

# 1 Increasing Frequency in Off-Season Tropical Cyclones and its 2 relation to Climate Variability and Change

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10  
11 **Abstract.** This article analyzes the relationship between off-season tropical cyclone (TC)  
12 frequency and climate variability and change for the Pacific and Atlantic Ocean basins. TC track  
13 data was used to extract the off-season storms for the 1900-2019 period. TC counts were  
14 aggregated by decade and the number of storms for the first six decades (pre-satellite era) was  
15 adjusted. Mann-Kendall non-parametric tests were used to identify trends in decadal TC counts  
16 and multiple linear regression models (MRL) were used to test if climatic variability or climate  
17 change factors explained the trends in off-season storms. MRL stepwise procedures were  
18 implemented to identify the climate variability and change factors that explained most of the  
19 variability in off-season TC frequency. A total of 713 TCs were identified as occurring earlier or  
20 later than their peak seasons, most during the month of May and in the West Pacific and South  
21 Pacific basins. The East Pacific (EP), North Atlantic (NA) and West Pacific (WP) basins exhibit  
22 significant increasing trends in decadal off-season TC frequency. MRL results show that trends  
23 in sea surface temperature, global mean surface temperature, and cloud cover explain most of  
24 the increasing trend in decadal off-season TC counts in the EP, NA, and WP basins. Stepwise  
25 MLR results also identified climate change variables as the dominant forces behind increasing  
26 trends in off-season TC decadal counts, yet they also showed that climate variability factors like  
27 El Niño-Southern Oscillation, the Atlantic Multidecadal Oscillation, and the Interdecadal Pacific  
28 Oscillation also account for a portion of the variability.

29  
30  
31 **Keywords:** Tropical Cyclones; Hurricane Season; Climate Variability; Climate Change  
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33

## 34 1. Introduction

35 Increasingly, scientific evidence has shown a link between tropical cyclones (TC) and global  
36 warming, especially following the dramatic rise in both the intensity and frequency of storms during  
37 the first two decades of the present century (Goldenberg et al., 2001; Holland and Webster, 2007).  
38 Scientific studies (Landsea, 2005; Emanuel, 2005; Trenberth and Shea, 2006; Trenberth, 2007) are  
39 not in agreement as to whether sea surface temperatures have a measurable effect on the frequency  
40 of tropical cyclones and other studies (Camargo and Sobel, 2005; Nogueira and Kim, 2007; Mahala  
41 et al., 2015; Zhao et al., 2018] have evaluated cyclonic activity on a time scale longer than  
42 interannual and have associated it with variability in the El Niño Southern Oscillation (ENSO), the  
43 Atlantic Multidecadal Oscillation (AMO) and the Interdecadal Pacific Oscillation (IPO). However,  
44 little is known about the changes in the frequency of off-season TCs, storms that occur before and  
45 after the peak TC season months, and their connections to climate variability and change.

46 A number of recent papers (Wang and Lee, 2008; Knutson et al., 2010; Emanuel, 2013) have  
47 documented global increases in the proportion of very intense cyclones as well as latitudinal trends  
48 in maximum tropical cyclone (TC) intensity, which are consistent with future climate projections. A  
49 detailed review of the behavior of TCs (Walsh et al., 2019) concluded that it remains uncertain  
50 whether past changes in TC activity have exceeded the variability expected from natural causes,

51 while concerns remain about the temporal homogeneity of the best record (Landsea et al., 2006;  
52 Mann et al., 2007). Another study (Mann et al., 2009) found that recent increases in the frequency  
53 of intense TCs in the North Atlantic (NA) were the product of reinforcing effects, such as La Niña-  
54 like climate conditions and relative tropical Atlantic warming. Yet, no study has focused on  
55 examining changing trends in off-season TC frequency and its relation to natural variability or  
56 climate change.

57 A synthesis (Christensen et al., 2013) of the then-available regional projections of future TC  
58 climatology for 2081–2100 in relation to 2000–2019, for a business as usual emissions scenario  
59 similar to A1B, shows that worldwide the consensus projection was for decreases in TC numbers by  
60 approximately 5–30%, increased frequency of Category 4 and 5 storms between 0 and 25%, an  
61 increase by a small percentage in the typical maximum intensity of life, and an increase in TC  
62 rainfall amounts by 5–20%. Nevertheless, it is clear that there is great uncertainty about these  
63 projections. Such projections do not consider changes in off-season TC development in any of the  
64 basins where TCs form

65 Several climatic reconstructions have been performed (Bradley et al., 2006; Mann et al., 2009)  
66 using proxy data by collecting sediments from the impact of hurricanes in the period 500–1850 and  
67 then calculated estimates from the statistical model of the activity of tropical cyclones based on  
68 modern instrumental weather indexes for the period (1851–2006). In analyzing these results and  
69 comparing them with the cyclone seasons fixed by the World Meteorological Organization, the  
70 hurricane season (tropical depressions, tropical storms and hurricanes) in the Atlantic Ocean was  
71 fixed as June 1 to November 30 in 1960, yet we observe a significant variability in off-season TC  
72 occurrence before/after the hurricane season after the 1960s.

73 Even though it not uncommon for TCs to develop outside of their peak TC season months, there is a  
74 need to examine trends in the number of storms that are forming during low activity months. The  
75 formation of the extratropical storm Andrea on May 20, 2019 marks the decade of 2010 as that with  
76 the greatest number of tropical cyclones in the Atlantic Ocean before or after the hurricane season  
77 dates established by official bodies like the World Meteorological Organization (WMO) and the  
78 National Oceanic and Atmospheric Administration (NOAA). The frequency of TCs in the North  
79 Atlantic basin has been found to be influenced by fluctuations in teleconnections such as ENSO and  
80 AMO (Trenberth et al., 2006; Nogueira et al., 2013). However, human-induced climate change  
81 manifested as higher sea surface temperatures (SST) and increasing evaporation rates in the tropical  
82 and sub-tropical North Atlantic basin could also be related to the higher frequency of off-season  
83 tropical or extratropical cyclone occurrences in more recent decades. That increasing trend in SSTs  
84 in the Atlantic and other ocean basins and its relation to out off-season TC occurrences during the  
85 last century has not been thoroughly examined by the scientific community.

86 This study aims to determine if off-season TCs have increased in their frequency since the 1900 and  
87 if that increment in the number pre and post off-season storms could be associated with normal  
88 climatic variability or climate change. The total number of out off-season TCs per decade for the  
89 North Atlantic (NA), West Pacific (WP), East Pacific (EP) and South Pacific (SP) ocean basins  
90 where analyzed to determine if any of the basins experienced an increase in the number of off-  
91 season tropical/extratropical cyclones over time that could be associated to climatic variability or  
92 climate change. The Indian Ocean basins were not included in this analysis due to limited data  
93 availability. Ocean basins that were found to have statistically significant trends were then analyzed  
94 further with multiple liner regression models (MRL) and regression stepwise procedures to  
95 determine if climate variability or change factors could explain increasing trends in off-season TC  
96 frequency over time.

