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Time series perspectives on North Atlantic tropical cyclones: a study of fractional integration patterns

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Abstract

This study uses fractional integration to analyze trends in tropical cyclones in the North Atlantic region. Our analysis covers annual data from 1851 to 2022 on storms, hurricanes, and major hurricanes. Findings indicate the presence of long-term components in the storm and storm daily series, though these patterns appear less evident for hurricanes and major hurricanes. A notable increase in trend estimates is observed in recent times, especially for storms and major hurricanes. Subsample analysis reveals a greater temporal trend, especially in the satellite era. While evidence of long-term persistence is observed in the storm-related series, the same cannot be concluded for hurricanes and major hurricanes due to possible short-term influences. In general, the weather events analyzed are experiencing an increase in their occurrence.

Keywords Tropical cyclones · Climate change · Latin America · Persistence · Time trends · Fractional integration

JEL Classification B22 · C01 · C22 · Q51 · Q54

1 Introduction

A tropical cyclone is defined, according to the World Meteorological Organization (WMO 2023a, b), as a rapidly rotating storm that begins over subtropical or tropical oceans, with torrential rain and very violent winds; sometimes it comes with thunderstorms. The changing patterns of natural hazards, such as tropical storms, are a consequence of climate change. Research has connected the growing intensity of storms in recent decades with rising ocean

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Table 1 Location versus cyclone name. *Source* WMO 2023a, b

Location	Cyclone name
Caribbean Sea, Gulf of Mexico, North Atlantic Ocean, Eastern and Central North Pacific Ocean	Hurricane
Western North Pacific	Typhoon
Bay of Bengal, Arabian Sea	Cyclone
Western South Pacific, Southeast Indian Ocean	Severe Tropical Cyclone
Southwest Indian Ocean	Tropical Cyclone

Table 2 Wind speed versus classification. *Source* WMO 2023a, b

Maximum sustained wind speed	Cyclone classification
$<$63 km/h	Tropical Depression
$>$63 km/h	Tropical Storm
$>$116 km/h	Hurricane, Typhoon, Tropical Cyclone, Very Severe Cyclonic Storm (depending on the basin)

surface temperatures attributable to climate change (Webster et al. 2005; Emanuel 2005; Mann and Emanuel 2006; Elsner et al. 2008; Knutson et al. 2010; Mei et al. 2013; Méndez-Tejeda and Hernández-Ayala 2023; Chiodi et al. 2023; United States Environmental Protection Agency, 2023; Copernicus 2023).

As shown in Table 1 below, terminology for this weather phenomenon varies depending on the location:

On the other hand, tropical cyclones exceeding a certain wind speed are classified according to public safety. According to maximum sustained wind speed, tropical cyclones are categorized as outlined in Table 2.

Extreme temperatures contribute to increased mortality (Huynen et al. 2001; Deschenes and Moretti 2009; Huang et al. 2011; Barreca et al. 2013; Can et al. 2019; de Schrijver et al. 2022; Frasch et al. 2025; Guo et al. 2014; Karlsson and Ziebarth 2018; Masselot et al. 2023); impact long-term health outcomes (Guerrero Compeán 2013; Deschenes 2014), and influence economic conditions (Dell et al. 2014). Between 1970 and 2002, weather-related natural disasters—including droughts, windstorms, and floods—resulted in over 1.7 million deaths (Guha-Sapir, Hoyois, and Below, 2015).

The death toll from such disasters tends to be highest in developing nations, where physical infrastructure and institutions are often weakest (Kahn 2005; Anbarci et al. 2005; Kellenberg and Mobarak 2011).

Tropical storms, a category of windstorms, have caused substantial economic damage (Yang et al. 2006; Belasen and Polachek 2009; Nordhaus 2012; Strobl 2011; Strobl 2012; Hsiang and Jina 2014; Juárez-Torres and Puigvert 2021; Mohan 2023), influenced migration patterns (Kugler and Yuksel 2008; McIntosh 2008), affected educational attainment (Bluedorn and Cascio 2005), and contributed to increased mortality (Hendrickson and Vogt 1996; Combs et al. 1999; Sadowski and Sutter 2005; Borden and Cutter 2008; Jonkman et al. 2009; Yeo and Blong 2010; Haque et al. 2012; Zahran et al. 2013; Centers for Disease

Control 2013; Anttila-Hughes and Hsiang 2013; Pugatch 2019; Boustan et al. 2020; Lee et al. 2021; Bell et al. 2023; Huang et al. 2023; Parks et al. 2023; Graff Zivin et al. 2023; Liu et al. 2025; Nguyen and Mitrou 2025).

A crucial aspect of climate series analysis is the identification of complex long-term patterns, and a well-suited approach here is the one defined as long memory (LM) or long range dependence (LRD). This approach was proposed in the 50 s by the hydrologist Harold Edwin Hurst in a number of papers (Hurst 1951, 1956, 1957). He found a long-term variability in the river Nile flow records in a way such that past events had a long-term influence on the future. Mandelbrot and Van Ness (1968) introduced a statistical explanation for this phenomenon throughout the fractional Brownian motion and the fractional Gaussian noise model. However, a simpler approach with similar features is obtained with the fractional integration methodology. Using fractional integration as the main methodology described below, we employ annual data from 1851 to 2022 with the purpose of identifying whether significant trends are present. The existence of non-stationary patterns, which signify shifts in the behavior of statistical parameters over time, is a crucial feature of climate time series. Fractional integration techniques allow for the modeling of both short- and long-term persistence within the series being analyzed, enabling the investigation of mean-reverting behavior and changing trends. These techniques offer advantages over traditional methods when working with stationary and non-stationary series, allowing a higher flexibility in the modelization of the data. In particular, the fractional approach permits hypoterbolical slower decays in the effects of shocks compared with the exponentially fast decay of the short memory models.

A defining feature of fractional integration is its ability to capture these extensive patterns, which are essential for comprehending and modeling climate processes. As mentioned just above, fractional integration belongs to a wider category of processes called “long memory” or “long range dependence” which are precisely characterized because the actual value of the series may be strongly influenced by observations far distant in the past. This might be explained by physical issues but this is not the purpose of this work but simply verify that this property holds in the data under examination.

Technically, one of the main advantages of the fractional integration methodology is its capacity to produce fractional values for the number of differences in the series’ integration order, providing greater flexibility than other methods that only permit integer levels of differentiation.

Moreover, a positive degree of integration supports the long memory hypothesis, a statistical characteristic of climate data supported by various authors (Jiang et al. 2017; Franzke et al. 2020; Lenti and Gil-Alana 2021; Yuan et al. 2022). Given the scale of the time series under analysis, it is possible to identify long memory behavior, enhancing the applicability of fractional integration methods. As a result, this proposed technique is appropriate for evaluating the nature of shocks, categorizing them as transitory if the order of integration is less than one, and as permanent if it is equal to or greater than one.

