March 10, 2016

Is climate change behind the rise in natural disasters?

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ABSTRACT

This paper studies the relationship between the increase of climate-related natural disasters worldwide and variables representing global climate change—notably atmospheric accumulation of carbon dioxide. The paper considers the incidence of the climate-related hazard on the risk of natural disasters while controlling for socioeconomic factors most importantly, rising exposure of the population and their greater vulnerability. We show that carbon dioxide accumulation is significantly associated with the dramatic increase of the hydro meteorological (floods and storms) disasters observed over the last few decades.

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I. INTRODUCTION

The frequency of natural disasters has increased almost three folds in the past four decades (EM-DAT). Also, global economic damage from natural disasters has been increasing steadily, reaching about $142 billion annually during the decade of 2005–2014, a steep increase from $36 billion a year two decades ago (1).

A hypothesis is that this increase in natural disasters worldwide is linked to global climate change. There is a growing literature on the evidence linking anthropogenic climate change with specific natural disasters occurring in certain regions or countries. While several studies have recently studied this connection, the vast majority of them have focused on particular regions and single events or the use of climate change models rather than on statistical analyses on a global scale, as we do in this paper.

Studies of the 2003 European heat wave and the wintertime droughts in the Mediterranean region of 1902-2010 indicate that human-induced climate change may have played a role (2, 3). Also, the global record high temperature of 2014 has been shown to have exacerbated the California 2012–2014 drought by 36% (4). Evidence of anthropogenic GHG emissions contributing to the observed intensification of precipitation events was found in two-thirds of the northern hemisphere regions (5).

Climate change models provide another piece of evidence. These models have analyzed increasing extremes climatic events (6). Climatic models indicate that the risk of floods occurring in England and Wales in autumn 2000 was higher by at least 20% due to 20-century anthropogenic GHG emissions (7). Case studies on three catchment regions in southeastern Australia show that a doubling of CO_2 levels would increase the frequency and magnitude of flood events (8).

According to these models a doubling of atmospheric CO_2 concentrations may be associated to a tripling of the number of Category 5 storms (9); these models also predict that for every 1℃ rise in global temperature the frequency of events of the magnitude of Hurricane Katrina will increase by at least two times, and possibly by as much as seven times (10). Climate models project a 3% to 5% increase in wind speed per degree Celsius increase in tropical sea surface temperatures (11).

The present study explores whether there is a significant relationship between *global* climate change and the increase in the frequency of intense hydro meteorological disasters in a sample that covers the vast majority of the countries in the world over the last forty three years. Its distinctive feature is the focus on understanding the effects of climate change on disasters across all continents rather than specific events or region-specific analyses as is the case with most previous studies. Our empirical econometric analysis is done in a global context covering 155 countries across all continents instead of regional or country sub-samples. One of the few studies using a multi-country multi-period statistical analysis is the one by Thomas et. al (2014) (12). However, this study focusses only on a sample of Asian countries considering only local climate conditions ignoring global climate factors.

By contrast, our analysis explicitly considers the effects of global climatic indicators as factors determining the frequency of intense of disasters in addition to the effects of country local conditions. It is important to control for global time effects as climate phenomena in a country may be a response to global and regional climate changes on top of local temperature and precipitation changes. Global climatic factors increase the vulnerability of countries to local weather fluctuations. For example, the rising sea levels caused by global instead of merely local climatic conditions may magnify the destructive effects of increased local precipitation. In addition, most storms including hurricanes and typhoons in a country can be caused by conditions prevailing in far distant geographic areas and not merely in the regions where they occur.

Previous statistical analyses of disasters do not explicitly address the causality between climate change and the number of intense natural disasters. By contrast, we perform a co-integration analysis to elucidate whether the estimated global time effects on disasters are meaningfully related to the accumulation of carbon dioxide in the atmosphere. We show that even controlling for country local conditions (socio-economic and otherwise) these global effects have an important positive effect on the number of hydro meteorological disasters reported in the countries considered.

Finally, this work considers the phenomenon of natural disasters as the result of both climatic factors on the one side and of socio-economic considerations, especially exposure of the population to the risks and their vulnerability in facing them, on the other. By contrast, most previous studies have dealt with one side or the other separately.

