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Trends in US climate-related disasters: evidence based on fractional integration over the last forty years

Luis Alberiko Gil-Alana[1,2*] and Nieves Carmona-González[2]

Abstract
This article deals with the time trend evolution of US natural catastrophes over the last forty years. However, instead of using classical methods that impose an I(0) structure for the error term, we allow for potential long memory features by using fractional integration. Count and costs series are investigated for the US as a whole but also using disaggregated data by climate regions. The results indicate the presence of time trends in the majority of the cases examined and evidence of long memory is also found in a number of climate regions.

Keywords Natural catastrophes, Time trends, Fractional integration, Persistence, Shocks

JEL Classification C22, Q51, Q54

Introduction

Continued global warming is increasing the frequency and severity of extreme weather events (IPCC, 2023; WMO, 2021). In the case of the United States, climate change is manifesting itself in an increase in extreme events such as tornadoes, hurricanes, wildfires, and heat waves, among others. Since 1980, the US has experienced 363 weather and climate disasters whose total damage and costs have reached or exceeded $1 billion (adjusted for inflation through 2023). The aggregate cost of these events exceeds $2.59 trillion (NOAA, 2023) and represents approximately 38% of global economic losses associated with weather, climate, and hydrological risks (United Nations, 2021).

Among the different types of disasters, tropical cyclones are the most costly category in the US during the period 1980–2022, with cumulative losses of $1333.6 billion, as well as being responsible for the highest number of deaths (6890) and the highest average cost per event ($22.2 billion). They are followed by severe storms ($383.7 billion), drought ($327.7 billion), and floods ($177.9 billion) (NOAA, 2022).

The number and cost of weather and climate disasters have increased steadily over time as a result of a combination of factors, including greater exposure (the set of assets that could potentially be damaged by a natural disaster), the increase in the value of assets at risk, vulnerability, and climate change itself (Smith 2023). Since 1980, the annual number of extreme events with costs exceeding $1 billion has grown significantly in real terms, and the total cumulative cost to the United States has exceeded $1.1 trillion. In this context, understanding the frequency, severity, and persistence of these events is essential to properly assess their economic implications and design effective adaptation and mitigation policies (NCA, 2018).

*Correspondence:
Luis Alberiko Gil-Alana
alana@unav.es
[1]Faculty of Economics, NCID and DATAI, University of Navarra, Pamplona, Spain
[2]Facultad de Derecho, Empresa y Gobierno, Universidad Francisco de Vitoria, Madrid, Spain

The temporal evolution of the number of disasters and their costs in the United States between 1980 and 2022 shows a clear upward trend in both variables, along with marked heterogeneity between types of events, with severe storms being the most frequent and tropical cyclones the most costly on average (NOAA, 2022). This evidence suggests that analysing the dynamic properties of these time series is key to understanding not only their past behavior but also their possible future evolution in the context of climate change.

The main objective of this study is to analyse the behavior of time series of meteorological and climatic disasters in the US, assessing whether the temporal trend coefficients are statistically positive during the period 1980–2023. Unlike much of the previous literature, model errors are not required to be zero-order integrated, but rather the order of integration is estimated from a fractional perspective, meaning that errors are integrated with a degree of order d or I(d), where d is a real value. Therefore, classical approaches are integrated into our fractional framework when the degree of integration of the series is 0.

The article has two specific objectives: first, to determine whether catastrophe series exhibit long-memory characteristics and, second, to verify whether, once this persistence is taken into account, the time trend coefficients are statistically significant. To this end, the data are disaggregated both by type of climatic event (droughts, floods, frosts, storms, tropical cyclones, forest fires, and winter storms) and by climatic regions (Central, East-North-Central, Northeast, Northwest, South, Southeast, Southwest, West, West-North-Central, Gulf Coast States, Great Lakes States, Southern Plains, and Tornado Corridor).

In other words, the goal of this paper is to determine whether U.S. disaster counts and damages have genuinely increased over time, and to show how accounting for persistence changes the interpretation of these trends.

The contribution of this work is fundamentally empirical, without attempting to introduce theoretical innovations into the econometric model. Its contribution lies in the joint estimation of temporal trends and long-term dependence, given that the omission of the latter can generate inconsistent estimates of the deterministic components of the model. In this regard, fractional integration methods are used to analyse persistence and long-term trends in aggregate data on natural disasters in the United States. The results obtained can contribute to better formulation of environmental and economic policies aimed at reducing the costs associated with natural disasters.

The literature on climate change and its effects is extensive and covers multiple approaches (Bloomfield 1992; Brunetti et al. 2001; Folland et al. 2018; Gil-Alana 2018; Gil-Alana et al. 2019, 2022; Li et al. 2022; Abedi et al. 2023). Some studies have focused on the analysis of precipitation (Jiang and Zhao, 2017), others on the effects of air pollution (Caporale et al. 2021), temperatures (Gil-Alana et al. 2022), or the economic consequences of climate change (Council 2013; National Academies of Sciences, Engineering, and Medicine 2017).

Within the latter area, Stern (2007) estimated that the economic costs of climate change could reach at least 20% of global GDP, while mitigation policies would require approximately 1% of annual GDP. Weitzman (2009) analysed the role of structural uncertainty and fat tails in the economics of disasters, highlighting that low-probability, high-impact risks can dominate climate policy analysis. Hsiang et al. (2017) showed, based on US sectoral data, that a 1 °C increase could reduce GDP by around 1.2%, integrating climate information with probabilistic economic projections.

The analysis of time series of climate and disaster variables is particularly relevant for assessing their evolution and persistence over time. In this context, fractional integration has been widely used in the analysis of climatological series (Gil-Alana 2018; Gil-Alana et al. 2019, 2022; Zhu et al. 2010; Franzke 2011; Yuan et al. 2013; Guan-Yu et al. 2022; Mei et al. 2023), with approaches that model these series as stationary I(0) processes (Woodward and Gray 1993) or as non-stationary I(1) processes (Stern and Kaufmann 2000; Hamdi et al. 2020) coexisting. Gil-Alana et al. (2018, 2019) demonstrated that fractional methods provide more accurate estimates of temperature trends in the US than traditional approaches.

The advantage of the fractional integration approach (Granger, 1980, 1981; Granger and Joyeux 1980; Hosking 1981) lies in the fact that the differentiation parameter can take any real value, allowing for a more flexible representation of temporal dependence and simultaneously capturing short- and long-term correlations (Huang et al. 2022), with more efficient estimates and less variability (Bhardwaj et al. 2020).

Beyond the literature focused on climate trends, the economics of disaster risk has undergone remarkable development recently. Current studies document that extreme events generate persistent macroeconomic losses, with heterogeneous effects across regions and sectors (Costa et al., 2025; Ehlers et al. 2025). Likewise, the role of the financial system as an amplifier of climate shocks has been highlighted (Peters et al., 2025), and macroeconomic models have been developed to estimate indirect impacts and recovery processes after disasters (Zhu et al. 2025). From a risk perspective, recent studies show that natural disasters act as macroeconomic tail risks, altering the distribution of growth and inflation (Chavleishvili et al., 2025).

At the same time, approaches based on extreme value theory have been widely used to model the frequency and severity of extreme events, although they focus primarily on tail behavior and do not explicitly capture long-term temporal dynamics. Similarly, traditional econometric time series models, such as ARIMA (Hamilton 1994; Woodward et al. 1993), impose short-term dependency structures and integer integration restrictions that may be inadequate when data exhibit long memory.

In contrast, the fractional integration approach adopted in this paper allows for flexible modeling of temporal dependence, capturing long-term persistence and possible mean reversion. This feature is particularly relevant in the analysis of natural disasters, where shocks can have prolonged effects on the frequency and costs of events. Therefore, our approach complements traditional econometric methods and offers different implications for the interpretation of trends and the design of public policies.

This paper is related to a growing body of studies on climate risk and the economics of natural disasters, where assessing trends and persistence in disaster losses is central for risk management and policy design. Our fractional integration approach contributes by jointly modelling time trends and long-range dependence in disaster counts and costs.