2 Literature review

Recent literature shows a growing interest in examining the rise in both the frequency and intensity of tropical cyclones (Landsea et al. 2009). Historical records of tropical cyclones in the Atlantic basin, dating back to the late nineteenth century, reveal a significant upward trend in storm frequency. This rise in the number of documented tropical cyclones has often been attributed to anthropogenic climate change.

Knutson et al. (2010) and the Intergovernmental Panel on Climate Change (IPCC 2012) have indicated that it is probable the frequency of intense hurricanes will rise due to future anthropogenic climate change. This increase is significant, nearly doubling the occurrence of Category 4 and 5 hurricanes according to the Saffir–Simpson classification (Simpson and Rielh 1981) for every degree Celsius of global warming (Bender et al. 2010; IPCC 2012; Done et al. 2012). Furthermore, the IPCC (2007) has asserted that the ongoing warming of the climate system is unequivocal.

Landesa et al. (2009) examine how the length of tropical cyclones (TC) affects the observed variations in TC frequency, utilizing the widely recognized Atlantic hurricane database (HURDAT). They find that the incidence of short-lived storms (lasting two days or less) has surged significantly, rising from fewer than one per year in the late nineteenth to early twentieth century to approximately five per year since around 2000. In contrast, the frequency of medium- to long-lived storms has seen little, if any, increase. Consequently, the initial rise in total TC frequency recorded in the database during the late nineteenth century can be largely attributed to the surge in very short-lived TCs.

According to Knutson et al. (2019), before the introduction of geostationary weather satellite monitoring in the 1970s, historical global 'best track' records of tropical cyclones (TCs) were often inconsistent and faced sampling issues, rendering them inadequate for studying climate change trends. Similarly, Klotzbach (2022) analyzes global tropical cyclone activity patterns from 1990 to 2021, a timeframe marked by relatively stable observational systems. During this period, several metrics of global TCs, such as hurricane counts and Accumulated Cyclone Energy (ACE), showed a decline. This decrease is largely attributed to significant negative trends in the western North Pacific.

However, there has been a substantial increase in short-lived named storms, rapid intensification events ($\geq$50 knots per day), and TC-related damage. The increase in short-lived named storms is likely attributed to advancements in technology, while the rapid escalation in tropical cyclone (TC) intensity may be influenced by an increase in potential intensity. The rise in damages can be primarily connected to the expansion of coastal assets. The decrease in hurricane counts and global accumulated cyclone energy (ACE) is probably related to a trend toward a more La Niña-like baseline from 1990 to 2021, which enhances North Atlantic TC activity while suppressing activity in the North and South Pacific.

Authors like Chand et al. (2022) examine the trend of decreasing tropical cyclone frequency in the context of global warming. They contend that although it is believed that warming has already influenced the occurrence of tropical cyclones (TCs) on both global and regional levels, the changes remain ambiguous and often contentious due to various confounding factors. These include issues related to data quality, which complicate the detection and attribution of TC trends. Nevertheless, improvements in monitoring and recording techniques provide an alternative explanation for these fluctuations: recent research suggests that the number of potentially overlooked TCs is sufficient to account for a significant portion of the observed increase in TC counts.

The investigation of how tropical cyclones respond to a changing climate has garnered significant interest, particularly regarding their translation speed. Kossin (2018) found that the global translation speed of tropical cyclones (TCS) has decreased by 10% from 1949 to 2016, attributing this trend to expected changes in atmospheric circulation resulting from anthropogenic warming.

However, Ju-Moon et al. (2019) challenge the validity of Kossin's findings for two main reasons: first, the translation speed of tropical cyclones typically increases with latitude, making it highly sensitive to biases in the detection of cyclones related to latitude; second, during the pre-satellite era (1949–1965), there is a significant likelihood of systematic biases in the detection of tropical cyclones within the best track data, which could create misleading trends in TCS. Consequently, the reported slowdown in TCS may not reflect a genuine climate signal or could be overstated. Ju-Moon et al. (2019) argue that data inhomogeneity could significantly affect the global trend of tropical cyclone translation speed (TCS) due to its strong dependence on latitude.

This does not allow us to quantify how much data inhomogeneity has influenced the underlying trend, as it is nearly impossible to separate genuine climate signals from data artifacts within observed trends. While utilizing latitude bands and normalizing tropical cyclone frequency can help reduce the impact of biased sampling on TCS, this approach does not justify the use of inhomogeneous tropical cyclone data from the pre-satellite era. The study concludes that when analyzing tropical cyclone trends and conducting climate research, caution is essential when working with any inhomogeneous data from the pre-satellite period, including position-based metrics like TCS, maximum intensity location, as well as intensity and frequency data.

In light of the challenges associated with relational data concerning tropical cyclones, several studies have been conducted. For example, Wahiduzzaman and Yeasmin (2019) explore the forecasting potential of tropical cyclone (TC) landfall probabilities along the North Indian Ocean (NIO) using ocean-climate predictor variables in a seasonal forecasting model. They employed a Poisson regression model to estimate landfall probabilities based on 35 years of TC observations (1979–2013) sourced from the Joint Typhoon Warning Center.

The predictor variables utilized in their analysis include sea surface temperature, the Southern Oscillation Index, and ocean heat content. The primary conclusion of the study is that the Poisson regression model effectively hindcasted the frequency of tropical cyclone landfalls in the North Indian Ocean (NIO) region, achieving a correlation coefficient of 0.65 in the forecasted hindcast time series. This model also demonstrated a 31% improvement over climatological estimates.

Statistical methods, including neural networks, have also been utilized in tropical cyclone research, as demonstrated by Kovordanyi and Roy (2009). Other studies have applied artificial neural network techniques to analyze NOAA-AVHRR satellite images. After undergoing training, the network provided accurate directional forecasts for 95% of the training images. Additionally, it successfully processed 95% of new test images, indicating a strong capacity for generalization. These findings indicate that multi-layered neural networks have the potential to be further enhanced as a powerful tool for predicting cyclone tracks utilizing remote sensing data.

Giffard-Roisin et al. (2020) utilized fused deep learning from aligned reanalysis data to forecast tropical cyclone tracks aimed at protecting people and property. While dynamic forecasting models can generate highly accurate short-term scenarios, they are computationally intensive, and current statistical models leave considerable room for enhancement as the database of historical hurricanes continues to grow.

Machine learning techniques, which can capture nonlinearities and complex relationships, have been minimally explored for this application. They introduce a neural network model that integrates past track data with reanalyzed atmospheric images (3D wind and pressure fields). The benefits of the fused network are demonstrated, and a comparison with existing forecasting models suggests that deep learning methods could yield valuable and complementary predictions.

Finally, there is research focused on the use of fractional integration and long memory models within climate science. This work offers a strong foundation for replication and testing in the analysis of tropical cyclones. Notable recent contributions include studies by Gil-Alana et al. (2018), Claudio-Quiroga and Gil-Alana (2022), Asturias-Schaub and Gil-Alana (2023), Gil-Alana et al. (2023), Yuan et al. (2013), Vyushin et al. (2012), Barassi et al. (2011) and Caballero et al. (2002), among numerous others.