97

98 **2. Data**

99 Six-hourly TC track data for all storms across all ocean basins were obtained from the International  
 100 Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al., 2018) and all TCs that  
 101 occurred at or after 1900 were extracted. The TC tracks were then then extracted for the northern  
 102 hemisphere basins that include the East Pacific (EP), the North Atlantic (NA) and the West Pacific  
 103 (WP) and for the southern hemisphere basin in the South Pacific (SP) (Fig 1a). The off-season TCs  
 104 were then aggregated by decades in order to identify decadal variability or trends in total storm  
 105 counts at the individual basin scales. Off-season TCs were defined as storms that occurred in the  
 106 three months before and after the six-month period of peak cyclone activity in the basin.

107 The monthly frequency of TCs for each basin were analyzed for the entire period and based on that  
 108 analysis we determined that off-season TCs that occurred during the three months (Mar-Apr-May)  
 109 before June 1<sup>st</sup> were pre-season and the three months (Dec-Jan-Feb) after November 30<sup>th</sup> were post-  
 110 season in the northern hemisphere basins (NA, EP and WP) In the southern hemisphere, the three  
 111 months before (Aug-Sep-Oct) November 1<sup>st</sup> were classified as pre-season and the three months  
 112 (May-Jun-Jul) after April 30<sup>th</sup> were classified as post off-season in the southern hemisphere basins  
 113 (SP) (Fig 1b). Pre-season and post-season decadal time-series for the Northern/Southern hemisphere  
 114 and individual basins were then constructed to calculate the total number of TCs per-decade from  
 115 1900 to 2019.

116 The climate variability indexes of ENSO (Niño 3.4), AMO (Trenberth et al., 2019) were  
 117 respectively obtained from the National Oceanic and Atmospheric Administration (NOAA)  
 118 Physical Sciences Lab and the National Center for Atmospheric Research. The IPO index was  
 119 obtained from the NOAA Physical Sciences Laboratory (Henley et al., 2015). The variables  
 120 associated with anthropogenic climate change used in this study were sea surface temperature  
 121 (SST), global mean surface temperature (GMST) and cloud cover (CC). SST data were obtained  
 122 from the HadISST1 1° reconstruction, GMST data were accessed from the GISTEMP v4 and CC  
 123 data was acquired from the International Comprehensive Ocean-Atmosphere Data Set (ICOADS)  
 124 v2.5, all for the 1900-2019 period. It is important to note that the ICOADS data set has some key  
 125 limitations, like data coverage been sparse and limited corrections that account for changes in  
 126 observing practices. A decadal average was calculated for all of the climate variability and change  
 127 variables in order to use them as predictors of decadal TC total counts (Table 1).

**Table 1. Tropical cyclone, climate change and variability variables used in this study.**

	Abbreviations	Units
Tropical Cyclone Counts	TCs	Decadal Total Counts
Climate Change Variables		
Sea Surface Temperature	SST	°
Global Mean Surface Temperature	GMST	°
Cloud Cover	CC	Oktas
Climate Variability Variables		
El Niño Southern Oscillation	ENSO 3.4	°SST anomalies index
Interdecadal Pacific Oscillation	IPO	°SST anomalies index
Atlantic Multi-decadal Oscillation	AMO	°SST anomalies index

128 **3. TC Adjustment Method**

129 TC counts before 1966 (pre-satellite era) are incomplete (Mann et al., 2007; Landsea, 2007) since a  
 130 lot of storms that didn't make landfall weren't recorded, so in order to make any comparisons  
 131 between the earlier and later decades, the series for each basin need to be adjusted accordingly.  
 132 Another issue related to pre-satellite era TC track data is the undercount of weaker tropical  
 133 depressions, since the detection and classification of those weaker storms that showed poor  
 134 organization was probably more difficult before 1966 (Moon et al., 2019). The average landfall  
 135 percentage of TCs were calculated for the periods 1900-1965 (pre-satellite) and 1966-2019 (satellite  
 136 era and new TC monitoring technologies available) in order to determine the share of storms that  
 137 made landfall in both periods. The percentage of landfalling TCs is expected to be higher in the  
 138 1900-65 period since a higher number of storms that remained over the ocean were not reported, so  
 139 the landfall percentage of the pre-satellite period is then adjusted so that it matches the 1966-2019  
 140 post-satellite period.

141 To obtain the estimated number of missing TCs for the 1900-65 period, the number of total storms  
 142 in the pre-satellite period is increased until its landfall percentage is equal to the one in the post  
 143 satellite era. The total number of additional TCs that resulted in the landfall percentages between the  
 144 two periods to be the same or near equal are then divided by the 7 decades of the pre-satellite era  
 145 and then the number of extra storms for each decade is multiplied by the percentage of off-season  
 146 storms for each basin and that resulting number is then added then to each of the individual decades  
 147 between 1900 and 1969. In a previous study (Landsea, 2007), this method was applied to adjust TC  
 148 counts in the North Atlantic to determine if the basin has experienced an increasing trend in annual  
 149 TC frequency since the 1900, and its results show that after adjusting the tropical storm counts no  
 150 trends were found.

151 Here we show how this TC series adjustment method was applied to the total TC count for the NA  
 152 basin for the 1900-2019 period . First, we calculate the landfall percentage for the pre-satellite period  
 153 1900-65 by dividing the number of landfalling TCs (LFTCs) with the total number of storms (TTCs)  
 154 and multiply by 100 to get the landfall percentage, check the equations below:  
 155

$$(LFTCs / TTCs) * 100$$

Example:  $(479/610) * 100 = 78.5\%$  (1)

156  
157

158 Then calculate landfall % for the period post-satellite period 1966-2019,  
 159

$$(LFTCs / TTCs) * 100$$

Example:  $(583/844) * 100 = 69.1\%$  (2)

160  
161

162 Then artificially increase the number of TCs (+83 for the NA basin) until the landfall % of the 1900-  
 163 65 period is equal to landfall % of the 1966-2019:  
 164

$$LFTCs / (TTCs + AddTCs) * 100$$

Example:  $479 / (610 + 83) * 100 = 69.1\%$  (3)

165  
166

167 Then calculate the percentage (OffP) of off-season TCs (OffTCs) by dividing it by total number of  
 168 TCs:  
 169

$$(OffTCs / TTCs) * 100$$

Example :  $(67/1454) * 100 = 4.61\%$  (4)

170

171 Then divide additional TCs (83) by the number of decades between 1900 and 1969 (7) and then  
172 multiply by the off-season TC percentage (.0461)  
173  
174

$$(AddTCs/Decades) * OffP$$

Example:  $(83/7) * .0461 = 0.54$  (5)

175  
176 In the case of the NA, we determined that by using the above TC series adjustment method the basin  
177 would get an additional 0.54 off-season TCs for each of the seven decades that go from the 1900 to  
178 1969. Finally, the additional 0.54 TCs per decade will be divided between pre and post off-season  
179 TCs by multiplying the added storms with the respective percentage of pre/post off season cyclones:  
180

$$DecOffTCs * Percentage/Post Season$$

Example:  $0.54/0.62 = 0.33$  and  $0.54/0.38 = 0.21$  (6)