Methodology

The most standard approach to determine the existence of trends in time series is to consider the following regression model (Bhargava 1986; Schmidt and Phillips 1992; etc.):

$$y(\mathrm{t}) \;=\; \beta_0 \;+\; \beta_1 \mathrm{t} \;+\; x(\mathrm{t}), \qquad t \;=\; 1,\;\; 2,..,\quad (1)$$

where y(t) refers to the observed time series data; β_0 and β_1 are the coefficients referring to a constant and a linear time trend, and x(t) are the regression errors. In this context, a significant β_1 supports the existence of a linear time trend in the data. Nevertheless, for these two coefficients (β_0 and β_1) to be consistently and efficiently estimated, the error term x(t) must satisfy some statistical properties; thus, for example, if x(t) is a random variable independently and normally distribution with zero mean and a constant variance, the estimates of β_0 and β_1 can be adequately conducted, and statistical inference can be obtained by t-and F-test statistics (Hamilton 1994). Moreover, the inference remains valid if x(t) displays some type of weak dependence structure like the one provided by the stationary and invertible AutoRegressive Moving Average, ARMA-type of model. Being more rigorous, it is required that x(t) be a short memory process or integrated of order 0, (I(0), a condition that may be violated by some type of data.

A short memory or I(0) process is a covariance (or second order) stationary process that is characterized because the infinite sum of its autocovariances is finite. On the other hand, in a long memory process, the infinite sum of the autocovariances is infinite, and within this category a commonly used model is the one based on the concept of fractional integration or I(d, d > 0) process. Thus, a process is integrated of order d or I(d) if it can be expressed as:

$$(1 - \mathrm{L})^{\mathrm{d}}\, \mathrm{x}(\mathrm{t}) \;=\; \mathrm{u}(\mathrm{t}), \qquad \mathrm{t} \;=\; 1,\;\; 2,\quad (2)$$

where L is defined as the lag–operator, such that $\mathrm{L}^{\mathrm{k}}\mathrm{x}(\mathrm{t}) = \mathrm{x}(\mathrm{t}-\mathrm{k})$, and u(t) is an I(0) process as earlier defined.

In the empirical application carried out in the following section, we consider a model given by the Eqs. (1) and (2), under the assumption that u(t) in (2) is a white noise process. Thus, all the time dependence is captured throughout the differencing parameter, noting that the polynomial in the left-hand-side of (2) can be expanded as:

$$(1-L)^d = \sum\nolimits_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - ...,\quad (3)$$

and thus, Eq. (2) can be expressed as

$$x(t) = dx(t-1) + \frac{d(d-1)}{2} x(t-2) - \cdots + u_t.\quad (4)$$

In this context, the parameter of integration d provides a measure of persistence, higher values of d corresponding to higher degrees of dependence between the observations. Moreover, this approach is more flexible than the standard ones based on integer differentiation and thus use the value of 0 for stationary series and 1 for nonstationary ones. It also permits us to consider cases of nonstationary series which display a mean reverting behavior if the order of integration is higher than 0.5 but strictly smaller than 1.

The estimation is conducted via likelihood function in the frequency domain, using a simple version of a testing procedure based on the Lagrange Multiplier (LM) principle, and described in Robinson and whose functional form can be found in Gil-Alana and Robinson (1997).

Data and empirical results

Data have been obtained from the NOAA's National Centers for Environmental Information Center, https://www.ncei.noaa.gov/access/billions/time-series, and they correspond to (CPI adjusted) annual data from 1980 to 2022 of US weather and climate disaster aggregated and disaggregated by climate event. In addition, we report the

Table 1 Descriptive statistics

Drought		**Flooding**	
N. of observations:	43	N. of observations:	43
Mean:	0.70	Mean:	0.93
Standard deviation:	0.46	Standard deviation:	1.01
Variance:	0.22	Variance:	1.02
Min./Max.:	0 / 1	Min./Max.:	0 / 4
Range:	1	Range:	4
Freeze		*Severe storm*	
N. of observations:	43	N. of observations:	43
Mean:	0.21	Mean:	3.88
Standard deviation:	0.47	Standard deviation:	3.76
Variance:	0.22	Variance:	14.11
Min./Max.:	0 / 2	Min./Max.:	0 / 13
Range:	2	Range:	13
Tropical cyclone		*Wildfire*	
N. of observations:	43	N. of observations:	43
Mean:	1.40	Mean:	0.49
Standard deviation:	1.58	Standard deviation:	0.51
Variance:	2.48	Variance:	0.26
Min./Max.:	0 / 7	Min./Max.:	0 / 1
Range:	7	Range:	1
Winter storm		*All disasters*	
N. of observations:	43	N. of observations:	43
Mean:	0.49	Mean:	8.09
Standard deviation:	0.67	Standard deviation:	5.52
Variance:	0.45	Variance:	30.42
Min./Max.:	0 / 2	Min./Max.:	0 / 22
Range:	2	Range:	22

US COUNTS (1980–2022)

Table 2 Descriptive statistics

Drought		**Flooding**	
N. of observations:	43	N. of observations:	43
Mean:	7.83	Mean:	4.34
Standard deviation:	11.045	Standard deviation:	8.36
Variance:	131.00	Variance:	69.82
Min./Max.:	0 / 52.8	Min./Max.:	0 / 44.9
Range:	52.8	Range:	44.9
Freeze		*Severe storm*	
N. of observations:	43	N. of observations:	43
Mean:	0.84	Mean:	9.27
Standard deviation:	1.99	Standard deviation:	10.27
Variance:	3.98	Variance:	105.39
Min./Max.:	0 / 8.1	Min./Max.:	0 / 43.8
Range:	8.1	Range:	43.8
Tropical cyclone		*Wildfire*	
N. of observations:	43	N. of observations:	43
Mean:	31.74	Mean:	3.16
Standard deviation:	65.91	Standard deviation:	6.25
Variance:	4344.54	Variance:	39.01
Min./Max.:	0 / 328.6	Min./Max.:	0 / 29
Range:	328.6	Range:	29
Winter storm		*All disasters*	
N. of observations:	43	N. of observations:	43
Mean:	2.22	Mean:	59.40
Standard deviation:	4.67	Standard deviation:	74.15
Variance:	21.77	Variance:	5497.59
Min./Max.:	0 / 26.3	Min./Max.:	0 / 383.7
Range:	26.3	Range:	383.7

US COSTS (1980–2022)

data disaggregated by climate region. The NOAA Billion-Dollar Disasters dataset reports annual direct damages in constant dollars (CPI-adjusted), but losses are not normalized by exposure or wealth. Therefore, cost trends should be interpreted as reflecting the combined effect of hazard and socioeconomic factors, and exposure-normalized losses are left for future research.

Descriptive statistics of the two variables are reported across Tables 1 and 2. Table 1 presents the sample periods for each event and provides some descriptive statistics for each series. It can be observed that severe storm presents the highest mean value (3.88) followed by tropical cyclone (1.40) and drought (0.70), while freeze has the lowest (0.21). On the other hand, severe storm also has the most volatile series, while drought has the least volatile.

Table 2 shows the costs of the different meteorological events. The highest average corresponds to tropical cyclone (31.74), followed by severe storm (9.27), drought (7.83) and flooding (7.83).

From these statistical data we can deduce that the two most worrisome meteorological events are severe storm (with a count range of 13) and tropical cyclone with a count range of 7 and the highest average cost (31.74). Another factor to take into account is that drought, despite having a low average counts (0.70), has high average costs (7.83).

Figure 1 plots the annual number of billion-dollar disasters in the United States over the sample period, together with the corresponding estimated linear time trend.

Figure 2 displays the annual evolution of total disaster costs (CPI-adjusted) in the United States, along with the estimated linear time trend.

