Government effectiveness and institutions as determinants of tropical cyclone mortality

Elizabeth Tennant[a,1] and **Elisabeth A. Gilmore**[b]

[a]Department of Economics, Cornell University, Ithaca, NY 14853; and [b]Department of International Development, Community and Environment, Clark University, Worcester, MA 01610

Edited by Arild Underdal, University of Oslo, Oslo, Norway, and approved October 7, 2020 (received for review April 6, 2020)

Strong institutions as well as economic development are generally understood to play critical roles in protecting societies from the adverse impacts of natural hazards, such as tropical cyclones. The independent effect of institutions on reducing these risks, however, has not been confirmed empirically in previous global studies. As a storm's path and intensity influence the severity of the damages and may be spatially correlated with human vulnerabilities, failing to accurately capture physical exposure in an econometric analysis may result in imprecise and biased estimates of the influence of the independent variables. Here, we develop an approach to control for physical exposure by spatially interacting meteorological and socioeconomic data for over 1,000 tropical cyclone disasters from 1979 to 2016. We find evidence that higher levels of national government effectiveness are associated with lower tropical cyclone mortality, even when controlling for average income and other socioeconomic conditions. Within countries, deaths are higher when strong winds are concentrated over areas of the country with elevated infant mortality rates, an indicator of institutional effectiveness through public service delivery. These results suggest that policies and programs to enhance institutional capacity and governance can support risk reduction from extreme weather events.

tropical cyclones | disasters | institutions | vulnerability

Between 1979 and 2016, over 418,000 people across 85 countries and territories have lost their lives in tropical cyclone disasters.* However, there is substantial variation in the degree of harm. Out of more than 4,000 tropical storms and cyclones recorded between 1979 and 2016, about 20% triggered humanitarian disasters, and less than 5% resulted in more than 100 deaths. As recently as 2008, Cyclone Nargis killed over 138,000 people in Myanmar. Nargis was a powerful category 3 or 4 storm at landfall, but tropical cyclones with similar wind speeds struck several other countries that year with far fewer fatalities. Understanding what drives this large variation in impacts may provide guidance on how we can prevent mortality from future storms, which will be of increasing importance as countries grapple with complex vulnerabilities to extreme weather events under climate change (5).

This paper investigates relationships between tropical cyclone mortality and institutional, economic, and human development (collectively referred to as "development"). We focus, in particular, on the role of institutional effectiveness, going beyond previous efforts in two important ways. First, we establish an empirical association between national government effectiveness and tropical cyclone deaths that cannot be explained away by income, health, or education. Second, we present a global analysis showing that locally elevated infant mortality rates (IMRs) in the exposure zone are associated with increased tropical cyclone mortality. We interpret this as evidence that tropical cyclones are more deadly when they impact areas with weaker public services due to limited local institutional capacity or the failure of national programs to be inclusive of all vulnerable populations.

Natural hazards, including tropical cyclones, result in disasters only when vulnerable human systems are exposed to hazardous conditions. This can be represented as follows (e.g., refs. 6–8):

$$risk = f(hazard, exposure, vulnerability), \quad [1]$$

where the *risk*, in this case, the probability of mortality from tropical cyclones, is a function of the *hazard* (the frequency and intensity of storms), *exposure* (the assets or population in the hazard zone), and the *vulnerability* (susceptibility to harm) of the exposed population.

Empirical efforts to relate vulnerability and risk will therefore be confounded by hazard and exposure if these variables are not also accounted for. Studies of vulnerability that include multiple classes of hazard are unable to control for intensity and exposure, as events of different types (i.e., earthquakes, storms, floods, and heat waves) are not directly comparable. As a result, estimates of socioeconomic risk factors for vulnerability will be imprecise. Indeed, previous large-*N* empirical efforts that have pooled different types of hazards have been unable to provide statistical evidence of the relative importance of different socioeconomic risk factors for natural disaster mortality (9, 10). Measures of democracy and the quality of institutions, including government effectiveness, are found to be correlated with natural disaster deaths, but these effects are not precisely estimated when considered in combination with other possible explanatory variables such as GDP per capita (10, 11). Furthermore, if hazard is correlated with socioeconomic conditions, the failure to control for characteristics of hazard exposure can result in biased estimates. In Fig. 1, we illustrate how, from 1996 to 2016, countries with more-effective governments had lower mortality from tropical

Significance

Tropical cyclone disasters frequently result in substantial loss of life. Institutional capacity and economic development are believed to play protective roles, but previous efforts have been unable to disentangle their relative effects. We establish empirically that stronger national and subnational institutions, independent of income, are associated with lower tropical cyclone mortality. This suggests that effective institutions play an important role in the success of disaster risk reduction strategies. Our approach of accounting for hazard intensity, population exposure, and socioeconomic conditions at high resolutions can be extended to other hazards and scales to further examine how institutions moderate risk.

Author contributions: E.T. and E.A.G. designed research; E.T. performed research; E.T. analyzed data; E.T. wrote the paper; and E.A.G. provided critical feedback.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]To whom correspondence may be addressed. Email: ejt58@cornell.edu.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2006213117/-/DCSupplemental.

First published November 3, 2020.

*The statistics presented in this paragraph are the authors' calculations based on data from refs. 1–3. All datasets and code for this study are publicly available via the replication files at https://doi.org/10.6077/89ba-bj79 (4).

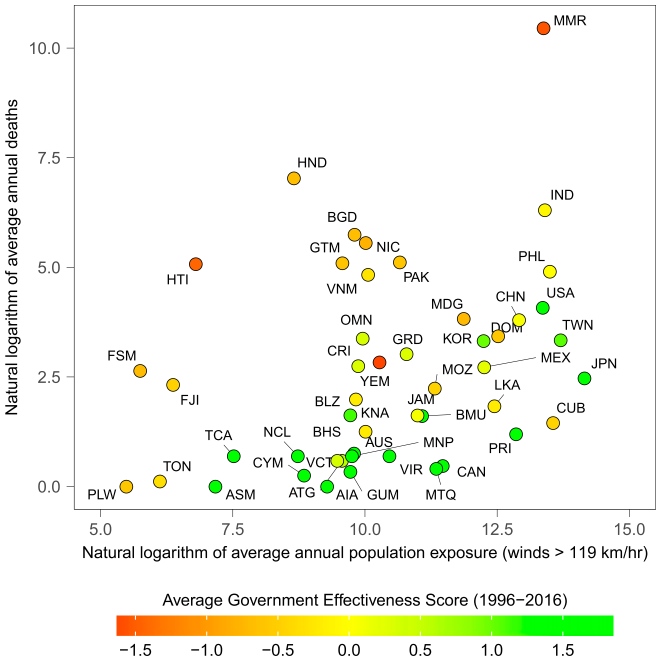

Fig. 1. Governance, mortality and exposure for tropical cyclone-affected countries, 1996–2016. Average national government effectiveness scores from 1996 to 2016 are taken from the WGI; higher scores indicate more effective governance (12). Average annual tropical cyclone disaster deaths from 1996–2016 are based on data from the EM-DAT (1). Average annual population exposure to tropical cyclone strength winds (exceeding 119 km/h) is modeled by country from 1996–2016. Country abbreviations are based on the ISO 3166 alpha-3 country codes (13). Exposure from tropical cyclones occurring in the Indian Ocean basin may be underestimated due to missing storm tracks in the underlying data (see *SI Appendix* for details).

cyclones even though more people within those countries were exposed to dangerous wind speeds. Correlation between tropical cyclone exposure and socioeconomic variables could be incidental, or could arise from the impacts of storms on socioeconomic development in areas of repeated exposure (e.g., refs. 14 and 15).

