



Impacts of Carbon Dioxide Emissions on Global Intense Hydrometeorological Disasters

Ramon E. Lopez¹ · Vinod Thomas² · Pablo A. Troncoso³

¹*University of Chile, Santiago, Chile*

²*Asian Institute of Management, Manila, Philippines*

³*University of Georgia, USA*

Received: 17 November 2018 / Accepted: 07 January 2020 / Published online: 23 January 2020

DOI: <https://doi.org/10.18783/cddj.v004.i01.a03>

Abstract

This research explains the factors that contribute to the global increase in the frequency of intense hydrometeorological disasters, particularly those related to floods and storms. It describes how the atmospheric carbon dioxide (CO₂) accumulation and its associated changes in climatic patterns contribute to the increased frequency of these intense events. The novelty of this study lies in how climate effects are examined within a socioeconomic framework that includes factors that turn natural hazards into intense disasters. These factors include people's increasing exposure and their vulnerability to these hazards.

This study uses climate data from 155 countries, with a period spanning 46 years (1970–2016). It adopts a statistical and econometric approach, instead of climate models, to assess the factors that have contributed to the increase in the frequency of intense flood and storm events. The findings show that in addition to socioeconomic factors, the continuous increase in atmospheric CO₂ concentration during the past four decades is significantly correlated with the increase in the number of extreme flood and storm events. Moreover, the results show that global climate conditions significantly affect the frequency of these disasters.

The estimates in this study further suggest that if current trends in environmental degradation and CO₂ accumulation remain unchecked, then the frequency of intense hydrometeorological disasters would increase. Our results also highlight the link between climate change and natural hazards, and support the broader pathways between climate hazards and socioeconomic variables traced by Mora et al. (2018). This scenario is a ground for the immediate implementation of adaptation measures and for taking strong mitigation measures to reverse runaway climate change.

Keywords: climate change, weather, carbon emissions, exposure, vulnerability, disaster risk

Corresponding Author:

Vinod Thomas

vndthomas49@gmail.com

Introduction

The frequency of natural hazard incidents across geographical regions and the steady rise in the number of economic disruptions resulting from these incidents have tripled in the past 40 years (Guha-Sapir, Hoyois, & Below, 2015). Although the trend in the number of geophysical events (e.g., earthquakes and volcanic eruptions) have remained relatively flat over the years, those of hydrometeorological (e.g., floods and related landslides, storms, and heatwaves) and climatological events (e.g., droughts and wildfires) have shown an uptick (Thomas 2017; Emanuel, 2005; Webster, Holland, Curry, & Chang, 2005). The crucial issue is whether climate change is related to this significant increase in the frequency of intense hydrometeorological and climatological disasters.

Our interest lies in the relationship between the climate phenomenon and human action. The body of published evidence indicates that the temperature of the Earth's atmosphere and oceans have been increasing, there is loss of sea ice and melting of ice sheet in the Arctic, and sea levels are rising (Levitus, Antonov, Boyer, & Stephens, 2000; Levitus et al., 2001). Moreover, over the past 60 years, greenhouse gas (GHG) emissions (i.e., carbon dioxide [CO₂], methane [CH₄], ozone, and nitrous oxide) have been increasing, mainly due to the contributions of economic-driven anthropogenic activities that have led to rising temperatures (Intergovernmental Panel on Climate Change [IPCC], 2013, 2014; Mora et al., 2018; Cheng et al., 2017).

Previous studies on the relationship of climate change and disasters have mainly focused on specific geographical regions (Stott, Stone, & Allen, 2004; Otto, Massey, van Oldenborgh, Jones, & Allen, 2012; Hoerling et al., 2012; Rahmstorf & Coumou, 2011) and particular events (Min, Zhang, Zweirs, & Hegerl, 2011; Stott et al., 2013; Nuccitelli, 2014; Kundzewicz et al., 2014; Arnell & Gosling, 2016; Hirabayashi et al., 2013; Herring, Hoerling, Peterson, & Stott, 2014). Some have applied climate change models to selected episodes (Lee & Lee, 2016; Diffenbaugh, Swain, & Touma, 2015). These climate change models have analyzed extreme climatic events in particular settings (Easterling et al., 2000; Pall et al., 2011; Schreider, Smith, & Jakeman, 2000).

In Mora et al. (2018), the authors have developed a global index of projected changes in hazards to predict the impacts of climate hazards on the population. Accordingly, they have found that floods and storms have affected the economy, infrastructure, health, and food and water security. The biggest impacts are expected to happen in South America, Southeast Asia, and northern Russia due to flooding and storms. Mora et al. (2018) have concluded that climate-related damages will greatly increase if GHG concentrations continue to rise throughout the 21st century.

Our research provides fresh evidence that connects climate change and hydrometeorological calamities based on econometric evidence that links atmospheric CO₂ accumulations to floods and storms. The present study considers all (reported) significant hydrometeorological disasters in 155 countries over the last 46 years. Furthermore, we include worldwide disasters, instead of selecting only a few cases as is usually done. In this way, we reduce the risk of selection biases (Heckman, Ichimura, Smith, & Todd, 1998). Also, hydrometeorological disasters have been more difficult than climatological ones to relate to climate change using climate models. As such, applying econometric techniques to these hydrometeorological disaster data and to their hypothesized contributing factors can help to solve this issue (Cornwall, 2016; Hsiang, 2016).

Climate models are constructs of physical relationships that can be used to predict future outcomes. This paper uses a different, but complementary, approach to examine the data on experiences (see also Pretis, 2019). Specifically, our study applies an econometric approach to determine behavioral relationships between disasters and their contributors in order to guide policy makers in formulating climate-related policies. Moreover, the method relies on the recorded natural hazards data of the Centre for Research on the Epidemiology of Disasters (CRED) to determine whether global climate factors—in addition to the effects of country conditions (e.g., local temperature and precipitation)—can explain the upward trend in the frequency of intense hydrometeorological disasters.

Aside from changes in local temperature and precipitation, global and regional climatic factors can increase the exposure and vulnerability of several countries against hydrometeorological and climatological disasters. Sea level rise due to climate change could exacerbate the destructive impact of increased local precipitation, whereas storm surges can be aggravated by sea level rise that results from the larger volume occupied by warmed water molecules and melting land ice (Mora et al., 2018). Nevertheless, these impacts would show considerable national and local differences.

Establishing causality beyond association is difficult due to the complex interrelationships among natural, geographic, and economic factors (see, Banholzer, Kossin, & Donner, 2014; Shaw et al., 2016). Thus, we rely on a cointegration analysis to determine whether there is a meaningful connection between the incidence of hydrometeorological disasters and the concentration of CO₂ emissions. If there is, then the following question remains: *what is their likely direction of causality?* Econometrically, having considered a country's conditions (e.g., exposure to the hazard, people's vulnerability, precipitation anomalies, and fixed effects per country), atmospheric CO₂ accumulation has a positive effect on the frequency of intense disasters due to floods and storms.

Finally, this paper places environmental and climate impacts within a framework that integrate geographic, economic, social, and institutional considerations into the research. Many studies have dealt with either the socioeconomic side or the climatic side only. This is mainly because disaster models stress the role of people's exposure to the calamities and their vulnerability or lack of resilience in facing them (Tyler & Moench, 2012; Banholzer et al., 2014; Hauer, Evans, & Mishra, 2016; Hallegatte & Rozenberg, 2017).

Country experiences tell us that risks result from the interplay among three elements. One of them is a highly intuitive factor, which is people's *risk exposure* due to their location or positioning of habitats, livelihoods, assets, and resources. The second factor is *vulnerability*, which is reflected on people's inability or lack of capacity to adjust and withstand hazards. The third consideration is the *nature of the hazard* itself, both in terms of its intensity and frequency of occurrence. The interplay of these three factors induces the transformation of a hazard into a disaster.

Accordingly, disaster risk can be understood as a product of the probability that the hazard would occur and of the impact that this hazard would have. By including these factors, we can see the additional contribution of climate factors (if any), and open the discussion for the interaction among all three variables. The implication is that planners need to use a multipronged approach that draws on different (but related) disciplines such

that adaptation responses will be effective against the increasing risk of these disasters.

Studies have predicted that if atmospheric CO₂ concentrations doubles, the frequency of Category 5 storms would triple (Anderson & Bausch, 2006). Moreover, Grinsted, Moore, and Jevrejeva (2013) cited that for every 1 °C rise in global temperature, the frequency of events like hurricane Katrina could increase by at least two times, and possibly by as much as seven times.

Climate models have also projected a 3%–5% increase in wind speed per degree Celsius increase in tropical sea surface temperatures (World Meteorological Organization, 2006), whereas some have indicated that the intensity of tropical cyclones would increase by 2%–11% by 2100 (Knutson et al., 2010). With climate change, global economic losses from hurricanes could double (Hallegatte, 2012). Recent projections have also raised new concerns on global warming. The continuous rise in GHG emissions has significantly increased the vulnerability of humanity to climate hazards (Mora et al., 2018).

This paper is complementary to these efforts, but goes further such that it determines the local and global climate impacts within a socioeconomic model of disasters (Figure 1).