181  
182 The pre off-season decades of the NA basin before 1970 will get an additional 0.33 TCs and the  
183 post off-season decades will get 0.21 more storms. This off-season TC adjustment method was  
184 applied to the other five basins.  
185

#### 186 4. Statistical Methods & Models

187  
188 Mann-Kendall (MK) tests for trends (Mann, 1945; McLeod, 2005) were applied to all the off-  
189 season TC decadal series for all basins in order to determine if the frequency of storms has increased  
190 or decreased over time. This test has the advantage of not assuming any special form for the  
191 distribution function of the data, while having a power nearly as high as their parametric equivalents  
192 and that is why its use is highly recommended by the World Meteorological Organization (Hipel and  
193 McLeod, 2005).  
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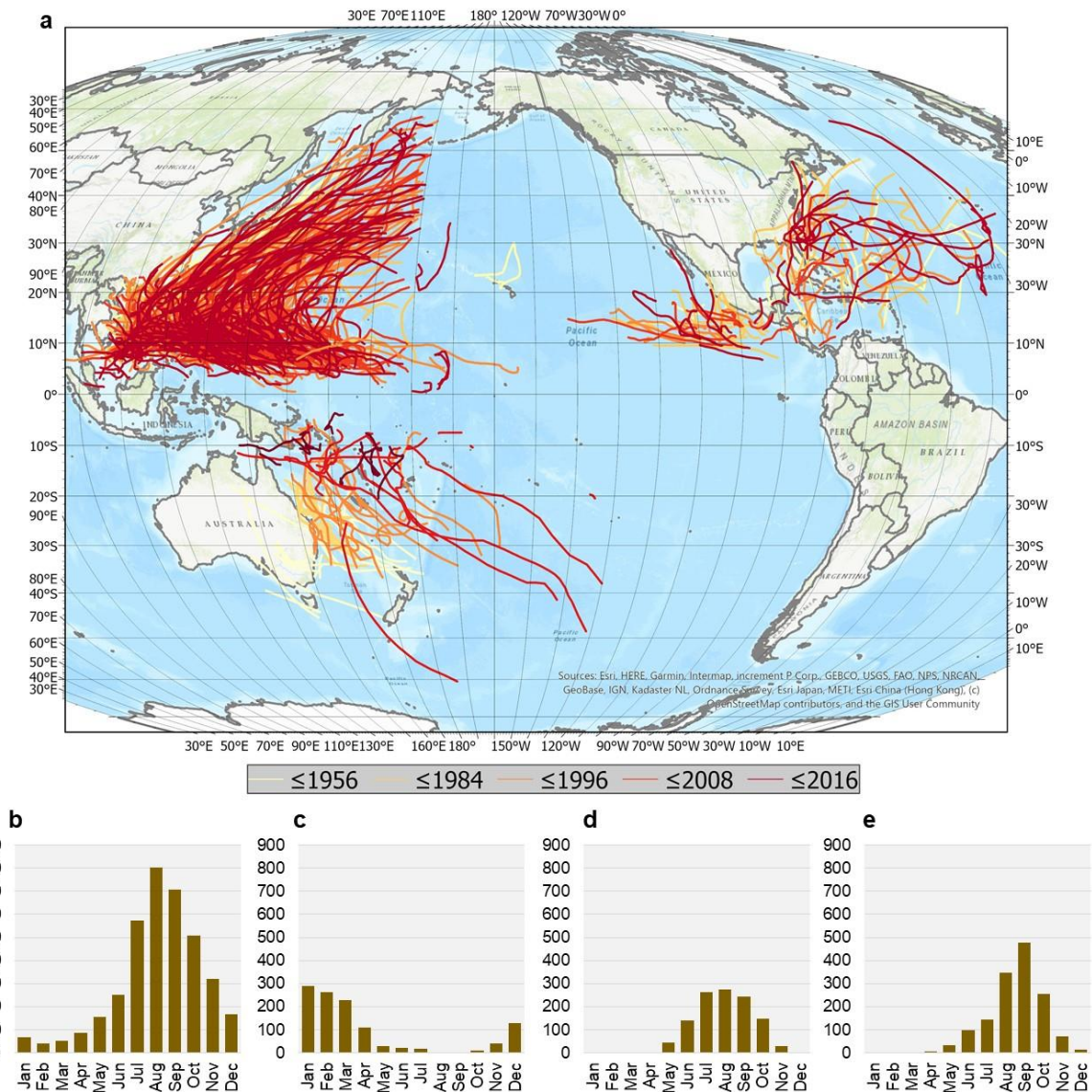
195 The decadal series that were then found to have a significant trend based on the MK results were  
196 then furtherly analyzed by applying a series of multiple linear regression models (MLR). MLR were  
197 used to model the decadal count of off-season TCs for basins that showed increasing or decreasing  
198 trends in storm numbers to test if covariates associated with climatic variability and climate change  
199 explained off-season TC frequency. MLR attempts to model the relationship between two or more  
200 explanatory variables and a response variable by fitting a linear equation to observed data.  
201

202 Three different MLR models were run for each off-season TC series that exhibited a statistically  
203 significant trend, one MLR model with the climate change variables (SST, GMST & CC) as  
204 predictors, another model with just the climate variability factors (ENSO, AMO & IOD) and a final  
205 model with all of the variables included. Then the three MLR models (pre-season, post-season and  
206 off-season) were run for each of the basins with increasing trends in off-season TCs, the best models  
207 (highest adjusted R-squared and lowest p-value) were then selected for each of the series. The MLR  
208 models were run in The R Project for Statistical Computing using the biglm package.  
209

210 Finally, stepwise selection MLR models were used to identify the climate variability or change  
211 factors making the most statistically significant contributions to off-season increasing TC frequency.  
212 Here we use stepwise selection which is a combination of the forward and backward procedures where  
213 you start with no predictors, then sequentially add the most contributive predictors. After adding each  
214 new variable, it removes the variables that no longer provide an improvement in the model fit (James  
215 et al., 2014; Bruce and Bruce, 2017). The MLR and stepwise for the off-season TC count series for  
216 each of the basins with significant increasing trends were run in The R Project for Statistical  
217 Computing using the MASS package (Venables and Ripley, 2002).