Studies restricted to a particular class of hazard are better able to account for variations in intensity and exposure. Recent studies of tropical cyclone risk and adaptation that include physical hazard observe that storms of similar intensity tend to result in fewer deaths when they strike countries with higher GDP per capita (16, 17, 18). This may reflect higher levels of individual or collective investment in assets and activities that reduce risk. However, the effects of economic development on risk are not unambiguously positive; growth-targeting activities can also exacerbate or create new vulnerabilities (7, 19, 20). Because existing tropical cyclone studies do not include multiple development factors in a single model, it is unclear whether income or other facets of development drive the observed relationship (16, 21, 22). The GDP effect may be a proxy for other correlated aspects of development that have also been theorized to reduce disaster deaths, such as higher levels of social capital, lower poverty rates, or better quality institutions (7, 19, 23).

Institutional effectiveness and inclusivity at multiple scales may be particularly important for reducing mortality from natural hazards, such as tropical cyclones. The Intergovernmental Panel on Climate Change Fifth Assessment Report concludes with "very high confidence" that the quality of institutions and governance are enabling factors for adaptation and disaster risk reduction in the context of climate change (23). The state plays a direct role in disaster preparedness and response, and further influences how conducive the national environment is to collective and individual adaptation (24). Government capacity may complement financial resources, particularly when the state acts as an intermediary in receiving and disbursing bilateral and multilateral aid (25). It is also important in its own right; economically less developed countries with high functioning states and civil societies have repeatedly demonstrated the capacity for adaptation to hazards (19, 24). In contrast, government failures such as the lack of capacity, will, and resources have been implicated in some of the deadliest tropical cyclone disasters in history. These include the 1970 Bhola cyclone that killed an estimated 250,000 to 500,000 people in former East Pakistan (now Bangladesh) (26) and the 2008 Cyclone Nargis that killed approximately 138,000 people in Myanmar (1, 27). Government programs for managing tropical cyclone risk—including early warning systems, shelters and evacuation plans, and integrating disaster risk and development planning—require an effective central bureaucracy but also depend upon local institutions for implementation (e.g., refs. 28 and 29).

Within countries, who benefits from disaster risk reduction policies and investments is shaped by existing patterns of vulnerability and marginalization (7, 30–32). People and locales may be excluded from national protections against tropical cyclone hazard due to the uneven quality of local institutions, the political marginalization of certain groups, and other forms of social or economic inequality. If these inequalities and their effects are large, they are likely to contribute to within-country variation in tropical cyclone mortality when patterns of physical exposure are sufficiently varied. Exposure to tropical cyclones is highly heterogeneous across but also within countries, with affected areas concentrated in coastal regions between 10 and 30 (±) degrees latitude (Fig. 2). However, most global studies of disaster mortality from tropical cyclones and other climate hazards are restricted to the country level (9–11, 16, 22), and therefore do not consider how local institutional quality and socioeconomic conditions may differ from national averages in affected regions. As a result, our understanding of the scales at which underdevelopment contributes to tropical cyclone vulnerability is limited. This constrains the ability of policy makers to target their actions, for example, whether to focus on building the capacity of federal agencies, local institutions, or both.

In this analysis, we address the limitations of previous efforts by testing for the importance of multiple risk factors at both the national and subnational level, using models that explicitly account for hazard exposure. We construct a dataset of nearly 1,500 tropical cyclone disasters from 1979 to 2016. Our analysis is based on two subsets of this dataset, the first from 1996 to 2016—where we test the relationship to national government effectiveness—and the second from 1979 to 2016—where we test subnational indicators of institutional capacity and inclusion. Because tropical cyclone mortality results from the interaction of the physical hazard and the human system, we use spatial methods to match meteorological and socioeconomic data for each storm. Time-variant gridded population estimates and socioeconomic data are spatially matched to parametrically modeled wind profiles based on storm tracks from the Best Track Archive for Climate Stewardship (IBTrACS) and to rainfall data from the National Oceanic and Atmospheric Administration Climate Prediction Center's Unified Precipitation Project (2, 3, 33, 35–38). This provides multiple advantages. First, controlling for storm intensity and population exposure increases precision and controls for the possibility that cyclone exposure may be correlated with socioeconomic conditions. Doing so improves our ability to identify relationships between socioeconomic factors and mortality. Second, we are able to study the importance of both national risk factors and local conditions in the exposure zone. We draw on data and insights from the civil conflict, development economics, and public health literatures to characterize subnational heterogeneities in institutional effectiveness (e.g.,