3 Methodology

We propose that the series examined in this study may exhibit long memory characteristics, and we model this feature using the fractional integration approach. This section draws from several empirical applications that have utilized a similar strategy to the one employed in this research, including works by Gil-Alana and Robinson (1997a, b), Gil-Alana (2018) and Gil-Alana et al. (2023).

We begin by outlining the concept of long memory. This is in the context of a second-order stationary process.,[1] $x(t),\ t=0, \pm 1,\ \ldots$, with $E(x(t))=\mu$, and by specifying its autocovariance function $\gamma(u)=E[(x(t)–\mu)(E(x(t+u)-\mu)]$, we assert that $x(t)$ exhibits long memory characteristics if the infinite sum of its autocovariances diverges. In other words, $x(t),$ is considered long memory if:

$$\lim_{T\to\infty}\sum_{u=-T}^{T}|\gamma(u)| = \infty. \tag{1}$$

Another definition can be formulated in the frequency domain by representing the spectral density function as the Fourier transform of the autocovariances,

$$f(\lambda) = \frac{1}{2\pi}\sum_{u=-\infty}^{\infty}\gamma(u)cos\lambda u, -\pi < \lambda \leq \pi. \tag{2}$$

[1] A second-order stationary process is defined as one in which the mean, variance, and autocovariance structure are not influenced by time. This condition is essential for conducting statistical inference.

x(t) exhibits long memory if the spectral density function has a singularity or pole at one or more frequencies within the spectrum, i.e.,

$$f(\lambda) \to \infty, as\lambda \to \lambda^*, \text{ for at least one } \lambda^* \in [0, \pi]. \tag{3}$$

Numerous processes meet the aforementioned two criteria. Notable examples include the fractional Brownian motion (fBm) and fractional Gaussian noise (fGn) models introduced by Hurst (1951, 1957), Mandelbrot and van Ness (1968), and Mandelbrot and Wallis (1968, 1969a,b). A particularly straightforward and commonly used model in time series analysis is based on the concept of fractional integration: a process is described as fractionally integrated or integrated of order d if it can be expressed as:

$$(1-L)^d x(t) = u(t), t = 0, \pm 1, \pm 2, ..., \tag{4}$$

with $u(t)=0$ for $t \leq 0$, where d is a positive fractional value, L is the lag operator, i.e., $Lx(t)=x(t-1)$ and $u(t)$ is $I(0)$ or short memory, characterized in the time domain by having a finite value for the infinite sum of the autocovariances, or in the frequency domain by possessing a spectral density function that is positive and bounded across all frequencies i.e., $0<f(\lambda)<\infty$, for all λ.[2]

In the context of real values of d, the polynomial in L in Eq. (4) can be expanded such that:

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots$$

and thus *x(t)* can be expressed as:

$$x(t) = dx(t-1) - \frac{d(d-1)}{2} x(t-2) + \ldots + u(t).$$

In this context, if d is a non-integer value, *x(t)* will depend of all its past history in a hyperbolic relationship, and higher the value of d is, the higher the dependence between observations. Note that in the model given by Eq. (4), the spectral density function of *x(t)* is:

$$f(\lambda; \tau, d) = \frac{\sigma^2}{2\pi} \left| \frac{1}{1 - e^{i\lambda}} \right|^d, \tag{5}$$

where λ indicates the frequency and σ^2 is the variance of the error term, and it tends to infinity as $\lambda \to 0^+$. These processes were proposed in the 80 s by Granger (1980), Granger and Joyeux (1980) and Hosking (1984) based on the observation that many aggregated data contained a periodogram (which is an estimator of the spectral density function) with a very large value at the smallest (zero) frequency, which may be indicative of the need for differentiation; however, once the series were first differenced, the periodogram presented a value close to

[2] Examples of I(0) processes include the white noise and the stationary, invertible Autoregressive Moving Average (ARMA) processes.

zero at the zero frequency, consistent with over differentiation. Since then, these models have been very much used in many disciplines including climatology and environmental sciences.[3] Surveys on fractional integration can be found at Baillie (1996), Doukham et al. (2003), Robinson (2003), Gil-Alana and Hualde (2009) and Hualde and Nielsen (2023).

In the empirical application presented in the next section, we examine a model similar to the one described by Eq. (4). However, to account for deterministic terms, the model includes an intercept and a linear time trend. Thus, the final specification is:

$$y(t) = \alpha + \beta t + x(t), (1-L)^d x(t) = u(t), \tag{6}$$

where α and β are jointly estimated with d, and $u(t)$ follows two different assumptions. First, we suppose that there is no autocorrelation, and $u(t)$ is a white noise process with zero mean and constant variance. Second, we incorporate (weak) autocorrelation by employing the exponential spectral model proposed by Bloomfield (1973). This model for $u(t)$, is formulated solely in terms of the spectral density function, represented by the following expression:

$$f(\lambda;\tau) = \left[\frac{\sigma 2}{2\pi}\right] exp[2\sum_{i=0}^{n} \tau_i cos(\lambda i)], \tag{7}$$

where σ^2 is once more the variance of the error term, while n represents the number of short-run dynamics.[4] Bloomfield (1973) demonstrated that the logged form of (7) is a very good approximation for the spectral density of a stationary and invertible ARMA (p, q) process of form:

$$u(t) = \sum_{r=1}^{p} \varphi_r u(t-r) + \varepsilon_t + \sum_{s=1}^{q} \theta_s \varepsilon(t-s), \tag{8}$$

where $\varepsilon(t)$ is a white noise process, and whose spectral density function is given by:

$$f(\lambda;\tau) = \frac{\sigma^2}{2\pi}\left|\frac{1+\sum_{s=1}^{q}\theta_s e^{i\lambda s}}{1-\sum_{r=1}^{p}\varphi_r e^{i\lambda r}}\right|^2. \tag{9}$$

Bloomfield (1973) showed that the logarithm of (7) can be closely approximated by the logarithm of (9) when p and q are small. This approach reduces the need to estimate as many parameters as in ARMA models, which often leads to challenges in estimation, testing and model specification. Additionally, Bloomfield's (1973) model remains stationary across all values and fits well within the context of the Robinson (1994) tests used in this study. (See, e.g., Gil-Alana and Robinson 1997a, b; Gil-Alana 2004).

The joint estimation of the intercept (α), the time trend coefficient (β) and the integration order (d) is crucial in this work since many previous studies that focus on the analysis of trends simply use OLS-GLS methods under the assumption that $x(t)$ is I(0), a property that is not always satisfied with this type of data. Note that if $x(t)$ is I(d) with $d \neq 0$, the estimation of α and β under standard approaches will be clearly invalid. This is one of the strengths of

[3] Earlier, Robinson (1978) justified these models through the aggregation of diverse autoregressive processes.

[4] We consider in the application that n = 1 in all cases. Applying higher values resulted in the same findings concerning the differencing parameter.