Putting together Eqs. (1) and (2) we get.

$$\begin{aligned} y(t) &= \beta_0 + \beta_1 t + x(t), \\ (1-L)^d x(t) &= u(t), \qquad t = 1, 2, \ldots, \end{aligned} \tag{5}$$

with $\varepsilon_t \sim NID(0, \sigma^2)$. Table 3 reports the estimates of d for the number of counts, while Table 4 refers to the costs. We work with all disasters as well as with the disaggregated data by class of disaster. In both cases, we present the estimates of d under three different specifications. Thus, in the last column of the two tables we report the values of the estimates of d and their 95% confidence bands under the assumption that the model contains a linear time trend, so β_0 and β_1 are freely estimated from

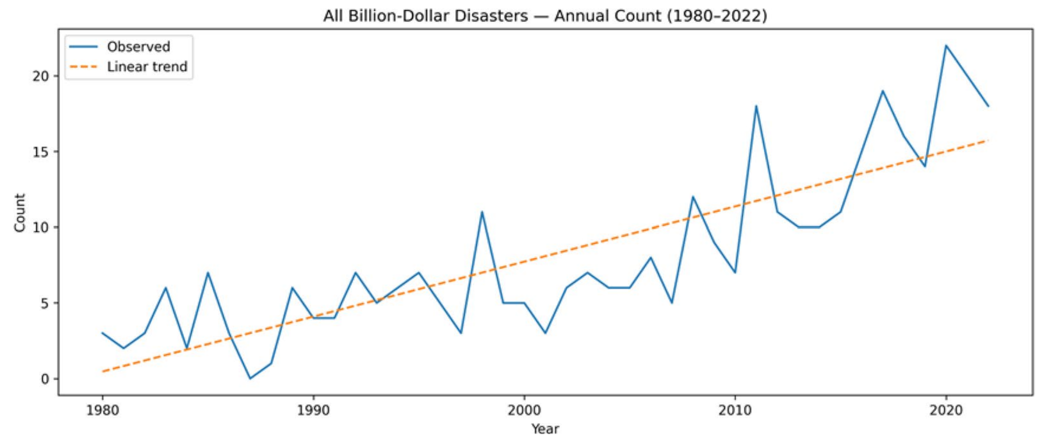

Fig. 1 Annual count (1980–2022)

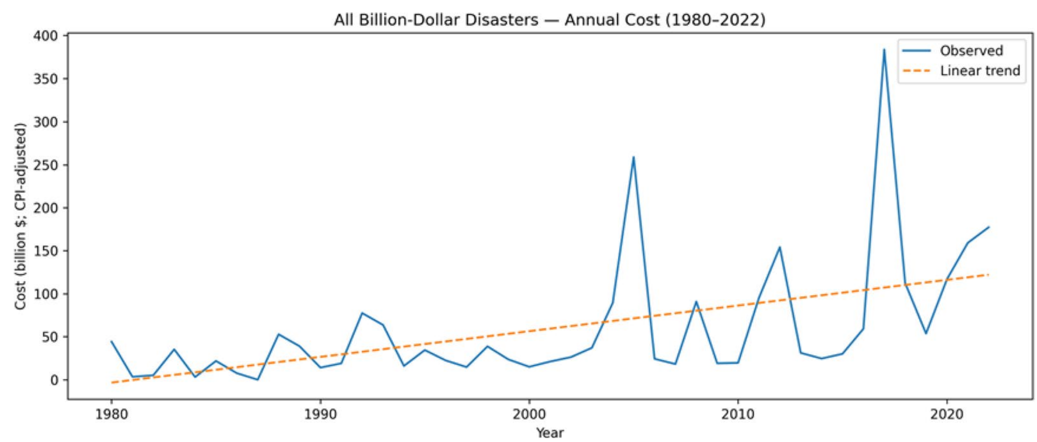

Fig. 2 Annual cost (1980–2022)

Table 3 Estimates of d: US COUNTS

Series	No deterministic terms	An intercept	An intercept and a linear time trend
All disasters	0.41 (0.31, 0.57)	0.47 (0.36, 0.61)	**0.25 (0.11, 0.46)**
Tropical cyclone	0.11 (−0.08, 0.40)	0.13 (−0.11, 0.43)	**0.04 (−0.24, 0.37)**
Drought	−0.05 (−0.11, 0.03)	−0.09 (−0.21, 0.07)	**−0.87 (−1.21, -0.50)**
Flooding	0.08 (−0.03, 0.28)	0.11 (-0.04, 0.32)	**−0.01 (−0.19, 0.24)**
Freeze	−0.44 (−0.56, 0.12)	−0.19 (−0.37, 0.09)	**−0.37 (−0.60, -0.01)**
Severe storm	0.48 (0.39, 0.60)	0.51 (0.41, 0.62)	**0.33 (0.20, 0.50)**
Wildfire	0.17 (0.04, 0.40)	0.23 (0.06, 0.46)	**−0.14 (−0.49, 0.32)**
Winter storm	−0.08 (−0.23, 0.25)	**−0.10 (−0.32, 0.24)**	−0.08 (−0.31, 0.26)

The values in bold refer to the selected specification in relation with the deterministic terms for each series. In parenthesis, the 95% confidence bands for the estimates of the differencing parameter d

Table 4 Estimates of d: US COSTS

Series	No deterministic terms	An intercept	An intercept and a linear time trend
All disasters	0.12 (−0.01, 0.36)	0.15 (−0.01, 0.40)	**−0.17 (−0.44, 0.24)**
Tropical cyclone	0.02 (−0.13, 0.27)	0.02 (−0.16, 0.30)	**−0.33 (−0.69, 0.17)**
Drought	−0.05 (−0.25, 0.40)	**−0.06 (−0.33, 0.38)**	−0.07 (−0.34, 0.42)
Flooding	−0.14 (−0.27, 0.10)	**−0.18 (−0.40, 0.11)**	−0.20 (−0.42, 0.10)
Freeze	−0.01 (−0.29, 0.31)	−0.01 (−0.17, 0.26)	**−0.38 (−0.71, 0.10)**
Severe storm	0.34 (0.23, 0.51)	0.38 (0.27, 0.54)	**0.09 (−0.09, 0.36)**
Wildfire	0.39 (0.22, 0.66)	0.41 (0.24, 0.67)	**0.29 (0.08, 0.62)**
Winter storm	0.14 (−0.25, 0.48)	**0.12 (−0.21, 0.47)**	0.18 (−0.10, 0.49)

The values in bold refer to the selected specification in relation with the deterministic terms for each series. In parenthesis, the 95% confidence bands for the estimates of the differencing parameter d

the data along with the parameter d. Column 3 reports the values of d under the presumption that $\beta_1 = 0$ in (5) so the model only contains an intercept, while column 2 refers to the model with $\beta_0 = \beta_1 = 0$ a priori, so no intercept and no trend are included in the model. We have marked in bold in Table 3 the selected case for each series, this selection being made according to the significance of the coefficients of these deterministic terms.

Starting with the counts, we see that the time trend coefficient is statistically significant in all except one single case (winter storm), implying the existence of linear trends. Table 5 displays the estimated coefficients of the selected models for each series. Focusing first on the orders of integration, we observe that for "All disasters" the estimate of d is equal to 0.41 and the confidence interval is strictly positive, supporting thus the hypothesis of a long memory pattern. However, looking at the disaggregated data, the hypothesis of short memory behavior (i.e., d = 0) cannot be rejected in six cases (tropical cyclone, drought, flooding, wildfire, freeze and winter storm), while only in one series (severe storm) is d found to be statistically positive, supporting again the long memory case. The time trend coefficient is significantly positive for "All disasters" but also for tropical cyclone, drought, flooding, severe storm and wildfire, while it is negative for freeze.

If we focus now on the costs, the time trend coefficient is statistically significant in the cases of "All disasters" along with tropical cyclone, severe storm and wildfire; negative for freeze, and statistically insignificant in the remaining cases. The orders of integration are all in the I(0) range except wildfire, with an estimate of d about 0.29 in the latter series. Thus, it seems that severe storms (in case of counts) and wildfire (for costs) are the only series that display long memory in both counts and costs, implying that in the event of an exogenous shock, its effect will last faster than in the remaining series. Nevertheless, the fact that the order of integration is smaller than 1 in all cases, indicates that reversion to the mean occurs in all series (Table 6).

For readability, Fig. 3 displays the U.S. climate regions considered in the regional disaggregated analysis. This map is included to facilitate interpretation of the regional heterogeneity in both the estimated time trends and the persistence measures reported in Tables 7, 8, 9 and 10.