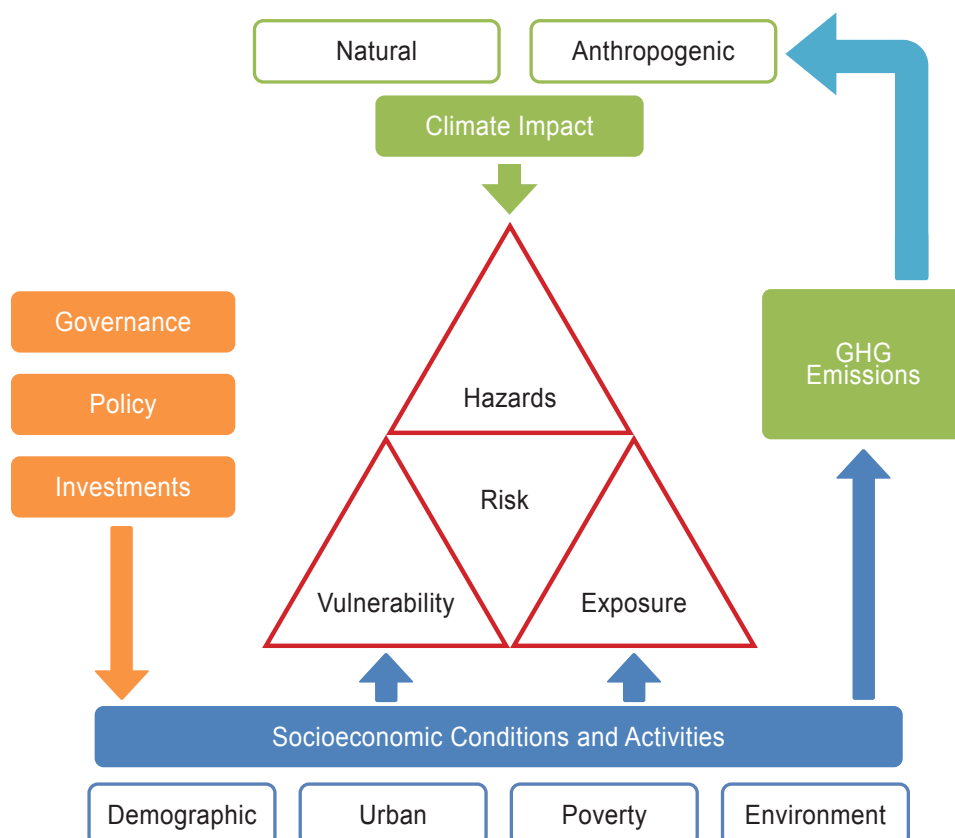


Figure 1. A framework for the disaster-climate relation

The Approach

Our approach builds on previous analyses on the climate-disaster link in order to analyze a large, global database of cross-sectional and time series data, and consequently investigate the key relationships among variables. We apply econometric and statistical methods to ensure robust findings. Note that global climate considerations that are beyond country effects¹ should be considered. Accordingly, the econometrics touches on attribution beyond contribution, without claiming too much in terms of causality. The framework we use is straightforward in establishing that the rise in the frequency of disasters depends on multiple factors, and the effects of this increase can be tested empirically.

This research provides the rationale for using the frequency of hydrometeorological disasters as the dependent variable. In this study, this variable is represented by the number of intense disasters² (per country). An intense hydrometeorological disaster is a subsample of all hydrometeorological hazards.

Also, there are other measures of disasters, such as damages in monetary terms. However, measuring natural disasters in financial terms raises data issues regarding its accuracy since standards for estimation vary across economies. Thus, the basic approach is to establish yearly data on the frequency of intense hydrometeorological disasters for as many countries, and then attempt to explain these events within a model that includes exposure and vulnerability while using climate indicators as the independent variables. In this paper, we use a full set of data from published sources for 155 countries for the period 1970–2016 using the Emergency Events Database (EM-DAT) of the CRED (see EM-DAT data in Guha-Sapir et al., 2015).

To see the likely contribution of global climate change to the frequency of intense hydrometeorological disasters beyond their country effects, one approach is to estimate the effect of global climate indicators on natural disasters. These climate indicators can be represented in the regression model by the atmospheric CO₂ concentration as a contributor, after considering the country-specific effects. This approach is called the *one-way fixed effect*; it postulates that different countries have their own distinct method of managing intense natural disasters. One problem with this approach is that the CO₂ level variable may correlate with the omitted variables

(i.e., variables that are not included because of lack of information); this may affect the disaster variable, and possibly render the estimates of the effect of CO₂ level to be biased. If these omitted variables are fixed over time, then they can be captured in the fixed effect by country; as such, the bias would not be an issue. However, if some of them vary over time, then they would be correlated with CO₂ levels or another explanatory variable, thereby generating bias in our results.

Accordingly, we employ another approach to correct this problem and then estimate the model in two stages. In stage I, we use a *two-way fixed effects* method, in which we control for both country-specific and global effects (which vary over time). These global effects are assumed to be the same among countries, albeit their size can be different through time. Global temperature, for example, is a variable that can be captured by the second fixed effect. The global effects, over and above the country effects, may include both global climatic effects and other global changes such as better technology for early warning.

In stage II, we do a cointegration analysis between atmospheric CO₂ accumulation and the estimated global time effects to test whether the latter are significantly related to CO₂ accumulation. Previous studies have established that CO₂ accumulation affects sea levels and their temperatures *inter alia* by reducing polar ice caps (Alley et al., 2003). As sea levels and their temperatures rise, the effects of local temperatures and precipitation on disasters may worsen (Griffiths et al., 2009; Huq et al., 2004). Higher precipitation may have a bigger effect on flooding if the sea level is already high (Magadza, 2000). Specifically, the dependent variable we employ is the annual frequency of intense hydrometeorological disasters (H_{it}), which is defined as floods and storms³ using data from EM-DAT (Guha-Sapir et al., 2015). On average, there were 0.7 intense hydrometeorological disasters per year among the 155 countries from 1970 to 2016 (Table 1).

One question that is often raised is: does improved disaster reporting due to the development of information and communications technology over time mean that we understand the incidence of past events? By focusing on intense hydrometeorological disasters, we consider here those events that would have been likely reported over time. Some studies consider the level of damages in US dollars based on past data; but meaningfully measuring the impact of disasters in monetary terms is constrained by the lack of standards to compare the estimates across countries.

¹ In this study, we refer to **country effects** as those climate change impacts that are specific to a country but can vary over time, such as temperature, precipitation. On the other hand, **global effects** are those that are common across countries, while varying over time such as carbon emissions in the atmosphere and global temperature.

² We define disasters in this study as those natural events that lead to a certain number of deaths (≥ 100 people) and/or people affected ($\geq 1,000$ people needing immediate assistance with food, water, shelter, sanitation, or medical assistance) in a given period of time.

³ In this study, we consider those flood and storm events as those events that cause at least 100 deaths and/or directly affect at least 1,000 people.

Table 1. Hydrometeorological disasters across countries, 1970–2016

Variable	Obs.	Mean	SD	Min.	Max.
Dependent Variable					
Frequency of intense hydro-meteorological disasters	6,109	0.723	1.660	0.000	25.000
Ln of population density (in people/km ²)	6,109	3.847	1.484	0.076	9.971
Ln of GDP, (per capita constant 2010 USD)	6,109	8.148	1.413	5.101	11.425
Square of Ln GDP (per capita constant 2010 USD)	6,109	68.255	23.452	26.021	130.526
Average precipitation deviation (in mm)	6,109	−1.836	16.654	−154.599	161.902
Population (in million)	6,109	39.197	134.527	0.040	1,378.665
Global Variables (1970–2016)					
CO ₂ level (parts per million)	47	359.550	20.606	324.933	398.123
CO ₂ deviation from level in 1970 (parts per million)	47	34.533	23.040	0.000	78.560

Source: EM DAT data, and authors' calculations.

Meanwhile, one independent or explanatory variable is the *people's exposure to hazards*, (U_{it}). This exposure pertains to the presence of people and assets in geographic locations affected by natural hazards. As a proxy for the degree to which people might locate in risky areas, we use some widely available measures of population density. Cities are naturally featured to be highly exposed as they have high population densities and asset exposures. Many cities with very high population densities (e.g., such as Bangkok, Jakarta, and Manila) are also built on flood plains or low-lying coastal areas. Among the highly exposed major cities in the world, the top seven are in Asia (Maplecroft, 2015).

A second explanatory variable is *people's vulnerability to the hazards* (V_{it}). This is influenced by socioeconomic factors and is related to the people's capacity to protect themselves. As a proxy, we use GDP per capita estimates. Looking at the data, we can see that the measure of vulnerability deteriorates as income initially increases before it improves at higher income levels (Kellenberg & Mobarak, 2008). Rising incomes in low-income countries seem to increase risky practices, disaster risks, and hence people's vulnerability. As income rises further, these risks seem to be more than compensated as the countries are able to afford infrastructure and institutions to ameliorate the risks.

The role of income in representing vulnerability is intuitive. Majority of the deaths from disasters have occurred in lower-income countries, whereas within countries, the poor are hit the hardest (IPCC, 2012; Mora et al., 2018). That said, natural hazards have been increasingly affecting both developed and developing

countries. Likewise, lower incomes are associated with weak government capacity and lack of basic facilities that would have enabled them to be resilient to disasters. A country with a GDP per capita of USD 12,800 would significantly suffer from fewer deaths than another country with a GDP per capita of USD 3,200 from a similar disaster (Kahn, 2005).

In this paper, we include a third variable—namely, a *climate variable*—within the socioeconomic model of disasters. That is, we look at the contribution of climate-related variables to the increase in the frequency of hydrometeorological disasters, in addition to the contribution of exposure and vulnerability. As a reflection of the effect of climate change, we use publicly available data on the average precipitation deviations in the country (Schneider et al., 2011). These deviations are estimated in terms of the divergence from the average for the time period 1961–1990 (W_{it}).

A crucial independent variable in this analysis is the *global effect* (G_t). In the first approach, the variable G_t is represented by the accumulated CO₂ in the atmosphere based on in situ air measurements by the Mauna Loa Observatory (Tans & Keeling, 2015). This is then coupled with country dummies to have a variable reflecting differing country response.