II. METHODS

In this section, we examine statistically the role played by various factors in affecting natural disasters. The variable sought to be explained is the incidence of disasters, which is represented here by the number of disasters causing a minimum number of deaths or people affected (that is, requiring immediate assistance with basic survival needs such as food, water, shelter, sanitation, or medical assistance) in a given period. There are other measures too, for example, the level of damages in monetary terms. However, measuring the impact of natural disaster in monetary terms involves a number of data issues, chiefly regarding accuracy, because of the lack of standards for comparable estimation across economies or across disasters.

A. Data and econometric model

We develop econometric estimations using annual data on disasters for a sample covering most countries in the world (the list of countries is shown on Supplementary Materials to this article). The model considers count data of disasters by country i and year t for 1970–2013 from EM-DAT (1) (Table. S1; see the Supplementary Materials).

We use two approaches.

Approach 1. Using the number of natural disasters per country and year as the dependent variable we estimate the effect of global climate indicators as a separate variable directly in the regression analysis, controlling for country-specific effects only (one-way fixed effects). The global indicator used is the atmospheric carbon dioxide (CO_2) accumulation. A hypothesis is that global climate variable exerts an independent effect on disasters over and above local country conditions. A problem with using Approach 1 is that the atmospheric CO_2 level may correlate with omitted variables which in turn, may affect natural disasters; thus the estimates of the effect of CO_2 level may be biased. To remedy this we use Approach 2 as detailed below.

Approach 2. We estimate the model in two stages. In stage I we use a two-way fixed effects method that includes controlling for both country-specific effects and common-to-all-country or global effects which vary over time (represented by time dummy variables). This allows detection of changing global effects affecting natural disasters in all countries over and above local country effects. In stage II we perform a co-integration analysis between atmospheric CO_2 accumulation and the estimated global time effects to test whether these changing global time effects are meaningfully caused by CO_2 accumulation. Atmospheric CO_2 accumulation, for example, affects sea levels and their temperatures as consequences of the reduction of polar ice caps and other phenomena (13). As world sea levels and their temperatures increase, the effects of local temperatures and local precipitation on the magnitude and frequency of disasters in a country may worsen over time. An increase in precipitation, for example, may have a much greater effect on flooding if the sea level is already high. However, the coefficients of time dummy variables that are common-to-all-countries may also capture the varying impact of global phenomena that may not necessarily be related to climatic variables. For example, technological and communication improvements worldwide may increase the number of reported natural disasters. Also, the common-to-all-countries time dummies may capture a worsening disaster effect due to increasing concentrations of population in exposed areas (14, 15). Since the dependent variable (number of disasters) corresponds to recorded disasters and not necessarily the number of actual ones, this could artificially increase the value of the global effects estimated. The co-integration analysis in stage II is directed to elucidate the specific role of atmospheric CO_2 accumulation on the global effects free from other non-climatic effects.

Given that the dependent variable (number of natural disasters) consist nonnegative count values, count regression models such as the Poisson (P) and Negative Binomial (NB) need to be used. We used the NB model (equation 1 below), which is more general than the P model by allowing for over dispersion between the mean and the variance of the distribution (16, 17).

Intense hydro meteorological disasters relate to floods and storms. The dependent variable is the annual frequency of intense hydro meteorological disasters (H_{it}) that cause at least 100 deaths or directly affect at least 1,000 people. The explanatory variables include W_{it}: average precipitation deviation in the country (18) (measured as departures from the average for its 30-year base climatology period 1961–1990), gross domestic product per capita as a proxy of vulnerability (V_{it}) and population per country for exposure (U_{it}).

The most important explanatory variable is the global factor G_t which has a different meaning depending whether we are using Approach 1 or 2. When we use Approach 1 the variable G_t is carbon dioxide accumulation in the atmosphere from in situ air measurements at the Mauna Loa Observatory (19). When we use Approach 2 the variable G_t corresponds to the common-to-all countries time dummy coefficients which subsequently in stage II (the co-integration analysis) we correlate with atmospheric carbon dioxide accumulation.

We estimate the following equation using annual data for a sample for 155 countries over the period 1970-2013 making a total of 5,830 observations. (Table. S2; see the Supplementary Materials for details).

$$E[y_{it} = H_{it} \mid X_{it}, \varepsilon_{it}] = \{\exp(\beta_0 + \beta_1 U_{it} + \beta_2 V_{it} + \beta_3 W_{it} + \beta_4 G_t)\} \qquad (1)$$

The count (occurrence) of intense disasters—the dependent variable—is characterized by excess zeros. In particular, 67% of the annual observations for hydro meteorological disasters have zero counts. Failing to account for the prevalence of zeros in the dependent variable would be likely to result in inconsistent estimators. For this reason, we use the Zero-inflated (ZI) count model (16, 17). This model allows elucidating whether the zero-observed dependent variable may either correspond to countries which in a particular year had a zero probability of having a disaster or countries that had a positive probability of a disaster but that, due to random conditions in that year, experienced no disaster and consequently also had a zero dependent variable (20). (See Supplementary Materials for the derivation of the ZI estimators).