Table 3 Key time series concepts

Concept	Definition
Short memory I(0)	A stationary process where the autocorrelations decay rapidly Shocks have only temporary effects and the series reverts to its mean
Long memory I(d) with d > 0	A process where autocorrelations decay very slowly Past values have a persistent, long-lasting influence on the future, even if the series is stationary
Fractional integration I(d)	A statistical framework that generalizes the concept of integration. A process is I(d) if it must be differenced d times (where d can be a fractional value) to become a short-memory I(0) process
White noise	The simplest I(0) process, characterized by a constant mean, constant variance, and no autocorrelation
ARMA model	(AutoRegressive Moving Average) A standard model for short-memory I(0) processes that captures short-term dynamics using autoregressive and moving average components
Bloomfield model	A parsimonious approximation to an ARMA model. It is specified in the frequency domain and often captures short-run dynamics effectively with fewer parameters, making estimation more robust

this methodology, where d can be any real value, including 0, but also negative or positive fractional numbers.

We now provide a brief description of the Robinson (1994) tests used in this study. Essentially, these tests involve examining the null hypothesis:

$$H_o : d = d_0, \quad (10)$$

in the model given by Eq. (6) for any real value d_0. The test relies on the Lagrange Multiplier (LM) principle and is based on the null hypothesis (10). Therefore, the model under (10) becomes:

$$y^*(t) = \alpha 1^*(t) + \beta t^*(t) + u(t), \quad (11)$$

where $y^*(t) = (1-L)^{d_0} y(t)$; $1^*(t) = (1-L)^{d_0} 1$; and $t^*(t) = (1-L)^{d_0} t$. This test statistic allows to consider a group of values of d_0 where the null hypothesis (10) cannot be rejected and, under correct specification, the test should be monotonically decreasing with d_0, producing a confidence band of values where (10) cannot be rejected. This method is chosen for several reasons. First, it allows testing any real value d_0, including values beyond the stationary range $d_0 \geq 0.5$; it has standard (normal) null and local limit distributions that apply regardless of whether deterministic terms, such as a constant or linear trend, are included. Additionally, it is the most efficient method in the Pitman sense when dealing with local departures. Details on its specific functional form can be found in Gil-Alana and Robinson (1997a, b) (Table 3).

4 Data

The data used in the research comes from the Colorado State University (2023) in the framework of the Tropical Meteorology Project using data officially provided by the U.S. National Hurricane Center (2023). The time series goes from 1851 until 2022 considering the period 1851 to 1965 the pre-satellite era and the satellite era from 1966 to 2022.

The different cuts, descriptive statistics are analyzed considering the technological eras mentioned above, as well as a graphic analysis of the following variables (Klotzbach 2022):

1. Hurricane (H): A tropical storm characterized by sustained low-level winds reaching 74 mph (33 m/s or 64 knots) or more.
2. Hurricane Day (HD) is a single unit of measurement for hurricane activity.
3. A Major Hurricane (MH) has a sustained low-level wind speed of at least 111 mph (96 knots or 50 ms-1) over its existence. This corresponds to a Category 3 or above on the Saffir-Simpson scale, defined by four consecutive 6-h periods during which a tropical cyclone exhibits or is predicted to have hurricane-force winds.
4. Major storm Day (MHD) refers to four 6-h periods when a storm reaches Saffir/Simpson category 3 or above.
5. Named Storms (NS) include hurricanes, tropical storms, and subtropical storms.
6. Storm Day (NSD)—Similar to Hurricane Day, but for four 6-h periods when a tropical or sub-tropical cyclone reaches tropical storm-force winds.

To facilitate understanding of the methodological steps for readers less familiar with fractional integration, Table 4 provides a concise roadmap summarizing the main elements of the study design.

5 Empirical results

Before presenting the numerical results, it is important to clarify the interpretation of the estimated coefficients. The time trend coefficient (β) represents the average annual rate of change in the corresponding variable —that is, the yearly increase in the number of storms, hurricanes, or major hurricanes. The intercept (α) denotes the estimated baseline level of each series, while the differencing parameter (d) captures the degree of persistence or long-term dependence in the data. A positive and statistically significant value of d indicates a slower decay of shocks over time, consistent with long-memory dynamics, whereas values close to zero suggest short-memory behavior.

Tables 4 and 5 display the estimates of the differencing parameter d in Eq. (6) respectively for the cases of no autocorrelation and with autocorrelation. Initially, we consider the three classical set-ups of:

(i) with no deterministic terms (i.e., with $\alpha = \beta = 0$ a priori).

Table 4 Methodological roadmap

Element	Description
Data source	Colorado State University (2023), within the framework of the Tropical Meteorology Project, using data officially provided by the U.S. National Hurricane Center (2023)
Data sample period	1851–2022 (annual frequency)
Modeling approach	Long memory framework (Baillie 1996)
Techniques	Fractional integration methods (Robinson 1994; Gil-Alana and Hualde 2009)
Robustness checks	Sowell (1992) maximum likelihood and Robinson (1995a,b) semiparametric methods
Subsample analysis	Pre-satellite era: 1851–1965; satellite era: 1966–2022; and 1900–2022

(ii) with an intercept only (i.e., with $\beta = 0$ a priori), and.
(iii) with an intercept and a linear time trend.

However, instead of presenting the results in terms of d for the three cases, we only report in the tables those corresponding to the selected specification for each series, this selection being made on the basis of the significancy of the deterministic terms. Thus, Tables 3 and 4 display the estimated coefficients for α, β and d based on the most appropriate specification in relation with the deterministic terms. Along with the estimates we also report the 95% confidence intervals of the non-rejection values of d and the t-values of α and β.

Starting with the results based on white noise errors (Table 4), the first thing we observe is that for the named values the time trends are required in the three series and the estimates of d are positive in all cases; however, the hypothesis of long memory (i.e. that d is strictly positive) is only accepted in case of storms, while for hurricanes and major hurricanes the null hypothesis of short memory or I(0) behavior (i.e., $d = 0$) cannot be rejected since the confidence intervals include the value 0 in these cases. The same evidence is found in case of the named days, with long memory being observed in case of storms but not in the other two series. Focusing on the estimated coefficients, the fractional differencing parameter is equal (d) to 0.20 and 0.17 respectively for storms and storm days.

For hurricanes and hurricane days the values the integration order (d) is 0.07 and 0.08 and for major hurricanes, 0.02 and 0.07. The time trend coefficients are statistically significantly positive in all cases, the largest values observed in the integration order for the storms (0.052) and storm days (0.218). In the rest of the cases, the values range between 0.013 (major hurricanes) and 0.043 (hurricane days).

Table 6 is similar to Table 5 but allowing for weak autocorrelation throughout the Bloomfield's (1973) model. The results are fairly similar to the previous case, with the time trends being significantly positive in all cases, and the higher coefficients being obtained in case of storms and storm days. In the remaining four series, the estimates of d are positive except for major hurricane days though in the four cases the I(0) hypothesis of short memory cannot be rejected, and the time trends seems to be slightly higher for hurricanes than for major hurricanes.