In what follows, we repeat the experiment but this time we focus on the climate regions. Results are reported across Tables 7, 8, 9 and 10. Starting with the counts or number of events, the time trend is required in all cases, and the estimates of d are in the I(0) interval in the majority of the cases. In fact, long memory is only detected for Gulf Coast States and South Plateau (with d = 0.20) and Tornado Alley (d = 0.21), and the highest coefficients for the time trend are observed in the cases of Tornado Alley ($\beta_1 = 0.269$) and South Climate ($\beta_1 = 0.252$). The results for the costs are reported in Tables 9 and 10. The time trend

Table 5 Elected coefficients: US COUNTS

Series	d	Intercept (tv)	Time trend (tv)
All disasters	0.25 (0.11, 0.46)	0.498 (2.31)	0.365 (6.13)
Tropical cyclone	0.04 (−0.24, 0.37)	0.308 (2.63)	0.049 (2.61)
Drought	−0.87 (−1.21, −0.50)	0.389 (32.47)	0.014 (21.92)
Flooding	−0.01 (−0.19, 0.24)	0.363 (2.26)	0.025 (2.26)
Freeze	−0.37 (−0.60, −0.01)	0.373 (7.06)	−0.007 (−3.15)
Severe storm	0.33 (0.20, 0.50)	−1.139 (−2.03)	0.250 (5.92)
Wildfire	−0.14 (−0.49, 0.32)	−0.013 (−2.15)	0.022 (6.08)
Winter storm	−0.10 (−0.32, 0.24)	0.488 (6.39)	–

In parenthesis, in columns 3 and 4, the *t*-values of the estimated coefficients for the intercept and the time trend respectively

Table 6 Selected coefficients: US COSTS

Series	d	Intercept (tv)	Time trend (tv)
All disasters	−0.17 (−0.44, 0.24)	−6.241 (−2.48)	2.922 (5.43)
Tropical cyclone	−0.33 (−0.69, 0.17)	−11.155 (−2.39)	1.900 (5.29)
Drought	−0.06 (−0.33, 0.38)	7.702 (5.68)	–
Flooding	−0.18 (−0.40, 0.11)	4.331 (6.45)	–
Freeze	−0.38 (−0.71, 0.10)	1.958 (8.98)	−0.051 (−5.16)
Severe storm	0.09 (−0.09, 0.36)	−4.000 (−2.56)	0.610 (6.19)
Wildfire	0.29 (0.08, 0.62)	−1.900 (−2.65)	0.248 (2.25)
Winter storm	0.12 (−0.21, 0.47)	2.311 (2.29)	–

In parenthesis, in columns 3 and 4, the t-values of the estimated coefficients for the intercept and the time trend respectively

Fig. 3 Climate regions (NOAA)

is statistically significant in all except one climate region (West North Central Climate); the only evidence of long memory is found for West Climate (d = 0.32) and the highest trend coefficients are those corresponding to Gulf Coast States ($\beta_1 = 1.497$) and South Climate ($\beta_1 = 1.139$).

As a final robustness checking we also estimated the differencing parameter using alternative approaches like the log-periodogram regression proposed in Geweke and Porter-Hudak (GPH, 1983) and improved later by Robinson (1995) and others. The results in this context were fairly sensitive to the bandwidth numbers, though

Table 7 Estimates of d: US COUNTS

Region	No deterministic terms	An intercept	An intercept and a linear time trend
Central climate	0.30 (0.20, 0.43)	0.35 (0.24, 0.48)	**0.03 (−0.13, 0.25)**
East North Central Climate	0.18 (0.08, 0.34)	0.22 (0.10, 0.37)	**−0.13 (−0.32, 0.15)**
Northeast climate	0.25 (0.14, 0.42)	0.30 (0.17, 0.46)	**0.03 (−0.17, 0.30)**
Northwest climate	0.04 (−0.06, 0.22)	0.06 (−0.09, 0.27)	**−0.51 (−0.79, 0.01)**
South climate	0.33 (0.23, 0.47)	0.39 (0.28, 0.55)	**0.10 (−0.05, 0.31)**
Southeast climate	0.23 (0.12, 0.38)	0.29 (0.17, 0.46)	**−0.09 (−0.28, 0.19)**
Southwest climate	0.25 (0.14, 0.42)	0.28 (0.16, 0.45)	**0.04 (− 0.13, 0.29)**
West climate	0.15 (0.03, 0.39)	0.21 (0.04, 0.47)	**−0.43 (−0.88, 0.28)**
West North Central Climate	0.30 (0.18, 0.51)	0.33 (0.20, 0.50)	**0.10 (− 0.11, 0.41)**
Gulf coast states	0.37 (0.26, 0.51)	0.42 (0.31, 0.57)	**0.20 (0.05, 0.41)**
Great lakes states	0.29 (0.18, 0.46)	0.34 (0.22, 0.50)	**−0.03 (−0.26, 0.31)**
Southern plains	0.38 (0.27, 0.52)	0.43 (0.32, 0.57)	**0.20 (0.05, 0.40)**
Tornado alley	0.38 (0.29, 0.52)	0.43 (0.33, 0.56)	**0.21 (0.07, 0.40)**

The values in bold refer to the selected specification in relation with the deterministic terms for each series. In parenthesis, the 95% confidence bands for the estimates of the differencing parameter d

Table 8 Estimates of d: US COSTS

Region	No deterministic terms	An intercept	An intercept and a linear time trend
Central climate	0.09 (−0.05, 0.35)	0.12 (−0.06, 0.41)	**−0.08 (−0.36, 0.33)**
East North Central climate	−0.05 (−0.19, 0.18)	−0.07 (−0.27, 0.21)	**−0.25 (−0.54, 0.11)**
Northeast climate	0.04 (−0.12, 0.35)	0.05 (−0.15, 0.37)	**−0.11 (−0.43, 0.32)**
Northwest climate	0.18 (−0.07, 0.55)	0.19 (−0.10, 0.57)	**0.14 (−0.19, 0.53)**
South climate	−0.02 (−0.13, 0.17)	−0.02 (−0.17, 0.20)	**−0.38 (−0.63, -0.03)**
Southeast climate	−0.07 (− 0.27, 0.61)	−0.08 (−0.38, 0.47)	**−0.11 (−0.61, 0.64)**
Southwest climate	0.28 (0.16, 0.47)	0.31 (0.18, 0.50)	**0.12 (−0.05, 0.39)**
West climate	0.38 (0.20, 0.66)	0.40 (0.20, 0.69)	**0.32 (0.11, 0.65)**
West North Central climate	−0.03 (−0.23, 0.32)	**−0.03 (−0.31, 0.31)**	−0.06 (−0.29, 0.31)
Gulf Coast States	0.05 (−0.12, 0.37)	0.06 (−0.13, 0.38)	**−0.13 (−0.50, 0.34)**
Great Lakes States	0.09 (−0.06, 0.36)	0.11 (−0.06, 0.39)	**−0.09 (−0.38, 0.32)**
Southern Plains	0.03 (−0.09, 0.22)	0.04 (−0.09, 0.25)	**−0.23 (−0.42, 0.06)**
Tornado Alley	0.05 (−0.06, 0.22)	0.06 (−0.07, 0.25)	**−0.23 (−0.39, 0.03)**

The values in bold refer to the selected specification in relation with the deterministic terms for each series. In parenthesis, the 95% confidence bands for the estimates of the differencing parameter d

Table 9 Selected coefficients: US COUNTS

Region	D	Intercept (tv)	Time trend (tv)
Central climate	0.03 (−0.13, 0.25)	−0.594 (−2.81)	0.220 (7.72)
East North Central climate	−0.13 (−0.32, 0.15)	−0.410 (−2.02)	0.129 (7.75)
Northeast climate	0.03 (−0.17, 0.30)	−0.021 (−2.04)	0.127 (6.47)
Northwest climate	−0.51 (−0.79, 0.01)	0.150 (2.36)	0.036 (11.86)
South climate	0.10 (−0.05, 0.31)	−0.176 (−2.17)	0.252 (6.41)
Southeast climate	−0.09 (−0.28, 0.19)	0.562 (2.05)	0.168 (7.74)
Southwest climate	0.04 (−0.13, 0.29)	−0.434 (−2.90)	0.108 (5.75)
West climate	−0.43 (−0.88, 0.28)	0.077 (2.92)	0.047 (12.22)
West North Central climate	0.10 (−0.11, 0.41)	−0.171 (−2.36)	0.106 (5.93)
Gulf Coast States	0.20 (0.05, 0.41)	0.197 (2.16)	0.238 (5.22)
Great Lakes States	−0.03 (−0.26, 0.31)	−0.382 (−2.63)	0.210 (8.70)
Southern Plains	0.20 (0.05, 0.40)	−0.434 (−2.40)	0.228 (5.62)
Tornado Alley	0.21 (0.07, 0.40)	−0.580 (−24.17)	0.269 (5.78)

In parenthesis, in columns 3 and 4, the t-values of the estimated coefficients for the intercept and the time trend respectively

qualitatively were very similar to those reported in this work and based on Robinson (1994).