B. A Co-integration Analysis

The estimated time dummy coefficients from the two-way fixed effects model (Approach 2) are subjected to a co-integration analysis (21) with annual data on atmospheric CO_2. We can think of co-integration as describing a particular kind of *long-run equilibrium* relationship. In particular we seek to understand whether the estimated time dummy coefficients and the global climate variable are positively correlated in a meaningful way.

First we regress the coefficients of the time dummies (y_t) on the series of atmospheric CO_2 (x_t). This can be expressed as:

$$y_t = a + \beta \cdot x_t + \mu_t \qquad (2)$$

Where a is a fixed coefficient, $\hat{\beta}$ is the predicted value of the co-integrating coefficient obtained from the ordinary least squares (OLS) estimation and μ_t is the predicted error series. The OLS estimation of equation (2) gives us an unbiased estimation of $\hat{\beta}$. However, its standard error estimates is inconsistent and are not normally distributed. Hence, in this case, the usual inferential procedures do not apply.

With respect to the significance of $\hat{\beta}$ —the co-integrating coefficient—it has been showed that both the dependent and independent variables co-integrate if and only if there is an error correction model (ECM) for either y_t and x_t or both (21, 22, 23).

The ECM form is (see Supplementary Materials for details of its derivation):

$$\Delta y_t = \delta + k_0 \Delta x_t + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \varepsilon_t \qquad (3)$$

Where $\Delta y_t \equiv y_t - y_{t-1}$, $\Delta x_t \equiv x_t - x_{t-1}$ and k_0, γ_1, and γ_2 are estimated coefficients.

We estimate equation (3) using the OLS method. As shown in the Supplemental Materials we can derive from (3) that,

$$\hat{\beta} = -\frac{\widehat{\gamma}_2}{\widehat{\gamma}_1} \qquad (4)$$

Thus, using the estimated coefficients γ_1, and γ_2 and their respective standard errors we can obtain a consistent measure for $\hat{\beta}$ and its correct standard error to analyze its significance.

C. Results

Table 1 shows estimates explaining the occurrence of intense hydro meteorological disasters. The first column shows the estimate using one-way fixed effects (approach 1), including as explanatory variable the annual level of atmospheric CO_2 as an indicator of global climate effect. The second column reports the estimates of the two-way fixed effects using time dummies in addition to country fixed effects (approach 2). All regressions use a ZINB method of estimation. Voung test rejects the hypothesis that zero inflated estimators are equal to the usual negative binomial estimators at 1% level. Therefore, there is evidence that the ZINB model is needed to avoid inconsistent estimators.

The estimates are remarkably consistent. The local climate variable is highly significant and has expected sign. Precipitation deviations exert a positive impact on the number of intense local hydro meteorological disasters. Moreover, the variable atmospheric CO_2 concentration according to one-way fixed effects, show positive and highly significant effect. However, it is possible that this global climate variable is correlated with other global variables over time which could also exert a positive impact on disasters. This would then imply that the coefficient of the CO_2 is inconsistent. This is why approach 2 is important.

In the two-way fixed effects model (Approach 2), the time dummy variables capture any global effects whether climate-related or otherwise. The estimated time dummy coefficients are highly significant and tend to become larger over the time period (their values are shown in the Supplementary Materials). In stage II we implement co-integration analysis between the estimated time dummy coefficients and the annual concentration of atmospheric CO_2.

Table 1. Determinants of the Frequency of Intense Hydro Meteorological Disasters (ZINB method), 1970–2013

Explanatory Variables	**One-Way Fixed Effect**	**Two-Way Fixed Effect[a]**
	(1)	**(2)**
Exposure		
Ln (population density)	0.196***	0.199***
	[0.0247]	[0.0224]
Population (million)	0.00221***	0.00219***
	[0.000109]	[0.000119]
Vulnerability		
Ln GDP per capita (constant 2005 US$)	0.219	0.241
	[0.212]	[0.186]
Square of Ln (GDP per capita)	-0.0169	-0.0184
	[0.0141]	[0.0125]
Local Climate Condition		
Average precipitation deviation	0.0155***	0.0158***
	[0.00235]	[0.00235]
Global climatic indicator		
Atmospheric CO_2 level	0.0177***	
	[0.00113]	
Observations	5830	5830
Akaike Information Criterion (AIC)	11,197.04	11,156.87
Bayesian Information Criterion (BIC)	11,290.08	11,483.74
LR Test	462.16***	408.74***
Vuong Test	11.49***	11.53***

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

a) The coefficients of the time dummy variables are available in Supplementary Materials.