Though proper structural breaks are not considered, it is an interesting issue since some authors argue that breaks and fractional integration are intimately related (Granger and Hyung 2004; Mikosch and Starica 2004, and Ohanissian et al. 2008). Instead, we divide the sample into two subsamples, one from 1865 to 1965, and the other one from 1966 to 2022. This division was primarily considered based on the results of Ju-Moon et al. (2019),

Table 5 Estimated coefficients. No autocorrelation

Tropical cyclones	Integration order (d) (95% band)	Intercept (tv)	Time trend (tv)
Storms	0.20 (0.11, 0.33)	5.530 (4.83)	0.052 (4.79)
Hurricanes	0.07 (−0.02, 0.19)	4.234 (8.70)	0.015 (3.20)
Major hurricanes	0.02 (−0.08, 0.15)	0.727 (2.98)	0.013 (5.68)
Storm days	0.17 (0.08, 0.29)	31.255 (4.85)	0.218 (3.52)
Hurricane days	0.08 (−0.01, 0.20)	17.861 (6.66)	0.043 (1.66)
Major hurricane days	0.07 (−0.03, 0.21)	1.819 (1.92)	0.031 (3.35)

The values in parenthesis in columns 3 and 4 are the associated t-values of the estimated deterministic terms

Table 6 Estimated coefficients. With autocorrelation

Tropical cyclones	Integration order (*d*) (95% band)	Intercept (tv)	Time trend (tv)
Storms	0.15 (0.00 0.33)	5.542 (5.39)	0.052 (5.24)
Hurricanes	0.06 (−0.07, 0.23)	4.236 (8.77)	0.015 (3.21)
Major hurricanes	−0.08 (−0.24, 0.13)	0.733 (3.99)	0.013 (7.19)
Storm days	0.18 (0.01, 0.36)	31.118 (4.53)	0.219 (3.32)
Hurricane days	0.07 (−0.09, 0.27)	17.897 (6.86)	0.043 (1.69)
Major hurricane days	−0.06 (−0.22, 0.13)	1.896 (3.14)	0.029 (4.84)

The values in parenthesis in columns 3 and 4 are the associated t-values of the estimated deterministic terms

Table 7 Estimated coefficients. No autocorrelation

Tropical cyclones	Integration order (*d*) (95% band)	Intercept (tv)	Time trend (tv)
i) First subsample			
Storms	0.17 (0.04, 0.35)	5.986 (5.79)	0.046 (3.09)
Hurricanes	0.10 (−0.01, 0.26)	5.067 (15.55)	–
Major hurricanes	−0.11 (−0.24, 0.06)	0.632 (3.62)	0.017 (6.16)
Storm days	0.20 (0.09, 0.34)	30.602 (4.06)	0.247 (2.28)
Hurricane days	0.07 (−0.03, 0.21)	20.635 (12.38)	–
Major hurricane days	−0.17 (−0.30, 0.01)	1.402 (2.99)	0.044 (5.94)
ii) Second subsample			
Storms	0.08 (−0.08, 0.31)	7.415 (5.08)	0.173 (4.04)
Hurricanes	−0.12 (−0.30, 0.13)	4.969 (9.55)	0.051 (3.17)
Major hurricanes	−0.05 (−0.24, 0.25)	1.293 (3.43)	0.043 (3.75)
Storm days	−0.07 (0.25, 0.21)	38.210 (7.01)	0.729 (4.35)
Hurricane days	0.11 (−0.04, 0.35)	23.858 (8.81)	–
Major hurricane days	0.17 (−0.09, 0.61)	2.303 (2.15)	0.118 (2.06)

The values in parenthesis in columns 3 and 4 are the associated t-values of the estimated deterministic terms

who indicated that during the period before the advent of satellites (1865–1965), systematic biases in the detection of tropical cyclones might exist.

These biases could produce spurious trends in TCS if automatically compared with the period 1965–2022. This technological change in the time series, specifically the introduction of satellites, could imply a lack of homogeneity in the data, which in turn would have a significant impact on the global trend of TCS. Therefore, the research divides the sample into a pre-satellite stage and a satellite stage to avoid confusion in data methodology and possible erroneous conclusions.

Table 7 displays the results based on white noise errors. The upper panel in the forthcoming tables refer to the first subsample (1851–1965), while the lower one to the second subsample (1966–2022). We observe that for storms the long memory hypothesis, i.e., $d>0$, holds for the first subsample, with an estimate of integration order (*d*) of 0.17; however, this hypothesis is rejected in the second subsample, with $d=0.08$, the I(0) or short memory hypothesis not being rejected in this case. For hurricanes and major hurricanes the I(0) hypothesis cannot be rejected in either of the two subsamples.

The most interesting thing observed in these three series is that there is a substantial increase in the estimate of the time trend when we move from the first subsample to the second one. Thus, for storms, the slope coefficients of integration order (d) changes from 0.046 to 0.173 and for major hurricanes from 0.017 to 0.043; for hurricanes, the time trend was statistically insignificant in the first subsample and becomes significantly positive (0.051) in the second one. This pronounced upward shift in trend estimates for the satellite era is visually evident in the raw data presented in Figs. 1 and 2.

Focusing now on the number of days, the same conclusion holds in relation with the degree of persistence, observing evidence of I(0) behavior in all subseries except for the number of days of storms in the first subsample. For the time trend coefficient, it remains insignificant in the two subsamples for hurricanes, but for storms and major hurricanes there is a substantial increase in its value (from 0.247 to 0.729 for storms, and from 0.044 to 0.118 for major hurricanes).

We next allow for weakly (Bloomfield) autocorrelated errors. Results are reported in Table 7. We observe that the I(0) hypothesis cannot be rejected in any of the series and for either of the two subsamples. However, as before, we observe a substantial increase in the estimates of the time trend coefficients. Precisely, for storms, it rises from 0.046 to 0.174 and for major hurricanes from 0.016 to 0.046; in the case of hurricanes, it becomes significant only in the second subsample. For the number of days, the slope in the storms increases from 0.248 to 0.766; for hurricanes it becomes significant in the second subsample, and for major hurricanes, it increases from 0.044 to 0.142. Thus, the same conclusion as in the previous table holds now, observing a significant increase in the estimates of the slope coefficient in all cases (Table 8).

As a robustness check we also tried with alternative parametric and semiparametric estimation methods (Sowell's, 1992 maximum likelihood and Robinson's 1995a,b semiparametric approaches) using both the whole data and the subsamples, and though quantitatively we observe some differences in some cases, qualitatively the results were very similar to those reported in this work.