In the second approach, we include time dummies per year in the regression analysis as additional dependent variables. They account for global impacts that are common-to-all-countries on the frequency of hydrometeorological disasters. Once we do the estimation, the estimated coefficients of our variable G_t

becomes the predicted coefficients of the time dummy variables. They capture global factors after controlling for exposure, vulnerability, and the climate hazard. The predicted coefficients of the time dummy variables can also capture global factors that are not necessarily related to climatic variables. For example, technological and communication improvements may increase the number of reported disasters. In the second approach, G_t can also capture the effect of more people locating in hazard-prone areas (Adger, Hughes, Folke, Carpenter, & Rockstrom, 2005; Barbier, 2015). In this case, we can artificially inflate the value of the global effects. The cointegration analysis in stage II brings out the role of CO_2 on global effects that is separate from these other non-climatic effects. Finally, v_{it} is the stochastic error, in which we assume the mean to be one. Its standard deviation σ_v is estimated inside the model (Table 2).

Since H_{it} represents the realization of a stochastic variable, we want to estimate correctly the parameters α_0 ,

α_1 , α_2 , α_3 and α_4 in Equation (1) to separate the effect of each independent variable and then determine how each affects the frequency of intense hydrometeorological disasters.

$$E[H_{it}|U_{it}, V_{it}, W_{it}, G_t, v_{it}] = \exp(\alpha_0 + \alpha_1 U_{it} + \alpha_2 V_{it} + \alpha_3 W_{it} + \alpha_4 G_t) \exp(v_{it}) \quad (1)$$

We then estimate the parameters of the following regression equation using the annual data for 155 countries during 1970–2016 (Appendix Table A1), thereby making a total of 6,109 observations. Since the dependent variable consists of nonnegative count values, count regression models such as the Poisson (P) or negative binomial (NB) need to be used. We choose the NB model because it is more general than the P model. Moreover, our preliminary statistic tests showed that the former fits the data better (see Appendix B1). Table 1 gives evidence that the model satisfies the NB assumptions because the mean and the variance (i.e., square of the standard deviation) are different.

Table 2. Determinants of intense hydrometeorological disasters using the NBZI method, 1970–2016

Explanatory Variables	Approach 1 (one-way fixed effects)	Approach 2 (two-way fixed effects) ^a
	(1)	(2)
Exposure		
Ln (population density)	1.291000*** [0.194000]	0.039600*** [0.233000]
Population (million)	0.000098 [0.000461]	0.0000345 [0.000415]
Vulnerability		
Ln GDP per capita (constant 2010 USD)	0.239000 [0.413000]	0.331000 [0.445000]
Square of Ln GDP per capita (constant 2010 USD)	−0.023000 [0.027300]	−0.035500 [0.030300]
Local Climate Condition		
Average precipitation deviation (mm)	0.001350*** [0.000124]	0.0011800*** [0.0001530]
Global climate indicator		
CO ₂ level (ppm)	0.007320*** [0.002700]	time dummy coefficients
Observations	6,190.000000	6,109.000000
Error' standard deviation (σ_v)	4.530000	3.440000
Akaike information criterion (AIC)	10,314.040000	10,156.810000
Bayesian information criterion (BIC)	11,422.430000	11,567.490000
LR Test	115.370000***	120.890000***
Vuong Test	2.50000***	2.530000***

Notes: *** pertains to estimates that are significant at 1%. Estimates in brackets are standard errors.

The dependent variable is the “count” or incidence of intense disasters. In this study, this variable is modeled for situations in which the data have an excess of zero count. As such, we find that about two-thirds of the annual country observations for intense hydrometeorological disasters have zero count. It is important to consider the presence of zeros in the dependent variable in order to avoid inconsistent estimators. Accordingly, we employ the zero-inflated (ZI) count model to avoid this issue (Johnson, Kemp, & Kotz, 2005; Lambert, 1992).

Our model also allows us to check the origin of the zero-observed dependent variable: either because a country in a year has a zero probability of having a disaster, or a country nevertheless has no disaster for random reasons despite having a positive probability of a disaster (Vuong, 1989) (see Appendix B2). By ignoring the zeroes in the dependent variable, the application of the ZI model lowers the risk of deriving inconsistent estimators. Thus, we use a combination of negative binomial and zero-inflated model (NBZI).

The estimated coefficients of the time dummies obtained from the two-way fixed effects model are subjected to a cointegration analysis (Engle & Granger, 1991) with the annual data on atmospheric CO₂. Cointegration helps us to know whether the estimated time dummy coefficients and the global climate variable are positively correlated in a non-spurious way.

However, one issue with this regression analysis is that the series may jointly trend upwards, thereby giving a positive and significant coefficient without necessarily implying that they are related (Granger & Newbold, 1974). This is the case when “the series is not covariance stationary”; this means that the series does not have finite means, and that the auto covariance changes over time. A second concern is that the relationship between the series may be influenced by the other omitted variables that are not considered in the regression.

López, Thomas, & Troncoso (2016b, p. 7) show how cointegration allows us to deal with these two problems by “testing whether particular transformations of the series yield covariance stationary processes, and hence can be used to obtain meaningful estimates, and whether omitted variables are still consistent with non-spurious correlations over the long run”. The covariance stationarity of the series of first differences does not mean that the first differences of the series must correlate. In fact, correlation between first differences exists if the series are only contemporaneously correlated. However, if the series correlates through lag effects, as is in fact the most likely case, then simply analyzing the series of first differences would not capture the lag correlation. Thus, cointegration testing allows both contemporaneous correlations and lagged effects.

If we pass the tests of cointegration, then we can assert that regardless of the omitted variables, the estimated

co-integrating coefficient may be biased (Lütkepohl, 1982) and consistent (Pashourtidou, 2003). Even here, the short-term coefficients may be biased. However, we are concerned with the long-term connection between atmospheric CO₂ concentration and the rise in the incidence of intense hydrometeorological disasters.

Note that significant correlations signaled by cointegration do not necessarily signify causality. However, we can view this as: if two variables show a non-spurious and meaningful correlation, then there must be causality in at least one direction (Granger, 1988; Asteriou & Hall, 2011). Moreover, previous knowledge may allow us to reject one of the two directions. Thus, we could have a causal relation to underlie a non-spurious correlation between the two series. Also, there are alternative causality tests that can be used to determine causality (Govindaraju & Tang, 2013).

Results

The data assembled in this study present an intuitive depiction of a rising incidence of intense hydrometeorological disasters within the socioeconomic settings of different geographical regions. The means presented give a one-shot picture, whereas the standard deviations bring out the wide variations geographically (Table 1). We focus on the incidence of what may be characterized as intense floods and storms, which vary greatly across countries and regions. Climate impacts and people’s exposure and vulnerability to climate hazards vary greatly among countries. However, what is common is the global effect of atmospheric CO₂ concentrations, which this study seeks to delineate.

The estimates in Table 2 present the core results of this study to explain the factors that determine the frequency of intense hydro meteorological disasters. The first column shows the estimate resulting from the first approach (one-way fixed effects), which uses country dummies and with the annual level of CO₂ proxying global climate change as an independent variable. The second column presents the estimates resulting from the second approach (two-way fixed effects), which uses time dummies and country fixed effects.

The estimates are intuitive and plausible. The local climate variable is highly significant and has the expected signs. Precipitation deviations exert a positive impact on the number of intense local hydrometeorological disasters. Moreover, according to one-way fixed effects, the variable atmospheric CO₂ concentration is positive and highly significant. However, this global climate variable could be correlated with other global variables, which can affect the frequency of disasters. This would imply that the CO₂ coefficient is biased.

In the two-way fixed effects model (stage I of the second approach), on the other hand, the coefficients of the time

dummy variables capture any global effects whether they are climate-related or not. The most important result is that around 70% of the estimated time dummy coefficients are significant at 10% significance level, and they also increase over time (Table 3 and Figure 2). Thus, beyond country effects, there are global effects that affect the frequency of intense disasters.

In stage II, we implement a cointegration analysis between the time dummy coefficients and the annual concentration of CO₂. The standard deviations of the errors are 4.5 and 3.40 in the first and second approaches, respectively. These values imply that although all the explanatory variables play a crucial role, there is still room for random behavior among countries. These results confirm that the population's increasing risk exposure and vulnerability to natural hazards play a role in determining the frequency of big hydrometeorological calamities. Furthermore, it shows how climate change factors help to explain the phenomenon.

Local precipitation deviations significantly affect intense hydrometeorological disasters. The parameters are positive and significant in both models, which confirm the importance of precipitation deviations as sources of intense hydrometeorological disasters. This variable has also been analyzed in the study of Thomas, Albert, and Hepburn (2014).

When we use the first approach, the global climate factor (as represented by the atmospheric CO₂ accumulation data of the Mauna Loa Observatory) appears to be very important in explaining disasters (Table 2). In the second approach, the coefficients of the time dummy variables, which may be related to CO₂ accumulation, also help to determine country disasters.

The estimates of the time dummy coefficients common to all countries in the second approach are increasing over time. They are significant when taken altogether; for the most part, each coefficient is also significant. This suggests that global factors, which are likely related to carbon emissions, impact climate disasters in addition to the influence of local factors. This finding makes a strong case for global action in addition to what is currently being done at the country and local levels.