Figures 4, 5, 6 and 7 display the observed data along with the estimated time trends. These plots reveal one of the limitations of the present work, focusing on linearity and not permitting any non-linear structure in the data. The latter is in fact a relevant issue since non-linearities (or even structural breaks) are closely related to the long memory property observed in this work (Diebold and Inoue 2001; Granger and Hyung 2004; Bisaglia and Gerolimetto 2009). In this context, we can replace the linear specification for the deterministic terms by non-linear ones still in the context of fractional structures like those based on the Chebyshev polynomials in time (Cuestas and Gil-Alana 2015), Fourier functions (Gil-Alana and Yaya 2021) or even neural networks (Yaya et al. 2021). Nevertheless, the low number of observations is a clear constraint on the use of these approaches in the present work.

On the other hand, the disaggregated analysis by climate regions reveals significant heterogeneity in both the intensity of temporal trends and the degree of persistence of meteorological and climate-related disasters

Table 10 Selected coefficients: US COSTS

Region	D	Intercept (tv)	Time trend (tv)
Central climate	**−0.08 (−0.36, 0.33)**	1.441 (2.99)	0.171 (2.90)
East North Central climate	**−0.25 (−0.54, 0.11)**	0.660 (2.99)	0.098 (3.43)
Northeast climate	**−0.11 (−0.43, 0.32)**	−1.320 (−2.42)	0.289 (2.28)
Northwest climate	**0.14 (−0.19, 0.53)**	−0.128 (−2.43)	0.025 (2.29)
South climate	**−0.38 (−0.63, −0.03)**	−5.282 (−2.20)	1.139 (5.70)
Southeast climate	**−0.11 (−0.61, 0.64)**	0.950 (2.17)	0.589 (2.60)
Southwest climate	**0.12 (−0.05, 0.39)**	−0.404 (−2.73)	0.084 (4.04)
West climate	**0.32 (0.11, 0.65)**	−0.772 (−2.26)	0.204 (1.82)
West North Central climate	**−0.03 (−0.31, 0.31)**	2.541 (5.03)	–
Gulf Coast States	**−0.13 (−0.50, 0.34)**	−5.716 (−2.52)	1.497 (3.29)
Great Lakes States	**−0.09 (−0.38, 0.32)**	−0.326 (2.13)	0.309 (3.05)
Southern Plains	**−0.23 (−0.42, 0.06)**	−5.757 (−2.48)	0.738 (4.43)
Tornado Alley	**−0.23 (−0.39, 0.03)**	−4.835 (−2.20)	0.866 (5.02)

In parenthesis, in columns 3 and 4, the t-values of the estimated coefficients for the intercept and the time trend respectively

in the United States. In terms of event counts, the time trend is statistically significant across all regions considered (Tables 7 and 9), suggesting a general increase in the frequency of extreme events over the analysed period. However, the magnitude of this trend varies substantially across regions, being particularly high in Tornado Alley and the Southern climate region, which are characterized by high exposure to severe storms and extreme convective phenomena (Fig. 4).

Regarding persistence, evidence of long memory is observed in the Gulf Coast states, the Southern Plains, and Tornado Alley for event counts (Tables 7 and 9). This indicates that shocks associated with disasters in these regions tend to have more lasting effects over time, potentially due to structural factors such as the recurrence of specific climate phenomena, the concentration of population and assets, and high exposure to persistent coastal or atmospheric risks. Conversely, events such as freezes show negative trends, which may reflect regional climate changes or improvements in mitigation, while some regional anomalies could be attributed to data limitations or local climatological patterns.

For economic costs, the results again show a positive temporal trend in most regions, with the Gulf Coast states and the Southern climate region experiencing the largest estimated increases (Tables 8 and 10; Fig. 5). The only clear evidence of long-term memory in costs is found in the Western climate region, likely linked to the recurrence and increasing intensity of wildfires and droughts, whose economic impacts tend to persist over time.

From a climate-risk perspective, these persistence patterns are consistent with the recurrence of specific hazard regimes and the accumulation of exposure in repeatedly affected areas. Although our framework is not causal, this interpretation provides a coherent link between the statistical evidence of long memory and plausible underlying climate-risk mechanisms.

Overall, these results indicate that while the increase in disasters is a widespread phenomenon, the persistence and intensity of their effects show a marked regional component, underscoring the need for region-specific analyses and policies, long-term adaptation strategies, and risk-based planning that account for both the frequency and persistence of climate-related disasters.

Conclusions

In this paper we have investigated the statistical properties of the time series corresponding to the number of cases and costs of natural catastrophes in the US, using data from 1980 to 2022. We have focused on two features of the data, in particular, the level of dependence, measured in terms of the order of integration, which is permitted to be fractional and the slope coefficient of the time trend.

Starting with the long memory features, this is clearly detected in the aggregated countries but also for the disaggregated data on severe storms (counts) and wildfire (costs), and the time trend coefficients are significantly positive in the majority of the cases. Looking at the results by climate region, long memory is found in Gulf Coast States, Southern Plains and Tornay Alley with counts and West Climate for costs, and the time trend is now significantly positive in all cases except one single region (West North Central Climate) with costs. These findings highlight the existence of substantial heterogeneity across disaster types and regions, suggesting that aggregate analyses may mask important underlying dynamics at more disaggregated levels.

We hope that this research can contribute to a better design of environmental policies, since generally the positive time trend coefficient for most series of both counts and costs could indicate an increase in natural disasters and even suggest an intensification of their magnitude, meaning that the events may be even more extreme in the future. Nevertheless, it should be emphasized that this study is not intended as a causal attribution exercise; that is, it does not disentangle whether these upward trends are driven by climate change or by factors such as