Taking into account the above empirical results, among the causes of these trends there are several arguments that can be proposed including natural variability, external forcing from both greenhouse gases and aerosols, as well as the inhomogeneous quality of the observing system. Which of these causes are the more relevant ones is still under debate

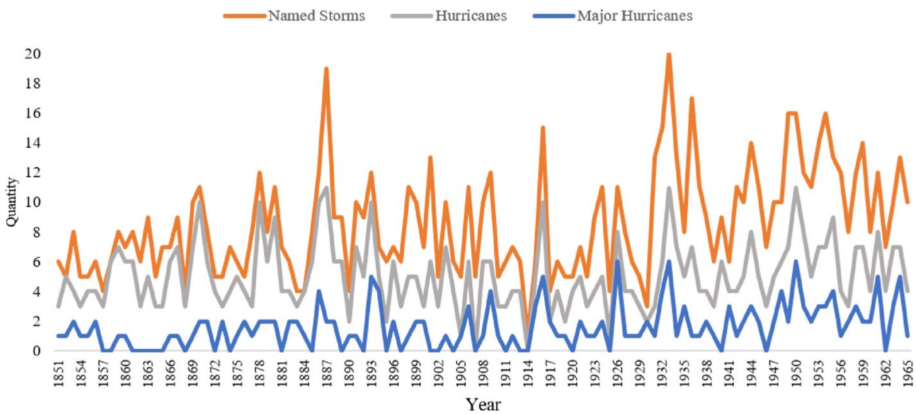

Fig. 1 Quantity Storms and Tropical Cyclones (Hurricanes) in the North Atlantic Region during the pre-satellite era -1851 to 1965-.
Source Colorado State University (2023)

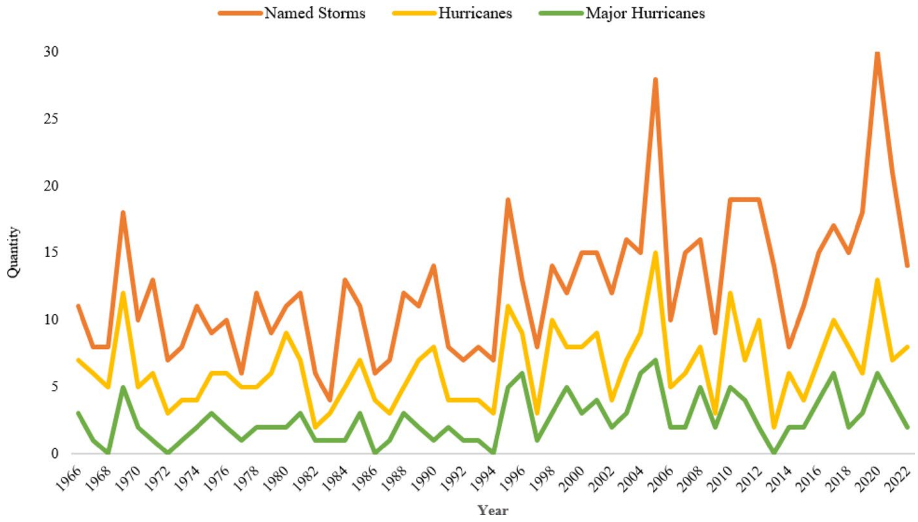

Fig. 2 Quantity Storms and Tropical Cyclones (Hurricanes) in the North Atlantic Region during the satellite era -1966 to 2022-.
Source Colorado State University (2023)

Table 8 Estimated coefficients. Autocorrelation

Tropical Cyclones	Integration order (*d*) (95% band)	Intercept (tv)	Time trend (tv)
i) First subsample			
Storms	0.02 (−0.15, 0.28)	5.990 (8.87)	0.046 (4.56)
Hurricanes	0.02 (−0.13, 0.24)	5.070 (21.90)	–
Major hurricanes	−0.25 (−0.46, 0.05)	0.636 (5.09)	0.016 (8.07)
Storm days	0.21 (0.05, 0.47)	30.461 (3.84)	0.248 (2.18)
Hurricane days	0.10 (−0.08, 0.33)	20.604 (11.30)	–
Major hurricane days	−0.37 (−0.59, −0.07)	1.391 (5.02)	0.044 (9.33)
ii) Second subsample			
Storms	0.03 (−0.27, 0.40)	7.307 (5.10)	0.174 (4.11)
Hurricanes	−0.27 (−0.59, 0.18)	4.926 (13.08)	0.053 (4.22)
Major hurricanes	−0.47 (−0.87, −0.03)	1.209 (9.07)	0.046 (9.67)
Storm days	−0.32 (0.6, 0.06)	37.080 (11.65)	0.766 (7.11)
Hurricane days	−0.33 (−0.71, 0.16)	17.683 (11.63)	0.206 (3.99)
Major hurricane days	−0.52 (−0.92, 0.01)	1.508 (4.54)	0.142 (11.70)

The values in parenthesis in columns 3 and 4 are the associated t-values of the estimated deterministic terms

(Vecchi and Knutson 2008; Klotzbach Landsea 2015; Lanzante et al. 2019; Knutson et al. 2019; Murakami et al. 2020; Seneviratne et al. 2021) and is something to be studied in future papers.

As a sensitivity analysis, we finally repeat the analysis but removing the earlier records, and focusing only on the data starting in 1900. Results for the two types of disturbances are reported in Table 9. In line with the previous results, long memory is only obtained in case of the storms, while for the hurricanes and major hurricanes data, we reject the hypothesis of long memory in favour of a short memory pattern. This may be explained by the level of aggregation of the data and the higher volume of data in the case of the storms.

It is important to note that the absence of persistence found in hurricanes and major hurricanes may reflect either genuine short-term dynamics or limitations in statistical power. Compared to the storm series, these categories involve a smaller number of cases, which increases sampling uncertainty and reduces the ability to detect long-memory behavior. Furthermore, the higher level of aggregation in the storm variable, encompassing a wider range of meteorological events, could contribute to the observed persistence. Hence, the apparent lack of long-term dependence in hurricanes and major hurricanes should be interpreted cautiously, as it may be partially influenced by data constraints rather than a complete absence of long-memory dynamics.

6 Concluding comments

This paper examines time trends in tropical cyclones in the North Atlantic region through a fractional integration model. It utilizes annual data on the average number of storm, hurricane, and major hurricane days from 1851 to 2022. One of the main findings in a model with no autocorrelation is that the presence of long-term components is only evident in the storm and storm days data series. For hurricane and major hurricane data, the long-term dependence in the time series is less noticeable, and it is not possible to reject the hypothesis that the temporal dynamics may be best modeled using short-memory processes. However, all series show a significantly positive linear time trend. When performing the analysis with autocorrelation, the previous results are confirmed, since significant positive trends are observed in all the analyzed series, highlighting that only for storms and storm days is it possible to identify a long memory process. This distinction between storm types is critical for interpreting the differing long-term impacts of these events and could guide future modeling approaches. This also suggests that storm events are experiencing more prolonged periods of recovery in the event of exogenous shocks affecting the series.