219 **5. Results & Discussion**

220 When analyzing the number of TCs for all basins for the 1900-2019 period we found that 713  
 221 off-season storms occurred during that time, most during the months of May (NH pre-season and SH  
 222 post-season) with 430 and December (NH post-season) with 341 (Figure 1a, 1b). When looking at  
 223 the count of off-season TCs per basin we found that as expected the West Pacific (611) and South  
 224 Pacific (85) accounted for 81.3% of all off-season storm occurrences. When grouping the basins  
 225 between northern and southern hemispheres, we find that 89% of all off -season TCs occurred north  
 226 of the equator for the 1900-2019 period (Figure 1a, 1b). The North Atlantic and East Pacific basins  
 227 were found to be the ones with the lowest numbers of off-season TCs when compared to the other  
 228 two Pacific basins.  
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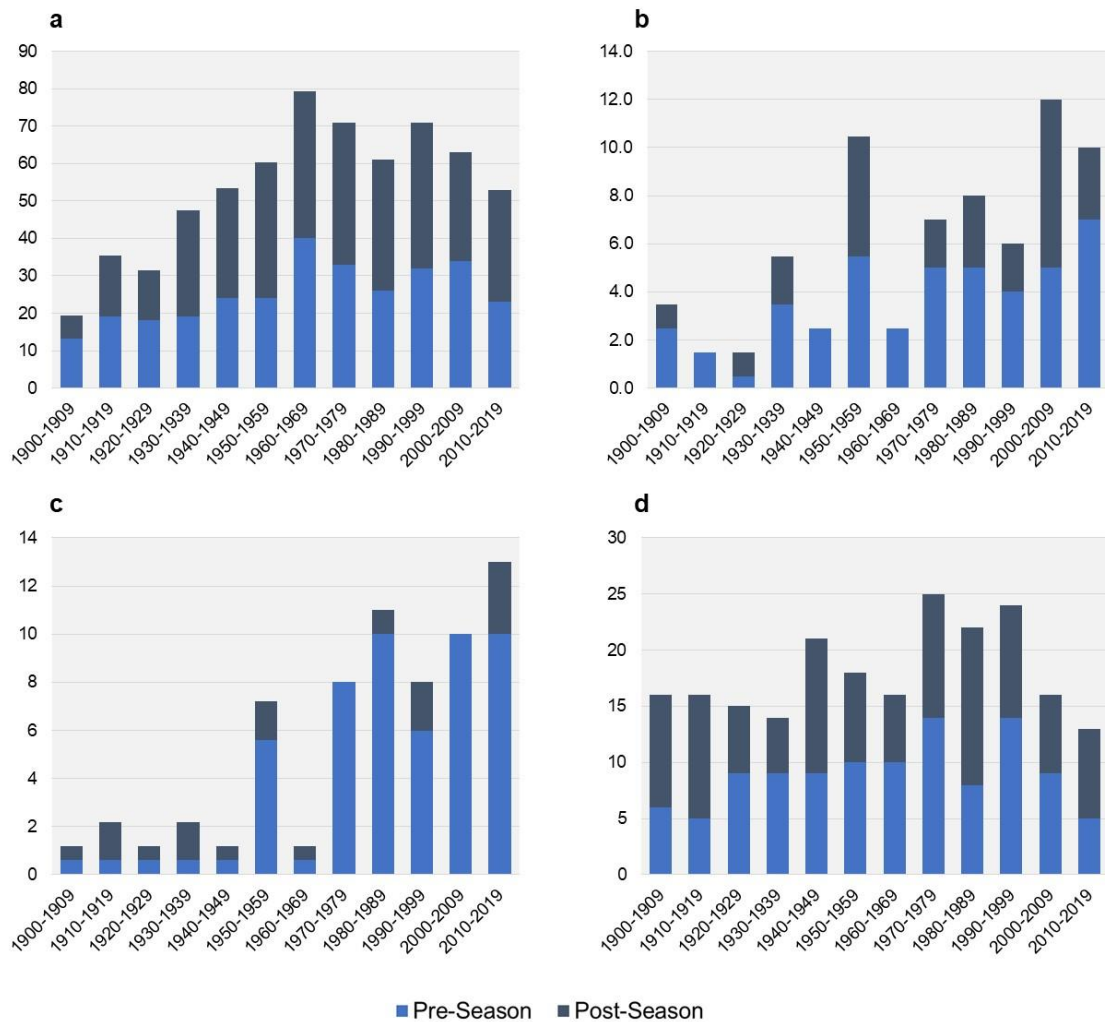


230

231 **Figure 1.** Tracks of all off-season TCs (a) and the number of storms per month for the WP (b),  
 232 SP (c), EP (d) and NA (e) basins for the 1900-2019 period.

233 As shown in Figure 2, even after adding the estimated missing storms before the 1970 decade,  
 234 most basins experienced their highest number of out off-season TCs (pre or post) in decades at or

235 after 1960-69. The 1960-69 decade for the northern hemisphere basins (WP, NA and EP) was found  
 236 to be the one with the highest number of pre off-season TCs with 69 and the 1950-1959 decade was  
 237 identified as the one with the most post off-season storms with 68 (Figure 2a, 2b, 2c and 2d). When  
 238 examining TC counts for all basins individually, we found that the NA and EP basins had their most  
 239 active decades after 1970 and that the WP and SP basins experienced their highest storm count decade  
 240 after 1960 (Figure 2c, 2d). It is important to note that these results already reflect the additional TCs  
 241 that were added to the pre-satellite era.  
 242



243

244 **Figure 2.** Adjusted decadal count of all observed and estimated off-season TCs for the WP (a), NA (b), EP (c)  
 245 and SP (d) ocean basins for the 1900-2019 period.

246 The Mann-Kendall non-parametric tests for trends for all basins show that three basins exhibited  
 247 statistically significant increasing trends in adjusted decadal off-season TC counts for the 1900-2019  
 248 period (Table 2). The basins with statistically significant increasing trends were the EP (pre and off-  
 249 season), NA (pre, post and off-season) and the WP (pre, post and off-season). The EP basin shows an  
 250 increasing trend in pre- and off-season TCs that is more evident from the 1950s to the present (Figure  
 251 2d), while the increasing trend in the NA basin can be observed from the 1970s to 2019.

252 The increasing trend in off-season TCs in the WP basin is more evident from the 1900 to 1969  
 253 (Figure 2a), which was during the pre-satellite era where missing TCs were added to the series.  
 254 However, no trend is found in the WP basin if the decadal counts are analyzed from the 1970s to the  
 255 present. In the post-satellite era in the WP basin, the 1990-1999 decade was identified as the one with  
 256 most off-season TCs, however the two following decades exhibited a decreasing trend. The EP and

257 NA basins show significant increasing trends in off-season TC counts (Table 2). Opposites to the  
 258 trends identified in the WP basin, the EP and NA also show increasing decadal counts after the 1960s  
 259 and 1970s decades. The SP basin also exhibited a positive Tau coefficient, yet it was statistically  
 260 insignificant (Figure 2d).