Source: Authors' calculations.

These results suggest that two of the three factors—rising population exposure, and changing climate—may play a role in explaining the global increase in the frequency of intense hydro meteorological disasters. More importantly, global climate factor, represented by atmospheric CO_2 accumulation, appear to be extremely important, an issue which we discuss in detail in the following section.

Local versus Global Climate Effects

As can be seen in the Supplementary Material, the estimates of the coefficients of the common-to-all countries time dummies are increasing over time, jointly significant and most of them are individually significant as well. We interpret this significance as an indication that, in addition to local country factors, there are global factors affecting the frequency of climate-related natural disasters that may be related to the accumulation of carbon emissions in the atmosphere. In the next section we use time series analysis to probe whether or not the values of these global effects co-integrate with the stock of CO_2 in the atmosphere.

D. Role of Atmospheric CO_2 Accumulation on Natural Disasters: Time series analysis

We implement time-series analysis to ascertain whether there is a meaningful relationship between the estimated increased global effect (represented by the increasing value over time of the coefficients of the common-to-all-countries dummy variables) and the accumulation of carbon dioxide in the atmosphere. To put this in time-series analysis jargon, do the series of CO_2 and of time dummy coefficients co-integrate?

The first panel of Figure 1 shows the evolution of the estimated coefficients of the time dummy variables for hydro meteorological disasters and the CO_2 concentrations in the atmosphere during 1970–2013. As can be seen, both series exhibit upward trends over the period. The series in levels appear to be non-stationary, suggesting that any regression between the two series in levels would yield spurious estimates of the goodness-of-fit of the regression, including the estimates of the standard errors of the coefficients. In fact, formal tests suggest that the series are indeed non-stationary.

The second panel in Figures 1 shows the series expressed in first differences, which appear to be stationary. In other words, each of the two series may be integrated of order one. Below we statistically test whether this is in fact the case.

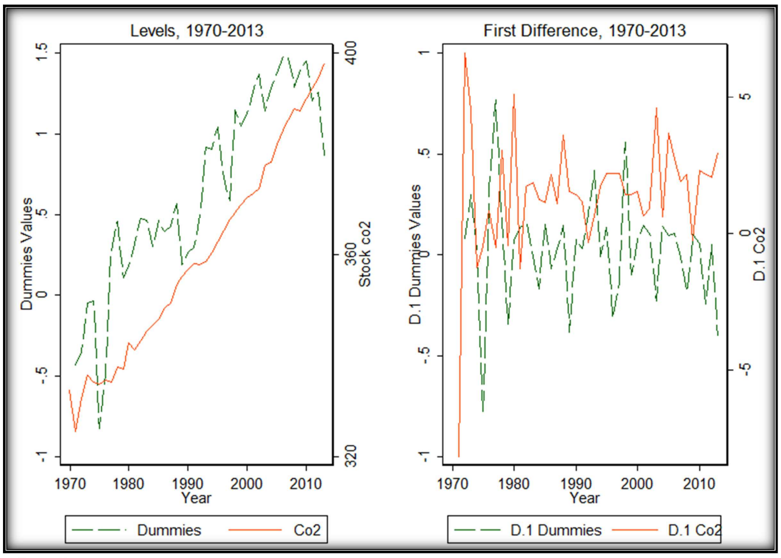

Fig 1. Trend Relationship between Hydro meteorological Time Dummy Values and Atmospheric CO_2 Stocks: Levels and First Difference (1970-2013).

First, we estimate ordinary least squares (OLS) regression in levels. Table 2 provides this regression estimate in the first column. We avoid showing the standard error of the coefficient given that the estimated coefficient is not in general distributed asymptotically normal given due to the lack of stationarity of the series so that the usual t-statics inferential procedures do not apply. However, we can use the estimated coefficients for further estimation to test for co-integration. The hypothesis to be tested is that the *predicted errors* obtained from this regression are stationary. Even if all individual series in levels are non-stationary, it is possible that the linear combination resulting from the estimates of both non-stationary series may be stationary.