Role of Global Warming

Several papers have argued that a global warming similar to the current trends had already occurred in the distant past, and that the current changes in climatic patterns cannot be solely attributed to human activities (see for example, Michaels, 2008). Most of the scientific evidence summarized in the 2014 IPCC report presents more broadly the link between the more recent global warming and the accumulation of CO₂ and CH₄ in the

Table 3. Estimated Coefficients of the Time Dummy Variables (Approach 2 Stage I)

Year	Coef.	Year	Coef.	Year	Coef.	Year	Coef.	Year	Coef.
1971	-0.507*	1981	0.332	1991	0.442*	2001	1.314***	2011	1.299***
	[0.288]		[0.265]		[0.260]		[0.265]		[0.302]
1972	-0.407	1982	0.482*	1992	0.709***	2002	1.357***	2012	1.375***
	[0.317]		[0.251]		[0.253]		[0.264]		[0.305]
1973	-0.307	1983	0.435*	1993	1.100***	2003	1.175***	2013	1.007***
	[0.302]		[0.236]		[0.240]		[0.271]		[0.309]
1974	-0.136	1984	0.297	1994	0.934***	2004	1.352***	2014	0.887***
	[0.296]		[0.246]		[0.259]		[0.275]		[0.325]
1975	-0.892**	1985	0.559**	1995	1.085***	2005	1.505***	2015	1.186***
	[0.347]		[0.240]		[0.249]		[0.283]		[0.319]
1976	-0.439	1986	0.483**	1996	0.886***	2006	1.554***	2016	0.924***
	[0.302]		[0.235]		[0.268]		[0.286]		[0.322]
1977	0.143	1987	0.580**	1997	0.738***	2007	1.550***		
	[0.269]		[0.237]		[0.257]		[0.285]		
1978	0.407	1988	0.653***	1998	1.059***	2008	1.436***		
	[0.261]		[0.244]		[0.270]		[0.289]		
1979	0.169	1989	0.303	1999	1.047***	2009	1.394***		
	[0.270]		[0.265]		[0.266]		[0.290]		
1980	0.212	1990	0.370	2000	1.207***	2010	1.477***		
	[0.239]		[0.246]		[0.269]		[0.296]		

Notes: * = significant at 10%, ** = significant at 5%, *** = significant at 1%. Standard errors in brackets.

atmosphere (IPCC, 2014). Figure 3 gives the basic motivation for tracking this link.

Accordingly, a time-series analysis could show whether there is indeed a significant relationship between the increased global effect and the accumulated stock of CO₂. The test is whether the series of time dummy coefficients and CO₂ accumulation would cointegrate. If they do, then there is likely a non-spurious relationship between global warming and disasters on the one side and atmospheric CO₂ accumulation on the other.

The first panel of Figure 2 shows the estimated coefficients of the time dummy variables for intense

hydrometeorological disasters and CO₂ concentrations from 1970 to 2016. Both series show rising trends during the period. The series in levels appear to be non-covariance-stationary, suggesting that any regression between the two data series that give values of the variables in levels would yield spurious estimates. Accordingly, the Dickey-Fuller test suggests that the series are indeed non-covariance-stationary (Elliott, Rothenberg, & Stock, 1996; MacKinnon, 1994).

The second panel of Figure 2 shows the series expressed in first differences, which appear to be stationary. We then test—as a necessary but not sufficient condition—for cointegration between the series. Also, although

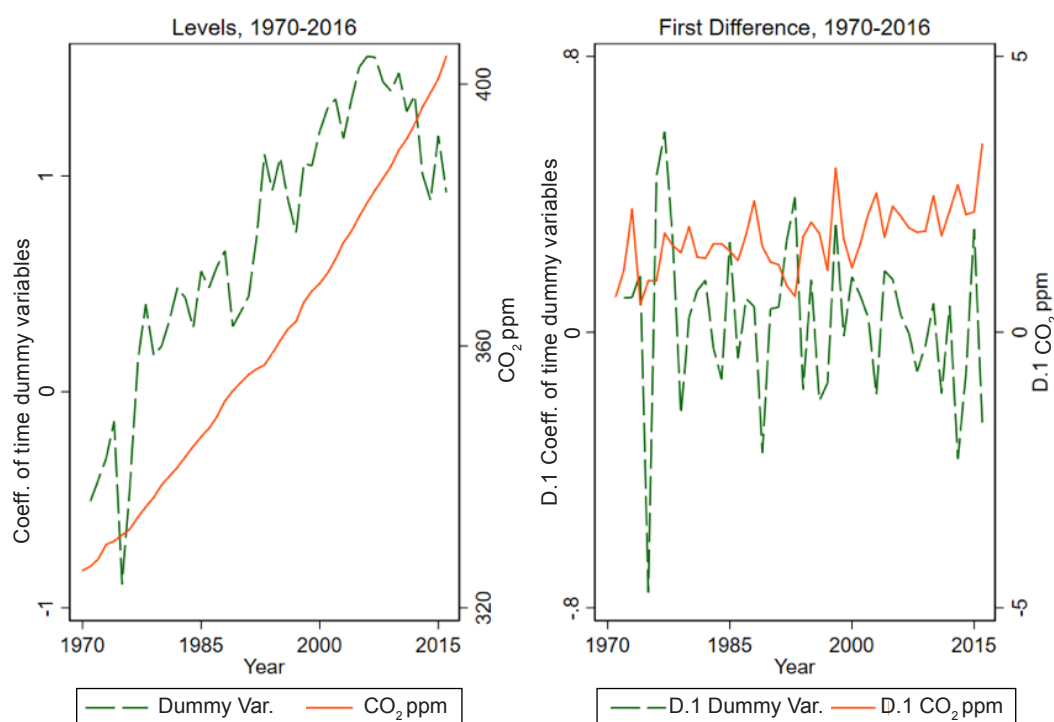


Figure 2. Coefficient of time dummy variables of hydrometeorological events and CO₂ stocks, 1970–2016

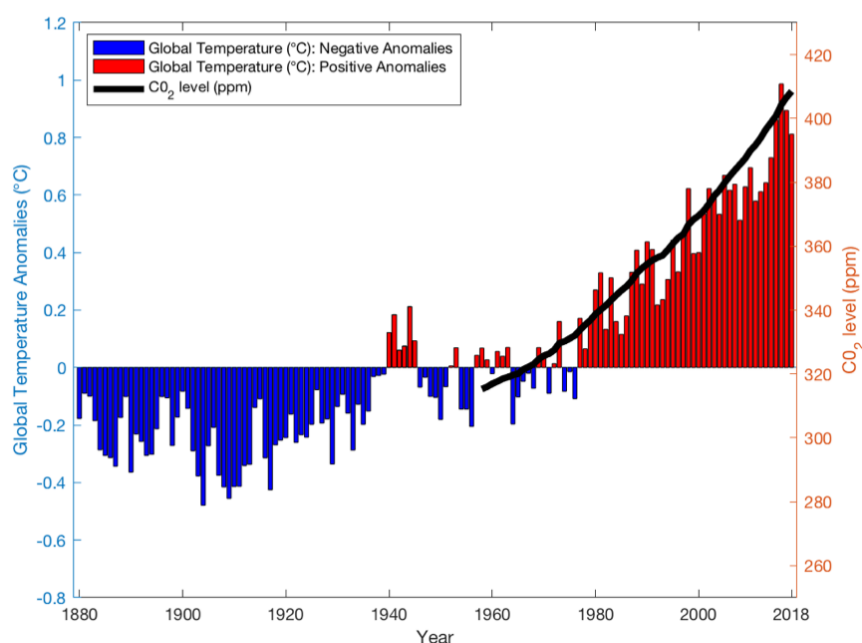


Figure 3. Global temperature anomalies (C) and CO₂ ppm
Source of basic data: NASA (2019) and NOAA (2018)

the first differences of the series may not correlate, a linear combination of the series that integrate is enough for cointegration. Thus, the lagged values of the series might correlate.

Table 4 provides this regression estimate in the first column.⁴ The standard error (not shown) is not distributed asymptotically normal, and thus the estimated coefficients can be used to test for co-integration. Even if all individual series in levels are nonstationary, the linear combination of the estimates of the two nonstationary series may be stationary. For instance, a nonstationary process with a deterministic trend becomes stationary after removing the trend (de-trending). If two series present the same “trend”, then a linear combination of both could remove the implicit trend. Indeed, it is what the cointegration process does.

Thus, given that both series in levels are not covariance stationary, if the *predicted errors* are stationary, then we have evidence of cointegration between the time

dummy values and CO₂. López, Thomas, & Troncoso (2016a, p. 7) provide details of “the tests of stationarity or cointegration using the series of predicted errors obtained from the regression estimation”.⁵ The tests allow rejecting the null hypothesis that the error is not covariance stationary, implying that the series cointegrate. We also implemented a stronger cointegration test, which estimates a vector error correction model (VECM) between intense hydrometeorological disasters and the CO₂ (Johansen, 1995). This too shows cointegration between the series (Appendix Table B1).

However, the autoregressive distributed lags (ARDL) is more advisable to use when the sample size is small (Pesaran, Shin, & Smith, 2001). Thus, we also apply ARDL as shown in the second column of Table 4. A non-spurious correlation between the series can be claimed because the coefficient of CO_{2(t-1)} is positive and significant, and the error correction coefficient ($\hat{\rho}_1$) is negative and significant.

Table 4. Regression and cointegration analysis for the disasters: CO₂

Parameter	Hydrometeorological	
	Level	First Diff. (D.1) (ECM)
CO ₂ level (in ppm)	0.0232 [0.00289]	
D.1 CO _{2 (t-1)} (in ppm)		0.0228 [0.0796]
Coefficients of the Time Dummy Variables _(t-1) ($\hat{\rho}_1$)		-0.230*** [0.101]
CO _{2(t-1)} ($\hat{\rho}_2$)(in ppm)		0.00430* [0.0026]
Constant	-7.661*** [1.034]	-1.254* [0.981]
Observations	46.00000	45.000
AIC	30.63511	-0.935
BIC	34.29239	6.291
Tests for Stationarity		
Dickey-Fuller (DF)	-3.02200**	
Dickey-Fuller Generalized Least Squares (DF-GLS)	-2.59900*	

Notes: * and *** refer to values that are significant at the 10%, and 1% levels, respectively. Values in brackets are standard errors.