261

**Table 2. Results of Mann-Kendall trend tests for the 1900-2019 period for all ocean basins where TCs form.**

Pre TCs	Tau S	P-value	Post TCs	Tau S	P-value	Off TCs	Tau S	P-value
EP	<b>0.746</b>	<b>0.002</b>	EP	0.098	0.723	EP	<b>0.679</b>	<b>0.004</b>
NA	<b>0.572</b>	<b>0.015</b>	NA	<b>0.485</b>	<b>0.042</b>	NA	<b>0.554</b>	<b>0.016</b>
SP	0.048	0.889	SP	0.015	1.000	SP	0.061	0.836
WP	<b>0.554</b>	<b>0.016</b>	WP	<b>0.485</b>	<b>0.034</b>	WP	<b>0.534</b>	<b>0.019</b>

**Significant trends in bold.**

262

263 MLR models were run on the basins that exhibited statistically significant ( $< 0.05$ ) increasing  
 264 trends in decadal total off-season TC counts over time and here we report the best models for each of  
 265 the series. The MLR results show that the statistically significant increasing trends in TC frequency  
 266 for the EP (pre and off-season) and WP basins is best explained by climate change factors SST, GMST  
 267 and CC at the 0.05 significance level (Table 3). Climate change factors accounted for 56% (pre-  
 268 season) and 52% (off-season) of the increasing trend in TC counts for the EP basin. In the WP basin  
 269 climate change factors explained 55% (pre-season), 64% (post-season) and 68% (off-season) of the  
 270 trends in off-season TCs. Increasing trends in SSTs, GMST and moisture (CC) outside of the prime  
 271 months of tropical storm development could promote more optimum conditions for higher off-season  
 272 TC occurrences (Klozback, 2006; Hansen et al., 2010). The MLR models were also done with  
 273 detrended decadal series of off-season TCs, and detrended decadal series of the different climate  
 274 variability and change factors, and similar results were found.

275

**Table 3. Best multiple linear regression models (MLR) for basins with statistically significant increasing trends in off-season TCs.**

Model	Multiple R-squared	Adjusted R <sup>2</sup>	Factors	p-value
EP pre-season	0.682	0.563	SST, GMST & CC	0.021
EP off-season	0.653	0.522	SST, GMST & CC	0.030
NA pre-season	0.622	0.481	SST, GMST & CC	0.041
NA post-season	0.687	0.427	ENSO & AMO	0.130
NA off-season	0.552	0.384	SST, GMST & CC	0.070
WP pre-season	0.673	0.551	SST, GMST & CC	0.020
WP post-season	0.742	0.645	SST, GMST & CC	0.000
WP off-season	0.774	0.689	SST, GMST & CC	0.005

276

277 The climate variability factors (ENSO, AMO & IOD) did not exhibit statistically significant  
 278 relationships with increasing off-season TC counts, which shows that natural variability does not  
 279 explain the incrementing number of storms in the EP and WP basins. MLR model results for the  
 280 NA basin also showed the climate change variables accounting for 48% (pre-season) and 38% (off-  
 281 season) of the increasing trend in TCs (Table 3). However, the MLR model results for the post-  
 282 season months in the NA basin showed that the climate variability variables (ENSO & AMO)  
 283 accounted for 42% of the increasing trend in TCs, yet the model was not found to be statistically



284 significant. It is well known that cold phases of ENSO (La Niña) and warm phases of AMO tend to  
 285 be associated with higher TC frequency in the North Atlantic ocean (Tang and Neelin, 2004;  
 286 Briggs, 2008) and this could explain why those teleconnections were found to have the most  
 287 significant influence on post-season TC frequency in the NA basin. Yet, it is important to note that  
 288 in most basin series, including the NA, climate change variables explained more of the off-  
 289 season TC increasing trend than the climate variability factors.

290 Stepwise MLR model results showed that climate change factors (SST, GMST & CC) were among  
 291 the selected variables that explained most of the increasing trend in off-season TCs for all basins  
 292 analyzed (Table 4). In the EP basin, SST, ENSO, and CC, accounted for 69% (pre-season) and 65%  
 293 (off-season) of the increasing trend in TCs. In the NA basin, the stepwise procedure selected CC as  
 294 the sole climate change factor that explained 52% (pre-season) and 40% (off-season) of the rising  
 295 frequency in TC counts. However, CC & AMO were selected as the variables that explained (43%)  
 296 most of the variability in TC frequency during the post-season months in the NA basin. Stepwise  
 297 procedure results for the WP basin show that climate change and variability factors were selected as  
 298 the best predictors of TC frequency, with GMST and CC accounting for 57% (pre-season), CC,  
 299 GMST, ENSO and IPO explaining 72% (post-season) and 74% (off-season) of the variability of  
 300 TCs.

**Table 4. Stepwise multiple linear regression models (MLR) for basins with statistically significant increasing trends in off-season TCs.**

Model	R-squared	Adjusted R <sup>2</sup>	Factors	p-value
EP pre-season	0.777	0.694	SST, ENSO & CC	0.005
EP off-season	0.747	0.652	SST, ENSO & CC	0.008
NA pre-season	0.569	0.526	CC	0.004
NA post-season	0.687	0.427	CC & AMO	0.098
NA off-season	0.460	0.406	CC	0.015
WP pre-season	0.655	0.578	GMST & CC	0.008
WP post-season	0.826	0.726	CC, GMST, ENSO & IPO	0.008
WP off-season	0.839	0.747	CC, GMST, ENSO & IPO	0.006

301

302 The EP experienced a steady increase in off-season TC total counts from 1900 to 2019 at a rate  
 303 of 1.1 additional storms per decade. The decadal off-season total TC count series for the EP basin  
 304 closely resembles the increasing trend in average SSTs and CCs (Fig 3a, 3c). When the EP off-season  
 305 TC tracks are examined, it shows that most storms have formed in areas that have experienced  
 306 statistically significant increasing trends in SST and CC (Fig 3d, 3e). The correlation between off-  
 307 season TCs in the EP basin and ENSO is not as clear as the one between SST and CC, with some  
 308 mostly warm ENSO decades like the 1990-1999 exhibiting lower storm counts and other periods with  
 309 cooler phases dominating showing a higher number of cyclones. When SST patterns for areas in the  
 310 EP basin where TCs develop are examined over time, we find that most tropical/sub-tropical ocean  
 311 waters have experienced a statistically significant increasing trend in ocean surface temperatures from  
 312 1900 to 2019 (Fig 3d). Similar to other studies (Hansen et al., 2010), we find that the EP tropical  
 313 ocean surfaces have increased by 0.051 degrees C° per decade. When CC patterns are examined, we  
 314 find that it has also experienced a statistically significant increasing trend in some areas in the EP  
 315 basin (Fig 3e).