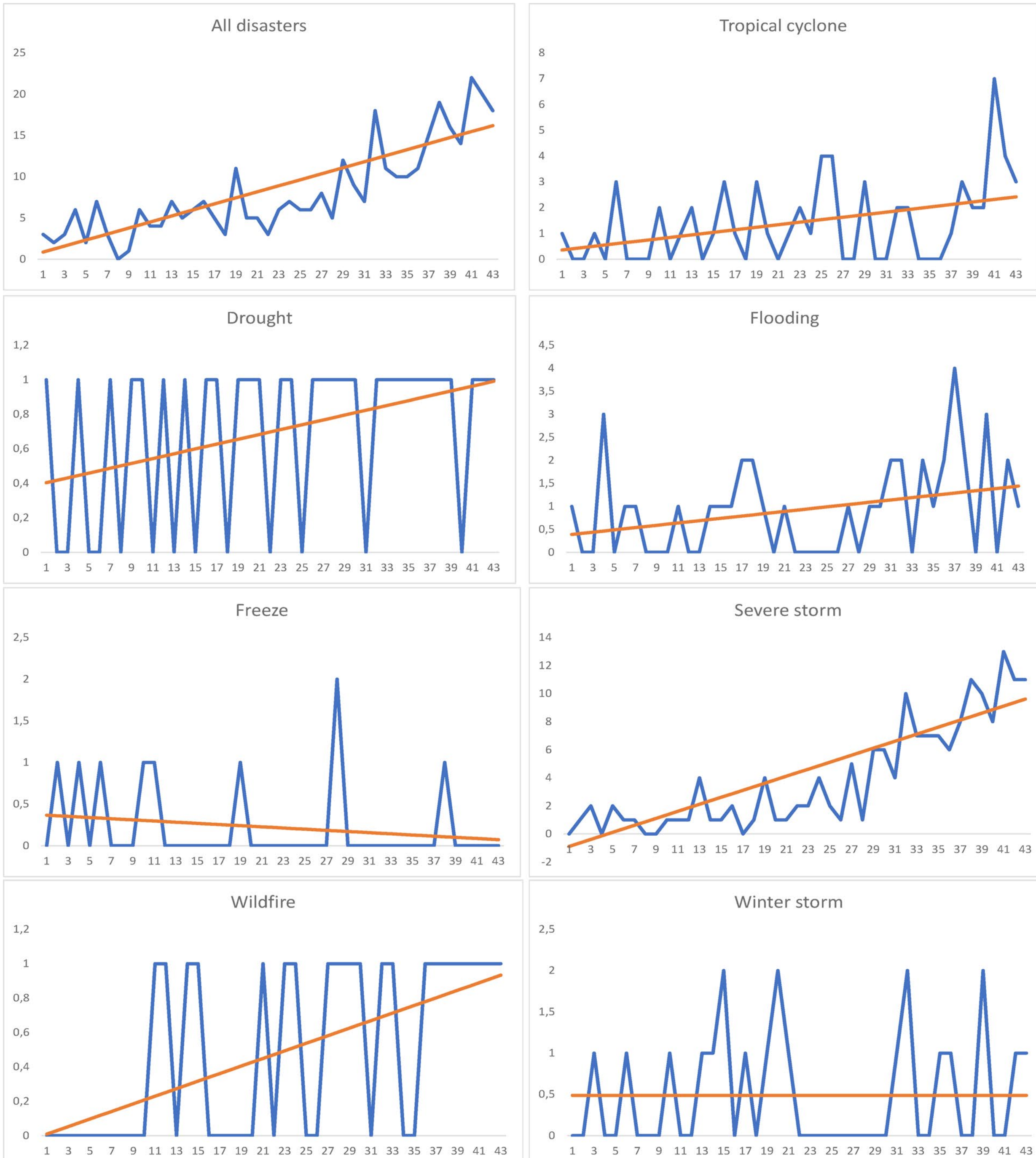

Fig. 4 Time series plots and trends. US COUNTS

greater exposure, wealth accumulation, or vulnerability. Importantly, once long-range dependence is explicitly accounted for, these positive trends remain statistically significant reinforcing the robustness of the evidence and indicating that the observed upward patterns are not merely the result of short-term fluctuations or transient shocks.

Furthermore, evidence of persistence or long-term memory detected in several series implies that shocks associated with natural disasters do not dissipate quickly but can affect future dynamics over prolonged periods. This persistence suggests that the economic and social impacts of disasters may accumulate over time increasing vulnerability and amplifying future losses if adaptive measures are not implemented. From an econometric

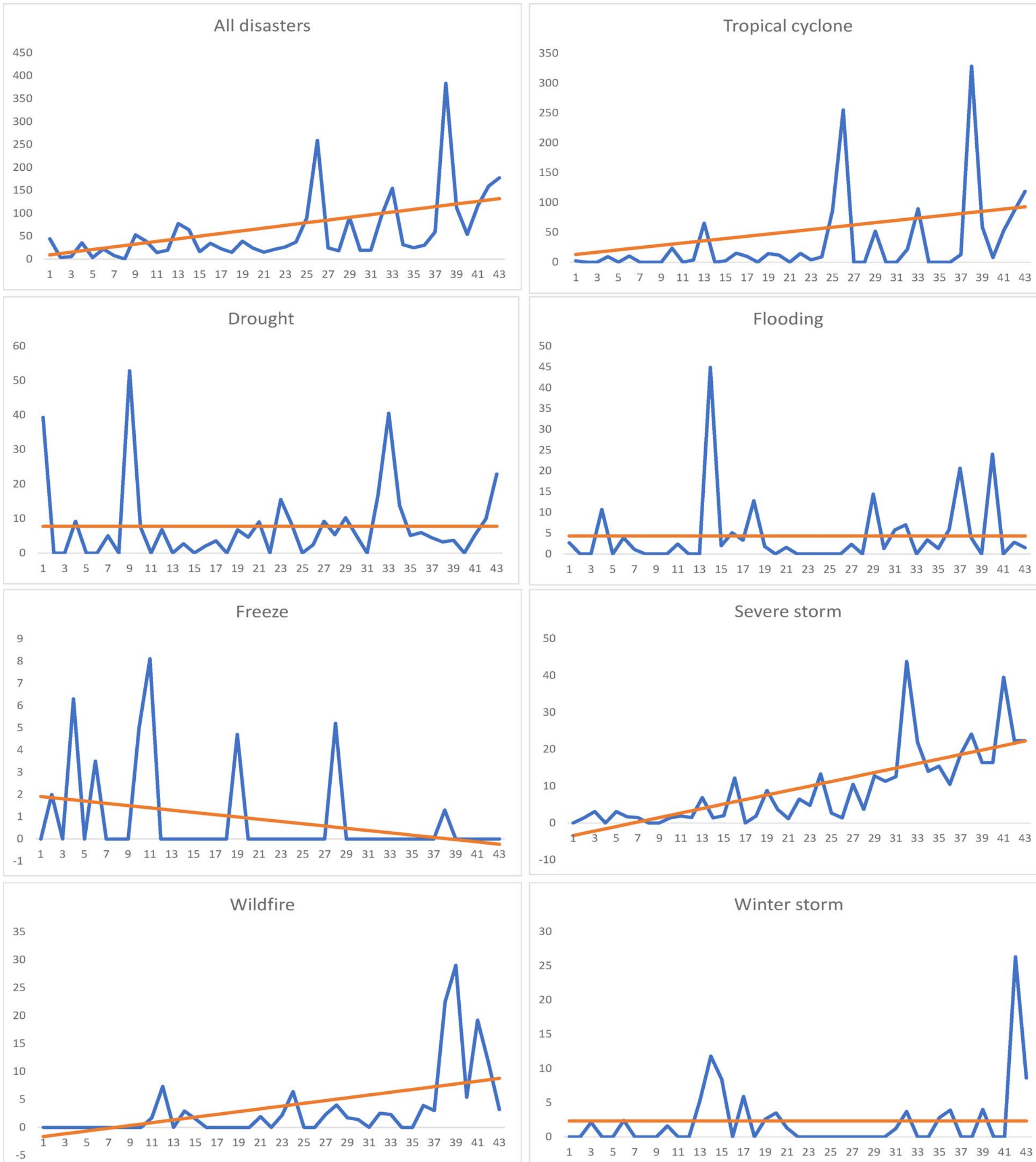

Fig. 5 Time series plots and trends. US COSTS

perspective, these results also imply that conventional short-memory models may underestimate the long-run effects of climate-related shocks potentially leading to misguided policy conclusions.

This result suggests that public policies based exclusively on short-term responses may be insufficient to mitigate the economic effects of disasters. Instead, policies need to internalize the long-term nature of disaster risk recognizing that both frequency and costs exhibit persistent dynamics that require sustained and forward looking interventions.