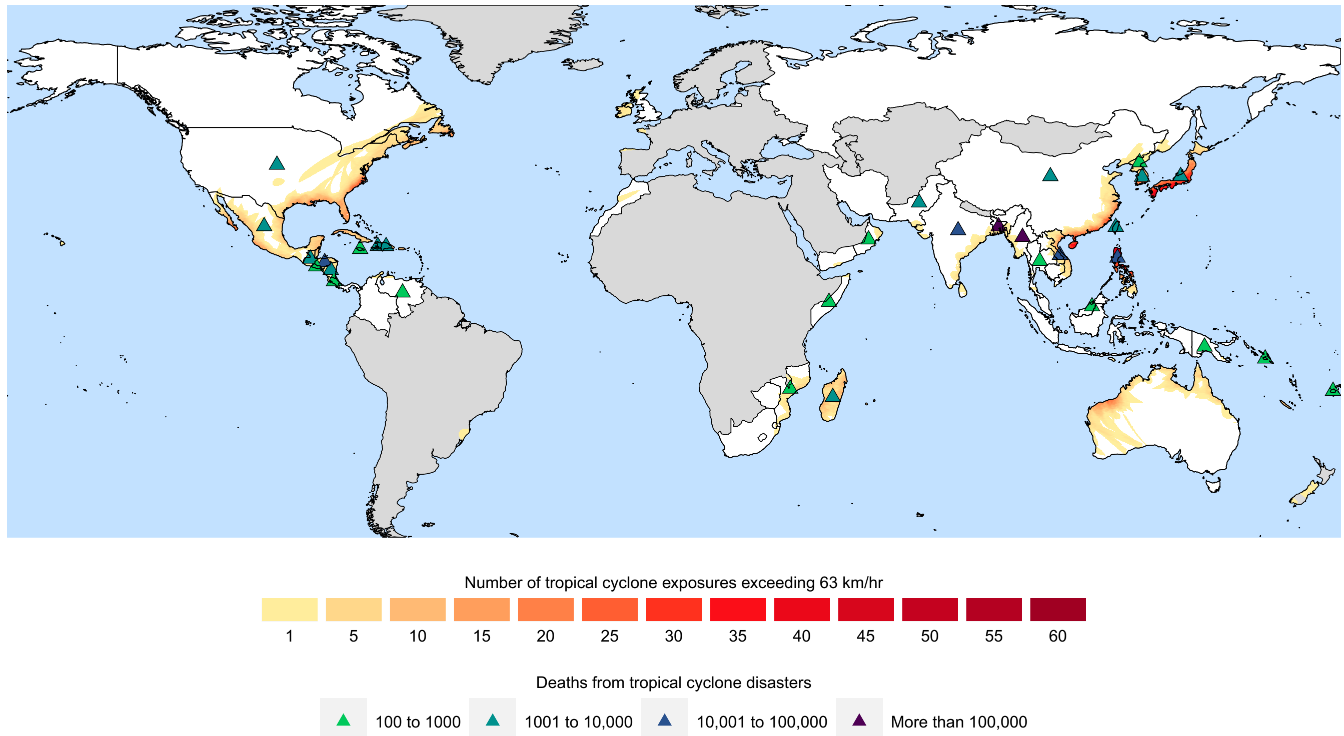

Fig. 2. National tropical cyclone disaster deaths and subnational wind exposure (1979–2016). Total mortality is indicated by the shaded triangles for all countries with at least 100 total deaths from 1979–2016 (1). Areas shaded in gray indicate countries that have not experienced tropical cyclone deaths during this period. The frequency of exposure to sustained winds exceeding 63 km/h is mapped at 2.5-min (∼ 5 km) resolution (author calculations based on data and models by refs. 2, 3, 33, and 34). Exposure from tropical cyclones occurring in the Indian Ocean basin may be underestimated due to missing storm tracks in the underlying data. This region is therefore excluded from the main empirical analysis (see *SI Appendix* for details).

refs. 39–41). Finally, because we construct hazard and exposure measures for all recorded tropical cyclones, we can examine the characteristics of storms that were not associated with a recorded disaster. This is a useful check on potential selection and measurement error issues in this literature and allows us to observe the conditions under which tropical cyclone disaster is avoided.

Results

The effects of institutions, income, and human capital on tropical cyclone mortality are estimated via two sets of multivariate negative binomial regression models. The first set of models tests the importance of different national characteristics for cyclone deaths, using data from over 900 events across 67 countries between 1996 and 2016. In addition to confirming the correlation between several facets of development and disaster deaths in the existing literature (9–11, 16, 22), our country-level models establish evidence of a robust association between national government effectiveness and mortality from tropical cyclones. Government effectiveness is represented in our models using annual country-level scores, published by the World Governance Indicators (WGI) and designed to capture the overall quality and independence of public policy and service delivery (12). The second set of models investigates the importance of subnational development patterns for disaster mortality, using data from tropical cyclone disasters in 59 countries between 1979 and 2016. Socioeconomic conditions in the path of the storm are found to have a large effect on expected mortality. Importantly, we control for hazard exposure in both the national and subnational specifications.

National Government Effectiveness and Socioeconomic Conditions. Government effectiveness, real GDP per capita, IMRs, and primary school enrollment are all good predictors of cyclone mortality in a country-level model that controls for hazard exposure. When we include only one of these four development indicators at a time, each has a highly statistically significant association with tropical cyclone deaths (*SI Appendix*, Table S5). This is consistent with existing evidence that GDP per capita is a useful proxy for tropical cyclone vulnerability (16, 22); an increase of one log-unit of GDP per capita is predictive of a 66% decrease in deaths in a model with no other socioeconomic variables. However, because institutions, income, health, and education are highly correlated, the independent effects of these variables cannot be identified by models with only a single socioeconomic variable.

To parse these relationships, we test multiple aspects of national development in combination (*SI Appendix*, Table S5). This yields evidence of a large and statistically significant association between national government effectiveness and lower cyclone mortality. In a model with no other socioeconomic variables, a 1 SD increase in government effectiveness is associated with a 71% decrease in deaths. As illustrated in Fig. 3, when we add GDP per capita and infant mortality to the model, government effectiveness accounts for a 49% decrease in mortality per SD, remaining practically and statistically significant. When we also include education, this reduces the number of observations due to missing data, but the effect of governance remains large and statistically significant. The association between government effectiveness and lower tropical cyclone deaths is robust to a range of sensitivity analyses, including ordinary least squares (OLS) estimation, as described in *SI Appendix*, section 2 and Tables S6–S14.

In contrast, GDP per capita, health, and education are more sensitive to multivariate specifications. The decrease in mortality associated with a one log-unit increase in GDP per capita falls from 66 to 44% when we add government effectiveness to the income-only model. The GDP per capita loses statistical

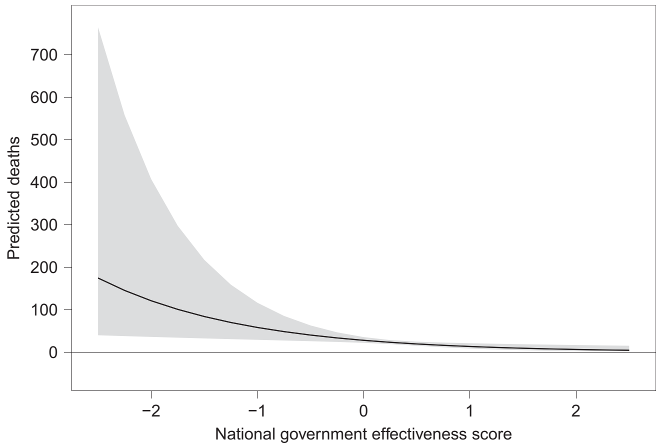

Fig. 3. Predicted effects of national government effectiveness score on deaths, based on the *SI Appendix*, Table S5. The shaded area represents the 95% CI. Variables not shown, including real GDP per capita and infant mortality, are held at mean values for prediction.

significance with the addition of infant mortality and education to the model. The effects of infant mortality and education also lose statistical significance in the joint model with GDP per capita and government effectiveness.

Disasters versus Hazard Exposures. The source of the mortality data for this analysis is the Emergency Events Database (EM-DAT), a global database of disasters based on reports from governments, United Nations agencies, and other nongovernmental organizations (NGOs). This raises two key concerns when the EM-DAT data are utilized to validate theories of vulnerability to natural hazards. First, when disaster is averted, perhaps due to the actions of effective and well-endowed institutions, hazard events are not represented in the EM-DAT. Second, the reliance on self-reported data creates the possibility of measurement error. For example, countries with lower institutional capacity or corruption may underreport disaster deaths. This has implications beyond this analysis, as the EM-DAT database is the primary source of mortality data used in global studies of the risks posed by tropical cyclones and other natural hazards (e.g., refs. 9–11, 16, and 22). The potential biases introduced by studying disasters versus hazards have been discussed in the literature (see ref. 22), but have not previously been assessed empirically.