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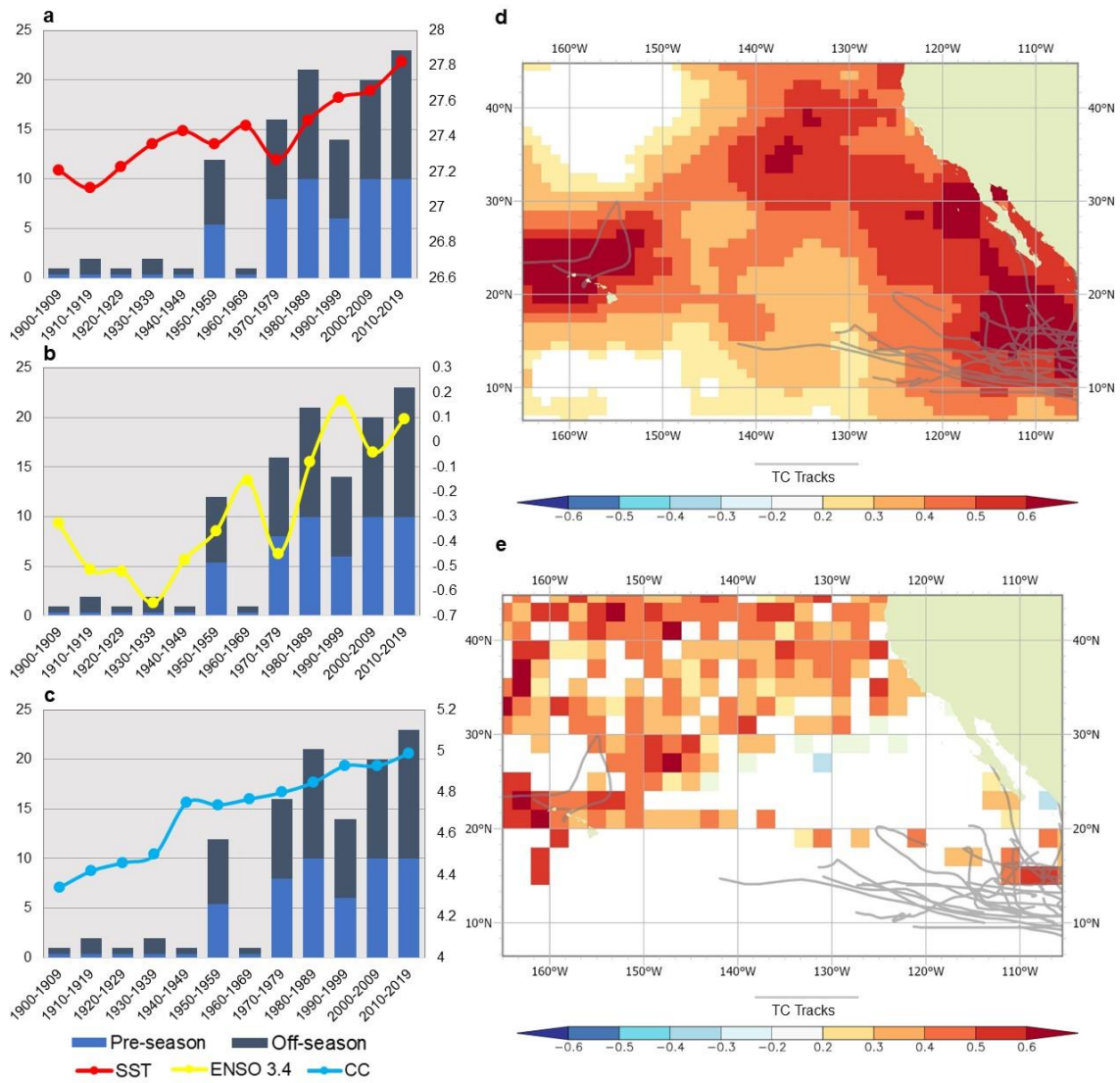
317 The decadal off-season total TC count series for the NA basin closely resembles the increasing  
 318 trend in average SSTs and CCs (Fig 4a, 4c). The NA decadal series shows a steady increase in off-  
 319 season TC total counts from 1900 to 2019 at a rate of 0.7 additional storms per decade and an SST

320 increasing trend of 0.055 C° per decade. Both the average decadal SST and CC series coincide with  
321 the peaks and valleys in off-season TC counts for the NA basin, with the 1950-1959 showing a high  
322 number of storms associated with high mean SSTs and CCs while the drop in storm counts in the  
323 1960-1969 decade matches a drastic drop in ocean surface temperatures (Figures 4a, 4c). The off-  
324 season TC tracks in the NA basin also formed in areas that exhibited increasing trends in SST and  
325 CC (Figure 4d, 4e) Even though average SSTs increase to 0.135 C° per decade from 1970 to 2019,  
326 off-season TC total counts went down in the 1990-1999 and 2010-2019 decades, with the decade in  
327 between (2000-2009) exhibiting the highest number of off-season TCs (14) of all decades examined.  
328 However, it is important to note that 5 out of the 6 decades with the most off-season TCs in the NA  
329 basin occurred after the 1970s.