Table 9 Estimated coefficients. Data starting at 1900

Tropical cyclones	Integration order (*d*) (95% band)	Intercept (tv)	Time trend (tv)
i) No autocorrelation			
Storms	0.19 (0.09 0.33)	6.545 (4.96)	0.074 (4.22)
Hurricanes	−0.05 (−0.16, 0.10)	3.742 (10.07)	0.031 (6.00)
Major hurricanes	0.03 (−0.08, 0.17)	1.171 (3.69)	0.017 (3.92)
Storm days	0.09 (0.01, 0.24)	38.556 (6.60)	0.256 (3.26)
Hurricane days	−0.02 (−0.14, 0.15)	15.478 (7.03)	0.099 (3.24)
Major hurricane days	0.11 (−0.01, 0.27)	3.078 (2.40)	0.035 (2.04)
ii) With autocorrelation			
Storms	0.18 (0.02 0.39)	6.538 (5.11)	0.074 (4.34)
Hurricanes	−0.09 (−0.27, 0.15)	3.752 (11.61)	0.031 (6.75)
Major hurricanes	−0.07 (0.25, 0.17)	1.202 (5.36)	0.016 (5.18)
Storm days	0.07 (−0.10, 0.31)	38.437 (7.03)	0.256 (3.47)
Hurricane days	−0.15 (−0.35, 0.11)	15.585 (11.21)	0.097 (4.78)
Major hurricane days	−0.02 (−0.20, 0.22)	3.243 (3.93)	0.032 (2.78)

The values in parenthesis in columns 3 and 4 are the associated t-values of the estimated deterministic terms

When creating two subsamples, with the range 1851–1965 (pre-satellite era) for the first subsample and 1966–2022 (satellite era) for the second one, if no autocorrelation is assumed, the only series that has long memory characteristics are the storms for the first subsample taking an estimated value for the differencing parameter of about 0.17; however, for the satellite era, the significance value does not allow us to reject the null hypothesis of a short memory pattern. In the case of hurricanes and major hurricanes, the *I(0)* hypothesis cannot be rejected in either of the two subsamples. The contrast between the two periods highlights the importance of improved data collection techniques in understanding tropical cyclone patterns.

One aspect that stands out in the research is a substantial increase in the estimation of the time trend in the six series examined. Thus, for example, in the context of no autocorrelation, for storms, the slope coefficient goes from 0.046 to 0.173, and for major hurricanes, from 0.017 to 0.043. For the hurricane series, the time trend was statistically insignificant in the first subsample and becomes significantly positive (0.051) in the second. When analyzing the series in number of days, the same behavior is detected, with the coefficient for the number of days for storms increasing from 0.247 to 0.729 and, for major hurricanes, from 0.044 to 0.118. If autocorrelation is permitted the numbers are very similar. Dealing with the long/short memory behavior, long memory or evidence of significantly positive orders of integration are only observed in the storms-related series.

In conclusion, although the results indicate evidence of a long-term effect particularly in storms, the same cannot be observed for major hurricanes or hurricanes. Also, in general terms, there is a statistically positive and, in some cases, substantially positive trend in the two subsamples of time analyzed, considering the growth of storms, hurricanes and large hurricanes.

This suggests that, although there may be short-term influences that affect their frequency, in general the climatological events analyzed are experiencing an increase in their occurrence. It is particularly relevant as it may indicate a heightened need for improved disaster planning and forecasting models.

The increase in the trend of occurrence of storms, hurricanes and major hurricanes has significant implications related, for example, to the risks for the population. In the Atlantic region, considering the Caribbean and Central America, this implies considerable risks, given that many people live near coastal areas, which would increase the risk of loss of life and property, especially since most of this population are communities that are particularly vulnerable to these impacts. In this context, it is essential to reinforce the importance of integrating early warning systems and public awareness programs into disaster preparedness.

Regarding adaptation and resilience to climate change, a rise in the frequency of extreme weather events poses greater challenges for communities and local governments, which logically suggests the need to implement measures that enhance adaptive capacity to cope with these events. This includes sustainable urban planning, disaster risk management and emergency preparedness. Specifically, enhanced infrastructure development and community-level preparedness plans can help mitigate the rising risks of such extreme events.

Considering the trends and results obtained on the frequency and intensity of tropical storms in particular, the proposal arises to recommend and incorporate the results in the calibration of early warning systems by updating mainly the activation thresholds as well as the delivery times in relation to trend-adjusted projections. This means that warnings could be triggered not only based on current weather indicators, but also considering increased storm activity, allowing authorities to issue warnings earlier and with greater confidence.

In regions where rapid-onset storms are becoming more frequent, this approach can significantly reduce response time, which could save lives and reduce damage to infrastructure. On the other hand, considering long-term weather trends in early warning systems allows for seasonal or inter-annual adjustments that can improve the bias of early warning systems.

Another contribution of the present research is related to insurance risk models, as they will be able to integrate the results in order to better quantify, evaluate and assess coastal exposure, especially vulnerable in Central America and the Caribbean where the probability of occurrence is high. Statistical evidence of an increasing trend in storm activity could be used to revise the historical bases used in catastrophe models, allowing more accurate estimates of return periods and loss exceedance probabilities. This has a direct link to premium setting, reinsurance and financial planning, which becomes a tool for analysis and use by both public entities and private companies. In addition, such integration would drive the development of climate-resilient financial instruments, such as parametric insurance and catastrophe bonds, adapted to emerging risks.

As a final remark, note that the main contribution of this research has been to examine the presence of time trends in the data in a very careful way that allows the errors to be *I(d)* rather than *I(0)* as was done previously in the standard literature. This allows us to better focus mitigation and resilience strategies on these phenomena. Given the critical nature of these trends, future studies should aim to explore more complex, non-linear models to capture potential fluctuations in tropical cyclone behaviors. Among the limitations of the present work is the linear nature of the model examined. Thus, though the anlaysis of subsamples has been conducted in the paper, a proper investigation of structural breaks in the context of fractional integration (based, for example, in the approach develop in Gil-Alana, 2008) will be conducted in a future paper. Moreover, the linear framework applied to the deterministic terms in this work can be readily adapted to various non-linear structures, such as Chebyshev polynomials over time (Cuestas and Gil-Alana 2016), Fourier functions in time (Gil-Alana and Yaya 2021a, b), or even neural networks (Yaya et al. 2021), but even this non-linear framework can be extended to the stochastic part of the model, substituting the break in the data by other less abrupt structures. Combining fractional integration with alternative machine learning approaches in the context of the present data or alternative ones based on reginal cyclone analysis is another potential line of research that could be enriched by the inclusion of additional variables such as mortality rates or economic losses.

Appendix 1

We see in Table 10 that for the years of the pre-satellite era, the average number of Named Storms was around 8.64 per year, with a relatively low standard deviation of 3.61. For the date range described (1851–1965), the maximum number of storms recorded was 20 per year.

In terms of the average number of hurricanes, 5.07 were recorded per year, with a maximum of 11 hurricanes and a variability of 2.31 with respect to the mean value. In terms of Major Hurricanes, the maximum number was six, with an average value of 1.61 and a standard deviation of 1.47, respectively.

