most important covariates. It is important to note however that, in this latter case, the appropriate SST variable actually depended on whether the underlying time series had a trend or not. When an upward trend in the TC time series was present (whether it is artificial or not), then the MDR SST was selected by the model whereas the relative SST was chosen for stationary time series. We believe that if AtlSST was selected as a predictor in past analyses, it is because it is capable of capturing interannual variability (just like RelSST) and also the artificial upward trend in many tropical cyclone time series.

We have looked at the climate influences on U.S. hurricane landfall and concluded that the NAO should not be used for modeling U.S. landfalling hurricane counts: the best Poisson-based models fail to have an adequate in-sample fit, and, more importantly, the NAO does not appear to have real predictive capability. To be fair, the predictive ability of the best statistical models for U.S. landfalling hurricanes is also very poor. As such, alternative count models should be chosen. As a proxy for landfalling hurricanes, we suggest instead using a combination of clusters 2 and 4 hurricanes, since a majority of these storms are making landfall.

Finally, the models with the best predictive capability were often the simplest: a one-predictor model based solely on RelSST (for TCs, LTCs, and HRs) or Nino3.4 (for clusters 2+4 hurricanes) was relatively skillful. The addition of more predictors did not increase the skill of these predictive models significantly.

Appendix A: Frequently Used Acronyms

AEW African Easterly Wave
AIC Akaike Information Criteria
AMM Atlantic Meridional Mode
AMO Atlantic Multidecadal Oscillation
ASO August-September-October
AtlSST Sea surface temperature over the MDR
BIC Bayes Information Criteria
CV Cross validation
ENSO El Niño–Southern Oscillation
GOF Goodness of fit
HR Hurricane
JJAS June-July-August-September
LRT Likelihood ratio test
LTC Long-duration (>48 h) tropical cyclone
MDR Main development region. Area bounded by 10°N, 25°N, 80°W, and 20°W
MJ May-June
MJO Madden-Julian Oscillation
MSE Mean-square error
NAO North Atlantic Oscillation
PI Potential intensity
RelSST Sea surface temperature over the MDR with respect to SST over the entire tropics
SPG Subpolar gyre
SST Sea surface temperature
TC Tropical cyclone

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