330

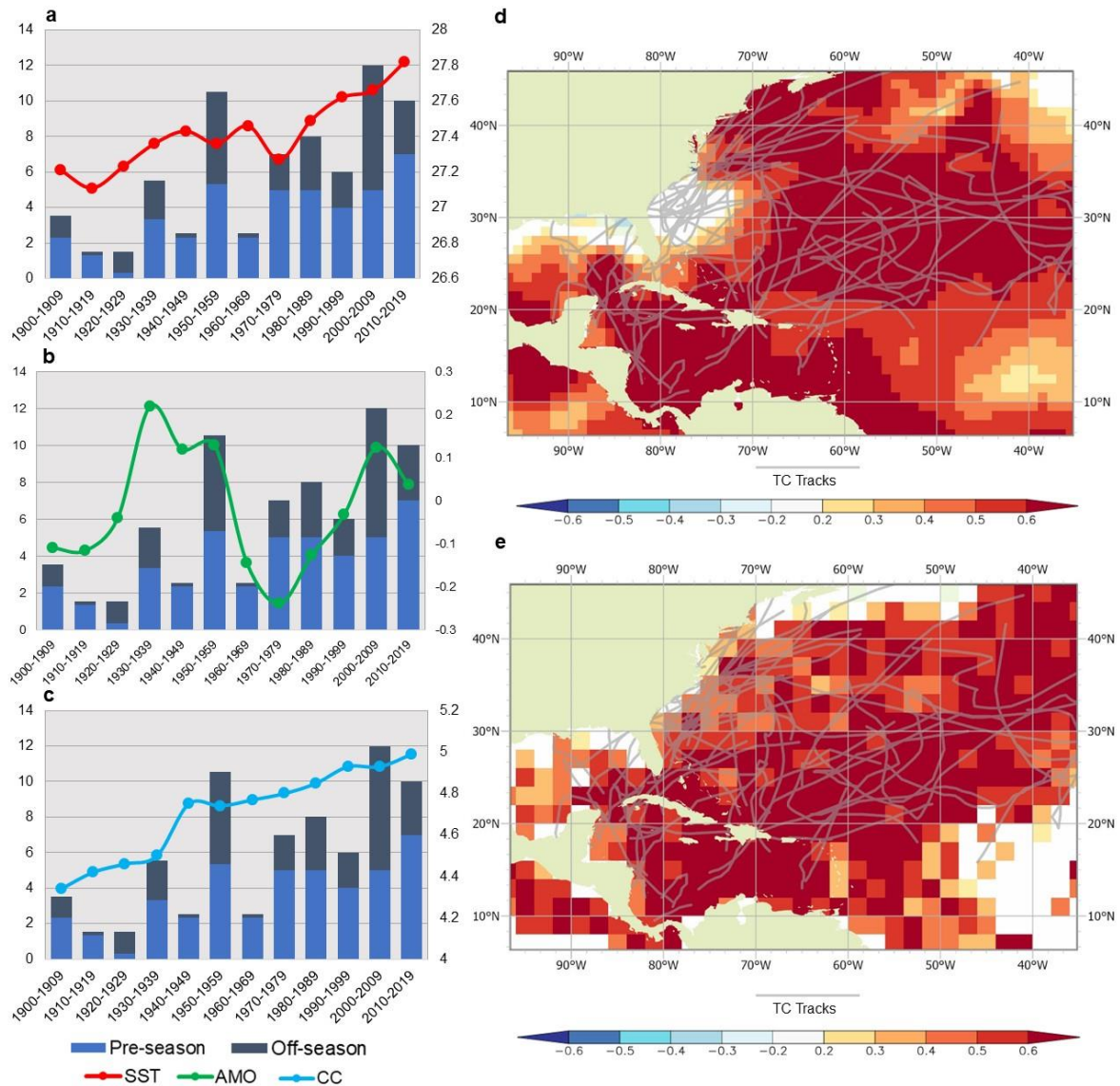
331 When North Atlantic SSTs are examined in areas where TCs form, we found that ocean surface  
332 temperatures have increased at a rate of 0.055 degrees C° per decade for the off-season months of  
333 Dec-March (Fig 4d). When CC patterns are examined, we find that it has also experienced a  
334 statistically significant increasing trend of 0.06 oktas (eighths of the sky that are covered in clouds)  
335 per decade in the North Atlantic basin since the 1900 (Figure 4e). If the NA pre/post off-season series  
336 is modified to begin in the 1960s, we find that SSTs have increased at a decadal rate of 0.082 C° per  
337 decade at a rate of 1.2 additional storms per decade. Overall, these results suggest that increasing  
338 trends in SSTs, which also drive increasing trends in evaporation rates associated with high CCs, are  
339 the physical mechanisms behind most of the recent increase in the total number of out of season TCs  
340 in the NA basin. The correlation between off-season TCs in the NA basin and AMO is not as clear as  
341 the one between SST and CC, with some warm AMO phases between 1930-1959 exhibiting lower  
342 storm counts while some cooler phases (1970-89) showing a higher number of cyclones.

343



344

345 **Figure 3.** Decadal TC counts for the EP off-seasons and decadal average SSTs (a), decadal TC counts for  
 346 the EP off-seasons and decadal average ENSO 3.4 (b), decadal TC counts for the EP off-seasons and  
 347 decadal average Correlation between Time and Dec-May averaged CC (c), correlation between Time and  
 348 Dec-May averaged SST (C°) and the off-season TC tracks for the 1900-2019 period (d) and correlation  
 349 between Time and Dec-May averaged CC (oktas) and the off-season TC tracks for the 1900-2019 period

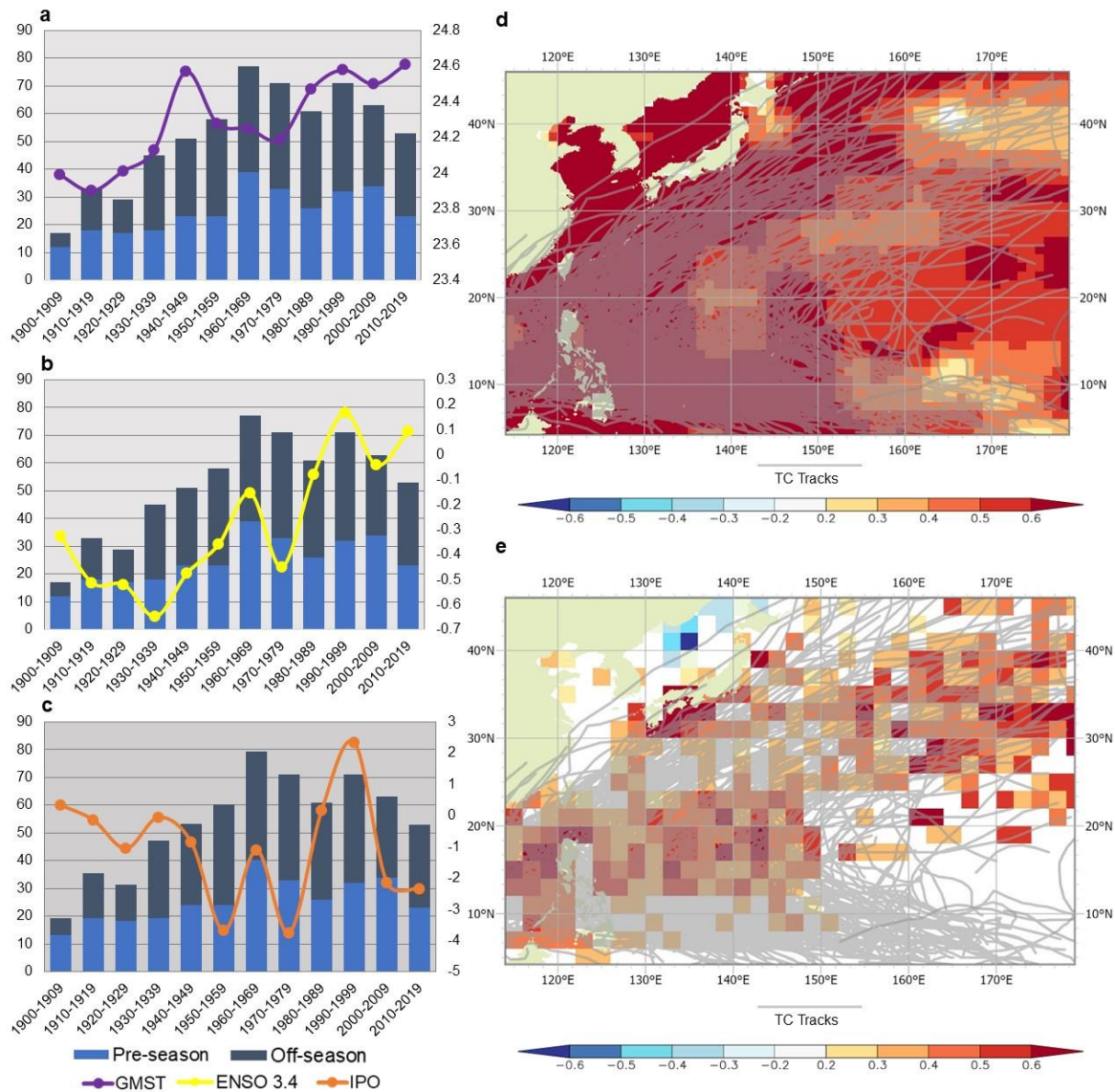


350

351 **Figure 4.** Decadal TC counts for the NA off-seasons and decadal average SSTs (a), decadal TC counts for the  
 352 NA off-seasons and decadal average AMO (b), decadal TC counts for the NA off-seasons and decadal average  
 353 Correlation between Time and Dec-May averaged CC (c), correlation between Time and Dec-May averaged  
 354 SST (C°) and the off-season TC tracks for the 1900-2019 period (d) and correlation between Time and Dec-May  
 355 averaged CC (oktas) and the off-season TC tracks for the 1900-2019 period (e).  
 356