When analyzing the number of days in which storms or hurricanes were recorded during the pre-satellite era, it is observed that on average a total of 45.81 days per year of

Table 10 Quantity Storms and Tropical Cyclones (Hurricanes) in the North Atlantic Region during the pre-satellite era 1851 to 1965.
Source Own elaboration based on Colorado State University (2023)

Named Storms pre-satellite era		Hurricanes pre-satellite era		Major Hurricanes pre-satellite era	
Mean	8.64	Mean	5.07	Mean	1.61
Std. Deviation	3.61	Std. deviation	2.31	Std. deviation	1.47
Min	1	Min	0	Min	0
Max	20	Max	11	Max	6

Table 11 Storms and Tropical Cyclones (Hurricanes) days in the North Atlantic Region during the pre-satellite era 1851 to 1965

Named Storms days pre-satellite era		Hurricanes days pre-satellite era		Major Hurricanes Days pre-satellite era	
Mean	45.81	Mean	20.68	Mean	3.95
Std. Deviation	23.40	Std. Deviation	12.86	Std. deviation	4.77
Min	3.25	Min	0	Min	0
Max	125.25	Max	61.5	Max	22.75

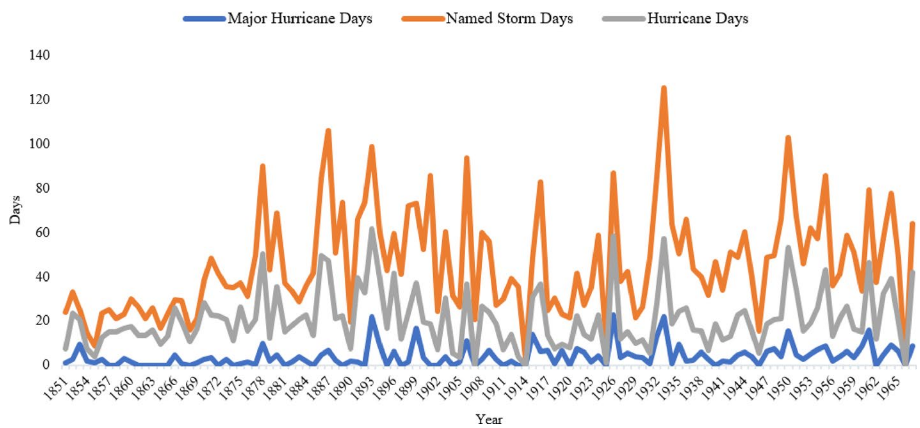

Fig. 3 Storms and Tropical Cyclones (Hurricanes) days in the North Atlantic Region during the pre-satellite era -1851 to 1965-.
Source Colorado State University (2023)

storms were recorded, with a high value in its standard deviation of 23.40. A maximum of 125.25 days was recorded. Similarly, hurricane days averaged 20.68 days, with a deviation of 12.86 and a maximum of 61.5 days per year.

As for Major Hurricanes, for the time series before the satellite era, the average was 3.95 days per year, with a smaller deviation compared to storms and hurricanes of lower category, registering a maximum of 22.75 days per year. These results are detailed in Table 11 and Fig. 3.

Looking at the satellite era from 1966 to the present date, the average number of storms by year is 12.53, with a standard deviation of 5.13, with a maximum of 30 storms and a

Table 12 Quantity Storms and Tropical Cyclones (Hurricanes) in the North Atlantic Region during the satellite era 1966 to 2022

Named Storms satellite era		Hurricanes satellite era		Major Hurricanes satellite era	
Mean	12.53	Mean	6.49	Mean	2.54
Std. Deviation	5.13	Std. deviation	2.85	Std. deviation	1.76
Min	4	Min	2	Min	0
Max	30	Max	15	Max	7

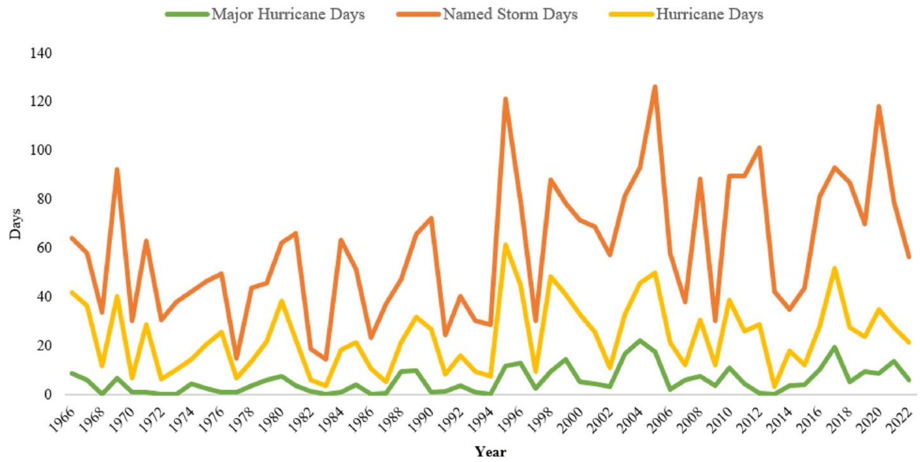

Fig. 4 Storms and Tropical Cyclones (Hurricanes) days in the North Atlantic Region during the satellite era -1966 to 2022-.
Source Colorado State University (2023)

Table 13 Storms and Tropical Cyclones (Hurricanes) days in the North Atlantic Region during the satellite era 1966 to 2022.
Source Own elaboration based on Colorado State University (2023)

Named storms days satellite era		Hurricanes days satellite era		Major Hurricanes days satellite era	
Mean	59.48	Mean	23.65	Mean	5.59
Std. deviation	27.40	Std. deviation	14.12	Std. deviation	5.39
Min	14.5	Min	3.25	Min	0
Max	126.25	Max	61.5	Max	22.25

minimum of four. In terms of hurricanes, during this era an average of 6.49 hurricanes a year is recorded, with a maximum of 15 and a minimum of two, considering a variability of the data around the mean of 2.85. As for Major Hurricanes, during the satellite era an average of 2.54 by year is observed, with a maximum of seven and a standard deviation of 1.76. These data are visible in Table 12 and Fig. 4, where the maximum periods of storms and hurricanes in the years 1996, 2005 and 2020 are highlighted.

Finally, in Table 13 and Fig. 4, we analyze the number of days of tropical storms and hurricanes in the satellite era, highlighting an average of 59.48 days of storms per year, with a high variability in the mean value of 27.40, registering years with a maximum of 126.25 storm days. In terms of hurricanes, an average of 23.65 days per year is recorded, with a deviation of 14.12, and a minimum of 3.25 and a maximum of 61.5 hurricane days per year being recorded. Now, in terms of Major Hurricanes, an average of 5.59 days per year is recorded, with a variation around the mean of 5.39, and with a maximum of 22.25 days per year. As can be seen in Fig. 4, the increase in storms, hurricanes, and major hurricanes since 1995 is clearly evident.

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Data availability Data can be obtained upon request from Prof. Luis Alberiko Gil-Alana (alana@unav.es). The computation program is based on Fortran, but new codes in R will also be available from the authors upon request.

Declarations

Ethical approval There are no ethical issues related with the publication of the present manuscript.

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