⁴ Method 3 in Appendix B describes the model for estimation using ordinary least squares.

⁵ See Appendix B4 for a detailed explanation of the model.

Results also show that the cointegrating coefficient is positive and statistically significant at 1% level (Appendix Table B2). Consequently, even if there are omitted variables, the estimated correlation measured by the regression analysis seems non-spurious. The estimated coefficient is then consistent (Pashourtidou, 2003) although it may be biased (Lütkepohl, 1982). Therefore, the possible existence of omitted variables does not invalidate a true relationship between the series (see one application of these tests in Shahbaz, Tang, & Shabbir, 2011).

Furthermore, if two variables exhibit a non-spurious correlation, then we can expect at least one direction of causality (Granger, 1988; Asteriou & Hall, 2011). The direction of causality, however, can be in either direction under alternative theories and computations.⁶ In the present analysis, the causal direction is likely from carbon emissions to intense hydrometeorological disasters, rather than the other way around.

Significance of the Results

Table 5 shows the estimated elasticity of the time dummy coefficients of intense hydrometeorological disasters with respect to the atmospheric CO₂ concentrations evaluated at the mean values. Elasticity is the measure of the proportional change of one variable in response to a change in another. In our case, it represents the

proportional change in the coefficients of time-dummy variables of intense hydrometeorological disasters due to a 1% change in the atmospheric CO₂ concentrations.

We now estimate the impact of the changes in the time dummy coefficients on the level of disasters by applying the measures from the two-way fixed effect regressions⁷ using the values of the second column in Table 4. The combination of these two effects gives the net effect of CO₂ on the frequency of intense disasters. Thereafter, we simulate the effects of the increases of CO₂ on the number of intense disaster by using the estimated elasticity of disasters with respect to CO₂.

Table 6 shows the elasticity of disasters with respect to CO₂ using information from 1970 to 2016. Our results show that if CO₂ level increases by 1%, then the hydrometeorological disasters would increase by 8.96 % (see Appendix B6). Using this elasticity, we then project the number of intense disasters in the future. For instance, the yearly increase in atmospheric CO₂ has been about 2.4 ppm, or about 0.6% of the base 396.54 ppm level, from 2010 to 2016. We choose this period to reflect the more recent and higher trend in the CO₂ level as compared to that between 1970 and 2016, in which the average CO₂ increase is around 1.70 ppm. Accordingly, the number of intense hydrometeorological disasters could increase by 5.4% annually for the “average”⁸ country or by 0.05 more disasters. This is with respect

Table 5. Elasticity of coefficient of time dummy variables with respect to CO₂

Parameter	Estimate
Marginal effect ($\hat{\beta}$)	0.0180
Standard deviation ($\hat{\beta}$)	0.0070
Average sample value of CO ₂ level, 1970–2016 (in ppm)	360.2134
Average value of coefficients of the time dummy variables, 1970–2016 (in number of disasters)	0.7117
Elasticity of coefficients of the time dummy variables with respect to the atmospheric CO ₂ level	9.1007

Table 6. Impacts of CO₂ emissions on the incidence of global intense hydrometeorological disasters

Parameter	Value
Elasticity of disasters with respect to CO ₂ (1970–2016)	8.96
For simulation (2010–2016)	
CO ₂ level (in ppm)	396.5
Current yearly CO ₂ increase (in ppm)	2.4
Simulated variation in intense disasters due to rate of increases in CO ₂ level (%)	5.4

⁶ See Appendix B4 for a detailed explanation of the model used in this study and Appendix Table B3 for the detailed results.

⁷ The method for deriving the estimated effects of CO₂ levels on disasters is explained in Appendix B3.

⁸ Average country stands for the simple mean across the 155 countries.

to the 2010–2016 average, which is 0.856 disasters per year. This implies that under the current trend in the increase in atmospheric CO₂ accumulation, the number of intense hydrometeorological disasters could double in 13 years or from an average of 0.856 to 1.71 disasters annually.

These estimated effects of CO₂ accumulation on disasters are not much larger than those obtained from climate change models. Likewise, climate change models predict that the increase in accumulated CO₂ stock would have massive effects on the number of intense hydrometeorological disasters. Climate model estimates predict that if CO₂ concentrations double, then the frequency of Category 5 hurricanes may triple (Anderson & Bausch, 2006). Moreover, the models estimate that an increase of 1 °C in global temperature would increase the number of Category 3 (e.g., hurricane Katrina) events by seven times (Grinsted et al., 2013). If GHG concentrations will continue to rise throughout the 21st century, then climate change—even under mitigation scenarios—will still continue to affect humanity, particularly those in the tropical coastal areas (Mora et al., 2018).

Sensitivity Analysis

Table 5 shows the cointegration coefficient (0.0180) and its standard deviation (SD = 0.007). Using the coefficient plus and minus the standard deviation, we get the interval [0.011, 0.025], which represents the most likely values for our parameter. These numbers allow us to recalculate the elasticities and the simulated variation in the frequency of intense disasters due to the rate of increase in atmospheric CO₂ level. Taking the minimum and the maximum values in the interval, we find that the number of intense hydrometeorological disasters could increase by 3.3%–7.5% annually for the “average” country. This translates to additional 0.03–0.06 intense disasters per year. Furthermore, this means that the number of intense hydrometeorological disasters could double in 10 or 21 years, depending on which extreme point in the interval we use. If we repeat the same process but use the values inside of the two standard deviations, then our cointegration coefficient moves between [0.004, 0.032]. Accordingly, we find that the number of intense hydrometeorological disasters could double between 8 and 58 years when we use both extreme numbers in the interval.

Conclusion

The frequency of intense hydrometeorological events worldwide has been increasing over the recent years. As such, governments and climate experts are scrutinizing the factors that contribute to this upward trend in order to guide policy actions. Climate experts generally agree that global warming has been observable since 1980 (Figure 3). However, there have been different views

on how much global warming contributes to the rise in intense hydrometeorological events, let alone how much of that can be attributed to anthropogenic factors.

This study has developed a framework that includes the role of socioeconomic factors (i.e., people’s exposure and vulnerability to the hazards) and has attempted to delineate the role of human-driven climatic factors in the increase in the incidence of intense hydrometeorological disasters. Specifically, we applied econometric and statistical methods to get robust results. Accordingly, our results show that atmospheric CO₂ accumulations and climate-related disasters are significantly and positively correlated. Furthermore, we find that a large proportion of the increase in the frequency of intense hydrometeorological disasters is correlated with the continuous increase in atmospheric CO₂ concentrations. Similar results have also been found in the study of Mora et al. (2018).

Reducing people’s exposure and vulnerability to climate hazards through developing and implementing appropriate climate adaptation and disaster risk reduction measures can help to lighten the increasing threats from natural hazards. The higher incidence of extreme natural hazards and even the population’s high exposure do not automatically lead to disasters. In view of this, governments should prioritize and invest in initiatives that would decrease people’s vulnerability to climate-related hazards; such initiatives could be in the form of prevention strategies and disaster risk reduction. These kinds of responses are included in our analysis either as country effects (i.e., some countries invest more than others) in approach I, or global effects (i.e., improvements among all countries, which vary over time) in approach II.

The link found in this paper between the incidence of natural calamities and increase in atmospheric CO₂ has implications for environmental and economic policies (Gaillard, 2012). Rather than reacting to events as one-off and unpredictable occurrences, human made events call for investments in prevention and mitigation programs. Our finding that the number of intense hydrometeorological disasters could double in 13 years under current trends then calls for far greater investments in disaster risk reduction and mitigation on the part of countries and the global community.

The global evidence presented in this study, together with the attribution of specific disasters to climate change in the growing literature, are grounds for far stronger economic and environmental policies to ameliorate the growing damages from natural calamities. On the one side, there needs to be climate adaptation efforts, such as relocating people from highly exposed coastal regions or building better disaster preparedness that would withstand extreme hurricanes. Equally, given the findings on the role of human-induced climate change, there is a strong case for stepping up climate change

mitigation. Countries need to invest substantially and urgently in decarbonizing their economies.