Table 2 also shows the results of tests for stationarity or co-integration using the series of predicted errors obtained from the regression estimation. Both Dickey-Fuller (DF) and Dickey-Fuller generalized least squares (DF-GLS) test whether a unit root is present in the series of the predicted errors. Tabulated critical values at 1% and 5% are in general more exigent than usual Test T (24, 25, and

26). The DF and DF-GLS statistics allow rejection of the null hypothesis that the series have a unit root. The time dummy coefficients and the CO_2 stock variable are integrated of order one-that is the predicted error is stationary. This fact suggests that the series co-integrate.

Table 2. OLS Regression Estimates and Co-integration Analysis of Disasters-CO_2 Series: Engle-Granger Three-step Method Results

	Hydro meteorological	
	Level	**First Diff. (D.1) (ECM)**
Stock CO_2	0.0258	
	[0.00263]	
D.1 $CO_{2\ (t-1)}$		0.002
		[0.038]
Time Dummy Coefficients $_{(t-1)}$ $(\hat{\gamma}_1)$		-0.413***
		[0.152]
$CO_{2\ (t-1)}$ $(\hat{\gamma}_2)$		0.009*
		[0.005]
Constant	-8.646***	-3.062*
	[0.947]	[1.793]
Observations	43	42
AIC	1.587.151	65.742
BIC	1.939.391	1.352.488
Tests for Stationarity		
Dickey-Fuller (DF)	-4.847***	
Dickey-Fuller Generalized Least Squares (DF-GLS)	-4.874***	

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

Source: Authors' calculations based on NOAA data.

In addition to the tests reported in the first column of Table 2, we also implemented a co-integration test developed by Johansen (22). This test also suggests that the series co-integrate (see Supplementary Materials). Thus all these tests conclude that the two series do co integrate.

However, these tests are not in general considered to have sufficient power, especially due to the fact that the sample comprised of 43 observations for each series is small. When samples are small the literature recommends the use of autoregressive distributed lags (ARDL) to obtain a more reliable test for co-integration (27). Thus we corroborate the existence of stationarity and co-integration using a three-step error correction model (ECM) as shown in equation (3) implemented using an AR(1)DL (see Supplementary Materials for its derivation). The second column in Table 3 shows the estimates of the ECM for hydro meteorological variables. The coefficient of $CO_{2(t-1)}$ $(\hat{\gamma}_2)$ is positive and significant, and the error correction coefficient, associated with the time dummy coefficients $_{(t-1)}$ $(\hat{\gamma}_1)$, is negative and significant. This confirms a dynamic process that is consistent with the existence of co-integration between the series in question. Moreover, the adjustment process is stable due to the fact that $|\hat{\gamma}_1| < 1$.

The estimates of the γ_1 and γ_2 coefficients allow us to obtain a measure of the key coefficient $\hat{\beta}$ by using equation (4). Most importantly, this estimate of $\hat{\beta}$ is unbiased and distributes according to a normal distribution; this allows us to obtain consistent statistical inference. Table 3 shows the short and long run estimates of $\hat{\beta}$ for hydro meteorological disasters-CO_2 series. As can be seen this coefficient is statistically significant at 1% and also is very similar to the short run coefficient. In fact, statistical test show that the short and long run estimates are not statistically different among each other.

Table 3. Co-integration Analysis of Disasters-CO_2 Series: Short run and Long run parameters

	Hydro meteorological disasters	
	Short Run	**Long Run**
Stock CO_2	0.0258	0.0225***
	[0.00263]	[0.0060]

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

Source: Authors' calculations based on NOAA data.

In summary, the satisfactory ECM-AR(1)DL estimates in conjunction with the rejection of the unit root tests and lack of rejection of the hypothesis that the series resulting from the combination of the global effects on hydro meteorological disasters and atmospheric CO_2 are stationary provide convincing evidence that the two series do co integrate. This is the key finding of this paper which implies that there exists a long run relationship between the two variables. This means that causality must exist in at least one direction (28). It is hardly plausible to postulate that the direction of causality goes from hydro meteorological disasters to atmospheric CO_2 accumulation. A causality test in the vector error correction model indicates that this is in fact the case (29) (see Supplementary Materials). Therefore, we conclude that the direction of causality must go from atmospheric CO_2 accumulation to hydro meteorological disasters.