In order to compare tropical cyclones that do and do not result in disasters recorded by the EM-DAT, we construct a dataset that includes all country-storm exposures from 1996 to 2016 based on the IBTrACS dataset. We can then estimate a logistical regression model of the probability that an instance of tropical storm or cyclone exposure is included in the EM-DAT, given a vector of regressors that includes government effectiveness and real GDP per capita as well as controls for hazard exposure. Our results indicate that tropical storm and cyclone exposures that occur in wealthier countries with more effective governments are less likely to be included in the EM-DAT (*SI Appendix*, Table S15). While we cannot completely disentangle the selection effects, this result indicates that selection bias does not account for the direction of the governance–mortality estimates in our main results and lends further support to our hypothesis that more-developed countries have a higher capacity to avert disaster when exposed to hazard.

Institutions and Socioeconomic Conditions in the Cyclone Wind Field. We also investigate whether the protections afforded by effective national governments and other country-level attributes are inclusive of areas of the country with weaker institutions or marginalized groups. We select IMRs and settlements of politically excluded ethnic groups as proxies for the quality and inclusiveness of institutions at the wind field level. IMRs are linked to the quality of institutions via their role in the provision of public services (40, 42), such as health care, education, sanitation, and social safety nets that protect against food insecurity and malnutrition. Elevated infant mortality may reflect a lack of will or capacity in the provision of such services, or else that not all segments of the population benefit from them. The political exclusion of ethnic groups was selected to more specifically capture the effects of marginalization; we anticipate that death tolls will increase when governments lack accountability to portions of the affected population (43). This could occur because areas settled by excluded groups receive fewer resources, group members have less trust in or access to them, or marginalized groups are forced to settle in more physically vulnerable locations (7, 44). We exploit the spatial variability in where storms occur over nearly four decades (1979–2016) to capture whether the population in the wind field is relatively better or worse off than the national average by these metrics. This allows us to compare outcomes across events that occurred in the same country but under different local institutional and socioeconomic conditions. The construction of the wind field variables is described in *Materials and Methods* and further elaborated in *SI Appendix*.

The main results of the subnational analysis are presented in Fig. 4 and based on the negative binomial regression model estimated in *SI Appendix*, Table S18. Using a model that controls

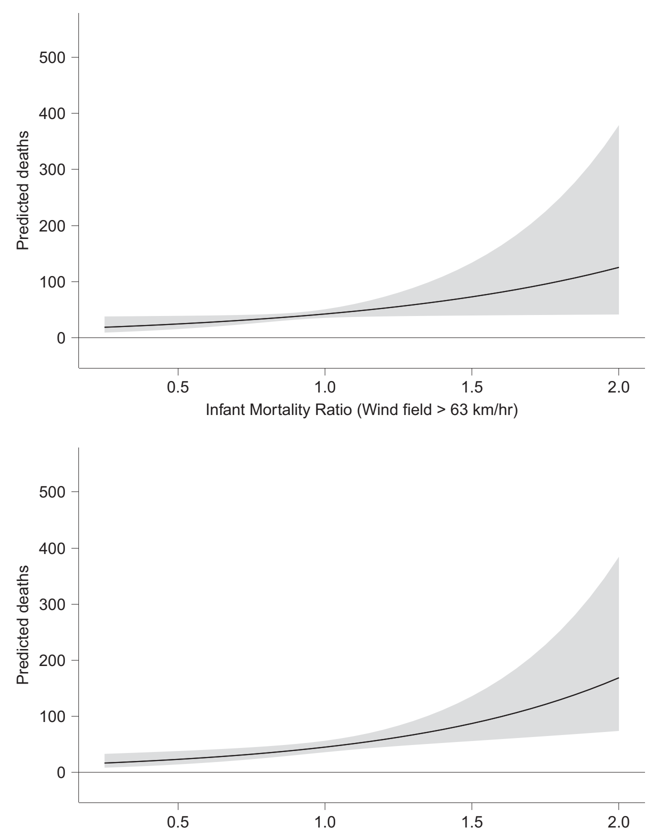

Fig. 4. Predicted effects of the wind field IM ratio on deaths. The IM ratio is the ratio of the IMR in the storm wind field compared to the national average. (*Top*) The predicted effect of the IM ratio in the tropical storm exposure zone (sustained winds of >63 km/h). (*Bottom*) The predicted effect of the IM ratio in the more intense tropical cyclone exposure zone (sustained winds of >119 km/h). Predictions are based on the estimated models presented in *SI Appendix*, Table S18. The shaded areas represent the 95% CIs.

for national socioeconomic conditions as well as hazard exposure, we find that death tolls are higher when IMRs are elevated within the cyclone wind field. For the tropical storm-strength wind field (sustained winds of >63 km/h), the model predicts an 11% increase in storm deaths when local IMRs are elevated by 10% above the national average. At higher wind speeds (sustained winds of >119 km/h), the effect is more pronounced; a 10% increase in wind field infant mortality is associated with a 14% increase in storm mortality. The results for these more intense tropical cyclone wind fields are robust to various permutations of the model and the dataset, while the results for the weaker tropical storm wind fields lose statistical significance in some alternative specifications (*SI Appendix*, Tables S19–S29).

The statistical relationship between elevated IMRs and disaster deaths may be interpreted in several ways. Infant mortality is a measure of public health and has also been employed as a proxy for overall well-being, poverty, or inequality (e.g., refs. 31, 39, 45, and 46), each of which is plausibly related to disaster deaths. However, the importance of within-country variation in IMRs clearly demonstrates that disaster deaths are not only a function of the national context and hazard exposure. Local vulnerabilities are important, and particularly so in areas that are exposed to sustained wind speeds in excess of 119 km/h, the "very dangerous" threshold for tropical cyclone winds (47).

Our analysis of the effects of politically exclusive institutions on disaster mortality is not conclusive and highlights the need for further research on this topic. Following the Ethnic Power Relations (EPR) classifications, we consider groups to be excluded from executive political power if they are powerless, discriminated against, or self-excluded (48, 49). By this measure, the effects of exclusion are not precisely estimated (*SI Appendix*, Table S18). However, we find that very few tropical cyclones in our dataset actually impact areas settled by groups that are discriminated against or self-excluded. Our measure of ethnic group exclusion therefore primarily captures the effects of powerless groups settled in the impact area (*SI Appendix*, Table S30). Powerless groups, which lack representation, may be less likely to be excluded from national protections compared to groups that are actively discriminated against. Our indicators of exclusion also do not unpack potentially important heterogeneities in the density of ethnic group settlements and the de facto and de jure forms of political power sharing (50–52).