References

- Adger, W. N., Hughes, T. P., Folke, C., Carpenter, S. R., & Rockström, J. (2005). Social-ecological resilience to coastal disasters. *Science*, 309(5737), 1036–1039.
- Alley, R. B., Marotzke, J., Nordhaus, W. D., Overpeck, J. T., Peteet, D. M., Pielke, R. A., ... & Wallace, J. M. (2003). Abrupt climate change. *Science* 299:2005–2010.
- Anderson, J. & Bausch, C. (2006, January). *Climate change and natural disasters: Scientific evidence of a possible relation between recent natural disasters and climate change*. (Brief No. 02a-2006). Brussels, Belgium: Policy Department Economic and Scientific Policy-European Parliament.
- Arnell, N. W., & Gosling, S. N. (2016). The impacts of climate change on river flood risk at the global scale. *Climatic Change*, 134(3), 387–401.
- Asteriou, D., & Hall, S. G. (2011). *Applied econometrics*. London, UK: Macmillan International Higher Education.
- Banhölzer, S., Kossin, J., & Donner, S. (2014). The impact of climate change on natural disasters. In Z. Zommer & A. Singh (Eds.), *Reducing disasters: Early warning systems for climate change* (pp. 29–49). Berlin, Germany: Springer Science and Business Media.
- Barbier, E. B. (2015). Policy: Hurricane Katrina's lessons for the world. *Nature News*, 524(7565), 285.
- Cheng, L. J., Trenberth, K. E., Fasullo, J., Abraham, J., Boyer, T. P., von Schuckmann, K., & Zhu, J. (2017). Taking the pulse of the planet. *Earth and Space Science News, Eos*, 99, 14–16.
- Cornwall, W. (2016). Efforts to link climate change to severe weather gain ground. *Science*, 351(6279), 1249–1250.
- Diffenbaugh, N. S., Swain, D. L., & Touma, D. (2015). Anthropogenic warming has increased drought risk in California. *Proceedings of the National Academy of Sciences*, 112(13), 3931–3936.
- Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R., & Mearns, L. O. (2000). Climate extremes: Observations, modeling, and impacts. *Science*, 289(5487), 2068–2074.
- Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, 64(4), 813–836.
- Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature*, 436(7051), 686.
- Engle, R., & Granger, C. (1991). *Long-run economic relationships: Readings in cointegration*. Oxford, UK: Oxford University Press.
- Gaillard, J. C. (2012). The climate gap. *Climate and Development*, 4(4), 261–264.
- Govindaraju, V. C., & Tang, C. F. (2013). The dynamic links between CO₂ emissions, economic growth and coal consumption in China and India. *Applied Energy*, 104, 310–318.
- Granger, C. W., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of econometrics*, 2(2), 111–120.
- Granger, C. W. (1988). Some recent development in a concept of causality. *Journal of econometrics*, 39(1–2), 199–211.
- Griffiths, M. L., Drysdale, R. N., Gagan, M. K., Zhao, J. X., Ayliffe, L. K., Hellstrom, J. C., ... & Suwargadi, B. W. (2009). Increasing Australian-Indonesian monsoon rainfall linked to early Holocene sea-level rise. *Nature Geoscience*, 2(9), 636–639.
- Grinsted, A., Moore, J. C., & Jevrejeva, S. (2013). Projected Atlantic hurricane surge threat from rising temperatures. *Proceedings of the National Academy of Sciences*, 110(14), 5369–5373.
- Guha-Sapir, D., Hoyois, P., & Below, R. (2015) *Annual disaster statistical review 2014: The numbers and trends*. Brussels, Belgium: Centre for Research on the Epidemiology of Disasters.
- Hallegatte, S. (2012). Economics: The rising costs of hurricanes. *Nature Climate Change*, 2(3), 148.
- Hallegatte, S., & Rozenberg, J. (2017). Climate change through a poverty lens. *Nature Climate Change*, 7(4), 250–256.
- Hauer, M. E., Evans, J. M., & Mishra, D. R. (2016). Millions projected to be at risk from sea-level rise in the continental United States. *Nature Climate Change*, 6(7), 691.
- Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). *Characterizing selection bias using experimental data* (NBER Working Paper Series No. w6699). Cambridge, MA: National Bureau of Economic Research.
- Herring, S. C., Hoerling, M. P., Peterson, T. C., & Stott, P. A. (2014). Explaining extreme events of 2013 from a climate perspective. *Bulletin of the American Meteorological Society*, 95(9), S1–S104.
- Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., ... & Kanae, S. (2013). Global flood risk under climate change. *Nature Climate Change*, 3(9), 816.

- Hoerling, M., Eischeid, J., Perlwitz, J., Quan, X., Zhang, T., & Pegen, P. (2012). On the increased frequency of Mediterranean drought. *Journal of climate*, 25(6), 2146–2161.
- Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, 8, 43–75.
- Huq, S., Reid, H., Konate, M., Rahman, A., Sokona, Y., & Crick, F. (2004). Mainstreaming adaptation to climate change in least developed countries (LDCs). *Climate Policy*, 4(1), 25–43.
- Intergovernmental Panel on Climate Change (IPCC). (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation. Special Report*. Cambridge, UK/ New York, USA: Cambridge University Press.
- IPCC. (2013). Summary for policymakers. In T.F. Tocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, ...& P.M. Midgley (Eds.) *Climate change 2013: The physical science basis. Contribution of Working Group I to the fifth assessment report of the Intergovernmental Panel on Climate Change. Fifth assessment report* (pp. 3–29). Cambridge, UK/New York, USA: Cambridge University Press.
- IPCC. (2014). *Climate change 2014: Impacts, adaptation, and vulnerability. Contribution of Working Group II to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge, UK/New York, USA: Cambridge University Press.
- Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford, UK: Oxford University Press.
- Johnson, N. L., Kemp, A. W., & Kotz, S. (2005). *Univariate discrete distributions* (Vol. 444). Hoboken, NJ: John Wiley & Sons.
- Kahn, M. E. (2005). The death toll from natural disasters: The role of income, geography, and institutions. *Review of Economics and Statistics*, 87(2), 271–284.
- Kellenberg, D. K., & Mobarak, A. M. (2008). Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics*, 63(3), 788–802.
- Knutson, T. R., McBride, J. L., Chan, J., Emanuel, K., Holland, G., Landsea, ...& Sugi, M. (2010). Tropical cyclones and climate change. *Nature Geoscience*, 3(3), 157–163.
- Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., ... & Muir-Wood, R. (2014). Flood risk and climate change: global and regional perspectives. *Hydrological Sciences Journal*, 59(1), 1–28.
- Lambert, D. (1992). Zero-inflated Poisson regression, with an application to defects in manufacturing. *Technometrics*, 34(1), 1–14.
- Lee, W. S., & Lee, M. I. (2016). Interannual variability of heat waves in South Korea and their connection with large-scale atmospheric circulation patterns. *International Journal of Climatology*, 36(15), 4815–4830.
- Levitus, S., Antonov, J. I., Boyer, T. P., & Stephens, C. (2000). Warming of the world ocean. *Science*, 287(5461), 2225–2229.
- Levitus, S., Antonov, J. I., Wang, J., Delworth, T. L., Dixon, K. W., & Broccoli, A. J. (2001). Anthropogenic warming of Earth's climate system. *Science*, 292(5515), 267–270.
- López, R. E., Thomas, V., & Troncoso, P. (2016a). Is climate change behind the rise in natural disasters? Unpublished manuscript, Lideres Empresariales por la Accion Climatica (Business Leaders for Climate Action), University of Chile, Santiago, Chile.
- López, R. E., Thomas, V., & Troncoso, P. (2016b). *Economic growth, natural disasters and climate change*. (Working Paper Series No. 434). Santiago, Chile: Economics Department, University of Chile.
- Lütkepohl, H. (1982). Non-causality due to omitted variables. *Journal of Econometrics*, 19(2–3), 367–378.
- MacKinnon, J. G. (1994). Approximate asymptotic distribution functions for unit-root and cointegration tests. *Journal of Business & Economic Statistics*, 12(2), 167–176.
- Magadza, C. H. D. (2000). Climate change impacts and human settlements in Africa: prospects for adaptation. *Environmental Monitoring and Assessment*, 61(1), 193–205. Chicago.
- Michaels, P. J. (2008). Global warming and climate change. In D. Boaz (ed.), *Cato handbook for policymakers* (7th ed.) (pp. 475–488). Washington, D.C., VA: Cato Institute.
- Min, S. K., Zhang, X., Zwiers, F. W., & Hegerl, G. C. (2011). Human contribution to more-intense precipitation extremes. *Nature*, 470(7334), 378–381.
- Mora, C., Spirandelli, D., Franklin, E. C., Lynham, J., Kantar, M. B., Miles, W., ...& Hunter, C. L. (2018). Broad threat to humanity from cumulative climate hazards intensified by greenhouse gas emissions. *Nature Climate Change*, 8(12), 1062.
- National Aeronautics and Space Administration. (2019, December 13). Global climate change [Facts and figures]. Retrieved from <https://climate.nasa.gov/vital-signs/carbon-dioxide/>
- NOAA National Centers for Environmental Information. (2018). State of the climate: Global climate report for annual 2017 (Annual Report 2017). Retrieved from <https://www.ncdc.noaa.gov/sotc/global/201713>
- Nuccitelli, D. (2014). California just had its worst drought in over 1200 years, as temperatures and risks rise. *The Guardian*. Retrieved from <http://www.theguardian.com>.