In this context, our results support the need for long-term adaptation and resilience strategies, such as sustained investment in climate-resilient infrastructure, risk-based land-use planning, and the development of risk insurance and transfer mechanisms. These measures

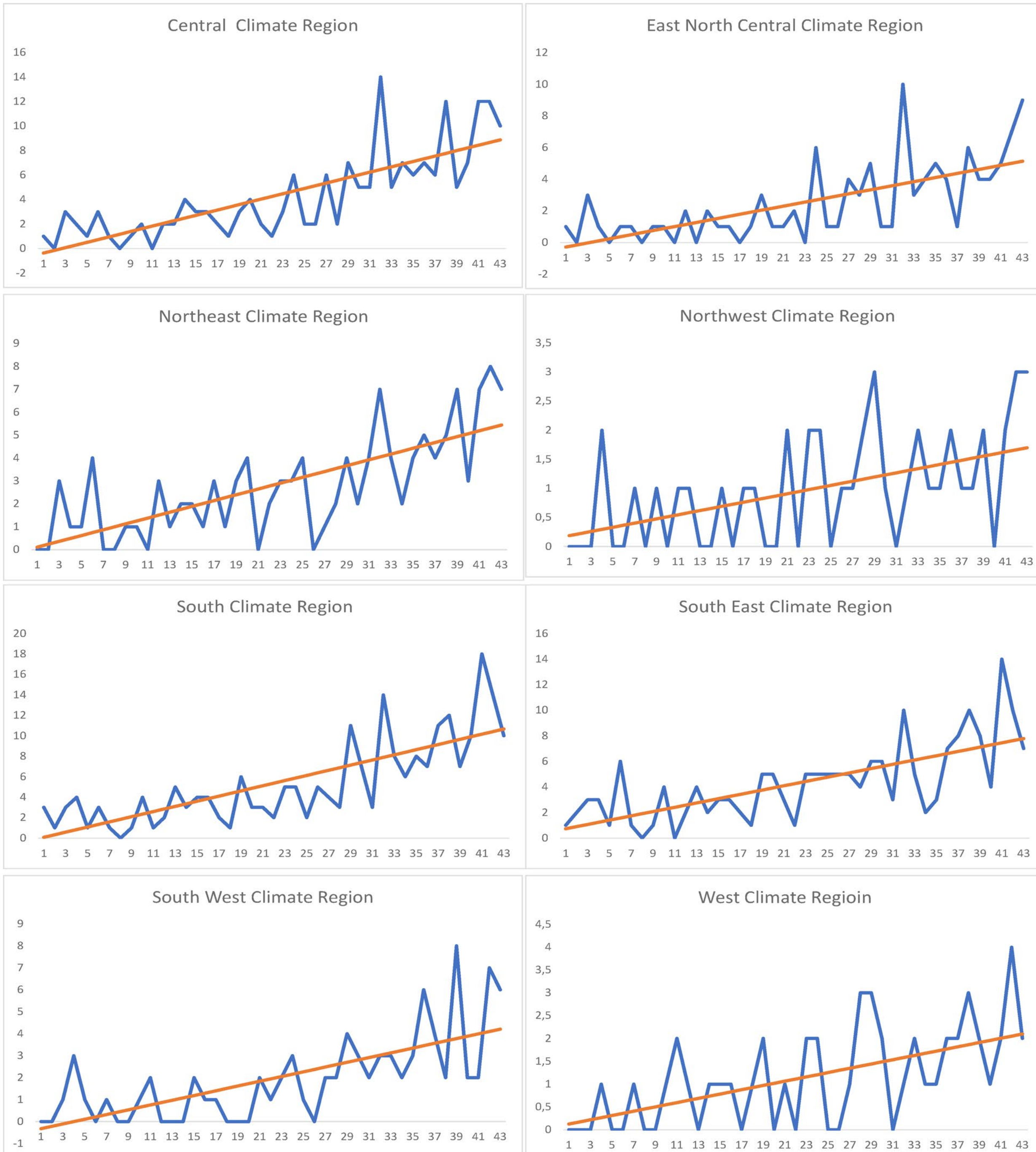

Fig. 6 Time series regional plots and trends. US COUNTS

are particularly relevant in regions where long memory and strong positive trends coexist as they indicate areas where disaster risks are likely to remain elevated over extended horizons.

Likewise, the regional heterogeneity observed in terms of persistence and temporal trends indicates that such policies should be designed in a differentiated manner, prioritizing those regions where the effects of disasters are more persistent and costs show more pronounced growth. Therefore, a uniform approach for all regions may prove inefficient, while region-specific strategies, informed by the statistical properties of disaster series, can improve the effectiveness of adaptation policies and resource allocation.

Finally, this study highlights the importance of incorporating flexible time series methods, such as fractional

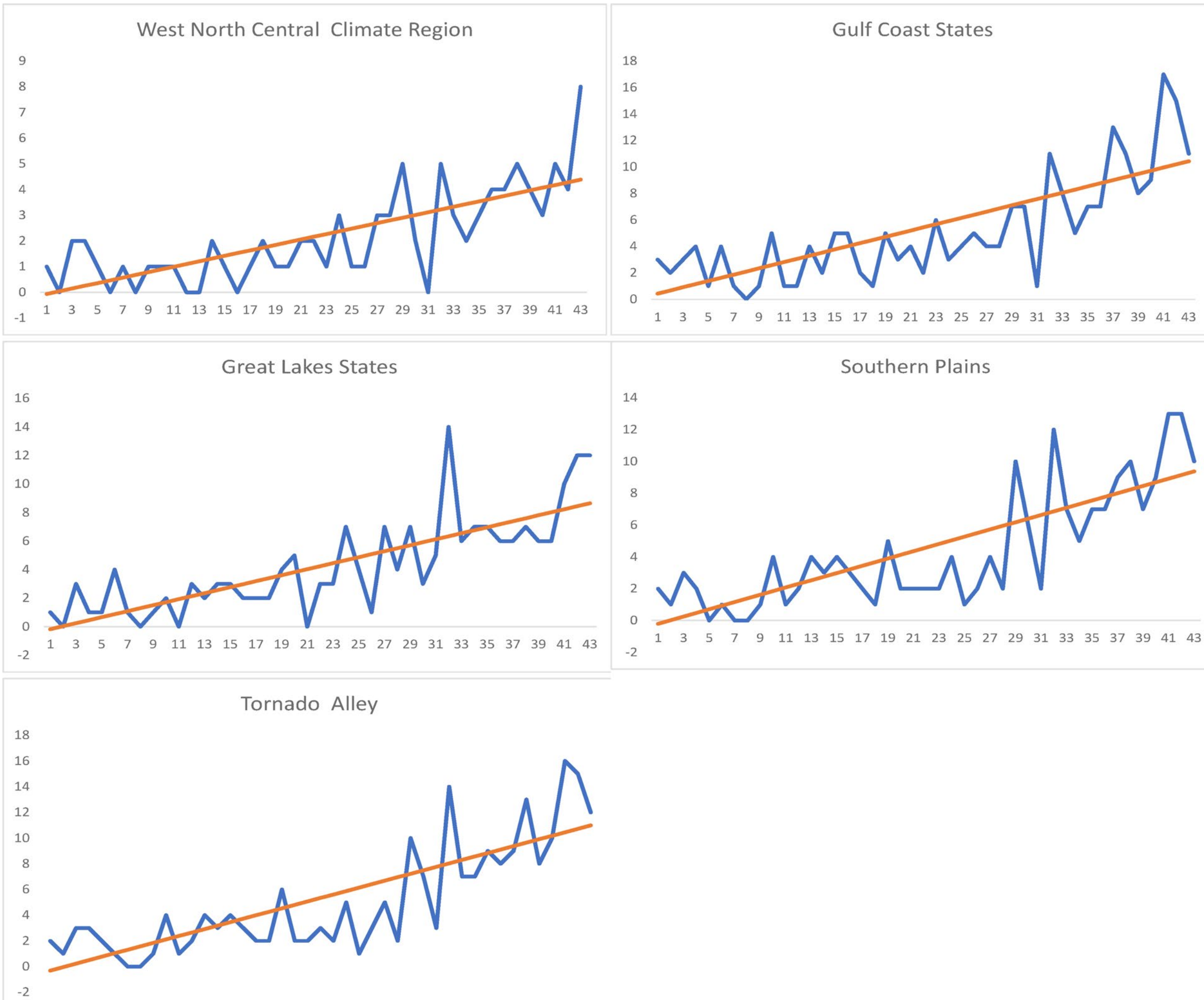

Fig. 6 (continued)

integration, into the empirical analysis of climate-related disasters, as they allow for the capture of long-term dependence and provide a more accurate characterization of their behavior, which is relevant for economic analysis and evidence-based policy design. Future research could extend this framework by incorporating climate-related variables and exposure-normalized loss measures, which would help distinguish more clearly between structural climate-change mechanisms and socioeconomic drivers underlying the observed trends.