Discussion

Our analysis generates empirical support for the role of governments and institutions in reducing tropical cyclone risk. First, we show that national government effectiveness is associated with lower mortality from tropical cyclones, independent of GDP per capita, health, and education. We then demonstrate the importance of within-country heterogeneities in vulnerability through global analysis of subnational institutional quality and tropical cyclone risk. Specifically, we find that death tolls are higher when IMRs, a proxy for the quality and inclusiveness of local institutions, are elevated compared to the national average within the cyclone wind field. These results lend support for general theories of how effective and inclusive institutions can moderate vulnerability and foster resilience to a range of shocks and stressors.

We acknowledge several limitations of this work. First, we rely on data that include only the direct, short-term disaster deaths. Our analysis does not capture how institutions may mediate longer-term mortality, for example, through their role in mitigating economic hardship or reestablishing health care and other services in the aftermath of the storm (14, 53). Second, these results may be sensitive to the data sources used to operationalize the latent concept of institutional capacity. Our analysis relies on the subjective WGI government effectiveness scores. While, to our knowledge, a suitable alternative measure of government effectiveness is not publicly available at present, we encourage future research to test the robustness of these findings using new or proprietary data sources. Future work could also investigate the importance of other facets of governance for disaster mortality, such as polity and sociopolitical goals (54, 55). Third, our data and research design are not suitable for demonstrating causality. The challenges of overcoming multicollinearity in the analysis of observational data and, in particular, disentangling different aspects of governance and the complex processes that underlie the correlation between income and institutions, are well documented (e.g., refs. 56–59). Our results, however, go beyond previous efforts, by demonstrating that the association between national government effectiveness and tropical cyclone mortality cannot be fully explained by indicators of income, health, or education. Finally, the trade-off of focusing on a single class of hazard is that it limits our ability to generalize these results to other types of natural disaster. However, our approach can be adapted to the study of additional hazards, scales, and outcomes to gain further insight into the role of institutions and economic development in risk reduction.

Our findings are salient to current questions about the intersection of institutions, sustainable development, and disaster risk, questions made more urgent under climate change. The intensity and rainfall of the strongest tropical cyclones are expected to increase under climate change (37, 60–62), and trends in population growth and sea level rise will further contribute to risk in the absence of effective adaptation (22, 37, 63). Many tropical cyclone-affected countries will also face increased risk from other climate change impacts, including extreme weather events such as droughts, floods, and heat waves (5). These challenges are amplified by uneven progress on eliminating poverty, hunger, disease, illiteracy, environmental degradation, and discrimination against women (5, 64). Enhancing institutions may have wide-ranging benefits for disaster risk reduction as well as climate adaptation and sustainable development. This underscores the value of understanding relationships between institutions and disasters.

Materials and Methods

Disasters occur when a population is exposed to hazardous conditions and is unable to adapt or cope. Understanding mortality from tropical cyclones therefore requires information about the spatial intersection of physical hazard and socioeconomic systems. Here, we describe the methods and data sources used to build our event-based dataset of tropical cyclone disasters that extends from 1979 to 2016. This is followed by a description of the econometric methods that underlie our results. The hazard exposure variables and the socioeconomic variables are summarized in *SI Appendix*, Tables S1 and S2; the source data and methods are also described in further detail in *SI Appendix*.

Dataset. Our approach recognizes the importance of accurately accounting not only for the intensity of the hazard but also for the number of people exposed to hazardous conditions and the local socioeconomic conditions of the affected population. Basic statistics such as a storm's maximum wind speed or minimum central pressure are indicators of hazard intensity rather than exposure, and therefore incomplete measures of the severity of the shock. Many intense storms never pass within striking distance of populated land or weaken sufficiently to pose little threat upon landfall. When intense storms do strike land, minor differences in storm trajectory can have large implications for the number of people exposed to hazardous conditions. The speed and longevity of a storm impacts the duration of wind exposure as well as the cumulative rainfall.

To translate from hazard to exposure, we develop a method to match storm tracks and rainfall to disaster data and then parametrically model the intensity and spatial extent of each storm. With the area of exposure spatially delineated, we can then determine the size and socioeconomic conditions of the population living there. In brief, this is done by first identifying the grid cells that fall within the storm's wind field, extracting the measures of interest for each of those grid cells (e.g., population, infant mortality), and then computing the average conditions in the wind field. Thus, while several variables in this analysis draw on subnational data specific to the area of the country impacted by the storm, these data are aggregated into country-storm measures. This allows for comparison with our principal outcome variable: the number of disaster deaths associated with each country-storm event. Our criteria for disaster are detailed in *SI Appendix*, section 2 and follow the EM-DAT, the source of the disaster mortality data for this analysis (1).

Measures of Hazard Intensity and Exposure. Tropical cyclone data obtained from the IBTrACS Project (2, 3) do not share a common identifier with the EM-DAT disaster data. The observations were therefore matched using a spatial algorithm that, for each disaster, looks for the closest storm in space and time. Automated matches between the EM-DAT and IBTrACS were manually reviewed for accuracy by consulting additional sources, such as storm reports published by governments and meteorological agencies.

Best track data consist of wind and pressure data georeferenced at 6-h intervals along the central track of the storm. In order to produce a spatial representation of storm winds, suitable for matching with gridded population and socioeconomic data, track data are interpolated and winds are modeled using a parametric tropical cyclone model (34). This is implemented using a globally adapted version of *stormwindmodel* in R (see *SI Appendix* for details) (33). The modeled winds are then rasterized at a 2.5-arc-minute resolution, and the spatial extent of the wind fields over land is mapped for each country-storm event. This is performed for multiple wind thresholds. Fig. 5 illustrates the steps of this process for a single country-storm event, the 2004 Cyclone Gafilo in Madagascar.

Once the wind hazard has been spatially delineated, we can then overlay the wind fields with population data to estimate the exposure. Time-variant, subnational population estimates from the Center for International Earth Science Information Network's Global Population Count Grid Time Series Estimates and Gridded Population of the World (Version 4.10) are interacted with the modeled wind fields to estimate the size of the populations exposed to winds of different intensities (36, 65). Rainfall exposure is based on the Climate Prediction Center Global Unified Gauge-Based Analysis of Daily Precipitation dataset, available at a 0.5° resolution from 1979 to present (38). Rainfall is represented by the maximum total rainfall over the duration of the storm for any grid cell in the country and within a 500-km buffer of the storm track.

This analysis is limited to the satellite era (1979+) of wind and rainfall data, and to more recent years (1996+) for specifications including national government effectiveness scores. Indian Ocean tropical cyclones are excluded from our main specifications, due to concerns about the quality and completeness of the data for this region during the study period. However, the main findings presented in this paper are robust to the inclusion or exclusion of any particular region, including the Indian Ocean basin. See *SI Appendix* for the sensitivity analyses and additional documentation of the Indian Ocean storms.