- Otto, F. E., Massey, N., van Oldenborgh, G. J., Jones, R. G., & Allen, M. R. (2012). Reconciling two approaches to attribution of the 2010 Russian heat wave. *Geophysical Research Letters*, 39(4). doi: 10.1029/2011GL050422
- Pall, P., Aina, T., Stone, D. A., Stott, P. A., Nozawa, T., Hilberts, ...& Allen, M. R. (2011). Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. *Nature*, 470(7334), 382–385.
- Pashourtidou, N. (2003). *Omitted variables in cointegration analysis*. (Discussion Papers in Economics and Econometrics Issue No. 304). Southampton: University of Southampton.
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326.
- Pretis, Felix. (2019). Econometric modelling of climate systems: The equivalence of energy balance models and cointegrated vector autoregressions. *Journal of Econometrics*, 214(1), 256–273.
- Rahmstorf, S., & Coumou, D. (2011). Increase of extreme events in a warming world. *Proceedings of the National Academy of Sciences*, 108(44), 17905–17909.
- Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., & Ziese, M. (2011). GPCC full data reanalysis version 6.0 at 0.5: Monthly land-surface precipitation from rain-gauges built on GTS-based and historic data. [GPCC Data Rep.]. Retrieved from <https://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html>.
- Schreider, S. Y., Smith, D. I., & Jakeman, A. J. (2000). Climate change impacts on urban flooding. *Climatic Change*, 47(1–2), 91–115.
- Shahbaz, M., Tang, C. F., & Shabbir, M. S. (2011). Electricity consumption and economic growth nexus in Portugal using cointegration and causality approaches. *Energy Policy*, 39(6), 3529–3536.
- Shaw, T. A., Baldwin, M., Barnes, E. A., Caballero, R., Garfinkel, C. I., Hwang, Y. T., ...& Voigt, A. (2016). Storm track processes and the opposing influences of climate change. *Nature Geoscience*, 9(9), 656–664.
- Stott, P. A., Stone, D. A., & Allen, M. R. (2004). Human contribution to the European heatwave of 2003. *Nature*, 432(7017), 610–614.
- Stott, P.A., Allen, M., Christidis, N., Dole, R.M., Hoerling, M., ...& Stone, D., (2013). Attribution of weather and climate-related events. In A. Ghassem & J. W. Hurrell (Eds.), *Climate science for serving society: Research, modeling, and prediction priorities* (pp. 307–337). Dordrecht, Netherlands: Springer Netherlands.
- Tans, P., & Keeling, R. (2015). Trends in atmospheric carbon dioxide. [Charts & figures]. Retrieved from www.esrl.noaa.gov/gmd/ccgg/trends/.
- Thomas, V., Albert, J. R. G., & Hepburn, C. (2014). Contributors to the frequency of intense climate disasters in Asia-Pacific countries. *Climatic Change*, 126(3–4), 381–398.
- Thomas, V. (2017). *Climate Change and Natural Disasters*. Rutledge.
- Tyler, S., & Moench, M. (2012). A framework for urban climate resilience. *Climate and Development*, 4(4), 311–326.
- Verisk Maplecroft. (2015). *Natural hazards risk atlas 2015*. Bath, UK: Verisk Maplecroft.
- Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica: Journal of the Econometric Society*, 57(2), 307–333.
- Webster, P. J., Holland, G. J., Curry, J. A., & Chang, H. R. (2005). Changes in tropical cyclone number, duration, and intensity in a warming environment. *Science*, 309(5742), 1844–1846.
- World Meteorological Organization. (2006, November). *Statement on tropical cyclones and climate change*. Statement presented at the 6th WMO International Workshop on Tropical Cyclones, San Jose, Costa Rica.

Appendices

Appendix A. Sample Countries

Table A1. Countries considered in the analysis, 1970–2016

No.	Country	No.	Country	No.	Country	No.	Country	No.	Country
1	Afghanistan	32	Comoros	63	Hong Kong	94	Morocco	125	Slovakia
2	Albania	33	Congo	64	Hungary	95	Mozambique	126	Slovenia
3	Algeria	34	The Democratic Republic of the Congo	65	India	96	Namibia	127	Solomon Islands
4	Angola	35	Costa Rica	66	Indonesia	97	Nepal	128	South Africa
5	Antigua and Barbuda	36	Cote d'Ivoire	67	Iran	98	Netherlands	129	Spain
6	Argentina	37	Croatia	68	Iraq	99	New Zealand	130	Sri Lanka
7	Armenia	38	Cuba	69	Ireland	100	Nicaragua	131	Sudan
8	Australia	39	Czech Republic	70	Israel	101	Niger	132	Suriname
9	Austria	40	Djibouti	71	Italy	102	Nigeria	133	Swaziland
10	Azerbaijan	41	Dominica	72	Japan	103	Norway	134	Switzerland
11	Bahamas	42	Dominican Republic	73	Jordan	104	Oman	135	Syrian Arab Republic
12	Bangladesh	43	Ecuador	74	Kazakhstan	105	Pakistan	136	Tajikistan
13	Belarus	44	Egypt	75	Kenya	106	Panama	137	Tanzania
14	Belgium	45	El Salvador	76	Korea	107	Papua New Guinea	138	Thailand
15	Belize	46	Eritrea	77	Kyrgyzstan	108	Paraguay	139	Timor-Leste
16	Benin	47	Ethiopia	78	Lao PDR	109	Peru	140	Togo
17	Bhutan	48	Fiji	79	Lebanon	110	Philippines	141	Trinidad and Tobago
18	Bolivia	49	France	80	Lesotho	111	Poland	142	Tunisia
19	Bosnia and Herzegovina	50	Gabon	81	Liberia	112	Portugal	143	Turkey
20	Botswana	51	Gambia	82	Lithuania	113	Puerto Rico	144	Uganda
21	Brazil	52	Georgia	83	Macao	114	Romania	145	Ukraine
22	Bulgaria	53	Germany	84	Macedonia	115	Russian Federation	146	United Kingdom
23	Burkina Faso	54	Ghana	85	Madagascar	116	Saint Kitts and Nevis	147	United States
24	Cambodia	55	Greece	86	Malawi	117	Saint Lucia	148	Uruguay
25	Cameroon	56	Grenada	87	Malaysia	118	Saint Vincent and The Grenadines	149	Uzbekistan
26	Canada	57	Guatemala	88	Mali	119	Samoa	150	Vanuatu
27	Central African Republic	58	Guinea	89	Mauritania	120	Saudi Arabia	151	Venezuela
28	Chad	59	Guinea-Bissau	90	Mexico	121	Senegal	152	Viet Nam
29	Chile	60	Guyana	91	Moldova	122	Serbia	153	Yemen
30	China	61	Haiti	92	Mongolia	123	Seychelles	154	Zambia
31	Colombia	62	Honduras	93	Montenegro	124	Sierra Leone	155	Zimbabwe

Appendix B. Statistical Models

1. Method 1: Poisson and negative binomial distributions.

Let H be a random variable for the number of disasters. If H follows a Poisson distribution, then the probability density function is

$$\Pr(H = h | \varsigma) = \frac{\exp(-\varsigma)\varsigma^h}{h!}, h = 0, 1, \dots$$

where h is a particular value of the variable H , and H has mean and variance.

$$E(H) = \text{Var}(H) = \varsigma$$

On the other hand, if H follows a negative binomial (NB) distribution, then the probability density function is

$$\Pr(H = h | \varsigma, \pi) = \frac{\Gamma(h + \pi^{-1})}{h! \Gamma(\pi^{-1})} \left(\frac{\pi^{-1}}{\pi^{-1} + \varsigma} \right)^{\pi^{-1}} \left(\frac{\varsigma}{\pi^{-1} + \varsigma} \right)^h, h = 0, 1, \dots$$

where:

$$\begin{aligned} \Gamma(\cdot) &= \text{gamma function, } E(H) = \varsigma \text{ and variance of } V[H | \varsigma, \pi] = \varsigma(1 + \pi\varsigma) \\ &\text{and} \\ \pi &= \text{measures the degree of overdispersion (the difference between the mean and the variance of the distribution).} \end{aligned}$$

If π converges to zero, then the NB model will reduce to Poisson model. Testing for over-dispersion ($\pi = 0$) is done using the likelihood ratio test, thereby proving that the variable satisfied the NB assumptions; that is, the variance exceeds the mean (Johnson et al., 2005; Lambert, 1992).

The standard mean parameterization of NB distribution is $\varsigma = \exp(R'\alpha)\exp(v)$ [Equation (1) in the main text] where:

$$\begin{aligned} R &= \text{a vector of explanatory variables (in our case } U_{it}, V_{it}, W_{it}, G_t) \text{ and} \\ \alpha &= \text{parameters to be estimated.} \end{aligned}$$

This parameterization ensures that $\varsigma > 0$. Moreover, v is the error term with mean equal to 1 and a variance equal to π . We denote its standard deviation as σ_v .

2. Method 2: Derivation of the zero-inflated estimators.

For each country in i and year t , there are two possible data generation processes for $H_{i,t}$ —the selection of which is a result of a Bernoulli trial. The first process, which generates only zero counts, is chosen with probability ρ_i . The second process $g(H_{it} | R_{it})$ with probability $1 - \rho_i$ generates positive counts from an NB distribution where R_{it} is a vector of explanatory variables (in our case $U_{it}, V_{it}, W_{it}, G_t$).

In general, we have

$$H_{it} \sim \begin{cases} 0 & \text{with probability } \rho_i \\ g(H_{it} | R_{it}) & \text{with probability } 1 - \rho_i \end{cases} \quad (\text{B1})$$

Then the probability of $\{H_{it} = h_{it} | R_{it}\}$, where h_{it} is a particular value of the variable $H_{i,t}$, can be expressed as (Johnson et al. 2005; Lambert, 1992):

$$P(H_{it} = h_{it} | R_{it}, I_{it}) = \begin{cases} \rho(\lambda' I_{it}) + \{1 - \rho(\lambda' I_{it})\} g(0 | R_{it}) & \text{if } y_{it} = 0 \\ \{1 - \rho(\lambda' I_{it})\} g(h_{it} | R_{it}) & \text{if } y_{it} > 0 \end{cases} \quad (\text{B2})$$

The probability ρ_i depends on the characteristics (a subset of the explanatory variables) of country i and year t . Hence, ρ_{it} is written as a function of $\lambda'I_{it}$ where I_{it} is the vector of zero-inflated (ZI) covariates and λ is the vector of ZI coefficients to be estimated.

A probit function [using the same explanatory variables as described in Equation (1) in the paper] is specified as the ZI link function; it relates the product $\lambda'I_{it}$ (which is scalar) to the probability ρ_{it} . We thus estimate the frequency of hydrometeorological disasters using a negative binomial zero-inflated (NBZI) regression model. In the study of Vuong (1989), results revealed significant positive test statistics, which favor the ZI models over the standard NB count regression models. This means that the ZI method is necessary given the preponderance of zeroes of the dependent variable.