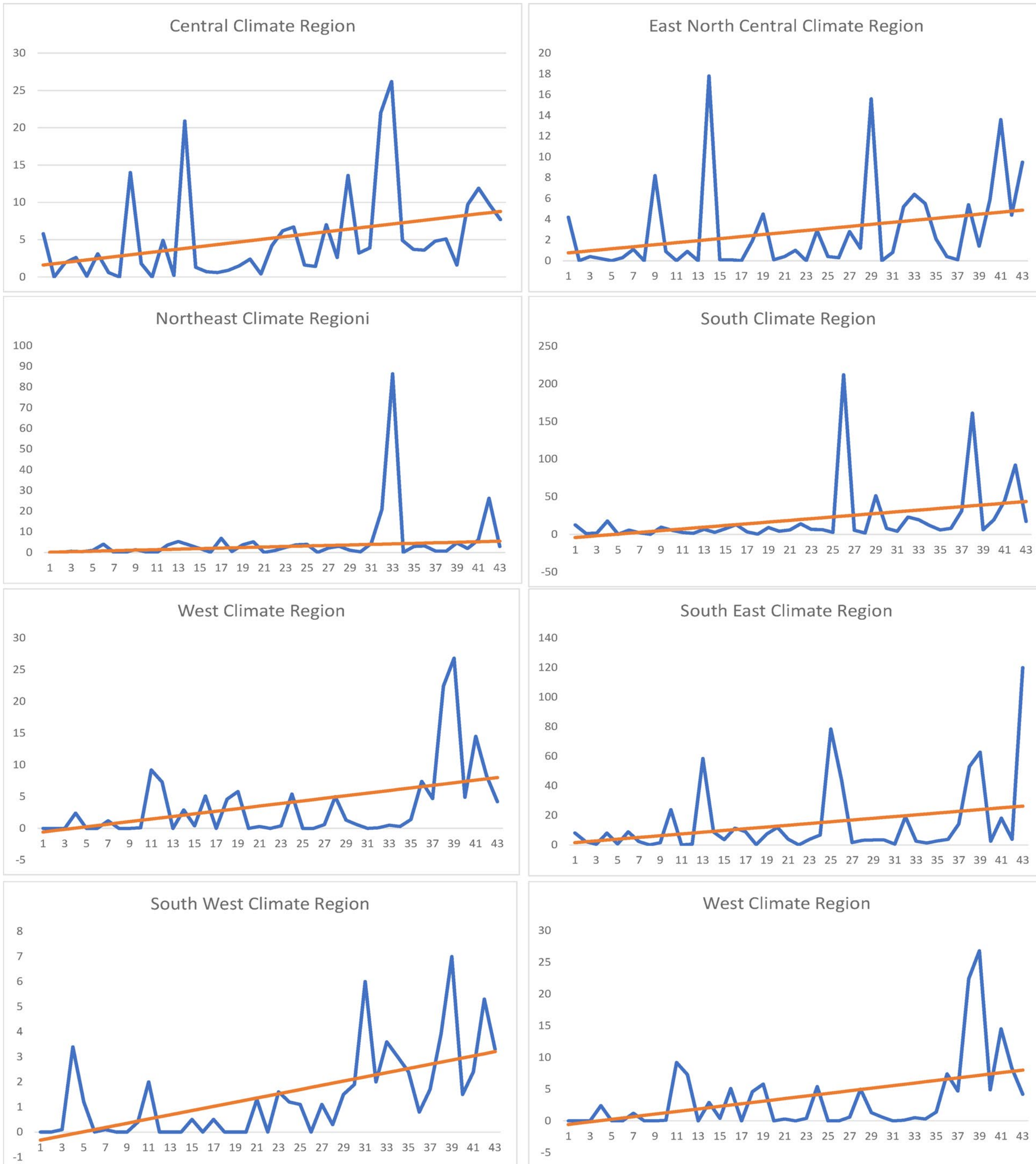

Fig. 7 Time series regional plots and trends. US COST

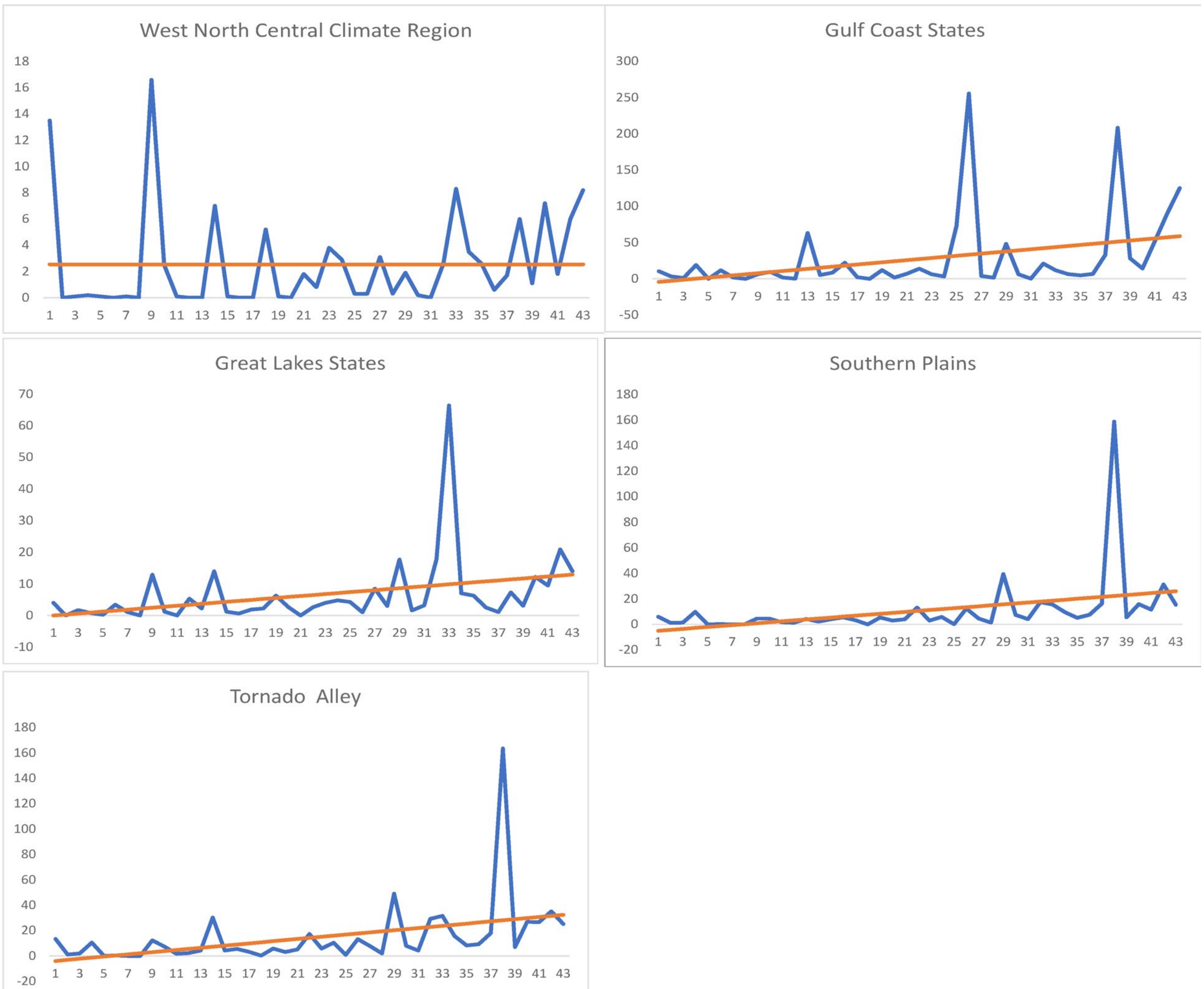

Fig. 7 (continued)

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Author contributions
L.A.GA proposed the original idea. He conducted the empirical results and their interpretation.N-CG was responsable for introduction, literature review and interpretation of the results.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Competing interests
The authors declare no competing interests.

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