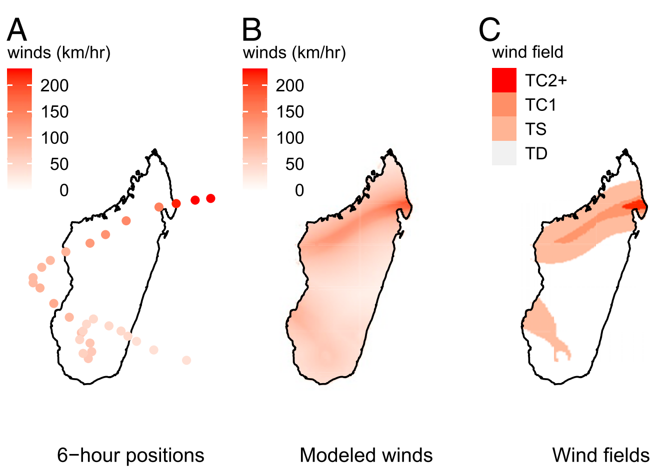

Fig. 5. Modeling tropical cyclone wind fields for Cyclone Gafilo (2004) in Madagascar. We begin with (*A*) the 6-hourly wind speeds and locations (2, 3). Using a parametric wind speed model (34) implemented in the software R (33), we then estimate (*B*) the maximum sustained wind speed over land at a 2.5-arc-minute resolution. Finally, we define (*C*) the spatial extent of the TD (Tropical Depression: <63 km/h), TS (Tropical Storm: 63–118 km/h), TC1 (Tropical Cyclone: 119–153 km/h), and TC2+ (Tropical Cyclone: > 153 km/h) wind fields.

Socioeconomic Variables. Country-level socioeconomic variables are matched to tropical cyclone events based on the year and the country. National indicators of income, health, and education are taken from the World Development Indicators (66) and other sources (67–69). The GDP per capita and IMRs are lagged by 1 y.

Following previous related work (e.g., refs. 10 and 22), we use the WGI to capture national government effectiveness, defined as the quality of public policies and service delivery by formal institutions (12, 70). The scores are based on surveys of public, private, and NGO experts combined using an unobserved components model. While perception-based measures are unavoidably imprecise, an advantage of the WGI methodology is the explicit characterization of the uncertainty. This allows us to conclude that there is meaningful variation in governance scores across the countries in our dataset.

Within countries, local institutional quality and inclusion are proxied using subnational IMRs and spatial data on the political exclusion of ethnic groups. For each storm, these variables are constructed for wind fields of multiple intensities (as illustrated in Fig. 5). Both the infant mortality and political exclusion variables are weighted by the grid cell population (36, 65), and therefore are restricted to the over-land wind field. The infant mortality ratio (IM ratio) is the ratio of the IMR in the storm wind field to the national IMR, based on data from the Poverty Mapping Project's Global Subnational Infant Mortality Rates for the year 2000 (35). Country dummies are included in all subnational models, as the resolution of the infant mortality data varies by country. Given that the underlying subnational IMR data are time invariant (for the year 2000), one concern is that infant mortality might be elevated in parts of the country due to the direct or indirect impacts of tropical cyclones. However, when we exclude the years 1999–2000 or only include the years 2001–2016 as a robustness check, the estimated effect of locally elevated IMR on disaster deaths remains consistently positive and, for the tropical cyclone strength wind fields, highly statistically significant (*SI Appendix*, Tables S19 and S20).

The population-weighted percentage of the wind field that is settled by an excluded ethnic group is also constructed. This is based on data from the EPR Dataset Family (48, 49, 71). The EPR provides annual data on politically relevant ethnic groups' access to state power, and classifies groups as excluded if they are powerless, discriminated against, or self-excluded. However, the excluded ethnic group settlements that overlap with the tropical cyclones are primarily classified as powerless rather than discriminated against or self-excluded. See *SI Appendix* for a discussion of the implications.

Methods

Tropical cyclone deaths y for event i are modeled using a negative binomial regression model. The use of a count data model is suitable given that storm deaths are nonnegative integer values. The simpler Poisson model is not used, because the data violate the equidispersion principle $E[y_i \mid \mathbf{x}_i] = Var[y_i \mid \mathbf{x}_i]$. The negative binomial regression model allows us to relax this assumption such that the variance depends on the mean and a dispersion parameter $\alpha = 1/\theta$. We use the Negbin 2 (NB2) form of the negative binomial regression model represented in Eqs. **2**–**4**, following Greene (ref. 72, p. 808). The NB2 model has several useful properties compared to other negative binomial models, including that it is robust to distributional misspecification (73). However, model standard errors may be inconsistent in cases of distributional misspecification (74). We therefore estimate robust standard errors for all negative binomial regressions presented in this analysis. The NB2 model is

$$\text{Prob}(Y = y_i \mid \mathbf{x}_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(y_i + 1)\Gamma(\theta)} r_i^{y_i}(1 - r_i)^{\theta}, \qquad [2]$$

where

$$\lambda_i = \exp(\mathbf{x}_i'\beta), \qquad [3]$$

and

$$r_i = \lambda_i/(\theta + \lambda_i). \qquad [4]$$

The characteristics of each country-storm event i, represented by the vector $\mathbf{x}_i$, include socioeconomic characteristics, measures of storm intensity and exposure, and geographic and other control variables. The parameters to estimate are β, θ.

One drawback of the negative binomial model is that it is not well suited to handle large outlier events. We therefore exclude events with more than 5,000 deaths from the negative binomial specifications. These outlier events

SOCIAL SCIENCES

are few in number, but catastrophic in their humanitarian impacts.† We therefore estimate comparable OLS models with a transformed dependent variable to accommodate these high-mortality events as a robustness check. As described in *SI Appendix*, the main results are robust to OLS estimation with and without the outlier events.

Data Availability. A replication package including the R code and data files generated for and analyzed during the current study has been deposited in the Cornell Institute for Social and Economic Research (CISER) Data & Reproduction Archive, https://doi.org/10.6077/89ba-bj79 (4). The replication package includes all publicly available and author generated source data. Due to copyright, the original EM-DAT data (1) is not included in the replication files; details on how the EM-DAT data can be accessed directly (for noncommercial use) are included.

†Our criteria exclude Thelma (1991) and Haiyan (2013) in the Philippines and Mitch (1998) in Honduras. See *SI Appendix* for additional Indian Ocean storms that exceed 5,000 deaths.

ACKNOWLEDGMENTS. We are grateful for the advice and guidance of Anand Patwardhan on this project. We also thank Anna Alberini, Brooke Anderson, Florio Arguillas, Christopher Barrett, Molly Elizabeth Brown, Christopher Foreman, Matthew Kahn, Richard Moss, Robert Sprinkle, Larry Swatuk, Mathieu Taschereau-Dumouchel, Brian Thiede, Catherine Warsnop, and seminar and conference participants at the American Geophysical Union, the International Studies Association, Cornell University, New York University, and the University of Maryland School of Public Policy. We acknowledge funding support from the University of Maryland Council of the Environment, the Anne G. Wylie Dissertation Fellowship, the University of Maryland, and Clark University. This material is based upon work supported, in part, by the US Army Research Laboratory and the US Army Research Office via the Minerva Initiative under Grant W911NF-13-1-0307.