This model can determine whether the zero-observed dependent variable can correspond to countries that, in a particular year, had zero probability of having a disaster or a country that had a positive probability of a disaster but, due to random conditions in that year, experienced no disaster and consequently also had a zero dependent variable (Vuong, 1989).

3. Method 3: Cointegration.

First, we have this model with the coefficient of time dummies (yt) and the series of atmospheric CO2 (xt). This can be expressed as

$$y_t = \beta_0 + \beta_1 \cdot x_t + \mu_t \quad (\text{B3})$$

where:

$$\begin{array}{ll} \beta_0, \beta_1 & = \text{parameters and} \\ \mu_t & = \text{stochastic error term.} \end{array}$$

To simplify, we assume an autoregressive model AR(1):⁹

$$\mu_t = \theta_1 \mu_{t-1} + \varepsilon_t \quad (\text{B4})$$

In particular, we can estimate Equation (B4) using ordinary least squares (OLS) and using the unrestricted autoregressive distributed lag (ARDL) model, in which the lag lengths are set to eliminate the residual autocorrelation, an ARDL(1,1) model. From Equations (B3) and (B4), we have

$$y_t - \beta_0 - \beta_1 \cdot x_t = \mu_t$$

and

$$y_{t-1} - \beta_0 - \beta_1 \cdot x_{t-1} = \mu_{t-1}.$$

Using both expressions and Equation (B4),

$$y_t - \beta_0 - \beta_1 \cdot x_t = \theta_1 (y_{t-1} - \beta_0 - \beta_1 \cdot x_{t-1}) + \varepsilon_t,$$

and by rearranging the following terms

$$y_t = (\beta_0 - \theta_1 \beta_1) + \theta_1 y_{t-1} + \beta_1 x_t + \theta_1 \beta_1 x_{t-1} + \varepsilon_t,$$

and

$$y_t = \delta + \theta_1 y_{t-1} + \varphi_0 x_t + \varphi_1 x_{t-1} + \varepsilon_t \quad (\text{B5})$$

where $\delta = (\beta_0 - \theta_1 \beta_1)$, $\varphi_0 = \beta_1$, and $\varphi_1 = -\theta_1 \beta_1$. Equation (B5) is an unrestricted autoregressive distributed lag model, ARDL (1, 1).

⁹ We also tried with AR(2) but the additional parameters were not significant.

To obtain the error correction model (ECM) form, we use the next two equalities:¹⁰

$$y_t - \theta_1 y_{t-1} = \Delta y_t - (\theta_1 - 1)y_{t-1}$$

$$\varphi_0 x_t + \varphi_1 x_{t-1} = \varphi_0 \Delta x_t + (\varphi_0 + \varphi_1)x_{t-1}$$

where $\Delta y_t = y_t - y_{t-1}$ and $\Delta x_t = x_t - x_{t-1}$. We then use both equalities from Equation (B3), and then rearrange the following terms:

$$\Delta y_t = \delta + \varphi_0 \Delta x_t + (\theta_1 - 1)y_{t-1} + (\varphi_0 + \varphi_1)x_{t-1} + \varepsilon_t$$

$$\Delta y_t = \delta + k_0 \Delta x_t + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \varepsilon_t \quad (\text{B6})$$

where $k_0 = \varphi_0$, $\gamma_1 = \theta_1 - 1$ and $\gamma_2 = (\varphi_0 + \varphi_1)$.

We estimate Equation (B6) using the OLS method. From (B6), the estimator of the cointegrated coefficient is given by the long-run solution:

$$\hat{\beta}_1^* = -\frac{\hat{\gamma}_2}{\hat{\gamma}_1} \quad (\text{B7})$$

4. Method 4: Vector error correction model and Johansen test.

In a bivariate model with y_t and x_t variables, there exist a β_0, β_1 such that $y_t - \beta_0 - x_t \beta_1 = \mu_t$ is stationary although x_t and y_t may be non-stationary series. This means that the two variables are cointegrated or have a stationary long-run relationship, albeit they are non-stationary series when taken individually.

A vector autoregressive model with l lags can be represented as shown in Equation (B8)

$$z_t = \rho_1 z_{t-1} + \rho_2 z_{t-2} + \dots + \rho_p z_{t-l} + \varphi \tau_t + \varepsilon_t \quad (\text{B8})$$

where:

$$\begin{aligned} z_t = \begin{pmatrix} y_t \\ x_t \end{pmatrix} &= 2 \times 1 \text{ vector of non-stationary variables} \\ \tau_t &= \text{vector of deterministic variable, and} \\ \varepsilon_t &= 2 \times 1 \text{ vector of identically and normally distributed errors with} \\ &\quad \text{mean zero and non-diagonal covariance matrix } \Sigma. \end{aligned}$$

Given that the variables are co-integrated, Equation (B8) can be represented by an equilibrium correction model shown in Equation (B9) below:

$$\Delta z_t = \eta \omega z_{t-l} + \sum_{i=1}^{l-1} \Gamma_i \Delta z_{t-i} + \delta \cdot t + \nu + \varepsilon_t \quad (\text{B9})$$

where:

$$\begin{aligned} \eta, \omega &= \text{key coefficients,} \\ \omega &= 2 \times r \text{ matrix of cointegrating vectors that explain the long-run} \\ &\quad \text{relationship of the variables,} \\ \eta &= 2 \times r \text{ matrix that explains the long run disequilibrium} \\ &\quad \text{of the variables, and} \\ \nu, t &= \text{deterministic trend component.} \end{aligned}$$

¹⁰ Developing the right sides of both equalities directly reaches the left sides.

Note that for cointegration to exist, matrices η and ω should have reduced rank r , where $r < 2$. The identification of the cointegrating vector uses the maximum likelihood method developed by Johansen (Johansen,1995).

Table B1. Johansen test for cointegration

Rank (r)	Johansen Test	Critical Value 1%
0	23.434***	16.31
1	4.1736	6.51

Notes: * and *** refer to value/s that are significant at the 1% level.

Table B2. Cointegration analysis of intense disasters-CO₂ series: Short-run and long-run parameters

Parameter	Hydrometeorological Disasters	
	Short Run	Long Run
CO ₂ level	0.0232 [0.00289]	0.0180*** [0.0070]

Notes: *** refers to values that are significant at the 1% level. Values that are in brackets are standard errors.

5. Method 5: Estimation of Granger causality test.

To test causality in the long run, we use Equation (B9), and then define

$$z_t = \begin{pmatrix} y_t \\ x_t \end{pmatrix}$$

We then estimate that the best model for our variables is the model that has five lags (i.e $l = 5$). Thus,

$$\Delta z_t = \eta \omega' z_{t-4} + \sum_{i=1}^3 \Gamma_i \Delta z_{t-i} + \delta \cdot t + \nu + \varepsilon_t$$

We verify whether the coefficients of $\{\Gamma_i\}_{i=1}^4$ in each element y_t are jointly different at zero. If this fact can be rejected, then it will prove causality in the long run. Table B3 below shows the results. When we test the causality from CO₂ to the coefficient of the time dummy variables, it is possible to reject the null hypothesis at 1% level. Conversely, when we test the causality from the coefficient of time dummy time variables to CO₂, it is not possible to reject the null hypothesis. Therefore, we conclude that the direction of causality must go from atmospheric CO₂ accumulation to hydrometeorological disasters.

Table B3. Test of Granger causality in the long run

Parameter	y_t	x_t
Hypothesis	CO ₂ → Coefficient of time dummy variables	Coefficient of time dummy variables → CO ₂
H_0	$\Gamma_1 = 0$	$\Gamma_1 = 0$
	$\Gamma_2 = 0$	$\Gamma_2 = 0$
	$\Gamma_3 = 0$	$\Gamma_3 = 0$
	$\Gamma_4 = 0$	$\Gamma_4 = 0$
Test F	7.6300*	5.1300
p-Value	0.009	0.2741

Note: * refers to values that are significant at 10% level.

6. Method 6: Estimating the elasticities of intense disasters with respect to CO₂ level (1970–2016).

We estimate the elasticities of the disasters, which were evaluated at the average values of the variables for the period 1970–2016. The coefficient values of the time dummy variables (y_t) are related to atmospheric CO₂ (x_t) as follows:

$$y_t = \beta_0 + \beta_1 \cdot x_t + \mu_t.$$

The elasticity of y_t with respect to y_t is

$$\frac{\partial \ln y_t}{\partial \ln x_t} = \frac{\partial y_t}{\partial x_t} \cdot \frac{x_t}{y_t} = \hat{\beta}_1 \cdot \frac{x_t}{y_t}.$$

In the case of CO₂, the $\hat{\beta}_1$ estimated is 0.0180, the mean sample value of CO₂ is 360.2134, and the mean sample value of y_t is 0.7117. Hence, the elasticity of y_t with respect to x_t when evaluated at the mean sample values is

$$\frac{\partial \ln y_t}{\partial \ln x_t} = 0.0180 \cdot \frac{360.21}{0.7117} = 9.1007.$$

Using the data for 1970–2016, the effect of y_t on the number of hydrometeorological disasters is 0.7117. Moreover, the number of intense hydrometeorological disasters of a “representative country” is 0.723. Hence, given that the dummy variables are all equal to one, the elasticity of the number of disasters of a representative country with respect to y_t is

$$\frac{\partial \ln H_t}{\partial \ln y_t} = \frac{y_t}{H_t} = 0.984.$$

Hence, using the chain rule, the elasticity of disasters of representative country with respect to CO₂ is

$$\frac{\partial \ln H_t}{\partial \ln x_t} = \frac{\partial \ln H_t}{\partial \ln y_t} \cdot \frac{\partial \ln y_t}{\partial \ln x_t} = 9.1007 \cdot 0.984 = 8.96. \quad (\text{B10})$$