357 The decadal off-season total TC count series for the WP basin closely resembles the increasing  
 358 trend in GMST (Fig 5a). However, the WP basin experienced the highest count of off-season TCs in  
 359 the 1960-69 decade, not in the more recent decades like the EP and NA basins. More importantly, if  
 360 trend analysis for off-season TC counts is done from 1960-2019 in the WP basin, we find no  
 361 statistically significant increasing or decreasing trend. However, it is important to note that four out  
 362 of the five decades with most off-season TCs in the WP basin occurred after 1960. However, the  
 363 2010-2019 decade was identified as the period with the lowest total number of off-season TCs even  
 364 though increasing trends in mean SST, GMST and CC continued (Fig 5a, 5d and 5e). Off-season TC  
 365 tracks in the WP basin also correlate spatially with areas that show increasing trends in SST and CC  
 366 (Fig 5d, 5e). The decreasing number of off-season TCs in the last two decades coincided with a  
 367 negative phase of the IPO, which suggests that TC frequency in the WP basin is influenced by  
 368 fluctuations in the IPO (Fig 5c), whose recent negative phase since 1998 resembles La Niña-like SST  
 369 anomaly patterns (Zhao et.al, 2018). Even though most of the variability in off-season TC frequency

370 in the WP basin can be explained by climate change trends in GMST, SST and CC, the rest of the  
 371 variance in TCs is account by fluctuations in the IPO and ENSO teleconnections.  
 372



373  
 374 **Figure 5.** Decadal TC counts for the WP off-seasons and decadal average SSTs (a), decadal TC counts for the  
 375 WP off-seasons and decadal average AMO (b), decadal TC counts for the WP off-seasons and decadal average  
 376 Correlation between Time and Dec-May averaged CC (c), correlation between Time and Dec-May averaged  
 377 SST (C°) and the off-season TC tracks for the 1900-2019 period (d) and correlation between Time and Dec-  
 378 May averaged CC (oktas) and the off-season TC tracks for the 1900-2019 period (e).

379 **6. Summary and concluding remarks**

380 The frequency of TCs that developed outside of their prime season months were analyzed to  
 381 determine if trends in higher storm totals in the Pacific and Atlantic Ocean basins were associated  
 382 with natural variability, climate change or both. Adjusted off-season decadal TC total counts for six  
 383 ocean basins were analyzed for the 1900-2019 period in order to determine if the number of storms  
 384 have been increasing over time. Mann-Kendall tests for trends were done and the basins that exhibited  
 385 statistically significant increasing trends were then furtherly analyzed using multiple linear regression  
 386 models and stepwise procedures to determine if those trends could be explained by fluctuations  
 387 associated with climate variability, climate change trends or a combination of both.  
 388

389 The main results of this study suggest that decadal total off-season (pre/post) TC counts have  
390 significantly increase over time since the 1900 in the East Pacific (EP), North Atlantic (NA) and West  
391 Pacific (WP) basins. The EP and NA basins exhibited statistically significant increasing trends even  
392 if the analysis was done from the 1960s instead of the 1900. The WP basin showed an overall  
393 increasing trend in the total number of off-season TCs per decade, yet if the analysis is done from the  
394 1960s to the present, no statistically significant increasing trend is found. However, the three basins  
395 that reflected an overall increase in decadal off-season TC frequency had their most active decades  
396 after the 1970s.

397  
398 Results from the best multiple linear regression (MLR) models show that the increasing decadal  
399 count of off-season TCs has been found to be strongly associated with climate change trends in sea  
400 surface temperature (SST), global mean surface temperature (GMST) and cloud cover (CC) in all  
401 three basins (EP, NA and WP). The MLR model where climate variability variables (ENSO and  
402 AMO) explained most of the variance in off-season TC counts was in the storm decadal counts for  
403 the post-season months of the NA basin.

404  
405 Results of the MLR stepwise procedures showed that the selected variables that accounted for  
406 most of the variability in off-season TCs for the EP basin were SST, CC and ENSO, while CC (pre-  
407 season and off-season) and AMO (post-season) were chosen as the best variables for the NA basin.  
408 The stepwise procedure identified the climate change trends in GMST and CC, and fluctuations in  
409 ENSO and IPO as the variables that accounted for most of the variability in decadal off-season total  
410 TC counts in the WP basin,

411  
412 The findings of this study suggest that trends in SST, GMST and CC associated with climate  
413 change are not only altering the frequency (Klotzback, 2006; Saunders and Lea, 2006; Hansen et al.,  
414 2010) and intensity of TCs that develop during the peak months of the season, they are also altering  
415 the total number of storms that form in the off-season months (Dec-May), especially in the EP and  
416 NA basins. The results of this study have important implications for the NA and EP basins, if off-  
417 season TCs have been increasing in frequency since the 1900 we can expect that this trend associated  
418 with climate change would continue in future decades. This increasing number of off-season TCs  
419 could potentially impact societies in their path during times of the year when storms are least  
420 expected, possibly increasing environmental and economic impacts in areas that are already  
421 experiencing the effects of climate change exacerbated phenomena.

422

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424

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429 surface temperature (HadISST1 1° reconstruction), and cloud cover (ICOADS v2.5 1°) datasets  
430 supporting this article are based on publicly available measurements that can be accessed from the  
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433 available measurements that from the NASA Goddard Institute for Space Studies (GISS;  
434 <https://climatedataguide.ucar.edu/climate-data/global-surface-temperature-data-gistemp-nasa-goddard-institute-space-studies-giss>.) The El Niño Southern Oscillation (ENSO 3.4) data supporting  
435 this article are based on publicly available measurements from the National Oceanic and  
436 Atmospheric Administration Physical Sciences Lab (PSL;  
437 [https://psl.noaa.gov/gcos\\_wgsp/Timeseries/Data/nino34.long.data](https://psl.noaa.gov/gcos_wgsp/Timeseries/Data/nino34.long.data)). The Atlantic Multidecadal  
438 Oscillation data supporting this article are based on publicly available measurements from the  
439 National Center for Atmospheric Research (NCAR; [440](https://climatedataguide.ucar.edu/climate-</a></p></div><div data-bbox=)

441 [data/atlantic-multi-decadal-oscillation-amo](#)). The Interdecadal Pacific Oscillation data supporting  
442 this article are based on publicly available measurements from the National Oceanic and  
443 Atmospheric Administration Physical Sciences Lab (PSL;  
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