1. D. Guha-Sapir, *EM-DAT: The Emergency Events Database* (Université Catholique de Louvain, Brussels, Belgium, 2018). www.emdat.be. Accessed 16 October 2017.
2. K. R. Knapp, M. C. Kruk, D. H. Levinson, H. J. Diamond, C. J. Neumann, The International Best Track Archive for Climate Stewardship (IBTrACS). *Bull. Am. Meteorol. Soc.* **91**, 363–376 (2010).
3. K. R. Knapp, H. J. Diamond, J. P. Kossin, M. C. Kruk, C. J. Schreck, International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 3.10 (NOAA National Centers for Environmental Information, 2017). https://doi.org/10.7289/V5NK3BZP. Accessed 8 November 2017.
4. E. Tennant, E. Gilmore, Replication package for government effectiveness and institutions as determinants of tropical cyclone mortality in Catalog No. 2845, Version 1 (2020). https://doi.org/10.6077/89ba-bj79. Deposited 22 October 2020.
5. Intergovernmental Panel on Climate Change, *Climate Change 2014: Impacts, Adaptation, and Vulnerability: Global and Sectoral Aspects*, V. R. Barros *et al.*, Eds. (Cambridge University Press, Cambridge, United Kingdom, 2014).
6. D. Alexander, Natural disasters: A framework for research and teaching. *Disasters* **15**, 209–226 (1991).
7. P. Blaikie, T. Cannon, I. Davis, B. Wisner, *At Risk: Natural Hazards, People's Vulnerability and Disasters* (Routledge, 2004).
8. United Nations International Strategy for Disaster Reduction, *Making Development Sustainable: The Future of Disaster Risk Management, Global Assessment Report on Disaster Risk Reduction* (United Nations, 2015).
9. A. Alberini, A. Chiabai, L. Muehlenbachs, Using expert judgment to assess adaptive capacity to climate change: Evidence from a conjoint choice survey. *Glob. Environ. Change* **16**, 123–144 (2006).
10. N. Brooks, W. N. Adger, P. M. Kelly, The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Glob Environ. Change* **15**, 151–163 (2005).
11. M. E. Kahn, The death toll from natural disasters: The role of income, geography, and institutions. *Rev. Econ. Stat.* **87**, 271–284 (2005).
12. D. Kaufmann, A. Kraay, M. Mastruzzi, Worldwide governance indicators: Methodology and analytical issues (World Bank Policy Research Working Paper No. 5430, World Bank, 2010). https://ssrn.com/abstract=1682130. Accessed 22 October 2018.
13. ISO 3166 Country Codes. https://www.iso.org/iso-3166-country-codes.html. Accessed 1 April 2016.
14. J. Anttila-Hughes, S. Hsiang, Destruction, disinvestment, and death: Economic and human losses following environmental disaster. SSRN:10.2139/ssrn.2220501 (18 February 2013).
15. S. M. Hsiang, A. S. Jina, The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones, National Bureau of Economic Research (2014) Working Paper Series. http://www.nber.org/papers/w20352. Accessed 18 November 2018.
16. S. M. Hsiang, D. Narita, Adaptation to cyclone risk: Evidence from the global cross-section. *Clim. Chang. Econ.* **3**, 1250011 (2012).
17. P. Peduzzi, H. Dao, C. Herold, Mapping disastrous natural hazards using global datasets. *Nat. Hazards* **35**, 265–289 (2005).
18. L. A. Bakkensen, R. O. Mendelsohn, Risk and adaptation: Evidence from global hurricane damages and fatalities. *J. Assoc. Environ. Resour. Econ.* **3**, 555–587 (2016).
19. W. N. Adger, S. Huq, K. Brown, D. Conway, M. Hulme, Adaptation to climate change in the developing world. *Prog. Dev. Stud.* **3**, 179–195 (2003).
20. F. Denton *et al.*, "Climate-resilient pathways: Adaptation, mitigation, and sustainable development" in *Climate Change 2014: Impacts, Adaptation, and Vulnerability: Global and Sectoral Aspects,* C. B. Field *et al.*, Eds. (Cambridge University Press, Cambridge, United Kingdom, 2014), pp. 1101–1131.
21. S. J. Camargo, S. M. Hsiang, "Tropical cyclones: From the influence of climate to their socioeconomic impacts" in *Extreme Events: Observations, Modeling, and Economics*, M. Chavez, M. Ghil, J. Urrutia-Fucugauchi, Eds. (American Geophysical Union, 2015), pp. 303–342.
22. P. Peduzzi *et al.*, Global trends in tropical cyclone risk. *Nat. Clim. Chang.* **2**, 289–294 (2012).
23. R. K. Pachauri, L. Mayer.., Eds. *Climate Change 2014: Synthesis Report* (Intergovernmental Panel on Climate Change, Geneva, Switzerland, 2015).
24. W. N. Adger, Social capital, collective action, and adaptation to climate change. *Econ. Geogr.* **79**, 387–404 (2003).
25. H. Eakin, M. C. Lemos, Adaptation and the state: Latin America and the challenge of capacity-building under globalization. *Glob. Environ. Change* **16**, 7–18 (2006).
26. N. Hossain, The 1970 Bhola cyclone, nationalist politics, and the subsistence crisis contract in Bangladesh. *Disasters* **42**, 187–203 (2018).
27. B. Howe, G. Bang, Nargis and Haiyan: The politics of natural disaster management in Myanmar and the Philippines. *Asian Stud. Rev.* **41**, 58–78 (2017).
28. B. K. Paul, Why relatively fewer people died? The case of Bangladesh's cyclone sidr. *Nat. Hazards* **50**, 289–304 (2009).
29. S. Veland, R. Howitt, D. Dominey-Howes, Invisible institutions in emergencies: Evacuating the remote indigenous community of Warruwi, Northern Territory Australia, from Cyclone Monica. *Environ. Hazards* **9**, 197–214 (2010).
30. W. N. Adger, Vulnerability. *Global Environ. Chang.* **16**, 268–281 (2006).
31. E. B. Barbier, J. P. Hochard, The impacts of climate change on the poor in disadvantaged regions. *Rev. Environ. Econ. Pol.* **12**, 26–47 (2018).
32. M. Pelling, The political ecology of flood hazard in urban Guyana. *Geoforum* **30**, 249–261 (1999).
33. B. Anderson *et al.*, Stormwindmodel: Model tropical cyclone wind speeds (2017). https://cran.r-project.org/web/packages/stormwindmodel/index.html. Accessed 17 August 2018.
34. H. E. Willoughby, R. W. R. Darling, M. E. Rahn, Parametric representation of the primary hurricane vortex. Part II: A new family of sectionally continuous profiles. *Mon. Weather Rev.* **134**, 1102–1120 (2006).
35. Center for International Earth Science Information Network, Poverty Mapping Project: Global Subnational Infant Mortality Rates (2005). http://dx.doi.org/10.7927/H4PZ56R2. Accessed 3 January 2018.
36. Center for International Earth Science Information Network, Gridded Population of the World, Version 4 (GPWv4): Population count adjusted to match 2015 revision of UN WPP country totals, revision 10, version 4 (2017). https://doi.org/10.7927/H4JQ0XZW. Accessed 3 January 2018.
37. K. J. E. Walsh *et al.*, Tropical cyclones and climate change. *Wiley Interdiscip. Rev. Clim. Change* **7**, 65–89 (2016).
38. National Oceanic and Atmospheric Administration, *CPC Global Unified Precipitation Data* (2018). https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html. Accessed 25 January 2018.
39. R. C. Briggs, Poor targeting: A gridded spatial analysis of the degree to which aid reaches the poor in Africa. *World Dev.* **103**, 133–148 (2018).
40. R. Pongou, B. K. Defo, Z. T. Dimbuene, Excess male infant mortality: The gene-institution interactions. *Am. Econ. Rev.* **107**, 541–545 (2017).
41. N. von Uexkull, M. Croicu, H. Fjelde, H. Buhaug, Civil conflict sensitivity to growing-season drought. *Proc. Natl. Acad. Sci. U.S.A.* **113**, 12391–12396 (2016).
42. A. Sirag, N. M. Nor, N. M. Raja Abdullah, J. A. Ghani, Public health financing and infant mortality: Does governance quality matter?*Publ. Finance Manag.* **17**, 341–368 (2017).
43. J. Busby, N. von Uexkull, *Climate Shocks and Humanitarian Crises* (Foreign Affairs, 2018).
44. J. M. Bretthauer, Conditions for peace and conflict: Applying a fuzzy-set qualitative comparative analysis to cases of resource scarcity. *J. Conflict Resolut.* **59**, 593–616 (2015).
45. P. D. C. Esty *et al.*, State Failure Task Force report: Phase II findings. *Environ. Change Secur. Proj. Rep.* **5**, 49–72 (1999).
46. S. Hillesund *et al.*, Horizontal inequality and armed conflict: A comprehensive literature review. *Can. J. Dev. Stud.* **39**, 463–480 (2018).
47. National Oceanic and Atmospheric Administration, Saffir-Simpson hurricane wind scale. https://www.nhc.noaa.gov/aboutsshws.php (2020). Accessed 1 January 2020.
48. L. E. Cederman, A. Wimmer, B. Min, Why do ethnic groups rebel?: New data and analysis. *World Polit.* **62**, 87–119 (2010).
49. M. Vogt *et al.*, Integrating data on ethnicity, geography, and conflict: The ethnic power relations data set family. *J. Conflict Resolut.* **59**, 1327–1342 (2015).
50. N. C. Bormann, Power sharing: Institutions, behavior, and peace. *Am. J. Polit. Sci.* **63**, 84–100 (2019).
51. J. Busby, Taking stock: The field of climate and security. *Curr. Clim. Change Rep.* **4**, 338–346 (2018).