Quantitative significance of the results

Table 4 shows the estimated elasticity of the time-dummy coefficients of hydro meteorological disasters with respect to the atmospheric CO_2 concentrations. This elasticity is evaluated at the mean values (1970-2013) of the coefficients of the time dummy variables and atmospheric CO_2 levels. Table 5, on the other hand, exhibits the simulated effects of CO_2 levels on disasters using mean values. The methodology used to measure this elasticity and the simulation is described in the Supplementary Materials. A 1% increase in the stock of atmospheric CO_2 would likely increase the average size of time dummy coefficients of hydro-meteorological disasters by approximately 12.48%.

Table 4. Elasticity of Time dummy Coefficients with Respect to atmospheric CO_2 concentration.

Marginal effect $(\hat{\beta})$	0.0225
Average sample value of **CO_2** Stock (in ppm) and (1970-2013)	359.55
Average value of time dummy coefficients (1970-2013)	0.648
Elasticity of time dummy coefficients with respect to the atmospheric CO_2 level	12.48

The elasticity reported in Table 4 indicates the effect of a 1% increase on the level of atmospheric CO_2 on the average time dummy coefficients. The next step is to measure the effect of the changes in the time dummy coefficients on the level of disasters themselves using the estimates of the two-way fixed effect regressions reported earlier. Thus, the combination of these two effects yields the estimates of the net effect of atmospheric CO_2 level on the number of disasters. This is the elasticity of disasters with respect to the global climate variables. (See Supplementary Materials for a detailed discussion).

Using this estimated elasticity of disasters with respect to atmospheric CO_2 we can simulate the effects of the increases of CO_2 level on the number of disasters. Table 5 shows what proportion of the variation of disasters in 2010–2013 are explained by the change in CO_2 level. We simulated this for the representative country in the sample.

To illustrate, the average observed occurrence of hydro meteorological disasters in the sample for a representative country was 0.48 per year. On average, the annual increase of atmospheric CO_2 level has been about 2 ppm per year, equivalent to 0.5% of the current 394 ppm level. Using the elasticity of disasters to CO_2 level which is equal to 11.44 (see the Supplementary Materials for derivation), we estimated a simulated variation on hydro meteorological disasters.

Table 5. Explained Variation on Hydro meteorological Disasters by the Atmospheric CO_2 Concentration Level Using the period 2010-2013 as baseline

Elasticity of disasters with respect to CO_2	11.44
For Simulation:	
CO_2 Stock (in ppm)	394
Average annual disaster occurrence	0.775
Average value of time dummy coefficients	1.190
Current annual increase	
Atmospheric CO_2	2.0
Simulated variation in disasters due to current rate of increases in CO2 Stock	
	5.7%

Source: Authors' calculations.

As shown in Table 5, the number of hydro meteorological disasters may increase by about 5.7% per year for the average country in the sample or 0.044 more disasters per year. This implies that if the rate of increase of CO_2 atmospheric concentration continues its current trend, in about 17 years the number of hydro disasters would double from the current average value of 0.775 to 1.55 disasters per year for the average country.

At first sight the estimated effects of carbon dioxide accumulation in the atmosphere on disasters may appear to be extremely high. However, these estimates are not much larger than those obtained using climate change models that predict massive effects of the increase of CO_2 accumulations even on the most devastating natural disasters. For example, according to climate models a doubling of CO_2 concentrations may be associated with a tripling of the number of Category 5 hurricanes (9); also, a one degree Celsius rise in global temperatures is predicted by these models to increase events of the magnitude of Katrina by as much as seven times (10).

III. Conclusion

This paper has shown the existence of a significant and meaningful association between climate-related natural disasters and atmospheric CO_2 accumulations. Underlying this connection, it has found that a large proportion of the rise in hydro meteorological disasters is due to the continuous increase of atmospheric CO_2 concentrations that have occurred during the past four decades analyzed.

If the current trends in CO_2 accumulations continue, the number of intense hydro meteorological disasters in the average country could double in less than twenty years, severely hurting the well-being of millions of people around the world.

The global evidence in this study together with the attribution elsewhere of specific climate disasters to climate change as well as evidence from climatic models support the hypothesis that, in addition to socio-economic factors, climate change is linked to the rise of intense natural disasters worldwide over recent decades. This evidence provides another powerful reason to address climate change urgently.

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ACKNOWLEDGMENTS. The authors thank the Centre for Research on the Epidemiology of Disasters and the Manila Observatory for collaboration and data support. Financial support for this research was provided by The Asian Development Bank, grant number SC 105799 REG.