52. K. W. Strøm, S. Gates, B. A. Graham, H. Strand, Inclusion, dispersion, and constraint: Powersharing in the world's states, 1975–2010. *Br. J. Polit. Sci.* **47**, 165–185 (2017).
53. N. Kishore *et al.*, Mortality in Puerto Rico after Hurricane Maria. *N. Engl. J. Med.* **379**, 162–170 (2018).
54. B. M. Haddad, Ranking the adaptive capacity of nations to climate change when socio-political goals are explicit. *Glob. Environ. Change* **15**, 165–176 (2005).
55. A. Lesnikowski *et al.*, National-level factors affecting planned, public adaptation to health impacts of climate change. *Glob. Environ. Change* **23**, 1153–1163 (2013).
56. D. Acemoglu, S. Johnson, J. A. Robinson, P. Yared, Income and democracy. *Am. Econ. Rev.* **98**, 808–842 (2008).
57. C. Boix, Democracy, development, and the international system. *Am. Polit. Sci. Rev.* **105**, 809–828 (2011).
58. R. L. Porta, F. Lopez-de-Silanes, A. Shleifer, R. Vishny, The quality of government. *J. Law Econ. Organ.* **15**, 222–279 (1999).
59. R. D. Putnam, *Making Democracy Work, Civic Traditions in Modern Italy* (Princeton University Press, Princeton, NJ, 1994).
60. J. H. Christensen *et al.*, "Climate phenomena and their relevance for future regional climate change" in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, T. F. Stocker *et al.*, Eds. (Cambridge University Press, Cambridge, United Kingdom, 2013), pp. 1217–1308.
61. Intergovernmental Panel on Climate Change, *Climate Change 2013: The Physical Science Basis: Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, T. F. Stocker *et al.*, Eds. (Cambridge University Press, Cambridge, United Kingdom, 2013).
62. J. P. Kossin, K. R. Knapp, T. L. Olander, C. S. Velden, Global increase in major tropical cyclone exceedance probability over the past four decades. *Proc. Natl. Acad. Sci. U.S.A.* **117**, 11975–11980 (2020).
63. R. Mendelsohn, K. Emanuel, S. Chonabayashi, L. Bakkensen, The impact of climate change on global tropical cyclone damage. *Nat. Clim. Change* **2**, 205–209 (2012).
64. United Nations *The Millennium Development Goals Report 2015* (United Nations, 2015).
65. Center for International Earth Science Information Network, Global Population Count Grid Time Series Estimates (2017). https://doi.org/10.7927/H4CC0XNV. Accessed 3 January 2018.
66. World Development Indicators (2020). https://datacatalog.worldbank.org/dataset/world-development-indicators. Accessed 13 May 2020.
67. R. C. Feenstra, R. I. Inklaar, M. P. Timmer, Penn World Table (Version 9.1, 2020). https://doi.org/10.15141/S50T0R. Accessed 12 May 2020.
68. Census and Statistics Department, Hong Kong Annual Digest of Statistics: 2016 Edition (Hong Kong Special Administrative Region, 2016).
69. Ministry of Health and Welfare, 2014 health and welfare indicators (Ministry of Health and Welfare ROC (Taiwan), 2017). https://www.mohw.gov.tw/lp-134-2.html. Accessed 18 August 2017.
70. World Governance Indicators (2020). https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators. Accessed 13 May 2020.
71. J. Wucherpfennig, N. B. Weidmann, L. Girardin, L. E. Cederman, A. Wimmer, Politically relevant ethnic groups across space and time: Introducing the GeoEPR Dataset1. *Confl. Manag. Peace Sci.* **28**, 423–437 (2011).
72. W. H. Greene, *Econometric Analysis* (Prentice Hall, ed. 7, Boston, MA, 2012).
73. A. C. Cameron, P. K. Trivedi, *Regression Analysis of Count Data* (Cambridge University Press, ed. 2, New York, NY, 2013).
74. J. M. Hilbe, *Modeling Count Data* (Cambridge University Press, New York, NY, 2014).